"8.2.2. specifiskā atbalsta mērķa "Stiprināt augstākās izglītības institūciju akadēmisko personālu stratēģiskās specializācijas jomās"
trešās atlases kārtas projektiem[1]

Mg. math., Mg. oec. **Santa Lemša**
Doctoral candidate of the joint doctoral study programme "Economics and Business"

CHALLENGES OF ADVANCED ANALYTICS ADOPTION IN THE ORGANIZATIONS OF LATVIA

Doctoral thesis

Research supervisor
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Abstract

The title of the doctoral thesis of Santa Lemsa is "Challenges of advanced analytics adoption in the organizations of Latvia".

The goal of the doctoral thesis is the development of an advanced analytics ecosystem maturity level assessment and recommendations tool for organizations.

The scientific novelty lies in the development of an advanced analytics ecosystem maturity assessment model for the organizations of Latvia, marking the first of its kind. It provides an opportunity for any organization in Latvia to assess their advanced analytics ecosystem maturity level and receive recommendations on how to improve it. As well, a methodology for assessing the level of maturity of advanced analytics has been developed, which can be used internationally.

The developed advanced analytics maturity assessment model and recommendation tool allow for the assessment of the maturity level of advanced analytics in Latvian organizations. The online tool provides an opportunity for any organization in Latvia to obtain free recommendations on how to implement, maintain, or improve advanced analytics solutions within the organization, following the principle of Open Science.

The doctoral thesis is structured into 4 sections. The first section covers an overview of the advanced analytics progress over the years and its definition, impact on business performance and the competitive advantage gains from advanced analytics globally and in Latvia. The author introduces a new Latvian term 'augstākā analītika'. The second section provides an explicit review and analysis of existing advanced analytics maturity assessment models and analytics maturity assessment tools available online. The third section describes the underlying approach and methodology used to build the advanced analytics ecosystem maturity assessment and recommendation tool. It covers questionnaire design, the data collection approach, and the methodology for developing a maturity model. The fourth section is devoted to the analysis of data obtained during the survey, the development of an advanced analytics ecosystem maturity assessment model, development of a set of recommendations for each advanced analytics maturity level. The assessment and recommendation tool has been developed and made available for online use.

The main text is laid out on 187 pages and includes 26 figures, 16 tables, as well as 21 appendices. The reference list of the doctoral thesis includes 165 sources.

Keywords: *advanced analytics, advanced analytics maturity, advanced analytics maturity assessment, advanced analytics maturity assessment model, advanced analytics maturity assessment tools.*

Anotācija

Santas Lemšas doktora darba nosaukums ir “Augstākās analītikas ieviešanas izaicinājumi Latvijas organizācijās”.

Promocijas darba mērķis ir izstrādāt organizāciju augstākās analītikas ekosistēmas brieduma līmeņa novērtēšanas un rekomendācijas sniedzošu rīku, kas ir pieejams jebkuram interesentam bez maksas tiešsaistē.

Zinātniskā novitāte ir pirmo reizi izstrādāts organizāciju augstākās analītikas brieduma līmeņa novērtēšanas modelis Latvijai. Tas sniedz iespēju jebkurai organizācijai Latvijā novērtēt savu augstākās analītikas ekosistēmas brieduma līmeni un saņemt ieteikumus, kā to uzlabot. Kā arī izstrādāta augstākās analītikas brieduma līmeņa novērtēšanas metodoloģija, kas var tikt izmantota starptautiski.

Izstrādātais organizāciju augstākās analītikas brieduma līmeņa novērtēšanas modelis un rekomendācijas sniedzošais rīks ļauj noteikt augstākās analītikas brieduma līmeni Latvijas organizācijās. Sekojot atvērtās zinātnes principiem, tiešsaistē pieejamais rīks ir pieejams bezmaksas ikvienai organizācijai Latvijā, kas dod iespēju iegūt rekomendācijas kā ieviest, uzturēt vai uzlabot augstākas analītikas risinājumus organizācijā.

Promocijas darbs sastāv no 4 nodaļām. Pirmā nodaļā ir sniegts pārskats par augstākās analītikas progresu gadu gaitā un definīciju, ietekmi uz uzņēmējdarbības sniegumu un to, kā augstākās analītikas priekšrocības tiek iegūtas visā pasaulē un Latvijā. Autore ieviesa latviešu valodā jauno terminoloģiju ‘augstākā analītika’ (advanced analytics). Otrajā nodaļā ir sniegts esošo augstākās analītikas brieduma novērtēšanas modeļu un tiešsaistē pieejamo analītikas brieduma novērtēšanas rīku pārskats un analīze. Trešajā sadaļā ir aprakstīta pieeja un metodoloģija augstākās analītikas ekosistēmas brieduma novērtējuma un ieteikumu rīka izveidei. Tas aptver anketu izstrādi, datu vākšanas pieeju, brieduma modeļa izstrādes metodoloģiju. Ceturtā nodaļa veltīta aptaujas laikā iegūto datu analīzei, augstākās analītikas ekosistēmas brieduma novērtējuma modeļa izstrādei, ieteikumu kopas izstrādei katram augstākās analītikas brieduma līmenim. Tiešsaistes vidē publicēts un pieejams lietošanai augstākās analītikas brieduma līmeņa novērtēšanas un ieteikumu rīks.

Pamatteksts ir atrodams uz 187 lappusēm, ilustrēts ar 26 attēliem, 16 tabulām un 21 pielikumu. Promocijas darba atsauču sarakstā iekļautas 165 literatūras vienības.

Atslēgvārdi: *augstākā analītika, augstākās analītikas briedums, augstākās analītikas brieduma noteikšanas modeļi, augstākās analītikas brieduma noteikšanas rīki.*

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Abbreviations

AA – Advanced Analytics

AI - Artificial Intelligence

IT – Information Technologies

IoT - Internet of Things

EU – Europe Union

HBR - Harvard Business Review

MTSloan - Massachusetts Institute of Technology Sloan School of Management

MIT – Massachusetts Institute of Technology

ICT - information communication technologies

SQL - structured query language

OLAP - online analytical processing

ML – Machine Learning

CSB - Central Statistical Bureau Republic of Latvia

ROI - Return on Investment

ROE - Return on Equity

NACE2 - Statistical Classification of Economic Activities in the European Community, Revision 2

ROC - Receiver Operating Characteristic

AUROC - Area Under the Receiver Operating Characteristic Curve

EBITA - Earnings before interest, taxes, and amortization

CSR - Corporate Social Responsibility

EDIC - Eiropas Digitālās inovācijas centrs

IIA - International Institute for Analytics

HBS - Harvard Business School

WEF – World Economic Forum

NRI – Network Readiness Index

DESI – Digital Economy and Social Index

INTRODUCTION

Advanced analytics is one of the core tools to provide competitive advantage, sustainable development and foster productivity of the organization. Digital transformation and advanced analytics are two key trends in the emerging age of data, analytics, and automation. Advanced analytics is the application of predictive and prescriptive models to analyse large, complex datasets in order to make critical business decisions. Digital transformation is the process of transforming how businesses operate when faced with digital disruption. Advanced analytics is often a crucial component of digital transformation. It plays a significant role in this process and helps organizations harness the power of data and insights to drive meaningful changes and stay competitive in the evolving digital landscape.

In this light, the future of the digital universe promises further growth driven by the development of technologies and mobile devices. This expansion is caused not only by the shift to online activities, but also by the interconnection of all devices to the Internet, which results in the generation of substantial data volumes. The data universe is growing very fast. According to Statista (2023), the total amount of data created, captured, copied, and consumed globally is forecast to increase from 64.2 zettabytes in 2020 to more than 180 zettabytes in 2025.

Briefly, a ‘data tsunami’ is imminent and shows no signs of slowing down. However, the question of how to harness it and leverage it as a competitive advantage remains unanswered.

The potential value of data is uncovered only when data-driven decision-making becomes a culture of organizations, similar to the vital role of blood circulation in the body. Data-driven decision-making entails leveraging factual information, metrics, and data to shape strategic business decisions that are in harmony with organization’s goals, objectives, and initiatives. Several studies argue that in order to establish data-driven decision-making, organizations need to introduce maximally automated processes to manage and use diverse and fast-moving data from internal and external sources to turn that information into deep and colourful insights (Gandomi & Haider, 2015). New approaches, algorithms, tools and platforms help to gain insights from large volumes of unstructured and structured data, and methods which ensure so called advanced analytics (United States Government Accountability Office, 2016). The latest research indicates an overwhelming advantage among organizations that are leaders in AI adoption across all business functions versus those that are not so proficient in this area. A survey conducted by the Harvard Business Review Analytics Services for Google Cloud (2022) obtained answers from 366 international executives who were familiar with organization's data and analytics strategies. The study shows that data and AI leaders outperform in almost all business metrics showing higher year-on-year growth, such as revenue growth by 77% vs 61% for other organizations, operational efficiency improvement by 81% vs. 58%, customer loyalty and retention 77% vs. 45%, employee satisfaction 68% vs. 39%, and IT cost predictability 59% vs. 44%. There is a tangible effect on sustainability where big data and advanced analytics are recognised as one of the drivers to improve sustainability in production and supply chain management (Hur S. et al., 2022).

Advanced analytics can be described as the use of complex data analysis techniques, such as machine-learning, artificial intelligence, and predictive analytics, to gain insights from data. Advanced analytics can be used to identify patterns, trends, and correlations in data that would otherwise be difficult to detect. It can also be used to make predictions about future outcomes and to identify opportunities for improvement. Advanced analytics plays a crucial role in shaping, influencing, and driving various aspects of the economy and the business world. Every day, countless business decisions are made to guide an organization's daily operations in meeting its financial and strategic goals. Advanced analytics equips decision-makers with the tools needed to make informed, data-driven decisions, leading to enhanced resource allocation, optimized business processes, improved risk management, support for innovation and product development, and strengthened fraud detection and security, as well as effective investment and asset management. Advanced analytics can help organizations make better decisions, improve operational efficiency, and gain a competitive advantage. For example, a predictive model which allows to assess a potential customer and facilitates a company to make an online real-time decision regarding further actions with this customer, whether to provide services or not, in what quality and at what price. Also, machine learning algorithms are used to identify and prevent the company from falling victim to fraudsters, which is achieved using internal data, digital footprint and device-provided data. The competition between companies is very tough and usually requires many business decisions on the company's part before launching a product or communication with potential customers. One of differentiators of success is the ability to make decisions that support customers' values and preferences. To ensure faster and smarter decision-making, organizations are compelled to use advanced analytics to analyse the past, understand the present behaviour and predict and influence future events, actions, decisions, and behaviour.

By implementing advanced analytics into operations, companies significantly increase control over daily business decisions, ensuring a higher potential to meet their business goals (Apte et al., 2003). According to Lee Y.S. et al, (2022), intensity of adoption of new advanced analytics can substantially influence such business metrics as revenue, where organizations with advanced analytics adoption intensity above 25% demonstrated revenue growth of 24%, but those below 25% showed no growth.

The research on the correlation between data-driven business decision-making and the performance of a company shows 5% higher productivity and 6% higher profitability in comparison to companies with less developed data-driven business decision-making (McAfee & Brynjolfsson, 2012). Studies conducted by the European Parliamentary Research Service (Davies, 2016) revealed a 5-10% higher productivity growth for data-driven organizations. Advanced analytics can provide significant benefits, decreasing administrative costs by 15-20% (assessment based on Europe's 23 largest governments) in the government sector through improvement of efficiency, decreased instances of fraud and mistakes, and increased tax collection.

Looking into the recent past, as noted by Kim and Gardner (2015), it is possible to observe that 83% of firms operating within the finance industry across North America, Europe, and Asia recognized data as their most valuable strategic asset. At the same time organizations claim that they are good at data management, but regarding advanced analytics 31% assess themselves as immature. At the same time, 75% of these firms rate themselves as above average or excellent in their ability to get meaningful insights and additional value to competitiveness from data. Regarding advanced analytics maturity, large organizations see themselves as mature. From regional perspectives, North America has been rated as more skilled than Europe or Asia. The EPRS (2016) briefing suggests that Europe lags behind the USA in adopting big data and advanced analytics. Still, Europe is a major player in the big data market, with some top companies in the field. At the same time, 70% of the data market are concentrated in the UK, Germany, France, Spain and Italy. Exploring recent comparisons on how regions and countries develop in the digital environment, we still see the United States in leading positions based on the Portulans Institute (2022) Network Readiness Index, and it holds strong positions by all 4 pillars – technologies, people, governance and impact. Europe also boasts strong positions, with the Scandinavian countries - Sweden, Norway, Finland, and Denmark - dominating the top 10 rankings in the region. Based on DESI (2022), the EU aims for more than 75% of EU companies to adopt AI technologies by 2030, however the current adoption rate of AI technologies in the European Union is considerably low, at

8%. The leaders are Denmark with 24% of companies using AI, followed by Portugal at 17% and Finland at 16%. Some countries have levels close to 10%, while Latvia reports that 4% of companies use AI technologies. Unfortunately, Latvia is highlighted as a country with the slowest development pace in the last 5 years, compared to other member states. Latvia's main factor contributing to its low DESI ranking is integration of digital technologies (23rd place among the 27 EU countries) which is mostly influenced by the SME segment and their digital intensity. However, the positions where large enterprises are measured in almost all drivers are below the EU average, resulting in a total digital intensity of only 38%, which is far below the EU average of 55%. It raises the question of what can be done to improve Latvia's position in the global market.

In the context described above, it can be argued that establishing advanced analytical systems or upgrading existing analytical tools is not simply 'nice to have' but rather a 'must have' for sustaining a competitive advantage. This seems to be even more important for industries in which not only the digital universe provides data (i.e., big data), but also internal data collection generates large data volumes. Thus, the seemingly logical questions to ask are: What further challenges can we expect regarding data management (infrastructure, storage, accessibility, quality, privacy, techniques, skills, experience, strategy, costs etc.) and how can we overcome them? What would it cost for organizations?

The context of Latvia has been chosen for the study due to data availability reasons. Nonetheless, it is worth noting that Latvia is part of the 'global data universe', making this topic relevant for organizations in the country as well. Indeed, the digital world has no borders, and from Latvia, it is possible to provide digital services or conduct business worldwide. Several studies have already attempted to provide with some insights into the question of whether Latvia's progress in information technologies and the opportunities offered by the digital universe are sufficiently advanced? The Global Information Technology Report, for instance, presents the Networked Readiness Index (NRI), which indicates how countries leverage the potential of information, communication technologies and digital transformation to increase competitiveness and well-being. According to the Global Information Technology Report 2016, Latvia was ranked in the 32nd out of 139 countries by the Networked Readiness Index (NRI). Unfortunately, the NRI 2022 shows a decline for Latvia, dropping to 39th place out of 131 countries. However, neighbouring Baltic states have higher rankings, with Estonia at 22nd place (NRI 2022) compared to 22nd place (NRI 2016) and Lithuania at 33rd place (NRI 2022) compared to 29th place (NRI 2016). One explanation for Latvia's relatively low ranking in this Index is the significant impact of the

People and Technology pillars, in which Latvia is not performing well. The pillar Technology serves as the core of the network economy, measuring people's access to information and communication technologies (ICT), their engagement with content in the digital environment (such as GitHub), research findings derived from scientific and technical articles, mobile app creation, and a country's readiness and utilization of Artificial Intelligence (AI), the Internet of Things (IoT). Another low-ranking pillar for Latvia is People, which assesses technology skills, productive usage of technologies, and how people apply ICT, both by individuals, businesses, and government. The author observes the same trend in the Digital Economy and Society Index DESI, where Latvia falls behind EU average numbers, but in case of subfactor Integration of Technologies it stands 4th from the bottom.

In the context of above discussion and considering that an advanced analytics ecosystem maturity level assessment has not been conducted in Latvia, nor is there an available tool to asses maturity levels in Latvian organizations and obtaining recommendations for the next steps toward becoming data-driven organizations, this doctoral thesis focuses on the development of a recommendation tool. This tool aims to evaluate and improve the advanced analytics ecosystem within Latvian organizations. Its goal is to seamlessly integrate advanced analytics into daily data-driven decision-making processes, ultimately boosting revenue, optimizing costs, and automating operations to ensure the sustainability of the organization. The findings can be used as a recommendation set for companies that are planning to implement advanced analytics, increase their overall analytics maturity, or adopt advanced analytics in their daily decision-making.

Within this doctoral thesis, the author defines advanced analytics as the utilization of large volumes of structured, semi structured or unstructured data. Complex data mining and analysis techniques, such as machine learning, artificial intelligence, and predictive analytics, are employed to gain insights from data. The concept of an advanced analytics ecosystem is understood as the interaction between technology, data, tools, techniques, processes, analytics, culture, and people within an organization. An advanced analytics ecosystem is a comprehensive framework that orchestrates the entire data analytics process within an organization. It's designed to seamlessly integrate a variety of elements, including state-of-the-art technologies, diverse data sources, specialized analytical tools, advanced methodologies, streamlined processes, and a culture of data-driven decision-making. The ecosystem leverages these components to facilitate the collection, storage, analysis, and interpretation of data to derive actionable insights. It fosters a collaborative environment where cross-functional teams work together to harness the power of data and create innovative solutions. The ultimate goal of an advanced analytics ecosystem is to empower organizations to make data-informed decisions, enhance operational efficiency, drive innovation, and gain a competitive edge in an increasingly data-centric world. By continually evolving and adapting to emerging technologies and market trends, it ensures that organizations remain agile and effective in their analytics capabilities. The advanced analytics ecosystem can be assessed from a maturity perspective, and organizations can be classified into specific maturity levels based on their technologies, data managements, overall culture, analytics processes, people, skills and various other factors that describe their utilization of data, analytics, technologies, data-driven decision-making, and process automation.

Research object: The advanced analytics ecosystem.

Research subject: Maturity level of the advanced analytics ecosystem.

Research goal: Develop an advanced analytics ecosystem assessment and recommendation tool.

To address the goal, research can be performed through the following tasks:

1) Review and analysis of academic and industry leading practitioners and organizations publications, researches, surveys and books on advanced analytics, analytics maturity assessment models and tools, and their impact on business performance:
    a. Historical evolution;
    b. Advanced analytics in the organizations of Latvia,
    c. Existing models and tools;
2) Development of an overall approach for building the model and tool based on literature review;
3) Development of an analytics maturity assessment model specific to Latvia;
4) Development of an analytics maturity assessment and recommendations tool for Latvia;
5) Formulate a set of recommendations to improve the existing state of advanced analytics or set up advanced analytics in the organization.

The current research faces the several research questions:

1) What is the overall level of the advanced analytics ecosystem maturity in Latvia?
2) What are the existing models/approaches for assessing advanced analytics maturity?
3) How can the best practices from the existing approaches be adapted to build a new advanced analytics ecosystem assessment model for Latvia?

4) What challenges are associated with the adoption of advanced analytics in organizations in Latvia, and what actions and initiatives can be undertaken to overcome them?

However, while models for advanced analytics maturity assessment can be found, there is a limited disclosure of the specific methodology for developing such models. The assessment process, specific factors and their weight in categorizing an analytics maturity level are more within the realm of analytics sector knowledge rather than transparently disclosed full methodologies that ensure reproducibility or validation of the models (Krol & Zdonek, 2020). Another issue involves time, data volumes, and the rapid development of technologies that requires regular adjustments to the model.

Thesis to be defended:

1) Incorporating advanced analytics enhances an organization's performance (financial, marketing, risk, quality, satisfaction, growth) and competitive advantage.
2) Assessing the maturity level of advanced analytics provides an opportunity for any organization to implement, maintain, and improve analytical solutions in line with the latest technological advancements.
3) The methodology developed in the doctoral thesis allows for the assessment of the maturity level of advanced analytics in Latvian organizations and can also be applied in other countries.

Research period

The research period can be divided into three periods. Literature review and analysis took place from 2020 to 2023. A quantitative online survey was conducted from December 20, 2021, to March 31, 2022. Survey data analysis and modelling was performed from June 2022 to June 2023.

Theoretical background

In the development of the doctoral thesis, the author explored academic and professional literature, research, surveys, and case studies. The author explored literature and researches on the following topics: advanced analytics, analytics maturity assessment models and tools, advanced analytics development, implementation, and their impact on business performance. This exploration was based on the following scientific publications: International Journal of Production Economics, Journal of Business Research, Business and Information Systems Engineering, International Journal of Information Management, Technovation, Journal of Personal Selling and Sales Management, Journal of Big Data, Information Systems Frontiers. According to SCImago Journal Rank (2022) all the mentioned journals are ranked in Quartile 1. The journals are accessible through databases such as SCOPUS, Web of Science, IEEE Xplore, JSTOR, Elsevier ScienceDirect, and MDPI.

As very valuable sources, world-class interdisciplinary and business magazines like the research-based magazine published by Massachusetts Institute of Technology Sloan School of Management (MTSloan) were used. The magazine covers topics such as digital transformation, innovation, leadership, strategy, sustainability, and social impact. Another notable source to mention is the Harvard Business Review, a general management magazine and digital platform published by Harvard Business Publishing, a wholly-owned subsidiary of Harvard University. HBR covers a wide range of topics that are relevant to various industries, functions, and regions. MIT Sloan and HBR mostly focused on Management of Technology and Innovation, Business and International Management, Decision Sciences, Strategy and Management. According to SCImago Journal Rank (2022) the mentioned journals are ranked in Quartile 2.

One more valuable source to mention is the International Institute for Analytics (IIA), which conducts numerous research projects and is led by the widely known academic and practitioner in Analytics, Tom H. Davenport. Tom Davenport is the President's Distinguished Professor of Information Technology and Management at Babson College, the co-founder of the International Institute for Analytics, a Fellow of the MIT Initiative for the Digital Economy, and a Senior Advisor to Deloitte Analytics. He has written or edited twenty books and contributed to over 250 print and digital articles, in addition to numerous other publications. He has been at the forefront of the Process Innovation, Knowledge Management, and Analytics and Big Data movements. He pioneered the concept of "competing on analytics" and his most known book is "Competing on Analytics: The New Science of Winning" (2007).

The author finds it necessary to mention consultancy companies such as McKinsey & Company, Gartner, and Deloitte, as they conduct regular and in-depth research and publish their findings in the field of advanced analytics.

Considering that the field of analytics is multidisciplinary, various researchers have made significant contributions. Summarizing the scientific research, the following researchers can be highlighted: Thomas H. Davenport, renowned for his research in business analytics and big data, and his work has influenced the adoption of analytics in organizations (SCOPUS: h-index = 43); Jeanne G. Harris, an author, researcher, and teacher in the field of business analytics, competing on analytics, analytics at work, digital transformation, and IT strategy (SCOPUS: h-index = 14); Erik Brynjolfsson, known for extensive research on big data and analytics, artificial intelligence, productivity paradox, digital transformation, innovation, platform economy, and social welfare (SCOPUS: h-index = 52); Bart Baesens, an internationally known data analytics consultant and author of several books and papers on topics such as predictive analytics, data mining, web analytics, fraud detection, and credit risk management (SCOPUS: h-index = 54); Jan Vanthienen, mostly recognized for his contributions to business process modelling, process mining and business engineering, processes and decisions, business analysis and analytics (SCOPUS: h-index = 39).

The doctoral thesis was developed based on actual EU policies, regulatory acts, and documents related to advanced analytics, such as regional policies and Europe Union funds for digital transformation, digital strategy. The National Development Plan for 2021-2027 for Latvia is one of core documents where significant attention is given to technologies, digital competence and digitization as important tools to support business, inclusion, opportunities and well-being. Another document that is closely related and provides a more focused and in-depth insight is "Guidelines for Science, Technology Development, and Innovation for 2021.-2027." document, as well as the Research and Innovation strategy for smart specialization - RIS3.

Methods

The doctoral thesis is based on a combination of quantitative and qualitative research methods. The author conducted a thorough review and analysis of publications by academic and industry-leading practitioners and organizations, employing qualitative research methods such as monographic or descriptive methods, content analysis, the analysis of regulatory documents, study of policy planning documents, grouping, comparison, and generalization. Additionally, an analysis of publicly available tools to assess advanced analytics ecosystem maturity was performed, with the aim of providing recommendations to maintain or improve the maturity level.

Quantitative research methods were employed for data collection, analysis, and model development. A comprehensive online survey was conducted from December 20, 2021, to March 31, 2022, to create a Latvia-specific tool for assessing advanced analytics maturity and providing recommendations. During the survey were collected 555 responses. To ensure the success of the online survey, a survey design was developed, including the use of the Likert scale technique, the determination of the sample size, and the identification of channels to attract respondents. Central Statistical Bureau of the Republic of Latvia was used as a source to create representative data set and validate it. Data analysis was carried out using statistical methods, including descriptive statistics, correlation analysis, and analysis of variance

(ANOVA). The model was developed using logistic regression. Online survey developed using Qualtrics - online survey platform. Quantitative data were analysed and modelled using MS Excel and R. Website building platforms JotForm utilized to facilitate the automated assessment of specific organizations and the generation of a set of downloadable recommendations.

Novelty and impact

Comprehensive models and tools for assessing the maturity of advanced analytics are available in the scientific literature and previous researches, but existing studies lack an actionable principle suitable for local conditions. While the literature reports the impact of advanced analytics on organizational performance, there is limited information on the challenges and steps required to leverage advanced analytics.

To address these shortcomings, a perspective based on Latvian organizations has been employed in the research, aiming to develop and test a model that describes and evaluates the maturity of advanced analytics in Latvian organizations and the challenges they need to face during the implementation of advanced analytics. The author obtains answers to the research questions through a survey of 555 representatives of Latvian organizations, using a previously created and tested questionnaire. The author's contribution lies in providing insights and recommendations for enhancing the utilization of advanced analytics.

The author conducts an assessment of the maturity level of the advanced analytics ecosystem in organizations in Latvia. First of all, the maturity level of the advanced analytics ecosystem can be employed for theoretical analysis, enabling a deeper understanding of the impact of advanced analytics on economic processes such as growth, competitiveness and employment. Thus, new research should be performed to assess the impact. Secondly, the advanced analytics ecosystem maturity level in the organizations of Latvia can be used for policy development regarding digital transformation, advanced analytics, automation, big data, and data-driven decisioning. Policy development can be undertaken by any interested party at any level, whether it's the government, an organization, or a department head. Thirdly, the assessment of the advanced analytics ecosystem maturity level is an investment in any organization’s strategy. It helps organization managers better understand the development directions of big data and advanced analytics. No assessment of the advanced analytics ecosystem maturity level has been conducted in Latvia so far, and there has been no scientific research dedicated to this assessment in Latvia. In this context, the author's research solves the current task of advanced analytics:

1. Developed an advanced analytics assessment methodology;

2. Developed a model to assess the advanced analytics ecosystem maturity level;
3. Developed a tool to assess the maturity level of the advanced analytics ecosystem and provided a relevant set of recommendations to maintain or improve the advanced analytics level (access location: http://www.raaconsulting.lv/home-1/)
4. Advanced analytics terminology introduced in Latvian – 'Augstākā analītika'.

The advanced analytics maturity assessment approach developed can be applied to any country or region. While the model developed for Latvia could be tested in Estonia and Lithuania, it would require conducting research in these countries to gather data and validate the hypothesis. Specifically, the research aims to determine whether the model, originally designed for Latvia using Latvian data, can effectively assess the maturity level of advanced analytics in Estonia and Lithuania.

Structure

This Doctoral thesis comprises an introduction, four sections, conclusions, suggestions, a list of references, and appendices. Section one provides a historical evolution of advanced analytics and its connection to business processes and overall performance. Section two describes existing advanced analytics maturity assessment models, tools, and localization issues. The third section describes the approach to building an advanced analytics maturity assessment model and tool, while section four presents the results and findings. The core text of the doctoral thesis comprises 187 pages and includes 26 figures and 16 tables. The literature list consists of 162 sources.

1. Historical evolution of advanced analytics.

This section provides an overview of the progress of advanced analytics over the years and its definition. It offers an understanding of the impact of advanced analytics on business performance and how competitive advantages are gained from advanced analytics both globally and in Latvia. Research on these topics revealed the nonexistence of the terminology 'advanced analytics' in Latvian. To address this gap, the term 'Advanced analytics' was introduced in Latvian.

2. Advanced analytics maturity assessment.

This section provides an explicit review and analysis of existing advanced analytics maturity assessment models, with the aim of exploring them for potential replication, adoption, or adjustment to be usable in Latvia. Online available analytics maturity assessment tools were explored to evaluate and understand how and what can be localized for Latvia.

3. Approach to building the advanced analytics ecosystem maturity assessment and recommendation tool.

This section contains the description of the approach and methodology used to build the tool. It covers quantitative survey questionnaire design, data collection approach, identification of maturity indicators, and maturity model development methodology. It also discusses the approach and tools used to make it available online and provide real-time recommendations for setting up, maintaining, or improving the advanced analytics ecosystem in the organization.

4. Development of the advanced analytics ecosystem maturity assessment and recommendation tool.

This section provides results from the quantitative survey, including the overall Latvia's advanced analytics maturity level in the organizations of Latvia, maturity levels by domains, and readiness by segments. It also includes the statistical analysis of data to build the model and the outcomes from the modelling process. Additionally, the section covers the development and launch of the tool, along with a set of recommendations and guidelines for the next steps.

The chosen structure enables a thorough review, definition, and analysis of advanced analytics and its maturity in organizations in Latvia. The analysed information and survey provide a solid foundation for building the advanced analytics ecosystem assessment tool, which will be publicly available online for free to any organization in Latvia, following the principle of Open Science. Therefore, the tool can be a significant contributor to Latvia's economy by strengthening digital transformation, fostering a more data-driven approach, and enhancing competitiveness in the global market.

Approbation

The author has extensive experience as a practitioner in the field of advanced analytics, with over 20 years of experience serving international companies such as RSA Insurance Group, PZU Insurance Group, 4 Finance, Robocash Group, Simpleros, and RAA Consulting. This experience has enabled the author to stay up-to-date with the latest theories, practices, trends, and technical solutions for improving business performance by harnessing data as the organization's most valuable asset. The author's existing professional experience and research of theory in the field of advanced analytics have led to the development of a publicly available advanced analytics maturity assessment and recommendation tool (public professional profile: https://lv.linkedin.com/in/santa-lemsa-8891888b).

Participation in the conferences as a speaker

July 3-5, 2023. EDULEARN23 15th International Conference on Education and New Learning Technologies, Spain. Presentation "Barriers to implement Advanced Analytics in Latvia's Education industry"

July 3-5, 2023. EDULEARN23 15th International Conference on Education and New Learning Technologies, Spain. Poster "The value of higher education perceived by employers: Latvian survey results"

June 15-16, 2023. ENVIRONMENT. TECHNOLOGY. RESOURCES 14th International Scientific and Practical Conference., Rezekne Academy of Technologies, Rezekne, Latvia (RTA), "Readiness of Latvia's Organizations for Advanced Analytics "

April 8, 2022. International Scientific Conference "SOCIETY. TECHNOLOGY. SOLUTIONS" (ViA), "Framework to build Advanced Analytics maturity assessment model-questionnaire design"

April 8, 2022. International Scientific Conference "SOCIETY. TECHNOLOGY. SOLUTIONS" (ViA), "Adaptation of Advanced Analytics in Latvian Educational institutions"

June 17-18, 2021. ENVIRONMENT. TECHNOLOGY. RESOURCES 13th International Scientific and Practical Conference., Rezekne Academy of Technologies, Rezekne, Latvia (RTA), "Challenges of Advanced Analytics Maturity Model Development"

Participation in the conferences as a listener:

Riga COMM, BUSINESS TECHNOLOGY FAIR AND CONFERENCES, Riga, Latvia, October 5-6, 2023.

EDULEARN23 15th International Conference on Education and New Learning Technologies, Spain, July 3-5, 2023.

ENVIRONMENT. TECHNOLOGY. RESOURCES 14th International Scientific and Practical Conference., Rezekne Academy of Technologies, Rezekne, Latvia (RTA), June 15-16, 2023.

Uzņēmuma elektronizācija, Riga, Latvia, September 28, 2022.

International Scientific Conference "SOCIETY. TECHNOLOGY. SOLUTIONS" (ViA), April 8, 2022.

Conference organized by ministry VARAM: "Atvērta digitālā transformācija", March 2, 2022.

ENVIRONMENT. TECHNOLOGY. RESOURCES 13th International Scientific and Practical Conference., Rezekne Academy of Technologies, Rezekne, Latvia (RTA), June 17-18, 2021.

Riga COMM, BUSINESS TECHNOLOGY FAIR AND CONFERENCES, Riga, Latvia, October 10-11, 2019.

WEB Summit, GLOBAL TECHNOLOGY EVENT, Lisbon, Portugal, November 5-8, 2018.

Riga COMM, BUSINESS TECHNOLOGY FAIR AND CONFERENCES, Riga, Latvia, October 11-12, 2018.

Other public presentations

AI meetup (lead by Aldis Erglis). "How to set up Advanced Analytics in the organization" Latvia, Riga, June 16, 2017.

Publications

1) Lemsa, S. (2023), Barriers to implement Advanced Analytics in Latvia's Education industry. *EDULEARN23 Proceedings of 15th International Conference on Education and New Learning Technologies*, Palma, Spain. 3-5 July, 2023. p. 978-986, https://library.iated.org/view/LEMSA2023BAR, doi: 10.21125/edulearn.2023.0356, to be available [Web of Science data base]
2) Lemsa, S. (2023), Readiness of Latvia's Organizations for Advanced Analytics, Environment. Technology. Resources. Rezekne, Latvia, Proceedings of the 14th International Scientific and Practical Conference. Volume 2, p 61-66. https://doi.org/10.17770/etr2023vol2.7256 , [SCOPUS database]
3) Mietule I., Lescevica M., Lemsa S., Gusta Z., Melbārde V., Kotāne, I. (2023), The value of higher education perceived by employers: Latvian survey results. *EDULEARN23 Proceedings of 15th International Conference on Education and New Learning Technologies*, Palma, Spain. 3-5 July, 2023. p. 319-324, https://library.iated.org/view/MIETULE2023VAL , doi: 10.21125/edulearn.2023.0157, to be available [Web of Science data base]
4) Lemsa, S. (2021), Challenges of Advanced Analytics Maturity Model Development, Environment.Technology.Resources. Proceedings of the 13th

International Scientific and Practical Conference June 17-18, 2021. Volume 2, p. 88-92. https://doi.org/10.17770/etr2021vol2.6621, [SCOPUS database]

Business publications

1) Lemsa, S., 2022. "Automatizācijas sistēmu izstrāde un izmantošana, lai veicinātu konkurences priekšrocības" (https://www.e-izstade.lv/post/automatiz%C4%81cijas-sist%C4%93mu-izstr%C4%81de-un-izmanto%C5%A1ana-lai-veicin%C4%81tu-konkurences-priek%C5%A1roc%C4%ABbas)

Other activities

Advanced analytics ecosystem assessment and recommendations tool – the tool is published and available for anyone online and was presented to the participants of the Actuarial Association of Latvia.

Internship at the author's company RAA Consulting was provided for students from the University of Latvia, Mathematics-Statistics program in 2022/2023 (agreement with the University of Latvia). 2 students were involved, who successfully completed a 5-month internship, during which they developed Machine Learning models to facilitate automated decision-making processes.

Guest Lecturer at Vidzeme University of Applied Sciences in 2022/2023: master's and bachelor's studies (3 courses).

Business Trainer: the author was leading modules for Digital business masterclasses in collaboration with mastertraining.lv during the years 2018/2019.

Risk advanced analytics services: starting from 2020, the author's company, RAA Consulting, has been providing risk advanced analytics services worldwide, helping organizations to become more digital and data-driven.

Participant: Latvian Actuarial Association, starting from 2008.

1. HISTORICAL EVOLUTION OF ADVANCED ANALYTICS

1.1. Evolution & Definition

This subsection will provide an overview of the historical evolution of advanced analytics, from its origins in statistics and mathematics to its current applications and challenges in the era of big data and AI.

The origins of advanced analytics can be traced back to the fields of statistics and mathematics, which have been used for centuries to analyse data and discover patterns, relationships, and causalities. Some of the earliest instances of statistical analysis include the use of census data by ancient civilizations for taxation and planning purposes, the formulation of probability theory by mathematicians such as Blaise Pascal and Pierre de Fermat in the 17th century, and the application of statistical methods to astronomy, biology, and social sciences by scientists such as Carl Friedrich Gauss, Francis Galton, and Karl Pearson in the 18th and 19th centuries.

Analytics in a form closer to what is known in 2023 can be traced back to the 1930s when the first forms of analytics began to emerge. These early forms of analytics were primarily paper-based and mostly related to accounting. However, the concept of computing machines already existed. An important development in the history of advanced analytics was the invention of computers and the evolution of computing technology, which enabled faster and more efficient processing and storage of data. The first electronic computers were developed in the 1940s and 1950s for military and scientific purposes, such as code breaking, ballistic calculations, and nuclear simulations. In the 1940s, the first predictive analytics models were developed by scientists such as Alan Turing and Norbert Wiener, and in the 1950s, the first computer-based analytics models were, including the first artificial intelligence algorithms, which were used to make predictions about future events (Council of Europe, 2023).

Speaking about the evolution of analytics, the approach of labelling specific periods like Analytics 1.0, Analytics 2.0 is often employed, drawing parallels with the industrial revolution. The author will adopt this approach.

Analytics 1.0 – The Era of Data Warehousing, Business Intelligence, and Traditional analytics.

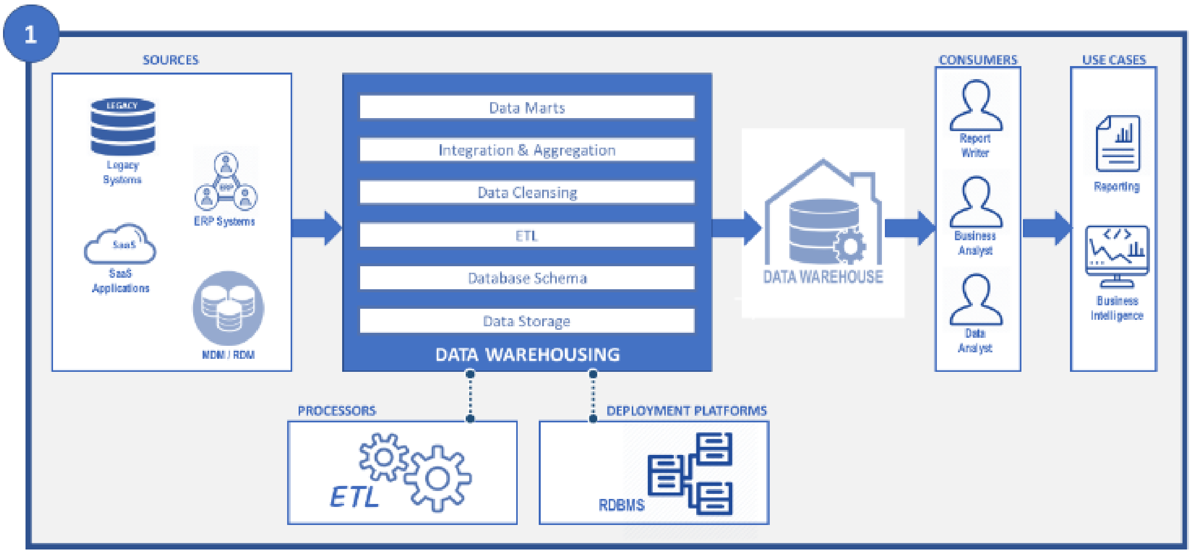
Analytics 1.0 refers to the traditional approach to data analysis, involving manual data collection, analysis, and interpretation. This approach is often time-consuming and labour-intensive, making it challenging to identify patterns and trends in the data. Analytics 1.0 is typically used to answer simple questions, such as “What is the average age of our customers?” or “What is the most popular product?” In Analytics 1.0, IT and business analysts spent a majority of their time exporting, transforming, and mining data for analysis and a minority of their time on the analytics itself (IIA, 2023).

The first era of analytics can be traced from the mid-1950s to the mid/late-2000s, when data analysis was mainly based on structured and small data stored in relational databases and data warehouses. The main tools and techniques used in this era were SQL queries, spreadsheets, OLAP cubes, dashboards, and reports. The main applications and fields were business intelligence (BI), operational research, management science, and decision support systems (IIA, 2023; Davenport, 2017).

In the 1960s and 1970s, computers became more accessible and affordable for commercial and academic use, leading to the emergence of new fields such as computer science, artificial intelligence (AI), information systems (IS), and decision support systems (DSS). In the 1960s, researchers began to develop more sophisticated analytical models, such as multivariate analysis and regression analysis. In the 1970s, businesses started using analytics to gain insights into customer behaviour. Researchers created sophisticated models and algorithms to analyse large datasets, uncover hidden patterns and correlations, and support decision-making. In the 1980s, analytics found applications in more advanced predictive analytics, such as customer segmentation and forecasting. In the early days of analytics, statistical methods were used to analyse data and develop insights. This included basic techniques such as correlation analysis, regression analysis, and cluster analysis. These techniques were used to examine relationships between variables and uncover patterns in the data. In the 1990s, the use of analytics increased significantly with the introduction of data warehouses and the development of data mining techniques. As technology advanced, so did analytics. In the 1980s and 1990s, the rise of the Internet and the development of powerful computer systems accelerated the growth of advanced analytics. Companies began using predictive analytics to anticipate customer needs and optimize their marketing strategies. The development of data mining algorithms enabled businesses to uncover valuable insights from large datasets. In the mid-1990s, the introduction of machine learning and artificial intelligence (AI) enabled businesses to gain deeper insights into their data. Machine learning algorithms allowed for more accurate predictions and deeper insights than ever before. The introduction of big data, analytics platforms and cloud computing in the early 2000s further increased the potential of analytics. Businesses could now process and analyse large amounts of data quickly and cost-effectively. This allowed organizations to uncover more meaningful insights and make better decisions (Council of Europe, 2023; Foote, 2021; IIA, 2023; Davenport, 2017; Vercellis, 2009; Davenport & Harris, 2017).

The main goals of analytics 1.0 were to improve operational efficiency, optimize business processes, monitor performance indicators, and support strategic decisions. The main challenges were to ensure data quality, security, and integration; to manage data storage and processing costs; to align business goals and analytical models; and to foster a data-driven culture (IIA, 2023).

The first-generation data management in other words could be described as Data Warehousing, where focus is on data integration and a single version of the truth using a one-size-fits-all data model (see Figure 1.1.1.).



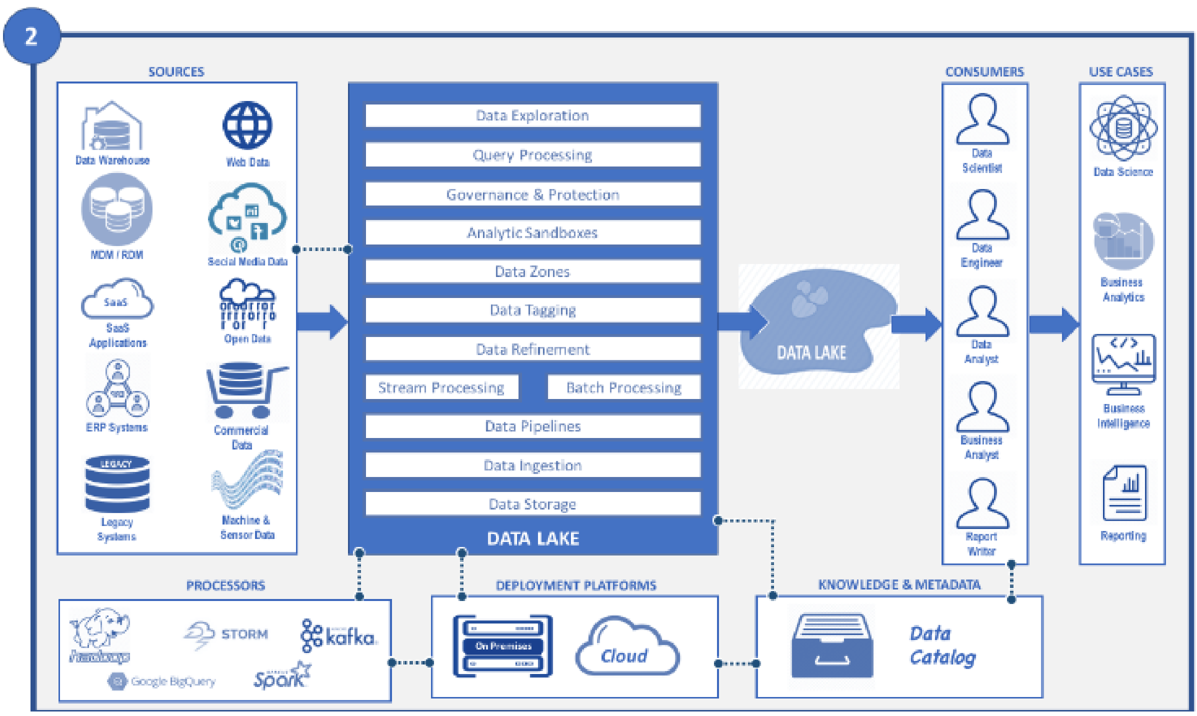
Source: Eckerson Group (2019)
Figure 1.1.1.
Continuing Evolution of Data Management – 1st Generation.

Analytics 2.0: The Era of Big Data and Data Science.

The second era of analytics can be dated from the late 2000s to the early 2020s, when data analysis was mainly based on unstructured and large data collected from various sources, such as online transactions, social media, sensors, images, videos, and texts. The main tools and techniques used in this era were distributed computing platforms, such as Hadoop and Spark; scripting languages, such as Python and R; opensource frameworks, such as TensorFlow and PyTorch; data visualization tools, such as Tableau and D3.js; and machine learning algorithms, such as regression, classification, clustering, recommendation, natural language processing, computer vision, and deep learning. This allowed for more sophisticated analysis of data, such as predictive analytics, which uses statistical models to predict future outcomes. This era saw the emergence of machine learning and artificial intelligence, which allowed for more complex analysis of data. In Analytics 2.0, the focus shifted from data preparation to analytics, and the use of predictive analytics became more widespread (Mayer-Schönberger & Cukier, 2013; Council of Europe, 2023; Foote, 2021; IIA, 2023; Davenport, 2017; Chen et al. 2012).

The main goals of Analytics 2.0 were to discover new patterns, insights, and opportunities from big data; to create new products and services based on data analysis; to enhance customer experience and loyalty; to enable innovation and differentiation; and to generate business value and impact. The main challenges were to ensure data privacy, security, and governance; to deal with data volatility, uncertainty, and complexity; to monitor model stability, performance, and ethics; to foster data collaboration and interoperability; and to bridge the talent gap and skills shortage (IIA, 2023; Council of Europe, 2023; Mayer-Schönberger & Cukier, 2013; Chen et al. 2012).

The second-generation data management could be described as a Data Lake where Data Warehouses become sources for the Data Lake (see Figure 1.1.2.).



Source: Eckerson Group (2019)
Figure 1.1.2.
Continuing Evolution of Data Management – 2nd Generation.

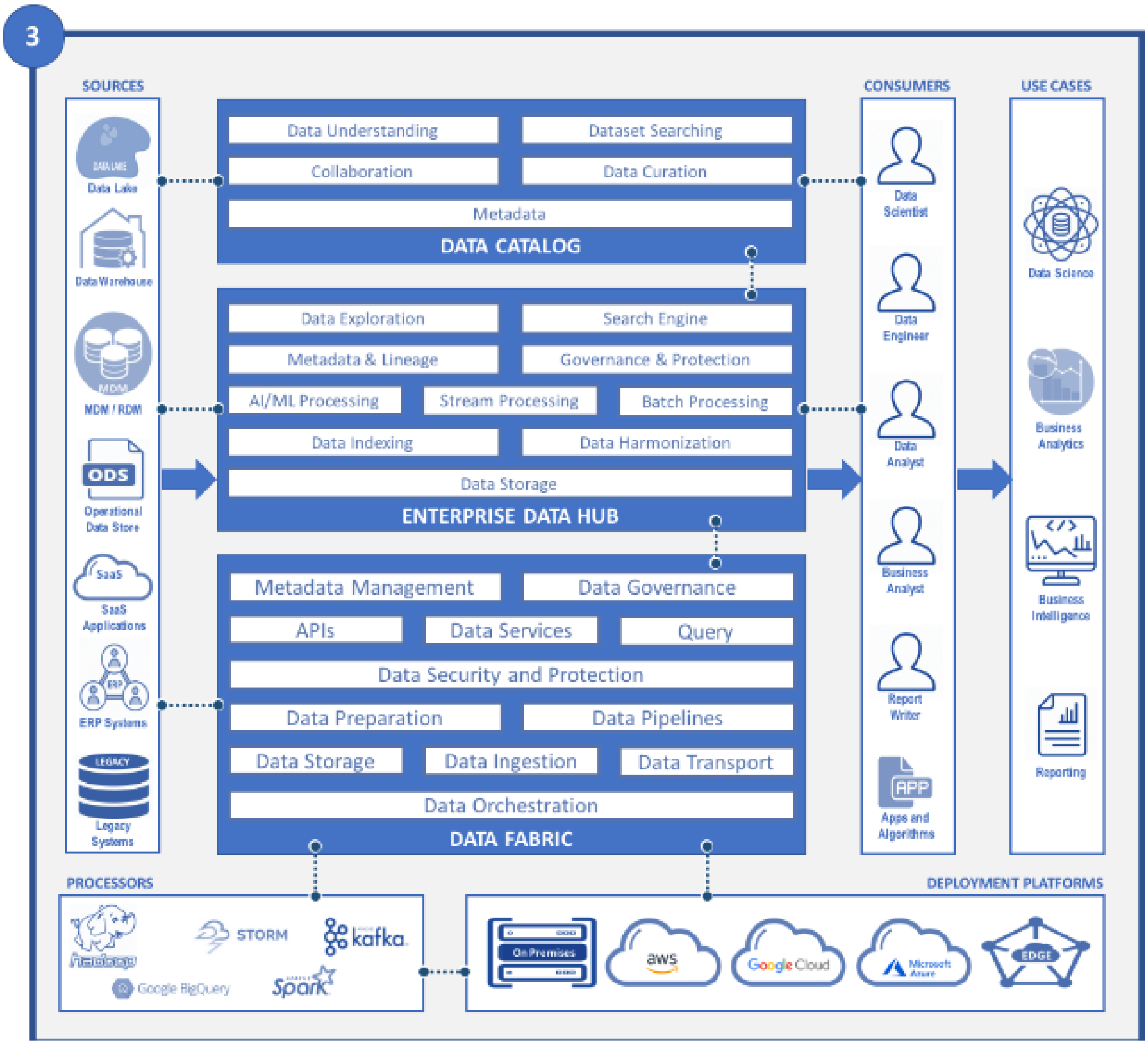
Analytics 3.0: The Era of Cloud, AI, and Digital Platforms or Fast Impact for The Data Economy

The third era of analytics can be dated from the early 2020s or even a little bit earlier to the present and beyond, when data analysis is mainly based on hybrid and dynamic data generated and consumed by various devices, platforms, and networks, such as cloud computing, Internet of Things, edge computing, blockchain, 5G, and artificial intelligence. The main tools and techniques used in this era are cloud-based analytics services, such as AWS, Azure, and Google Cloud; AI-based analytics platforms, such as IBM Watson, Salesforce Einstein, and SAP Leonardo; low-code/no-code analytics tools, such as Alteryx, Dataiku, and Knime; augmented analytics tools, such as AutoML, NLG, and NLP; and explainable AI tools, such as LIME, SHAP, and XAI. At the same time, a term Analytics 3.0 can be used to describe the next generation of analytics. It is a term used to describe the shift from traditional analytics (Analytics 1.0) to more advanced analytics that are predictive, prescriptive, and adaptive. This era is characterized by the use of advanced algorithms and artificial intelligence to provide actionable insights and recommendations. Prescriptive analytics uses data to not only predict future outcomes, but also to suggest the best course of action to take in order to achieve a desired result. This allows for more efficient decision-making, as well as the ability to optimize processes and resources. In Analytics 3.0, the focus is on providing actionable insights and recommendations, rather than just descriptive or predictive analytics and much faster (Mayer-Schönberger & Cukier, 2013; Council of Europe, 2023; Foote, 2021; IIA, 2023; Davenport, 2017; Chen et al. 2012).

The main goals of Analytics 3.0 are to embed data and AI capabilities into the products and services that customers buy; to enable personalized, contextualized, and proactive analytics solutions; to empower data democratization and literacy; to foster data innovation and experimentation; and to create data ecosystems and networks. The main challenges are to ensure data quality, reliability, and availability; to deal with data diversity, heterogeneity, and interoperability; to balance model complexity, efficiency, and explainability; to manage data ethics, trust, and responsibility; and to cope with data uncertainty, ambiguity, and change (Council of Europe, 2023; IIA, 2023; Davenport, 2017).

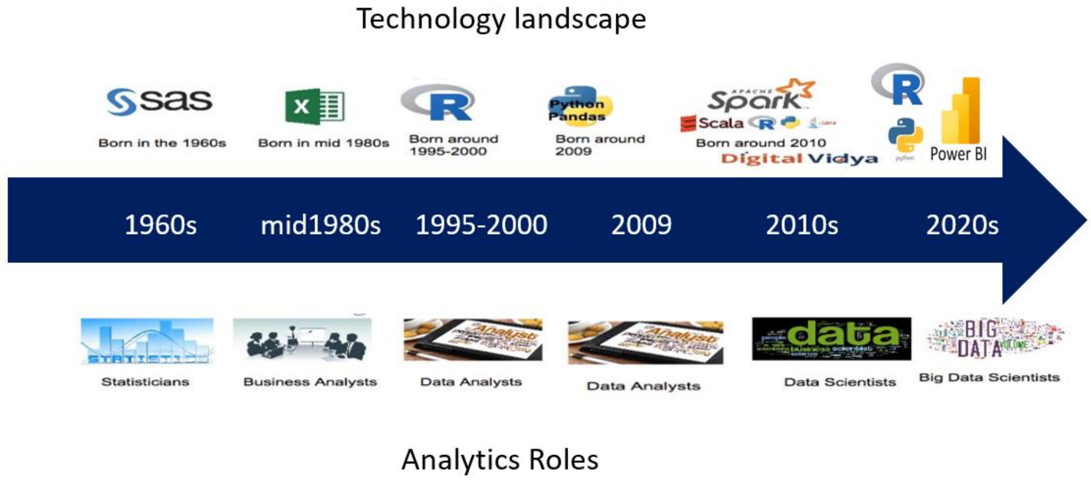
In case of Analytics 3.0, there is a huge challenge already how to adapt everyday operations and processes to obtain and maximize the advantage that new technologies, tools and methods can provide (IIA, 2023). The author believes this will be one of the reasons why the development of advanced analytics will slow down for some time, and the time window between Analytics 3.0 and Analytics 4.0 will be extended. Human beings are not able to learn and adapt to new technologies and opportunities as rapidly as these technologies require for effective utilization.

The third-generation data management can be described as an Enterprise Data Hub with a Data Fabric. Here, the data lake and warehouse serve as sources for the enterprise data hub, and a data catalogue becomes a centrepiece of data management (see Figure 1.1.3.).



Source: Eckerson Group (2019)
Figure 1.1.3.
Continuing Evolution of Data Management – 3rd Generation.

Similarly, the analytics tools have evolved from scripting (e.g., SAS), where every smallest action or data transformation is coded, to a drag and drop approach (KNIME). Additionally, the data volumes used for mining, transformation, and modelling have increased dramatically, thanks to the development of analytical tools and technologies that provide higher computation power. At the same time, this required changing the content of work of statisticians and/or analysts, leading to the creation of many specialized roles. This shift is due to the varying knowledge and skills needed to handle new responsibilities and opportunities, which can differ significantly. Figure 1.1.4 provides insight into the development of tools and the evolution of roles.



Source: created by the author
Figure 1.1.4.
Evolution of Data Analytics tools.

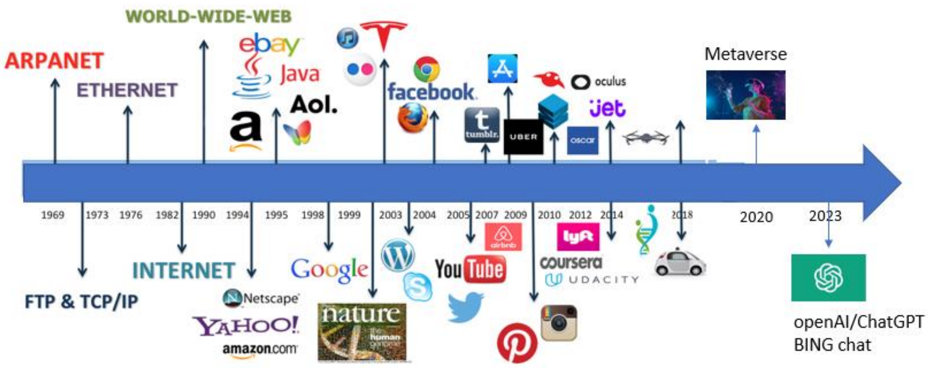
What’s next for analytics? There is the already known field of quantum analytics, which involves the use of quantum computing to analyse data. It is a relatively new field but is expected to revolutionize the way data is analysed. Quantum analytics uses the principles of quantum mechanics to process data more quickly and accurately compared to traditional methods. It can be used to analyse large datasets, identify patterns, and make predictions. For example, in medicine. It can be used for calculations and analyses at the molecular or gene level to understand the impact of specific drugs or drug ingredients. Quantum computing can perform operations on data much faster than a traditional binary computer. Large corporations like IBM, Google, Microsoft have research labs and they have made progress to make quantum computing possible. Despite research laboratories and startups supported by large corporations, it will take time before full usage of quantum analytics takes off (Elsevier, 2023; Bova et al.,2021; Ruane et al., 2022). Is this the Analytics 4.0 era? It is expected that the fourth era could start in the mid-2020s and continue into the future when data analysis is primarily based on decentralized and real-time data processed at the edge of the network, closer to the source or destination of the data.

According to Davenport and IIA (2023), the Analytics 4.0 era can be characterised by the following: full automation and integration of analytics into business tasks and processes; augmentation of human capabilities rather than replacement; emergence of data sociologists who focus on sociotechnical issues that arise when technology impacts established work practices of individuals and groups; implementation of large-scale, near real-time data engineering platforms and pipelines; adoption of AI and ML automation frameworks, APIs, and tools, combined with low-code integration strategies; utilisation of a formalized “analytical applications” lifecycle model across analytics teams and IT groups; focus on data fitness-for-a-purpose, rather than a fitness for-all-purposes approach; close attention to legal and social frameworks within which Analytics 4.0 must operate.

It seems that the main challenges will remain, but they will become more crucial. These challenges include ensuring data quality, consistency, and synchronization; dealing with data heterogeneity, diversity, and sparsity; balancing model accuracy, complexity, and communication; managing data governance, ownership, and sharing; and coping with data dynamics, variability, and uncertainty.

To summarize the evolution of advanced analytics described in this section, the author has observed a shift in focus from descriptive analytics to predictive and prescriptive analytics, from simple, structured data to unstructured, vast volumes of big data. Data management has transformed from simple data warehousing to data lakes and, subsequently, to data enterprise data hubs along with data fabrics, enabling the storage, access, and utilisation of various data formats and volumes to make rapid decisions. Additionally, the shift has been observed from simple techniques to machine learning (ML) algorithms, artificial intelligence (AI), and natural language processing (NLP). This has enabled the development of more powerful predictive and prescriptive analytics, while also highlighting the significance of data governance, security, and privacy. The advancement of advanced analytics has also led to the emergence of new applications and services, such as robotic process automation (RPA), a form of AI that automates repetitive tasks. Additionally, the emergence of cloud computing has enabled the development of analytics-as-a-service (AaaS) solutions, allowing organizations to analyse and visualise data in real-time. The emergence of the Internet of Things (IoT) has enabled the development of connected analytics solutions, which can be used to gain insights about anything (for example, from smartwatch health measures like heart rate, insights about a person’s health), where any device connected to the internet collects and provides data.

The author concludes that there are five main drivers of the historical evolution of analytics: Technology, Data, Tools, Techniques and Application (the ability of human beings to adopt/use). Technology development enables the collection of increasingly vast amounts of data, which, in turn, necessitates more advanced data management to facilitate access and the integration of structured, semi-structured and unstructured data. More complex data access, mining, transformation, analytical, visualisation tools, and platforms are required to obtain insights from vast data volumes. Furthermore, specific computing, statistical, and modelling techniques are required (ML and AI algorithms). Consequently, anyone working with data must be capable of transforming large volumes of data into insightful outcomes, such as visualization, decision-making, and reporting in very short time or even real-time. Thus, the ability to apply the newest tools, solutions, and analytical platforms is required, but much of this capability is linked to the ability of human resources to consistently and quickly learn new solutions, and to obtain new skills every day. If it does not occur, stagnation sets in, and further development and improvement are hindered.



Source: Created by the author
Figure 1.1.5.
Evolution of Technology/Digital Environment (Data Generation).

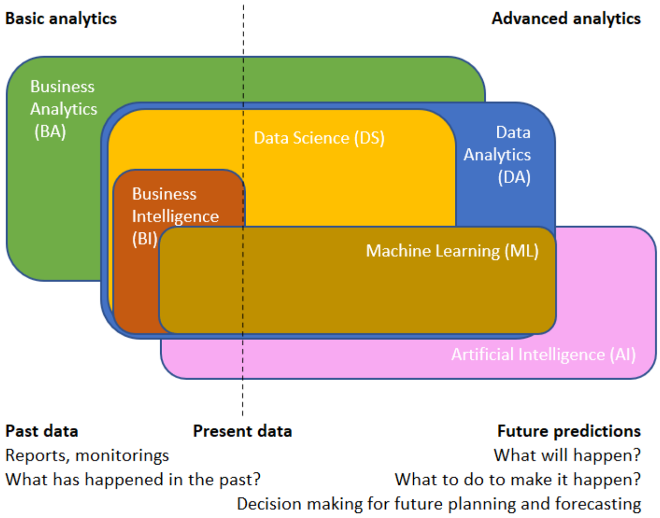
In the world of business, analytics is used to make informed decisions, optimize processes, and identify opportunities. Analytics is the process of gathering and analysing data to gain insights into a given situation.

Advanced analytics, however, is a term that has evolved to encompass more complex methods of data analysis. This includes predictive analytics, which uses data to predict future outcomes, and prescriptive analytics, which uses data to prescribe action, like in the finance industry, providing lending. It helps assess credit risk and prescribe appropriate credit limits, interest rates, and loan terms for individual customers, or in human resource management, optimizing employee schedules to meet staffing requirements while minimizing labour costs and overtime. Advanced analytics also includes machine learning, which uses algorithms to learn from data and make decisions. These methods are used to uncover patterns, trends, and insights that can be used to make better decisions. According to Coursera (2023), Advanced Analytics can be described as an umbrella term referring to a range of data analysis techniques used primarily for predictive purposes, such as machine learning, predictive modelling, neural networks, and AI. Businesses employ advanced analytics primarily to forecast future outcomes and to guide their decision-making, not just to gain business insights.

Advanced analytics has become an increasingly important tool in the modern business world. It helps organizations identify opportunities, optimize processes, and make informed decisions. This is why many organizations are investing in advanced analytics tools and techniques to help them make better decisions and achieve their goals.

Many scholars and research institutions seem to agree that advanced analytics is a process of turning huge volumes of structured or unstructured data, statistical and predictive analytics into decision-making with a value to business (Bose, 2009; Davenport, 2007; United States Government Accountability Office, 2016; Gartner, n.d.; Sheikh, 2013; Russom, 2011 and others). In addition, it is often referred to as predictive analytics, big data analytics, data mining, etc. This forward-looking technique provides insights from large volumes of structured or unstructured data.

Author created a visualisation of often used analytics ‘names’ to show their relation to analyses of the past or future and advancement level (Figure 1.1.6.).



Source: Created by the author
Figure 1.1.6.
Advancement Level of Analytics and Type of Analytics.

Advanced analytics can be defined as follows: “Advanced analytics is the autonomous or semi-autonomous examination of data or content using sophisticated techniques and tools, typically beyond those of traditional business intelligence (BI), to discover deeper insights, make predictions, or generate recommendations. Advanced analytic techniques include those such as data/text mining, machine learning, pattern matching, forecasting, visualization, semantic analysis, sentiment analysis, network and cluster analysis, multivariate statistics, graph analysis, simulation, complex event processing, neural networks.” (Gartner, n.d., para. 1). For example, a predictive model allows for the assessment of a potential customer and enables a company to make real-time decisions regarding whether to provide services, the quality of those services, and the pricing. as Additionally, machine learning algorithms are employed to identify and prevent fraudulent activities within the company, utilizing internal data, digital footprints and device-provided data. Recommendation solutions, for instance, involve suggesting what to watch next on YouTube based on the analysed behaviour data of the viewer while they are watching a specific video.

To successfully implement advanced analytics, it's imperative to have a robust data management environment, diverse data sources, specific tools and analytical platforms, streamlined data access processes, effective reporting and analysis mechanisms, support from management, and a skilled workforce capable of harmoniously integrating these components to deliver business value. This symbiotic relationship among these elements forms an analytics ecosystem where they interact, reinforce, support, and sometimes even replace each other.

In general use, an ecosystem is described as a system formed by the interaction of a community of organisms with their physical environment (Princeton University). Specifically, concerning analytics, as per Mittal from Deloitte (2017), an analytics ecosystem can be described as the interaction or symbiosis between analytical tools, platforms, data, people, applications, techniques, partners, external service providers, and outsourced resources. The term 'ecosystem' is a prevalent concept in the analytics industry, encompassing not just the physical infrastructure for analytics (data storage, tools, computers, and training), but also the 'soft' factors that significantly contribute to analytical success. These include well-structured processes for running analytical projects or data initiatives, effective collaboration between business and analytics teams, seamless communication among various analytical teams, strong management support, and the alignment of organizational strategies with analytics strategies (Mittal, 2017; Stobierski, 2021; Adner, 2017). In other words, an analytics ecosystem is the interconnected network of tools, technologies, and processes used to collect, store, process, analyse, and visualize data within an organization. It includes various components such as data sources, data warehousing and storage, data processing and analytics tools, data visualization and reporting tools, and various other supporting technologies and processes. The analytics ecosystem allows organizations to collect data from various sources, process it, and turn it into actionable insights that can be used to drive business decisions. The ecosystem can be composed of both proprietary and open-source technologies, and it can be customized to meet the unique needs of each organization. The primary goal of an analytics ecosystem is to enable organizations to make data-driven decisions based on insights derived from their data. By leveraging analytics tools and techniques, organizations can gain a deeper understanding of their business operations, customers, and market trends, and use this information to optimize their performance and drive growth.

Based on the analysed information in this subsection, the author has created a ‘needs’ pyramid of advanced analytics (Figure 1.1.7) to visualize the maturity or the level of one aspect (techniques, complexity of algorithms used, tools, or analytical platforms used) of the overall development of analytics, indicate next steps and provide a brief overview of each level. There can be as many maturity levels as the individual author prefers, with no limitations. The author of this doctoral thesis visualizes analytics maturities in 5 stages where stage 1 serves as a pre-requisite for starting any analytics, while the subsequent 4 stages different levels of maturity. The more complex analytical solutions an organization is able to apply in its operations, the more mature the overall advanced analytics ecosystem should be in the specific organization from various factors’ perspectives. These factors include data, technologies, processes, analytical skills, a data-driven culture, and the availability of tools.

The foundation for any kind of analytics is data: internal and external data sources, data quality, data format, accessibility, data dictionary, data models, and connectivity. This stage can be referred to as data management and serves as the basis for developing analytics.

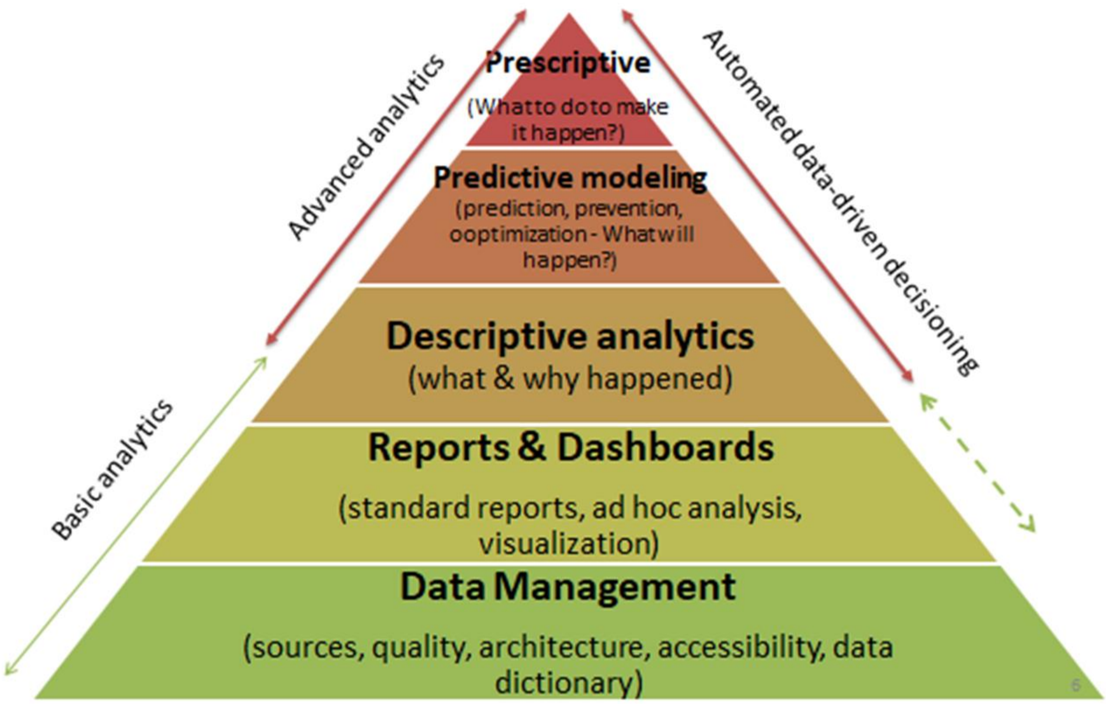
The next level is the ability to create reports, analyses, and dashboards that provide information about business, processes, products, and financial situations. It requires a certain level of business intelligence (BI) and business analysis (BA) capability within the organization.

Descriptive Analytics, the most basic form of analytics, involves summarizing data to understand past events. It is used to identify patterns and trends in the data, and provides a data summary.

The next level of advancement is Predictive Analytics, which uses past data to predict future outcomes. It uses data mining, statistical models, and machine learning algorithms to identify data patterns and make predictions about future events. Predictive analytics can be used to identify customer trends, market opportunities, and potential risks. Usually, this stage includes at least some level of Big Data usage. Big data is a term used to describe the large amounts of data collected from various sources, including social media, mobile devices, and the internet. Big data is used to gain insights into customer behaviour and to develop precisely targeted marketing campaigns.

The highest level is Prescriptive Analytics. It takes predictive analytics one step further by providing recommendations on what actions to take based on the predictions. It uses advanced algorithms to analyse data and provide insights into how to best optimize processes and operations.

Once an organization has reached a solid level of descriptive analytics, it can start to plan and introduce fully automated real-time data-driven decision-making.



Source: Created by the author
Figure 1.1.7.
'Needs' Pyramid for Advanced Analytics.

It is essential to note that the state of advanced analytics implementation can vary significantly depending on factors such as the organization's size, budget, data maturity, and the availability of skilled data professionals. Additionally, the landscape of advanced analytics is continuously evolving, and new trends and practices emerge.

1.2. Impact on Business Performance

Advanced analytics has a significant impact on businesses across various industries. It enables organizations to gain deeper insights, make data-driven decisions, and optimize their operations, resulting in improved productivity, profitability, reduced fraud and risk, improved customer experience, driving innovation, optimizing marketing, sales, and supply chains, with the potential to improve overall business performance or any operational function (Intel, 2018). At the same time, it is not possible to implement and improve everything in one day or in the short term, as it requires serious planning, strong management support, an analytics strategy, as well as internal and external resources to ensure such changes. However, it is all worth it as it increases the probability of organizational sustainability (Aziz, 2023).

According to the survey performed by NewVantage Partners led by Davenport & Bean (2022) where 94 companies from Fortune 1000 (North America top 1000 companies by revenue) and industry-leading organizations participated and based on senior data and technology executives' answers, 92% of large companies achieved return on their data and AI investments. It is a substantial jump from 2017 when only 48% of organizations could report return on their advanced analytics investments. Another survey, conducted by McKinsey & Company (2021, 2022), collected responses from 1843 participants representing a wide range of regions, industries, company sizes, functional specialties, and tenures. It also demonstrates a growing impact on the bottom line of organizations. 27% of respondents reported at least 5% of EBIT attributable to AI, however top performers claimed even 20% of EBIT attributable to AI.

Overall, the impact of advanced analytics on business performance is transformative. By leveraging data-driven insights, organizations can optimize their operations, enhance decision-making, improve customer experiences, and gain a competitive edge, ultimately driving greater profitability and long-term success. Business performance can be evaluated by various indicators, such as profitability, productivity, growth, customer satisfaction, innovation, quality and many other indicators. This helps to ensure the best monitoring and describing the performance of a specific business field (Shabbir et al., 2020; Enholm et al., 2021; Parks & Thambusamy, 2017; Wamba et al., 2015). The latest research demonstrates a more compelling effect on the correlation between the utilization of data, cloud services, data-driven decision-making, analytics, and an organization's performance This effect is particularly pronounced in organizations that extensively embrace business transformation, enhanced decision-making, and the modernization of systems and processes (referred to as AI Leaders), when compared to other organizations. For example, the PwC 2022 AI Business Survey report demonstrates significantly superior performance among AI Leaders compared to other organizations in key metrics. These metrics include increased productivity (44% vs. 20%), enhanced decision-making (41% vs. 19%), improved customer experience (40% vs. 21%), innovation in products and services (40% vs. 15%), and enhanced employee experience and skills acquisition (37% vs. 17%). The "Top 10 Emerging Technologies of 2023" report, along with the research by Noy & Zhang (2023), highlights the significant enhancements in productivity and output quality attributed to Artificial Intelligence (AI). In the following paragraphs, the author describes the most common measures and the potential effects of advanced analytics on them.

Based on the Cambridge dictionary (2023), **productivity** is “the rate at which a country, company, etc. produces goods or services, usually judged in relation to the number of people and the time necessary to produce them”. In other words, productivity is a measure of the efficiency and effectiveness of an entity (such as a firm, a country, or an individual) in producing outputs (such as goods, services, or knowledge) from inputs (such as resources, time, or effort). Productivity can be improved by increasing the quantity or quality of outputs, or by reducing the quantity or cost of inputs (Haynes, 2020; Krugman, 1994). Advanced analytics can have a positive impact on productivity by enabling entities to enhance business decision-making by using data and evidence to support choices and actions, improve performance by using data and feedback to monitor their progress and outcomes, and to identify and address gaps and issues. It supports innovation of products, services, processes, or business models by using data and insights to discover new opportunities, trends, patterns, and solutions. Data-driven decisioning allows automate tasks, workflows, or operations by using data and algorithms to reduce human intervention and errors. Optimize resources, processes, or systems by using data and models to find the best or most efficient ways to achieve goals (European Investment Bank, 2023; Damioli et al., 2021; Brynjolfsson et al., 2019; Krawitz et al., 2018; Manyika et al., 2017; Tambe, 2014).

Data-driven automated decision-making is an excellent example of an approach that significantly impacts various aspects of business performance, such as productivity, sales and revenue increase, cost optimization, and customer satisfaction. Data-driven automated decision-making is widely used in the finance industry. For example, decision-making in cases of solvency for providing mortgages, auto leasing, consumer loans, or post-paid mobile devices can be done manually by a human being reviewing the application of potential customers. Alternatively, it could be done fully automatically based on data and risk assessment models. As a result, if the business grows, there is no need for more and more employees to perform solvency checks. When the risk assessment procedure is data-driven and automated, the business becomes less dependent on human resources. It can be sufficient to have just one employee to handle either 100 applications or 1000 applications. However, when people are involved, the organization needs to hire and manage them constantly, and if the business grows, provide hardware and allocate premises for them. However, this requires a different skill set for the few employees who support such data-driven decision-making processes. They must possess a strong background in mathematics and statistics, data mining, modelling, and the ability to learn new technologies and tools. In other words, they should be highly technology, data and analysis-oriented individuals. It's easy to notice cost savings in terms of reducing headcount, but it's important to consider response speed. Humans can't respond in real-time, unlike data-driven automation, where responses are nearly instant, driven by machine calculations and internet speed. For example, an employee can provide an answer to the customer in 15 minutes, if the customer reads the email or message as soon it is received, or if an automated process instantly responds as soon as all the requested data is provided. As a result, this approach leads to much higher productivity. With data-driven automated decision-making, it becomes possible to process a significantly larger number of applications per employee than in a manual or semi-manual review process. Another advantage of data-driven decision-making is improved risk assessment of customers. When humans are involved in the assessment, emotions can lead to different decisions, even when customers have identical factors. Using data, it is possible to issue loans with a higher likelihood of repayment, resulting in increased revenue and profit.

Based on the Cambridge dictionary (2023), **profitability** is “the situation in which a company, product, etc. is producing a profit” and profit is “money that is earned in trade or business, especially after paying the costs of producing and selling goods and services”. In other words, profitability measures how well a company, country, or person can make money by generating more revenue than the costs of producing goods, services, or knowledge. It can be improved by increasing the revenues, or by reducing the costs and expenses. Profitability metrics, such as net profit margin, return on investment (ROI), return on equity (ROE), and others, are used to assess a company's financial performance and compare it with industry peers. Advanced analytics can improve profitability by enabling organizations to advance evidence to support choices and actions that maximize revenues or minimize costs, improve performance by using data and feedback to monitor progress and outcomes, and to identify and address gaps and issues that affect profitability. Automate tasks, workflows, or operations by using data and algorithms to reduce human intervention and errors that incur costs or reduce revenues. Optimize resources, processes, or systems by using data and models to find the best or most efficient ways to achieve the goals with the least amount of costs or resources (Parks & Thambusamy, 2017; Dilda et al., 2017; Akter et al., 2016; Chen et al., 2012; LaValle et al., 2010; Elgendy & Elragal, 2014).

According to Rachel & HBS (2018) where the Starbucks' (Starbucks is one of the largest and best-known companies in the world, with over 36,000 stores and $32.25 billion revenue in 2022) success of data analytics is analysed, extensive data analysis is used to find out where to open the new store. This method allows to Starbucks to estimate the profitability of potential new stores, and therefore decide whether opening a new store will be economically viable. Additionally, digital menu boards are used, enabling the use of dynamic pricing based on time of the day, seasonality, weather, and the ability to change the positions of drinks on the board, moving them from top positions to the end of lists and vice versa. Linking all that together, the digital menu board, purchased products and data from the loyalty program provides Starbuck with the remarkable ability to predict when, what, and how events will happen and estimate the resulting earnings.

Based on the Cambridge dictionary (2023), **sales growth** is "the increase in a company's sales over a particular period of time, usually given as a percentage". In other words, it is a measure of how much the sales revenue of a company increases over a period of time, usually expressed as a percentage. Sales growth is an indicator of the demand and competitiveness of a company in its industry, as well as its ability to generate profits and create value for its owners and stakeholders. Sales growth can be influenced by various factors, such as market size, demand, competition, pricing, promotion, distribution, innovation, (Iskandar D., 2021). Advanced analytics has a notable impact on sales growth, as highlighted in academic literature and research studies. By leveraging sophisticated data analysis techniques and predictive modelling, organizations can make data-driven decisions that positively influence their sales strategies and performance. The author highlights improved customer segmentation, where advanced analytics allows organizations to more effectively segment their customer base based on various attributes such as demographics, behaviour, preferences, and purchase history. By understanding distinct customer segments, businesses can tailor their marketing and sales strategies to target the right audience with personalized offerings, leading to increased sales. Predictive Sales Forecasting, with the help of advanced analytics, can forecast future sales based on historical data, seasonal patterns, market trends, and other relevant factors. Accurate sales forecasting helps organizations plan inventory, resource allocation, and marketing efforts, ensuring they can meet demand and capitalize on opportunities for sales growth. Pricing optimization is a dynamic tool in the hands of organizations to overcome competitor pricing, and predict customer behaviour, potentially leading to increased sales and market share. Knowing their customers allows to organizations to effectively use cross-selling and upselling opportunities by analysing customer purchase patterns. By recommending complementary or upgraded products and services to customers, organizations can increase the average order value and drive additional sales growth. Predicting customer churn enables businesses to implement targeted retention strategies. By proactively addressing customer attrition, organizations can retain valuable customers and reduce the cost of acquiring new ones, contributing to sustained sales growth. Real-time personalization of customer experiences across various touchpoints, such as websites, mobile apps, and customer support interactions, helps enhance customer engagement and satisfaction, leading to higher conversion rates and repeat business. By using analytics to measure the effectiveness of marketing campaigns and allocate resources based on ROI, organizations can optimize marketing spend and generate higher-quality leads, resulting in increased sales growth. Advanced analytics can assess the performance of sales teams, identify top-performing sales representatives, and analyse sales strategies' effectiveness. This insight helps optimize sales operations and drive overall sales growth (Shahbaz et al., 2021; Agnihotri et al., 2016; Wamba et al., 2015).

There are interesting use cases of advanced analytics in the education sector in North America. America's Largest Online Public University, the University of Maryland University College (UMUC), used advanced analytics to achieve a 20 percent increase in new student enrolment while spending 20 percent less on marketing. Northeastern University used advanced analytics to help grow its U.S. News & World Report ranking among national universities from 115 in 2006 to 40 in 2017 (Krawitz et al., 2018 In the first case it is possible to do if marketing activities are very precisely targeted based on historical data, digital footprint, and real-time website visits data to focus marketing activities on those who most probably will apply and enrol.

As mentioned in Walter & HBS (2018), Amazon collects and analyses data about all processes on its sites, including any purchase, customer behaviour, and seller behaviour. For sellers, the data and other metrics provided by Amazon can help to manage operations while optimizing how they display information on the site or conduct advertising. As a result, customers buy more, Amazon receives a percentage from the sold products and advertising revenue, and hopefully, customer and seller satisfaction is increased.

According to a survey performed by McKinsey & Company on the state of AI in 2022, and looking back over the past five years, 70% of respondents across the globe reported an increase in revenue driven by AI adoption in the organization, in Marketing and Sales and Products, and/or Service Development areas. In case of Marketing and Sales, 9% of respondents claimed a revenue increase of more than 10%, while 20% reported a revenue increase between 6-10%. In the product and/or service development area, 13% reported a revenue increase of more than 10%, and 24% of respondents indicated an increase between 6-10%.

According to the Cambridge dictionary (2023), **cost** is “money that has to be spent in order to buy, do, or make something”. To put it another way, costs refer to the amount of money or resources needed or spent to produce or deliver outputs (such as goods, services, or knowledge). Costs can be classified into different categories, such as fixed or variable, direct or indirect, capital or operating (Horngren C.T. et al., 2006). It is possible to reduce or avoid costs by using data and evidence to support choices and actions that minimize resource consumption or expenditure. Advanced analytics can identify bottlenecks and inefficiencies in business processes, enabling organizations to streamline operations and improve overall efficiency. By optimizing workflows and resource allocation, companies can reduce costs and improve productivity. In areas like supply chain optimization, analytics allows businesses to analyse supply chain data, optimize inventory levels, and enhance logistics and distribution processes. This optimization can result in reduced carrying costs, minimized stockouts, and improved delivery times, ultimately lowering supply chain-related expenses. Similarly, it is possible to make procurement optimization, energy savings, detect fraudulent activities in financial transactions and insurance claims, helping to prevent financial losses due to fraud (Rocks et al., 2020; Parks & Thambusamy, 2017; Dilda et al., 2017).

The cost decrease is one of the most tangible effects as soon advanced analytics is implemented and started to use in production. Of course, the first year of implementation is usually more like an investment with no positive effect on actual financial year or even with a negative effect (because of additional costs on skilled and experienced human resource), but afterwards cost optimization and savings accumulate every year. According to a survey conducted by McKinsey & Company on the state of AI in 2022, and looking back over the past five years, 32% of respondents across the globe reported decreases in costs thanks to AI adoption, and simultaneously, revenue increase was reported by 63% of respondents. The highest decrease in costs because of AI adoption is reported in supply-chain management, 52% of respondents reported a cost decrease of at least 10%. The major decrease in costs was reported by 42-45% of respondents in areas such as service operations, manufacturing, risk and strategy, and corporate finance.

All of the aspects described in this subsection can be turned into a **competitive advantage** where organizations can effectively leverage advanced analytics to gain a competitive edge in the market. For example, if one organization conducts marketing activities targeting the entire population, and another organization focuses only on the part of the population that is most likely to buy or use their product and/or service due to their collection and analysis of data on customers' behaviour, the former will incur significantly higher marketing costs and run the risk of not reaching their actual customers or achieving sales goals. The second organization has a significant competitive advantage over the first organization. Or, in the case of data-driven automated decision-making, if one organization has implemented automated decision-making while another tries to work without it, the first organisation benefits from lower costs, much higher speed in providing services and products, potentially higher customer satisfaction, and the potential of a rapid increase in sales and revenue with minimal dependence on human resources. According to Porter (1985), competitive advantage allows to respond quickly to market changes, stay ahead of competitors, and continuously improve products and services.

In conclusion, the examples mentioned before evidence that by harnessing the power of data and leveraging sophisticated analytical tools, businesses can achieve better performance, improved business decision-making, and a more competitive position in the market. However, despite all the above-mentioned benefits, the latest report of NewWantage (2023), the Data and Analytics Leadership Annual Executive Survey 2023, reveals that just 23.9 % of companies characterize themselves as data-driven, and only 20.6% say that they have developed a data culture within their organizations, reflecting that becoming data-driven is a long and difficult journey. Cultural factors dominate as the greatest obstacle to delivering business value from data investments, with 79.8% of the respondents still claiming organizational resistance to change and business transformation, modifications to organizational processes, people and skills, alignment within the organization, and communication as major barriers to business transformation.

1.3. Current Trends in Gaining Competitive Advantage

Competitive advantage is not static or permanent. It is constantly challenged and eroded by the changing market conditions, customer preferences, technological innovations, and competitor actions. Therefore, organization need to constantly monitor their external environment and internal performance and adapt their strategies and capabilities accordingly. The definition of competitive advantage has shifted from a static and industry-based perspective to a dynamic and resource-based perspective, and from a long-term and stable view to a short-term and adaptive view.

Based on Porter (1985), competitive advantage is the ability of an organization to achieve superior performance and create value for its customers and shareholders by outperforming its rivals in the industry. Competitive advantage can be achieved by offering superior value to customers, such as better quality, lower prices, faster delivery, more innovation, or better customer service. Competitive advantage can also be derived from the entity's unique resources, capabilities, or strategies that are difficult to imitate or replicate by competitors. Porter identified two types of competitive advantage: cost advantage and differentiation advantage. As described in Section 1.2, implementation of advanced analytics within an organization can ensure the creation of both types of competitive advantage. In case of cost advantage, when a company can offer the same products or services as its competitors, but at a lower cost, one of the solutions is to implement automated decision-making and/or automate processes. This allows the company to earn higher profits or charge lower prices than its rivals. The same implementation of automated decision-making and/or automated processes can bring differentiation advantage when a company can offer products or services that are unique or superior in some aspects than those of its competitors. The same services can be provided significantly faster compared to competitors, for example, providing a real-time response when a customer applies for a loan through an online platform. If the customer assessment process is data-driven and fully automated, the answer to the customer can be provided within seconds. This allows the organization to attract more customers, increase their satisfaction, charge higher prices, or increase customer loyalty. Later in the 1990s, Jay Barney introduced the resource-based view of competitive advantage, which argues that a firm's resources and capabilities are the primary sources of value creation and that a firm can achieve a sustained competitive advantage if its resources and capabilities are valuable, rare, inimitable, and non-substitutable. According to Barney (1991), a competitive advantage is defined as follows: “a firm is said to have a competitive advantage when it is implementing a value creating strategy not simultaneously being implemented by any current or potential competitors. A firm is said to have a sustained competitive advantage when it is implementing a value creating strategy not simultaneously being implemented by any current or potential competitors and when these other firms are unable to duplicate the benefits of this strategy". The resource-based view forms the foundation for competitive advantage by examining the interaction between a company's performance and its internal environment (Barney, 1991). Augier & Teece (2009) propose the dynamic capabilities view of competitive advantage, which emphasizes the importance of a firm's ability to sense, seize, and transform opportunities and threats in a rapidly changing environment. Augier & Teece (2009) also suggests that a firm's competitive advantage depends on its ability to integrate, build, and reconfigure its resources and capabilities to match the changing market conditions. McGrath (2013) challenges the notion of sustainable competitive advantage and argues that in a volatile and uncertain world, competitive advantages are transient and need to be constantly renewed. McGrath (2013) also advocates for a strategy of continuous innovation and experimentation to create and exploit temporary advantages.

The author's conclusion is that, over time and in the face of changing external conditions, a competitive advantage remains something that allows an organization to outperform its competitors. It helps in attracting more customers and expanding market share. However, an increasingly vital factor is the organization's flexibility and agility in embracing digital transformation, adopting new technologies, and leveraging emerging opportunities. This includes treating data as assets, implementing automated decision-making, and automating processes through various robotic solutions.

Before COVID-19, the main challenges, according to Bingham et al. (2014), were obtaining buy-in (advocacy) from executive leaders and aligning corporate strategy with analytics, ensuring strong alignment with IT, producing models in real-time (both post-factum and real-time data), effective project management, establishing clear business ownership of results, involving end-users during the development of solutions, translating from data science language to business language, ensuring transparency or explainability of results, and managing changes in business processes (communication, guidelines, metrics, trainings etc.). In addition, Bose (2009) highlighted data privacy and regulation issues, the availability of appropriate advanced analytics platforms, systems or technologies, and concerns regarding data accessibility, confidentiality and sharing across the organization. Furthermore, costs or operational expenditures, along with the overall data journey from data acquisition and warehousing to data interpretation (Sivarajah et al., 2017), as well difficulties in finding people with specific advanced analytics and data science skills (Kim and Gardner, 2015) should be mentioned in this regard. After COVID-19, the following challenges are identified: people, business process, and organizational alignment as the main barriers to substantial transformation into a data-driven organization, especially for large, complex structured organizations (NewVantage Partners, 2023). The above description leads to the conclusion that organizations have not made substantial progress in addressing cultural issues (organizational alignment, agility, resistance, people and processes) over the past 5-10 years.

Before COVID-19, advanced analytics had already been widely adopted by many organizations across industries and geographies to improve their performance, efficiency, innovation and customer experience. Some of the applications of advanced analytics before the pandemic included predicting customer behaviour and preferences using historical data and personalization algorithms, optimizing supply chain operations and inventory management through demand forecasting and simulation models, enhancing product development and innovation with data-driven insights and experimentation, detecting fraud, anomalies, and risks through pattern recognition and anomaly detection techniques, and improving health outcomes and the quality of care with clinical data analysis and diagnosis support systems. After COVID-19, advanced analytics has become even more essential and transformative for organizations. It helps them cope with unprecedented challenges and opportunities brought about by the pandemic. This includes accelerating digital transformation and adopting cloud-based platforms and tools to enable remote work, collaboration, and data access. It also involves leveraging real-time data sources and alternative data sets to capture changing market dynamics, customer behaviour, supplier trends, and competitor activities. Additionally, organizations are developing agile data science methodologies and minimum viable models to deliver solutions quickly and iterate based on feedback. They are also incorporating uncertainty and scenario analysis into models to account for the volatile and unpredictable situation. Furthermore, fostering a culture of data literacy, ethics, and governance is crucial. This ensures the quality, reliability, and trustworthiness of both the data and the models used in decision-making.

Already before COVID-19, Digital Transformation was one of the most significant trends in gaining competitive advantage, but COVID-19 accelerated it significantly. COVID-19 pushed everything to be as distant as possible, in other words, as remote as possible without any human interaction, which means it became as digital as possible. It even pushed industries such as education and catering to become purely digital. In case of education, there were no more in-person contacts, and in case of catering, only kitchens and food delivery were needed, with no space for in-person food service and no human interaction during meals. Driven by the shadow of COVID-19 and continuing to escalate with the war in Ukraine, digital transformation and technology integration have become the most significant trends for gaining a competitive advantage. Digital technologies and data are creating new or modifying existing business processes, products, services, and customer experiences. However, digital transformation also requires organizations to develop new capabilities, such as data analytics, cybersecurity, agile management, and digital leadership. The integration of advanced technologies, such as artificial intelligence, big data analytics, machine learning, and the Internet of Things (IoT) enables organizations to enhance operational efficiency, deliver personalized customer experiences, enables organizations to make data-driven decisions and develop innovative products and services (Sneader & Sing, 2021; WEF & Kearney, 2023). For example, Amazon uses digital technologies to provide personalized recommendations and content to its customers based on their viewing history and preferences (Govindarajan & Venkatraman, 2022). To deliver such solutions, the application of advanced analytics is required.

Customer have always been at the centre of business, but now, in the digital age, we can monitor customers 24/ 7, thanks to IoT devices like mobile phones, smart watches, and laptops connected to the Internet. This enables us to predict customer behaviour under specific conditions. Another significant trend is a strong focus on being customer centric, prioritising customer experience and satisfaction. Organizations have come to realize that understanding customer preferences, needs, and behaviours is essential for driving loyalty and retention – turning from cost-driven to customer value-driven (WEF & Kearney, 2023). It emphasizes the importance of leveraging customer data, implementing personalized marketing strategies, and using customer feedback to continuously improve products and services. An example from marketing: Netflix uses advanced analytics to recommend content to its users based on their viewing history, preferences, and ratings. In healthcare, advanced analytics can help healthcare providers improve diagnostics, treatment, prevention, and research. For example, IBM Watson uses advanced analytics to analyse medical records, clinical trials, and scientific literature to provide evidence-based recommendations to doctors. In manufacturing, General Electric uses advanced analytics to monitor and improve the performance of its industrial machines and equipment (Coursera, 2023).

One more significant trend is sustainability. Sustainability and corporate social responsibility (CSR) can help organizations gain a competitive advantage by improving their reputation, reducing their costs, increasing their resilience, and creating new opportunities.

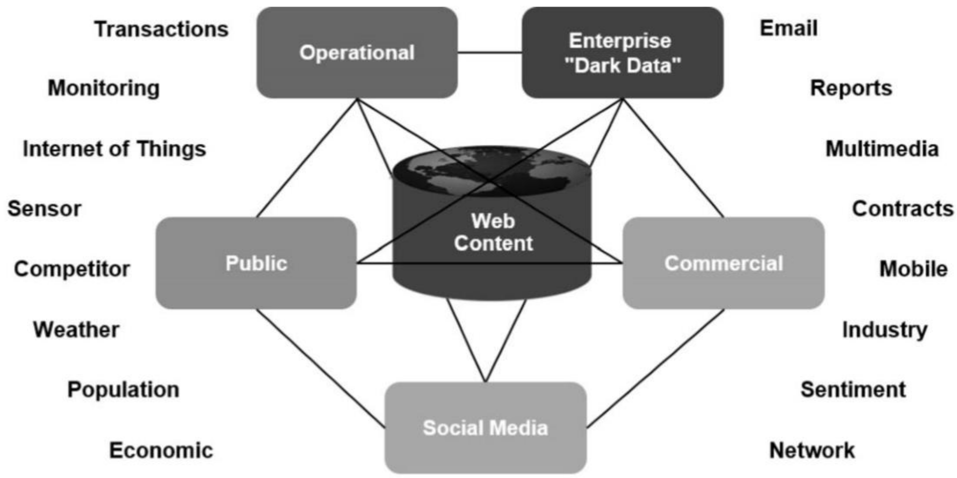
The application of advanced analytics is one solution to help achieve CSR goals. For example, it can assist in cost reduction to promote environmentally friendly practices or optimize processes to improve work-life balance. However, sustainability also requires organizations to balance the economic, social, and environmental aspects of their activities and to engage with multiple stakeholders (WEF & Kearney, 2023). Incorporating sustainability and CSR practices has gained popularity as a means to distinguish brands and gain a competitive advantage. Consumers are increasingly demanding ethical and sustainable business practices - aligning business strategies with environmental and social responsibilities. Organizations that prioritize sustainability and CSR can attract environmentally conscious consumers and enhance their reputation (WEF, 2019).

Another trend is innovation, where new or improved products, services, processes, or business models are created or adopted to meet the needs or expectations of customers or markets (WEF & Kearney, 2023). Innovation can help organizations gain a competitive advantage by providing access to diverse resources, knowledge, partners, and markets. For example, Apple innovates constantly to provide premium products and services that integrate seamlessly with its ecosystem and offer superior user experience.

The studies on the future of technology (WEF et al., 2021; WEF and Frontiers Media S.A., 2023) and innovation trends show an emerging demand for advanced analytics. As advanced analytics can provide solutions to complex business questions, such as process optimisation, real-time risk assessment, pricing strategies, fraud detection, customer attraction, predicting customer intentions and preferences, and cost optimisation in customer attraction, organizations capable of performing well in these areas (faster, smarter, more efficiently) will gain a competitive advantage. An increasing number of organizations want to make data-driven decisions. This can be explained by the continuous interest to increase revenue and save costs. The latest survey by the European Investment Bank (2023) indicates that 53% of organizations in the European Union are actively taking steps to become more digital. However, only 30% of micro-organizations are trying to become more digital, while 62% of large organizations are actively working to become more digital. The adoption of advanced digital technologies is significantly influenced by the size of an organization based on the number of employees. According to the European Investment Bank (2023), 80% of organizations with more than 250 employees are using advanced digital technologies, such as 3-D printing, advanced robotics, the Internet of Things, big data analytics, artificial intelligence, drones, online platforms, and augmented reality. In contrast, only 45% of organizations with less than 10 employees have adopted these advanced technologies.

Taking into account all the points mentioned above, any activity generates a substantial amount of data, often referred to as big data. Without advanced analytics, is not possible to derive valuable insights from this data, making the advanced analytics ecosystem a ‘must have’ rather than a ‘nice to have’ in any organization, particularly at a certain level of maturity if the organization wishes to ensure its sustainability in the future. AA is a core function within an organization to gain or strengthen competitive advantage. If advanced analytics is considered a strategic tool for competitiveness, it calls for a sustainable approach. Talking about advanced analytics, it is not so easy to precisely replicate something owned by a competitor, unless the author or creator of models, approaches, solutions is employed by a competitor and “steals” the solution. And even in that case it's not so easy because of different systems, data availability, tools and platforms, and the management should be convinced that exactly these approaches will bring the added value.

Another factor that drives a demand for advanced analytics is data volumes; an abnormal daily increase is, on the one hand, an opportunity, on the other - a challenge. Those who not only will be able to access the data, but also to understand their meaning (internal and external data combinations) will “win the race” (company’s resources).



Source: Gartner (2015)
Figure 1.3.1.
Range of Available Sources.

The state of the implementation of advanced analytics in organizations varies depending on the industry, size, maturity, region, budget, data maturity, availability of skilled data professionals and culture of the organization where some general trends and challenges can be observed. According to Agarwal et al. (2022), organizations are increasingly starting to accept advanced analytics as a core pillar of innovation across all of their functions, which uses AI to automate and augment data analysis; the use of data fabric to enable seamless data access and integration across diverse sources and platforms; the use of data stories involving natural language generation and visualization to communicate insights; and decision intelligence, which combines data, analytics, rules, and AI to support decision-making. Comparing organizations (organizations who apply advanced analytics vs. those that do not apply it) it is possible to observe that implementation of advanced analytics improves the organization's performance (financial, marketing, risk, quality, satisfaction, growth) and enhances competitive advantage (Shabbir & Gardezi, 2020; Wamba et al., 2017).

1.4. Evidence from Various Contexts Including Latvia

This section examines the evidence of advanced analytics in Latvia from various contexts, such as the national level, the regional level, the industry level, organization's level, challenges encountered in implementing and developing it, and use cases. In addition, the education industry is investigated more thoroughly because of its significant role in Latvia's global success in the near future. The Education Development Guidelines 2021-2027 of Latvia (Ministry of Education and Science, 2021) which is a most significant part of National Development Plan of Latvia for 2021-2027 (Cross-Sectoral Coordination Centre, 2020) and Digital Transformation Guidelines 2021-2027 (Ministry of Environmental Protection and Regional Development of the Republic of Latvia, 2021) should bring Latvia to a much higher level through different programmes that will ensure digital skills for the labour force, digital skills for ICT professionals and other digital experts, digital skills in education, digital skills for everyone, and allocate a budget of 4.5 billion EUR for the entire period (Ministry of Education and Science, 2021).

Advanced analytics is one of the core tools that provide competitive advantage, sustainable development, and enhance the productivity of organizations (OECD, 2021). In general, organizations in Latvia, like those worldwide, need to have a solid understanding of the data they possess and the questions they need to address. They should also have access to skilled and experienced data scientists who can use advanced analytical techniques to create models and insights from their data. Additional resources may include sufficient computing power, storage, software and tools for data mining and analytics, as well as support for implementation and integration of the results. Organizations also need the right culture and attitude towards analytics. Successful analytics initiatives usually require buy-in from the organization's leadership, which is needed to commit the necessary resources and prioritize analytics within the organization. Staff should receive training in the use of the necessary technologies and have opportunities to experiment with and explore their data to derive meaningful insights. Organizations should have a clear vision of how advanced analytics can benefit the organization.

At the national level, Latvia is facing several challenges and opportunities related to digital transformation and advanced analytics. According to the OECD report "Going Digital in Latvia” and latest DESI 2022, Latvia has made significant progress in developing its digital infrastructure, such as broadband coverage, internet speed, and mobile network. However, Latvia still lags behind other OECD countries in terms of digital skills, digital innovation, and integration of digital technologies. According to latest DESI (2022), Latvia significantly lags behind the rest of Europe Union countries in the development speed of digital economy and social index (DESI), in other words, slower development of human capital in case of digital skills, slower development of integration of digital technology by businesses, at the same time having broadband connectivity on top positions and digital public services for citizens in EU middle level. The report suggests that Latvia needs to improve its digital policies and strategies, enhance its digital education and training, foster its digital entrepreneurship and innovation ecosystem, and accelerate the integration of digital technologies (OECD, 2021).

At the regional level, Latvia is divided into five planning regions: Kurzeme, Latgale, Riga, Vidzeme, and Zemgale. Each region has its own characteristics and challenges in terms of economic development, social cohesion, and environmental sustainability. According to the European Commission's Regional Policy (2020), Latvia is eligible for funding from the European Structural and Investment Funds (ESIF) to support its regional development and cohesion. One of the priorities of the ESIF is to promote smart growth by enhancing research and innovation, digital transformation, and competitiveness of small and medium-sized enterprises (SMEs). The Europe Union cohesion policy (2020) has set a menu of 5 policy objectives supporting growth for the period 2021-2027, with the first one focused on creating ”a more competitive and smarter Europe”. Most of the funds will be allocated to support innovative and smart economic changes - research and skills development, entrepreneurship, digitization, and digital connectivity. Advanced analytics can play a key role in achieving this priority by enabling regions to identify their strengths and weaknesses, design and implement smart specialization strategies, and monitor and evaluate their results.

Digital transformation and advanced analytics are two key trends in the emerging age of data, analytics, and automation. Digital transformation is the process of transforming how businesses operate when faced with digital disruption. Companies generally use digital transformation to either revolutionize entire industries or help them become more efficient and effective in their operations. Advanced analytics is the application of predictive and prescriptive models to analyse large, complex datasets in order to make critical business decisions. It includes the use of machine learning, deep learning, artificial intelligence, and other cutting-edge analytics technologies. By leveraging advanced analytics, companies can gain insight into customers, markets, processes and products, and use this data to make better decisions. This helps them to automate strategies that can improve performance and realize goals faster, more efficiently, and with greater accuracy.

At the industry level, Latvia has a diverse economy that consists of various sectors, such as agriculture, manufacturing, services, tourism, information technology and other. Each sector has its own opportunities and challenges in terms of productivity, innovation, and competitiveness. According to the OECD working paper "Policies for stronger productivity growth in Latvia" (2019), Latvia has experienced a slowdown in productivity growth since the global financial crisis of 2008-2009. The paper suggests that Latvia needs to improve its business environment, enhance its innovation performance, increase its investment in human capital and infrastructure, and foster its integration into global value chains Advanced analytics can help industries improve their productivity by optimizing their processes, reducing their costs, increasing their quality, and creating new products or services.

At the educational level, Latvia has a well-developed and diversified education system that covers all levels from pre-school to higher education. Education plays a vital role in developing the skills and competencies that are needed for the digital age. However, according to the Digital Economy and Society Index (DESI, 2022) and NRI 2022, there is ample room for improvement, not only within the education industry, but across Latvia as a whole, for Latvia to significantly improve how individuals use technology and leverage their skills to participate in the network economy and how businesses use ICT, including their spending on R&D. Thus, it puts even higher pressure on the education industry to enhance industry skills and competences to provide them to the wider population - individuals and businesses. The study suggests that there is a need to raise the awareness and interest of advanced analytics among educational stakeholders, integrate advanced analytics into curricula and teaching methods, provide training and support for educators and students on advanced analytics tools and techniques (OECD, 2021). Advanced analytics can help education improve its quality by enhancing learning outcomes, personalizing learning paths, and evaluating learning effectiveness. The Guidelines for Science, Technology Development, and Innovation 2021-2027 (Ministry of Education and Science, 2020) provide clear development areas, priorities for the near future, action directions, and specific tasks for the education industry. One of the six priorities is digital transformation and open science, where digital transformation is planned with the help of the following actions: 1) access to the digital infrastructure and tools, 2) development of digital and data governance competences for academic and administrative resources, 3) development and support of research data management and governance, 4) promotion of open science to ensure public access to data and results of research projects. There are specific measures and expected results to evaluate the successful implementation of these activities and whether the expected results have been achieved (Ministry of Education and Science, 2021).

All of the above is supported by financial backing from the various sources indicated. According to the Latvian Education Development Guidelines 2021-2027 (2021), the total available funding for this planning period from national, municipal, private sector, and European resources is EUR 4,491,661,342. Thera are different projects and their corresponding funding allocation, for example, digital skills development, ICT and digital resource capacity building activities within higher education institutions: EUR 14,137,500; advanced digital skills development opportunities within higher education institutions: EUR 26,100,000; promotion of digital education and e-learning development: EUR 10,875,000; digitalisation of higher education institutions, including material-technical enhancements and innovative study and research processes: EUR 157,046, 600.

The competition between organizations is very high and to ensure faster and smarter decision-making, organizations are forced to use advanced analytics to analyse the past, understand the present behaviour and predict and influence the future events, actions, decisions and behaviour. By implementing advanced analytics into operations, organizations significantly increase a control over daily decisions that ensures a higher potential to meet their business goals (Gandomi & Haider, 2015; Apte et al., 2003).

Global research and surveys about advanced analytics include Europe, but not all countries. Usually UK, France and Germany are represented. There is global level research, such as the Network Readiness Index, which assess how countries use the potential of information, communication technologies and digital transformation to increase competitiveness and well-being and which is published annually by the World Economic Forum in collaboration with INSEAD, as part of their annual Global Information Technology

Report. The NRI 2022 shows a decline for Latvia, which has fallen to the 39th place out of 131 countries, compared to its 32nd position in 2016. However, Latvia's neighbouring Baltic states are ranked higher, with Estonia at 22nd place in NRI 2022 (unchanged from NRI 2016) and Lithuania as 33rd place in NRI 2022 (compared to 29th in NRI 2016). One explanation for the relatively low standing of Latvia in this Index comes from the relatively high impact of People and Technology pillars, in which Latvia is not performing well. The pillar technology is at the core of the network economy, and under this pillar, people's access to information and communication technologies (ICT) is measured. Another low standing pillar for Latvia is "People", which assesses technology skills, productive usage of technologies, and how people apply ICT, including individuals, businesses, and government. The same picture is observed on the Digital Economy and Society Index DESI, where Latvia lags behind EU average numbers. In the case of the subfactor "Integration of Technologies", Latvia ranks as the 4th from the bottom. Latvia has worked out a strong action plan to improve digital and technological skills and competences, primarily within the education industry for academic and administrative human resources, as well as for individuals and businesses (Ministry of Environmental Protection and Regional Development of the Republic of Latvia, 2021; Ministry of Education and Science, 2021).

This Index aims to measure the degree of readiness of countries to exploit opportunities offered by information and communications technology, however it does not give understanding about advanced the development of analytics in specific countries. In general, there is a correlation, where a higher index for a specific country indicates a higher probability of having a more mature advanced analytics ecosystem.

There are very few reports, surveys, and research studies that can be directly linked to the maturity of analytics or advanced analytics and the usage of advanced analytics in the Baltic States or Latvia. Several studies have addressed related and more global areas under the Smart Specialization Strategy of Latvia (2015) and the following monitoring (2014-2020), but this only provides insights whether there is a potential for analytics to be mature enough to adopt advanced analytics (Ministry of Education and Science, 2014-2018).

The report of the Smart Specialization Strategy about Information and Communication Technologies shows a medium-high science excellence level in Latvia that can increase the interest to explore exactly what is the level of advanced analytics in Latvia. The latest Smart Specialization Strategy of Latvia for 2021-2027 gives some insight about the analytics ecosystem and potential support for organizations to develop it (Ministry of Education and Science, 2021).

Looking at it from another perspective, the question arises whether advanced analytics are essential and profitable to be implemented in any type of organization (employees <10, more than 500, etc., revenue more than 5 million or 100 million EUR, industry – education, finance, IT, health care, manufacturing, logistics, government, marketing, etc.). Every organization is different - what works successfully for large corporations, does not work for smaller firms. The basic principle is to have access to data – internal and external, proper tools and platforms in places to access and mine them. The costs related with having such tools could be an issue, but it can be substituted to some extent with open-source tools and platforms, followed by the right people with the right skills. According to Lavastorm Analytics (2013), it all has to do with costs, besides it is more difficult to implement advanced analytics in smaller companies unless a company is not providing advanced analytics or similar services. Speaking about industries, mainly analytics, finance, IT, healthcare, and education are the ones that prevail.

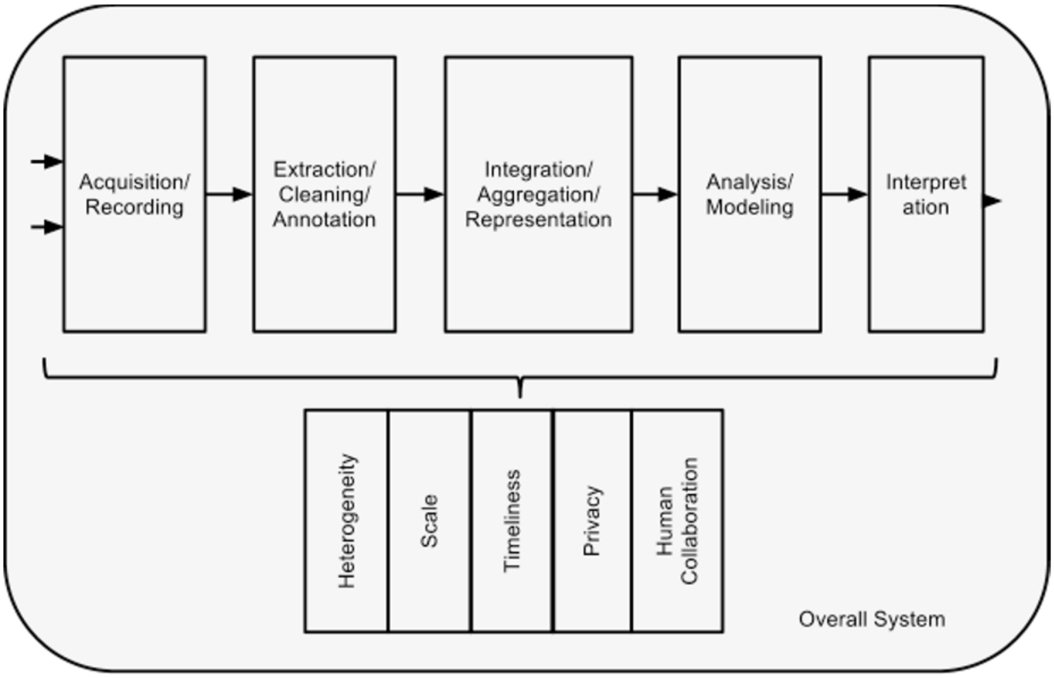
Global research and surveys about advanced analytics include Europe, but not all countries. Usually UK, France and Germany are represented. It’s worth noting that Scandinavia is not included as a respondent, despite the fact that it has the highest Network Readiness Index among European countries (NRI, 2022).

There are very rare reports, surveys, researches which could be connected directly to the maturity of analytics, or advanced analytics and usage of advanced analytics about the Baltic States or Latvia. Several studies have addressed related and more global areas under the Smart Specialization Strategy of Latvia (2016) and following monitoring of 2014-2020 (Ministry of Education and Science, 2020), but this only gives an idea whether there is a potential for analytics to be mature enough to adopt advanced analytics. The report of the Smart Specialization Strategy about Information and Communication Technologies shows a medium-high science excellence level in Latvia that can increase the interest to explore exactly what is the advanced analytics level in Latvia. Some evidence can be derived from job advertisements for positions that require specific skills. Every day it is possible to observe at least a couple of advertisements in the Latvian market requiring such skills and/or experience as data transformation, SQL, powerBI, Tableau, R, Python, Machine learning, data/text-mining, predictive modelling – in many industries, but especially in those businesses that purely or mostly operate in the digital environment: online shops, online gaming, online finance services, finance services, and digital marketing.

There are reasons why organizations in Latvia are struggling with digital transformation and, consequently, the implementation of advanced analytics. DESI 2022 and

NRI 2022 show that Latvia is declining and is not even maintaining the existing level of digitalisation and the required skills for the digital century. Latvia is not the only country facing serious challenges in developing with the necessary technologies and required knowledges and competences. In general, researchers' views are similar, especially in determining the challenges organizations have faced. Several authors find that the main challenges are advocacy from the management, a non-existing corporate strategy for analytics, close interaction with IT, real-time decision-making, business ownership, the involvement of end-users in the development process and the whole management of process changes (Bose, 2009; Bingham, et al., 2015; Davenport & Harris, 2007; Sivarajah et al., 2017, Sheikh, 2013). Kim & Gardner (2015) highlight the following issues: hiring people with the necessary skills, the challenge of integrating new technology solutions into existing legacy systems developed over the years, and an unclear vision regarding analytics. The data privacy and regulation are a crucial barrier identified by Bose (2009), Kim & Gardner (2015) and Davenport & Harris (2007). Sivarajah et al. (2017), pointing out challenges related to costs and operational expenditures and the overall data journey from data acquisition and warehousing to data interpretation.

Some researchers have taken an extended look at challenges from a technical point of view, highlighting the entire data path (Agrawal et.al, 2012; Sivarajah et al., 2017) (Figure 1.4.1.) or exploring the technologies and data flow within organizations (Bose, 2009).



Source: Agrawal et.al. (2012)
Figure 1.4.1.
Data Path (Top) and Challenges of the Path (Bottom).

Others look at it from a managerial perspective. Sivarajah et al. (2017) describes the management challenges developing such analytics functions as data governance, security, privacy, ownership, and costs.

A review of the surveys and quantitative research gives an overall impression on the most frequent challenges. It is interpretable as the severity or importance of a barrier we need to overcome to be successful in advanced analytics. Davenport (2013) states that data quality (access, categorization, transformation, analyse) is one of the key issues, where 35% of respondents claim that their data quality is below an adequate level and 31% report it as adequate, but without a central data warehouse. The next serious issue which is relevant to nearly 50% of respondents, is the lack of people with the required analytical skills; in addition, 29% state that their employees need better skills. Furthermore, 67% disclosed an inadequate technological infrastructure for analytics (too elementary and outdated). Kim & Gardner's (2015) survey shows that 43% are worried about regulatory issues, 36% about data privacy issues and 31% about unstructured data collection and transformation-related issues. The Economist Intelligence Unit (2015, October) highlights the following main challenges observed from their survey: 43% report data and analytics sharing and accessibility within an organization as a challenge, 41% mention the lack of executive support, and another 41% point to a lack of proper expertise. The Global Technology Adoption Index by Dell (2015 October) reports that costs and security are significant barriers. 35% of respondents point out the high costs of infrastructure, 35% mention security issues and 34% are concerned about the costs associated with the acquisition of analytical operation.

Summarizing the challenges described above, the most crucial ones are the quality and accessibility of data, data privacy and the lack of proper analytical skills, but an exact ranking and some specific issues depend on the industry. For example, social media data raises questions about privacy boundaries? When something is posted, shared or retweeted, it is publicly available information. However, on the other hand, using this data may raise concerns about whether a person has obtained permission from a third party to do so. When it comes to analytical skills, it's the same story as with doctors – everyone has to develop them all the time. Technologies and available solutions are changing and developing so rapidly that training to increase one's professional level should be ensured on a regular basis.

At the same time, there are organizations in Latvia that can be used as role models or motivators for other organizations regarding digital transformation and the usage of advanced analytics. The finance industry is one of the first to be mentioned when discussing advanced analytics. The financial industry extensively uses advanced analytics for fraud detection, credit risk assessment, and customer churn prediction. It can also help them forecast demand, revenue, and profitability, as well as optimize their resources and processes. For example, PayPal uses advanced analytics to monitor transactions, protect data, enforce policies, and respond to incidents (Coursera, 2023). In the European banking sector, big data and advanced analytics are used for risk mitigation, fraud detection using ML algorithms, automated credit scoring based on ML, customer care and engagement with natural language processing (NLP), which converts a customer's voice into text for automated analytics, and back-office automation to save costs or maintain staff resourcing levels during business growth (European Banking authority, 2020). The author, from her personal experiences and evidence, can mention international financial institutions with headquarters in Latvia that have implemented advanced analytics and exploit it every day, including automated risk credit scoring, fraud prevention models and many other data-driven automated solutions, like 4finance, Twino, Sun Finance Group, Eleving Group. In case of FinTech Latvia is the centre of excellence in advanced analytics, attracting international organizations to consider Latvia as a source for their workforce. Thanks to the digital working environment, there is no longer a need to relocate to other countries. Professionals can be primarily located in Latvia, while working for international companies and providing services worldwide.

Worldwide, advanced analytics is frequently used in healthcare. It can be used to predict patient readmission, disease outbreak forecasting, patient risk stratification, and predict heart failure readmissions with high accuracy using machine learning algorithms (Ru et al., 2023). It can also help enhance the efficiency and effectiveness of healthcare processes and resources. For example, advanced analytics can be used to provide diagnosis, treatment, and research support to doctors and patients based on natural language processing and machine learning. In Latvia, there are 2 well-known names in the healthcare industry: Grindeks and Olainfarm. A study performed by Eremina et al. in 2019 revealed a positive correlation between digital maturity and financial metrics in the case of Grindeks, but in the case of Olainfarm the correlation was negative.

In the manufacturing industry, advanced analytics can help organizations improve the quality and reliability of their products and services, predictive maintenance can reduce downtime and production optimisation, improve the operational efficiency of industrial equipment, leading to cost savings and improved asset reliability. It can also help them enhance the efficiency and productivity of their operations and resources. A study performed by Eremina et al. in 2019 disclosed a positive correlation between digital maturity and financial metrics in the case of SAF Tehnika that was even recognised as one of the most digitally mature organizations from the main listed Baltic organizations included in the study.

In conclusion, the contexts suggest that advanced analytics is not only a technical issue but also a strategic concern that requires a comprehensive and collaborative approach involving various stakeholders. There are organizations in Latvia that harness the full potential of advanced analytics to improve their business performance. However, it appears that the widespread adoption of advanced analytics usage is not yet prevalent, and there is pressure to implement it to avoid losing a competitive edge. Organizations capable of embracing advanced analytics and adapting their strategies accordingly will be able to achieve and sustain a competitive advantage in the dynamic and complex environment not only locally in Latvia, but will also position themselves as significant players in the global market

1.5. Terminology Introduction in Latvian

The 21st century is a time of rapid technological developments and advancements. The fast-paced changes can create a situation where appropriate terminology in Latvian has not yet been established, but it is necessary.

The Latvian society is, on the whole, open to change and innovation. This is essential because the future of small nations, including their language, depends directly on the ability to adapt to the processes of globalisation and accept innovations and values offered by globalisation. This is vividly illustrated by the fact that there are ~ 7 000 languages in the world (Anderson, 2012), but only ~ 70 languages have access to, for example, technological support in the field of information science (Veisbergs, 2008). In today's modern world, the future of such languages and their users is at stake.

Also, given that language reflects not only historical but also contemporary reality – the social, political, economic, scientific, technological progress and cultural situation – it is true that Latvians "have to be able to speak in their own language about everything that is happening in the world" (Druviete, 1998). In addition, the spoken language must be of high quality in all spheres of life. Advanced analytics, data science and related interdisciplinary industries play an important role in the economic development of Latvia, unfortunately, the terminology of exactly these sectors faces significant problems.

Terminology used by advanced analytics professionals in their practical and scientific work is largely based on the language of literature that is available on topical issues in the field, as well as on the terms used in the country of origin of the specific innovation. In the field of advanced analytics, as in other growing industries, e.g., computer science, maritime and military fields, English is the most common donor language. This is explained by the prestige of English and the fact that English terms belong to internationally accepted designations (Baldunčiks, 2001).

On the positive side – in the context of closer contacts between the English and Latvian languages, the knowledge of the Latvian society is expanding; on the negative side – the analytics, data science, information technology and similar industries terminology in Latvian experiences a massive inflow of literal translations of English terms. The Latvian language is often squeezed out and replaced by global English.

The dominant presence of English in the analytics terminology in Latvian poses the following problems:

1) many English terms express new concepts and phenomena in advanced analytics, so the understanding and interpretation of terms, i.e., definitions, in Latvian is a problem in itself;

2) even when proper equivalents have been developed for English terms in Latvian, they often have not undergone the legal process of terminology development, i.e., they are not officially approved, made public and therefore not known to wider range of users;

3) the understanding and interpretation of many English terms in Latvian differs, and thus many different self-made terms emerge;

4) many English terms often function untranslated or hardly translated and have no proper equivalent in Latvian.

The English term *advanced analytics* is an excellent example of the aforementioned problems in terminology of analytics, data science and allied industries. Although the relevant term is clear and understandable for advanced analytics professionals and does not express any new phenomenon or a view regarding this phenomenon, the equivalent of the term and its definition have still not been officially approved in Latvian.

Industry experts therefore often face the dilemma, i.e., whether to use the untranslated English term *advanced analytics* in mutual communication and research, or to pay tribute to mother tongue and use various self-made versions in Latvian.

Although such self-made variants do not completely distort the substance and essence of matters under consideration, they do indeed create confusion, and that makes the very process of transmitting and perceiving information unpredictable.

The advanced analytics sector is expected to expand, and therefore, there is clearly a need for a carefully thought-out equivalent of the English term *advanced analytics* in Latvian. The author of the thesis believes that the failure to find such a term as soon as possible will pose the following risks:

1) industry experts can get used to the English term *advanced analytics,* and a delay of the entry into use of the Latvian term may make it difficult to use it, and consequently cause even negative emotions (as it was the case with many computer science terms in Latvian);

2) it is possible that the English term *advanced analytics* can eventually have endless variants in industry terminology, thus creating chaos and making the work of industry experts and information transfer challenging.

In view of the aforementioned terminology problems and risks in the field of advanced analytics, the author of the doctoral thesis has set herself a task, in addition to the main objective and tasks of the thesis, of clarifying the use of term *advanced analytics* – to draw clear conceptual boundaries of this term and determine its role in a common terminology system of the field, namely to:

1) develop a proper equivalent for the English term *advanced analytics* in Latvian, as well as provide a definition of the term – to formulate briefly and concisely the essential characteristics of the term in question that distinguish the concept from other concepts;
2) obtain official approval and publication of the newly developed term, thereby strengthening the position of this term, making it accessible to a wider range of language users, but above all – expanding and improving the terminology of the sector.

In order to achieve the objective – to select a proper equivalent for the English term *advanced analytics* in Latvian and obtain the official status for the term, it is necessary to follow a certain procedure from the formation to the introduction of the term into the language. That is, terminology development in Latvia is strictly regulated. Unlike in previous centuries, when the work on terminology development could have been individual (one-person initiative and activity), private (without a certain mandate and responsibilities) and spontaneous (according to the needs of certain specialists), it is now collective (in cooperation with industry experts, linguists and the public), planned (in order not only to cover individual terms, but also include these terms in the system of specific sectors) and, above all, institutionalised (under the supervision of the public administration) (Baltiņš, 2006).

Nowadays, the final word in the process of terminology development, namely the adoption and publication of an official term, remains with the Terminology Commission of the Academy of Sciences. Decisions of the Terminology Commission are collective decisions of experts in the field and language specialists. In addition, for scientific terminology to be uniform, the use of newly created terms is mandatory for every user. If a term turns out to be unacceptable in practice, the decision can be changed; however, with the approval of the Terminology Commission (Skujiņa,1993).

It is true that the procedural steps for the development and introduction of new terms are relatively simple. The fact that the terms enter the Latvian language relatively slowly is not determined by bureaucracy. There is another fundamental problem – a burdensome, time-consuming and complex terminology development process. According to the Terminology Commission, when developing a new term in Latvian, and it directly applies to development of equivalent for the English term *advanced analytics*, the following semantic features must be observed and introduced in the new term:

1) systemicity – the new term must be sector-specific, it fits harmoniously into the system of all terms of this sector, e.g., the new term is based on analogy with other industry terms;

2) accuracy of meaning – the term must be designed in a way that it accurately reflects the essential features of the concept;

3) monosemy – one term should express only one concept; synonymy is not accepted;

4) context independence – the term must be clearly understandable, regardless of the context;

5) emotional neutrality – the term should be designed in such a way that it has neither positive nor negative nuances of meaning (Skujiņa, 1998).

The author is very familiar with the field of advanced analytics both at national and international level, and from both – the theoretical and practical aspect, and also knows and understands the concept *advanced analytics* and its essential characteristics. However, it must be admitted that the author does not have the specific knowledge required by the Terminology Commission in such linguistic branches relevant for terminology as lexicology and morphology. Therefore, already at the very early stage of development of the term, the author is aware that the new term and its definition in Latvian proposed by her is not authoritative and absolute, and the final word regarding the approval will remain with the experts of the Terminology Commission.

However, apart from doubts about her linguistic competence, the author of the thesis submitted a proposal for rendering the English term *advanced analytics* in Latvian to the Terminology Commission on 20 October 2022. The proposal has the following composition and content:

1. Justification for the development and implementation of the English term *advanced analytics*

The English term *advanced analytics* expresses the processes that have already been practiced and described in other large countries, but only recently in Latvia. Being confronted with these new processes, trends and, eventually, concepts of advanced analytics in Latvia, it is necessary to explain these processes, namely, a precise and uniform representation – the concept and definition of the concept, in Latvian are required. To date, there is no proper equivalent for the term *advanced analytics* in analytics terminology in Latvian. In fact, the process of transmitting information has become unpredictable in scientific research and practical work.

2. Latvian equivalents of the term *advanced analytics* and definition in Latvian

The Terminology Commission was provided with the following equivalents for the term *advanced analytics* in Latvian: 'progresīvā analītika', 'augstākā analītika' or 'augstākās pakāpes analītika' and 'padziļinātā analītika', defining them as:

– application of a set of modern high-level analytical methods, processes and tools for deeper and wider use of data - to forecast trends, events and behaviours in the future; get recommendations on how to take action to implement the intended as well as automated processes and decision-making. Advanced analytics includes techniques such as machine learning, semantic and graph analysis, data mining, predictive analytics, data visualisations, neural networks, cluster analysis, multifactor statistics, simulations, as well as many other traditional and ever-new adapted methods.

– mūsdienīgu augsta līmeņa analītisko metožu, procesu un rīku kopas pielietošana, lai dziļāk un plašāk izmantotu datus – prognozētu tendences, notikumus un uzvedību nākotnē; gūtu rekomendācijas tam, kā rīkoties, lai īstenotu iecerēto, kā arī automatizētu procesus un lēmumu pieņemšanu. Augstākā analītika ietver tādas metodes kā mašīnmācīšanos, semantisko un grafu analīzi, datizraci, paredzošo analītiku, datu vizualizācijas, neironu tīklus, klasteru analīzi, daudzfaktoru statistiku, simulācijas, kā arī daudzas citas tradicionālas un arvien jaunas pielāgotas metodes.

3. Equivalents of the English term in other major languages

The linguistic material collected for the thesis suggests that the English term *advanced analytics* has been widely used in several languages. In terms of sound, spelling and meaning, the term in these languages is similar and could, in some sense, be regarded as an acquisition - internationalism. (see Table 1.5.1.).

Table 1.5.1.

Equivalents of the Term ‘Advanced Analytics’ in the Largest Language Groups.

<table>
<tr><th colspan="6">Equivalents of the term advanced analytics
in largest language groups</th></tr>
<tr><td colspan="2">Germanic languages</td><td colspan="2">Romance languages</td><td colspan="2">Slavic languages</td></tr>
<tr><td>ENG</td><td>advanced analytics</td><td>FR</td><td>l’analytique avancée</td><td rowspan="3">RU</td><td rowspan="3">углубленная аналитика
продвинутая аналитика</td></tr>
<tr><td>SWE</td><td>avancerade analysteknik</td><td rowspan="2">ESP</td><td rowspan="2">analítica avanzada</td></tr>
<tr><td>DE</td><td>erweiterte Analytik
fortgeschrittene Analytik</td></tr>
</table>

Source: Created by the author (2022)

However, after close examination of the linguistic material, it must be acknowledged that there are languages such as German and Russian, which have not taken over the English term *advanced analytics* one-to-one, namely, they have only borrowed the so-called overarching-term ‘analytics’, but have replaced the characterising word or word bearing the characteristics ‘advanced’, for some reason, with another component that is more suitable for their language system.

The author of the doctoral thesis also chose a similar approach to term development, i.e. when creating an equivalent for the English term *advanced analytics*, the author refused to borrow or transfer the component ‘*advanced’* into Latvian, first, for a purely prosaic reason – it is a word that is easy to understand, but difficult to translate and apply, and, secondly, because of language culture – direct transfer of the component ‘advanced’, or the so-called calque, i.e., ‘advancēts’, is not desirable in the Latvian language (Tezaurs).

It is also important to note that, in large languages, as thus far also in Latvian, there are inconsistencies and semantic ambiguities in the use of the national term, when the concept of global English exists in parallel. Consequently, the aforementioned problems are present in almost all languages listed in Table 1.

1) For the sake of clarity, the English term *advanced analytics* is left untranslated in industry texts (see Table 1.5.2.):

Table 1.5.2.

Examples of the Term ‘Advanced Analytics’ in English and German.

ENG	DE
We are talking here about advanced analytics. (Glosbe dictionary)	*Wir sprechen hier zunächst von Advanced Analytics.* (Glosbe dictionary)
This also includes the use of Big Data infrastructures, Data Mining, advanced analytics, predictive analytics and Customer Journey management and xIntelligence: multi-channel analytics. (Glosbe dictionary)	*Darunter fällt auch die Nutzung von Big Data Infrastrukturen, Data Mining, Advanced Analytics und Predictive Analytics sowie Customer Journey Management und xIntelligence: Multi Channel Analytics.* (Glosbe dictionary)

Source: Created by the author (2022)

2) The English term *advanced analytics* has numerous equivalents in national terminology, but such formations and synonyms, as established above, are not acceptable in terminology (see Table 1.5.3. and Table 1.5.4.):

Table 1.5.3.

Examples of the Term ‘Advanced Analytics’ in English and German.

ENG	DE
It brings together intelligent machines, advanced analytics, and the creativity of people at work. (Glosbe dictionary)	*Es vereint intelligente Maschinen, fortgeschrittene Analytik, und die Kreativität der Leute bei der Arbeit.* (Glosbe dictionary)
By finding patterns through using advanced analytics however, new business opportunities and smarter applications could be opened up in numerous fields. (Glosbe dictionary)	*Indem jedoch mithilfe erweiterter Analytik Muster gefunden werden, können sich neue Geschäftsmöglichkeiten und intelligentere Anwendungen in zahlreichen Bereichen eröffnen.*

	(Glosbe dictionary)

Source: Created by the author (2022)

Table 1.5.4.

Examples of the Term 'Advanced Analytics' in English and Russian.

ENG	RU
It brings together intelligent machines, advanced analytics, and the creativity of people at work. (Glosbe dictionary)	*Она объединяет умные машины, глубокий анализ и творческий подход к работе.* (Glosbe dictionary)
To be sure, workers skilled in data management and advanced analytics are in short supply, as are members of an emerging class of "translators" – those whose talents bridge IT and data, analytics, and business decision-making. (Glosbe dictionary)	*По правде говоря, работники, разбирающиеся в управлении данными и сложной аналитике, на вес золота, как и представители только зарождающейся группы «трансляторов» – тех, кто благодаря своим талантам может объединить ИТ с данными, аналитикой и принятием бизнес-решений.* (Glosbe dictionary)
There are in the market advanced analytics tools and applications, especially designed to analyse in depth the enormous amount of data inside the organizations, and to make predictions based on the information obtained from analyzing and exploring those data. (Glosbe dictionary)	*На рынке существуют передовые аналитические инструменты, специально разработанные для глубокого анализа огромного количества данных внутри организаций, а также для прогнозирования на основе информации, полученной в результате анализа и изучения этих данных.* (Glosbe dictionary)
The user may also run special queries (through automatic transformation from XML based rules to SQL statements) and analysis on files from other statistical analysis systems (including the Statistical Package for the Social Sciences (SPSS), the Statistical Analysis Software (SAS) and the R-programming language) for advanced analytics. (Glosbe dictionary)	*Пользователь также может вводить в систему специальные запросы (путем автоматического перевода правил на основе XML в SQL-операторы) и обрабатывать файлы из других систем статистического анализа (включая Пакет программ обработки статистических данных общественных наук (SPSS), Программу статистического анализа (SAS) и язык программирования "R") в целях углубленного анализа.* (Glosbe dictionary)

Source: Created by the author (2022)

4. Positive and negative aspects of proposed Latvian terms

According to the author of the thesis, the proposed Latvian equivalents for the English term *advanced analytics*, have both pros and cons, which determine their conformity with the best terminology practice and could affect their implementation or non-implementation in linguistic practice.

Positive and negative aspects of the term ‘progresīvā analītika’*:*

(+) the term’s components ‘progresīvā’ and ‘analītika’, in terms of both form and content, are the borrowings, which are already entrenched in the Latvian language. They are customary for language users and no longer cause a negative reaction.

(+) the term's components ‘progresīvā’ and ‘analītika’ are widely used in many languages of the world;

(–) the term's component ‘progresīvs’ is widely used in various spheres and meanings, and in certain situations it also has nuances of emotional significance;

(–) the term's component ‘progresīvs’ does not systematically relate to other words in the field of data science and does not really reveal what it is about. The critics of this term may therefore consider that it is necessary to choose something more specific to describe the concept of analytics than the proposed medium of the feature ‘progresīvā’.

Positive and negative aspects of the terms ‘augstākā analītika’, ‘augstākās pakāpes analītika’*:*

(+) the terms naturally fit into the system of industry and allied industries, as they already have a base term ‘augstākā matemātika’;

(–) the terms include the so-called qualitative characteristics, and, with the development of science, characteristics may change, i.e., the ‘highest degree’ is no longer the highest, because an even higher degree is possible.

The negative aspect of the term ‘padziļinātā analītika’:

(–) the meaning of the term, e.g., the transfer of meaning, would come from Russian (intermediate language), although English is the language of origin of the term.

Having examined the proposal by the author of the doctoral thesis, the submitted language material and its analysis, the Terminology Commission approved the Latvian term ‘augstākā analītika’ as the official equivalent of the English term *advanced analytics* on 22 November 2022.

The decision of the Terminology Commission was also based on similar considerations already put forward in the proposal by the author of the thesis – the term ‘augstākā analītika’ is systemic as to the meaning, it fits, by analogy, in the existing framework of base terms, namely: ‘augstākā analītika’ resembles with ‘augstākā matemātika’ (Terminoloģijas komisija).

Finally, it must be recognised that every new term must go through its own path of development, from its developer to the user. There are terms that stick immediately and are widely used, but in most cases almost every new term initially seems funny, strange, unacceptable or even ridiculous (Nītiņa, 2004) and only over time, when users increasingly face the term by reading and hearing, a habit of use emerges and the term starts to develop in the language.

It should be recognized that the future of the term ‘augstākā analītika’, as proposed by the author of the thesis and officially approved by the Terminology Commission, largely remains uncertain. The specific understanding of this term is still being formed among the users.

2. ADVANCED ANALYTICS MATURITY ASSESMENT

Considering the increasing demand for advanced analytics, including automated decision-making based on data or process automation, it is essential to understand the maturity level of the advanced analytics ecosystem in any country, industry, or organization. Typically, assessing analytics maturity or evaluating the level of analytics development involves measuring various domains, which represent different areas of knowledge, activities, and responsibilities. For instance, these domains could include categories like Human or Data. Within each domain, there are multiple contributing factors, often referred to as sub-domains. For example, in the context of Data, these factors encompass governance, accessibility, quality, privacy, security, and numerous others. Domains and the factors assessed are crucial for ensuring proper analytics performance. The assessment of maturity helps to identify strengths and weaknesses of the organization's analytics ecosystem and can provide a detailed action plan step by step for moving the existing analytics ecosystem to the next level or a level relevant to the organization to meet its strategic goals. However, while we can find the models for assessing advanced analytics maturity, there is limited information available regarding the methodology for developing such models. The assessment process, specific factors, and their weight in advancing the organization to the specific level of analytics maturity, are considered more as the 'know-how' of the analytics sector than openly disclosed methodologies that ensure reproducibility or validation of the models. Another issue is time, data volumes, and the rapid development of technologies, which require regular adjustments to the model.

The section aims to review and analyse previous models with insights of the methodology and the overall process to build or replicate such assessment models. Analytics maturity models developed by various organizations are publicly available, sometimes accompanied by a disclosed methodology. These models aim to identify domains or spheres of influence, such as Human, Technologies, and Organization. They consider factors like Culture, Strategy, Governance, among many others. These models employ questions and statements to aid in assessment. For instance, one question might be, "Which statement best describes your organization's analytical community?" with answer choices like "Uncoordinated analytical activities," "Local analytical teams that are beginning to share tools, data, and experience," and so on. The responses are used to determine the overall maturity level, maturity within each domain, and the next steps to be taken. These models also incorporate drivers or indicators to rank the organization's maturity level. This comprehensive approach allows for the creation of effective assessment models. 15 models reviewed and 4 analysed deeper in this doctoral thesis.

2.1. Advanced Analytics Maturity Models

Advanced analytics maturity models are frameworks designed to assess and measure an organization's capabilities and level of sophistication in implementing advanced analytics practices, in other words - to use data and analytics for deriving value and supporting decision-making. These informative models help organizations understand their overall current state, current state by domain and factor, identify gaps, and create a roadmap for progressing to higher levels of analytical maturity. The informative models typically measure the organization's advanced analytics ecosystem capabilities across various dimensions, such as data, technology, culture, process, analytics, and people. They also serve as guides for improving analytics maturity and achieving business goals.

Several analytics maturity models exist, each with its own unique characteristics, but they generally follow a common structure, and the key components are Levels of Maturity and Domains or Capabilities. Typically, advanced analytics maturity models consist of several maturity levels or stages, ranging from the lowest level (ad hoc or basic analytics) to the highest level (advanced or predictive analytics). The number of levels may vary depending on the model, but they usually represent increasing levels of analytical sophistication and organizational integration. According to Davenport & Harris (2007), Comuzzi & Patel (2016), Watson (2002), Grossmann (2018), Cosic et al. (2012), Piyanka (2012), Blast Analytics & Marketing (2021), Association Analytics & King (2017), Davenport & Harris (2017), Logi Analytics (2017), Cardinal Path (2021), PharmaVOICE & SAS (2014), Halper (2020), Hamel (2009), Lismonta et al. (2017), the most frequently used domains are:

- **Analytical**: Each maturity level defines the specific analytical capabilities that an organization should possess. These capabilities encompass the use of data, analytics tools, methodologies, and the integration of analytics into business processes;
- **Data Governance and Management**: Maturity models emphasize the importance of data governance and data management practices. Higher

maturity levels require robust data quality, data integration, and data security measures to ensure reliable and accurate data for analytics;

- **Organizational Culture**: This model often assesses the organization's analytical culture and its readiness to embrace data-driven decision-making. Higher maturity levels promote a data-driven culture that values analytics and encourages collaboration between business and analytics teams;
- **Technology and Infrastructure**: This maturity model evaluates the organization's technology stack and infrastructure to support advanced analytics. This includes data storage, processing capabilities, analytics tools, and software integration;
- **Talent and Skills**: A crucial aspect of this model is assessing the organization's talent pool and the availability of analytical skills. Higher maturity levels require a skilled analytics workforce with expertise in data science, statistics, machine learning, and domain-specific knowledge;
- **Alignment with Business Objectives**: This model measures how well advanced analytics align with the organization's strategic objectives. At higher maturity levels, analytics initiatives are closely tied to business goals, driving tangible value and competitive advantage;
- **Continuous Improvement**: Maturity models often emphasize continuous improvement. Organizations are encouraged to measure progress regularly, identify areas for improvement, and develop plans to advance to higher maturity levels.

Based on these aspects, most models define three to six levels of analytics maturity, from low to high. According to Davenport & Harris (2007), Comuzzi & Patel (2016), Watson (2002), Grossmann (2018), Cosic et al. (2012), Piyanka (2012), Blast Analytics & Marketing (2021), Association Analytics & King (2017), Davenport & Harris (2017), Logi Analytics (2017), Cardinal Path (2021), PharmaVOICE & SAS (2014), Halper (2020), Hamel (2009), Lismonta et al. (2017), the most frequently used maturity levels are:

- **Analytically Impaired/Beginners**: This is the lowest level of analytics maturity, where the organization has no clear vision or strategy for analytics and uses it only for basic reporting or descriptive analytics. The data is siloed and inconsistent, and the analytics are limited and manual. The users are mainly analysts who use the analytics for ad hoc queries and reports. The value of the analytics is low and hard to measure;

- **Localized Analytics**: This is the second level of analytics maturity, where the organization has some awareness and interest in analytics but lacks coordination and alignment across different business units or functions. The data is more centralized and standardized, but still fragmented and isolated. The analytics are more systematic and structured, but still limited by scope and scale. The users are more diverse and include managers who use the analytics for operational decision-making. The value of the analytics is moderate and tangible;
- **Analytical Aspirations**: This is the third level of analytics maturity, where the organization has a clear vision and strategy for analytics but faces challenges in execution and implementation. The data is more integrated and coordinated, but still incomplete or inaccurate. The analytics are more sophisticated and automated, but still constrained by resources or skills. The users are more skilled and proficient, but still lack empowerment or support. The value of the analytics is high but not fully realized;
- **Analytical Companies**: This is the fourth level of analytics maturity, where the organization has a competitive advantage from analytics, but faces competition from other analytical companies. The data is high quality, available, and integrated across the entire organization. The analytics are intelligent, adaptive, and innovative across different types of analysis. The users are empowered, satisfied, and engaged with the analytics across different levels of decision-making. The value of the analytics is very high and transformational;
- **Analytical Competitors/Visionary**: This is the highest level of analytics maturity, where the organization has a transformational impact from analytics that differentiates it from its competitors. The data is visionary, creative, and leveraged for new opportunities or insights. The analytics are visionary, creative, and leveraged for new products or services. The users are visionary, creative, and leveraged for new strategies or actions. The value of the analytics is exceptional and visionary.

The review and analysis of the analytics maturity models is based on the literature review, including scientific publications, reports of the research, books published by experts and opinion leaders, materials published online, and practical assessment of the publicly available analytics maturity assessment tools provided by analytics, technical or IT consulting companies. There are many maturity models related to advanced analytics proposed by various researchers, consultants, and vendors. They were explored to gather and analyse the methodology used to build or replicate such a model. Initially, the author identified 15 models reviewing literature. Then, their maturity levels and domains were reviewed considering 3 characteristics: the disclosure of the survey questionnaire, the availability of an online tool based on that model, and the disclosure of the maturity level detection (methodology). All 15 models were compared to select a few of them for a more in-depth analysis to build a new advanced analytics maturity model for Latvia.

The literature review process took place in 2 stages: identification, collection, and review of the materials to highlight analytics maturity models with the most extensive information about the methodology behind the development of the models, the most accurate, the most known, and the most widely used. The second stage was a practical experiment taking the online tests to assess the organizations' analytics maturity level to complement the existing description of the models from the literature review conducted during the first stage. This resulted in the creation of a summary of the characteristics of the 4 models that can serve as a foundation to replicate, adjust, or build a new model for a specific region, country, industry, or segment.

These are 15 analytics maturity models that were reviewed and analysed:

1. **Watson's data warehousing maturity model** (Watson, 2002): A framework that describes the evolution of a data warehouse over time in terms of people, processes, and technology. It consists of three stages: initiation, growth, and maturity. Each stage has different characteristics and challenges that need to be addressed by the organization. This is one of the first models for data warehousing maturity, covers domains such as people, processes, and technologies. Here is a brief overview of each stage (Watson, 2001):
    1) Initiation: This is the first stage of data warehousing, where the organization decides to build a data warehouse and identifies the business objectives, scope, and requirements. The data warehouse is usually focused on a specific subject area or business function, such as sales or finance. The data warehouse team is small and consists of technical experts who design and develop the data

warehouse architecture, data models, ETL processes, and BI applications. The users are mainly analysts who use the data warehouse for ad hoc queries and reports. The main challenges in this stage are to obtain management support, secure funding, define the business value, and ensure data quality;

2) Growth: This is the second stage of data warehousing, where the organization expands the data warehouse to cover more subject areas and business functions, such as marketing, operations, or customer service. The data warehouse becomes more complex and heterogeneous, as it integrates data from multiple sources and supports different types of BI applications, such as dashboards, scorecards, OLAP cubes, or data mining. The data warehouse team grows and includes more roles and skills, such as project managers, business analysts, data stewards, or trainers. The user become more diverse, including managers, executives, or external partners who use the data warehouse for strategic decision-making and performance management. The main challenges in this stage are to manage the increasing complexity, scalability, and diversity of the data warehouse environment;

3) Maturity: This is the third and final stage of data warehousing, where the organization optimizes the data warehouse to achieve operational excellence and competitive advantage. The data warehouse is fully aligned with the business strategy and goals and provides a single source of truth for the entire organization. The data warehouse team is mature and well-organized and follows the best practices and standards for data warehousing development and maintenance. Users are empowered and satisfied with the data warehouse services and capabilities and use the data warehouse for innovation and value creation.

2. **Comuzzi's & Patel's Big Data Maturity Model** (Comuzzi & Patel, 2016): A framework that describes how organizations leverage big data to generate value for their business. It consists of five stages of maturity, from Initial to Optimized, based on four dimensions: business strategy, information management, analytics, and governance. Here is a brief overview of each stage and dimension:

   1) Initial: This is the lowest stage of big data maturity, where the organization has no clear vision or strategy for big data and uses it only for basic reporting or descriptive analytics. The information management is fragmented and siloed,

and the data quality and integration are poor. The analytics are limited and ad hoc, and the governance is non-existent or ineffective;

2) Developing: This is the second stage of big data maturity, where the organization has some awareness and interest in big data and uses it for some exploratory or diagnostic analytics. The information management is more centralized and standardized, and the data quality and integration are improved. The analytics are more systematic and structured, and the governance is more formalized and aligned with the business objectives;
3) Defined: This is the third stage of big data maturity, where the organization has a clear vision and strategy for big data and uses it for more advanced or predictive analytics. The information management is more integrated and coordinated, and the data quality and integration are high. The analytics are more sophisticated and automated, and the governance is more mature and effective;
4) Managed: This is the fourth stage of big data maturity, where the organization has a competitive advantage and differentiation from big data and uses it for more innovative or prescriptive analytics. The information management is more agile and scalable, and the data quality and integration are optimal. The analytics are more intelligent and adaptive, and the governance is more proactive and collaborative;
5) Optimized: This is the highest stage of big data maturity, where the organization has a transformational impact and value from big data and uses it for more disruptive or cognitive analytics. The information management is more dynamic and flexible, and the data quality and integration are exceptional. The analytics are more visionary and creative, and the governance is more strategic and visionary.

3. **Early DELTA Maturity Model by Davenport & Harris** (Davenport & Harris, 2007): A framework that describes the five foundational elements of a successful analytics program. The acronym DELTA stands for Data, Enterprise, Leadership, Targets, and Analysts. There are 5 maturity levels: Analytically Impaired, Localized Analytics, Analytical Aspirations, Analytical Companies, and Analytical Competitors. Here is a brief overview of each domain:
   1) Data: This element refers to the quality, availability, and integration of data used for analytics. The data should be consistent, accurate, accessible, and

relevant for the business objectives and analytical needs. The data should also be integrated across different sources and systems, and stored in a centralized data warehouse or a distributed data lake;

2) Enterprise: This element refers to the organizational structure, culture, and processes that support analytics. The enterprise should have a clear vision and strategy for analytics and align its resources and capabilities with its analytical goals. The enterprise should also foster a culture of data-driven decision-making, collaboration, and innovation among its stakeholders;
3) Leadership: This element refers to the role and influence of senior executives and managers in promoting and sponsoring analytics. The leadership should have a strong passion and commitment for analytics and communicate its value and benefits to the organization. The leadership should also provide guidance, direction, and support for the analytical initiatives and projects;
4) Targets: This element refers to the identification and prioritization of the business domains and areas that can benefit from analytics. The targets should be aligned with the strategic objectives and competitive advantages of the organization and have clear metrics and outcomes to measure the impact of analytics. The targets should also be feasible, realistic, and actionable for the analytical teams;
5) Analysts: This element refers to the skills, competencies, and roles of the people who perform analytics. The analysts should have a high level of analytical expertise and proficiency in using various methods, techniques, and tools for data analysis. The analysts should also have a good understanding of the business context and domain knowledge, as well as communication and presentation skills to convey the analytical insights and recommendations.

4. **Business Analytics Capability Maturity Model (BACMM) by Cosic et al**. (2012): A framework that describes how organizations can develop and improve their business analytics (BA) capabilities over time. The BACMM consists of five stages of maturity, from Non-existent to Optimised, and four dimensions of capabilities, namely Governance, Culture, Technology and People. Here is a brief overview of each stage:
   1) 0: Non-existent: The organization does not have this capability;
   2) Initial: The capability exists but is poorly developed;

3) Intermediate: The capability is well developed but there is much room for improvement;
4) Advanced: The capability is very well developed but there is still a little room for improvement;
5) Optimised: The capability is so highly developed that it is difficult to envision how it could be further enhanced. At this point the capability is considered to be fully mature.

5. **Analytic Processes Maturity Model (APMM) by Grossman** (2018): A framework that describes how an organization can develop and improve its analytic capabilities over time. The APMM consists of five stages of maturity, from Build reports to Strategy-driven analytics, and six dimensions of processes, namely Building Analytic Models, Deploying Analytic Models, Managing and Operating Analytic Infrastructure, Protecting Analytic Assets, Operating an Analytic Governance Structure, and Identifying Analytic Opportunities. Here is a brief overview of each stage:
   1) Build reports: An organization can analyse data, build reports summarizing the data, and make use of the reports to further the goals of the organization;
   2) Build models: An organization can analyse data, build and validate analytic models from the data, and deploy a model;
   3) Repeatable analytics: An organization follows a repeatable process for building, deploying, and updating analytic models. In our experience, a repeatable process usually requires a functioning analytic governance process;
   4) Enterprise analytics: An organization uses analytics across its operation, and analytic models in the organization are built with a common infrastructure and process whenever possible. They are deployed with a common infrastructure and process whenever possible, and the outputs of the analytic models are integrated together as required to optimize the goals of the organization as a whole. Analytics across the enterprise are coordinated by an analytic governance structure;
   5) Strategy-driven analytics: An organization has defined an analytic strategy, aligned the analytic strategy with the overall strategy of the organization, and uses the analytic strategy to select appropriate analytic opportunities and to develop and implement analytic processes that support the overall vision and mission of the organization.

6. **Analytics Maturity Quotient Framework (AMQ) by Piyanka** (2019): A framework that describes how an organization can measure and improve its analytics maturity over time. The AMQ consists of five components, namely Data Quality (DQ), Data-Driven Leadership (L), People with Analytic Skills (P), Data-Driven Decision-Making Process (D), and Agile Infrastructure (I). Each component has a score from 0 to 20, and the total AMQ score is the sum of the five components. Here is a brief overview of each component:
   1) Data Quality (DQ): This component measures the quality, availability, and integration of data that is used for analytics. The data should be consistent, accurate, accessible, and relevant for the business objectives and analytical needs. The data should also be integrated across different sources and systems, and stored in a centralized data warehouse or a distributed data lake;
   2) Data-Driven Leadership (L): This component measures the role and influence of senior executives and managers in promoting and sponsoring analytics. The leadership should have a strong passion and commitment for analytics and communicate its value and benefits to the organization. The leadership should also provide guidance, direction, and support for the analytical initiatives and projects;
   3) People with Analytic Skills (P): This component measures the skills, competencies, and roles of the people who perform analytics. The people should have a high level of analytical expertise and proficiency in using various methods, techniques, and tools for data analysis. The people should also have a good understanding of the business context and domain knowledge, as well as communication and presentation skills to convey the analytical insights and recommendations;
   4) Data-Driven Decision-Making Process (D): This component measures the process of making decisions based on data and analytics. The process should be systematic, structured, and transparent, and involve relevant stakeholders from different functions and levels. The process should also be agile, iterative, and adaptive, and incorporate feedback loops and learning mechanisms;
   5) Agile Infrastructure (I): This component measures the infrastructure that supports analytics. The infrastructure should be agile, scalable, and flexible, and enable fast and easy access to data and analytics. The infrastructure should

also be secure, reliable, and cost-effective, and comply with the legal and ethical standards.

7. **Analytics Maturity Assessment Framework by Blast Analytics & Marketing** (2021): A framework that describes how an organization can measure and improve its analytics maturity over time. The framework consists of five components, namely Culture, Capability, Technology, Data and Process. Each component has a score from 0 to 20, and the total score is the sum of the five components. Maturity levels: Laggard, Follower, Competitor, Leader, Innovator.
    1) Culture: The extent to which the organization fosters a culture of data-driven decision-making, collaboration, and innovation among its stakeholders;
    2) Capability: The extent to which the organization has the resources and skills to perform analytics effectively and efficiently;
    3) Technology: The extent to which the organization has the infrastructure and tools to support analytics in a fast and easy way;
    4) Data: The extent to which the organization has the quality, availability, and integration of data that is relevant and accessible for analytics;
    5) Process: The extent to which the organization has the process of making decisions based on data and analytics in a systematic, structured, and transparent way.
8. **Data Analytics Maturity Model (DAMM) by Association Analytics** (2017): A framework that describes how an organization can measure and improve its data analytics capabilities over time. The DAMM consists of five stages of maturity: Learning, Planning, Building, Applying and Leading, and four components of capabilities, namely Organization and culture, Architecture/technology, Data governance, and Strategic alignment. Here is a brief overview of each stage and component:
    1) Learning: to the organization assesses the location of its data and the accessibility of data for all employees;
    2) Planning: Recognition that there is a lack of trust in the accuracy of the data. The team is uncertain about their data needs and where to locate the required data;
    3) Building: he organization has formulated a data strategy and action plan for analytics, and they have received approval from the executive team.;

4) Applying: The organization views data as a valuable organizational asset and progressively gains proficiency in data analysis. Data becomes a primary source for understanding the organization and its members;
5) Leading: The organization operates its businesses guided by their data, Member experiences and internal operations are managed and optimized using analytics. Data-guided decision-making is prevalent throughout the organization, providing a strategic advantage for these associations in terms of advancing their missions.

9. **DELTA Plus Maturity Model by Davenport & Harris** (2017): A framework that describes how an organization can measure and improve its analytics capabilities over time. The framework consists of seven components, namely Data, Enterprise, Leadership, Targets, Analysts, Technology, and Analytical Techniques. Each component has a score from 0 to 5, and the total score is the sum of the seven components. There are 5 maturity levels: Analytically Impaired, Localized Analytics, Analytical Aspirations, Analytical Companies, Analytical Competitors. The framework covers the following dimensions of analytics maturity:
    1) Data: This dimension measures the quality, availability, and integration of data that is used for analytics. The data should be consistent, accurate, accessible, and relevant for the business objectives and analytical needs. The data should also be integrated across different sources and systems, and stored in a centralized data warehouse or a distributed data lake;
    2) Enterprise: This dimension measures the organizational structure, culture, and processes that support analytics. The enterprise should have a clear vision and strategy for analytics and align its resources and capabilities with its analytical goals. The enterprise should also foster a culture of data-driven decision-making, collaboration, and innovation among its stakeholders;
    3) Leadership: This dimension measures the role and influence of senior executives and managers in promoting and sponsoring analytics. The leadership should have a strong passion and commitment for analytics and communicate its value and benefits to the organization. The leadership should also provide guidance, direction, and support for the analytical initiatives and projects;
    4) Targets: This dimension measures the identification and prioritization of the business domains and areas that can benefit from analytics. The targets should

be aligned with the strategic objectives and competitive advantages of the organization and have clear metrics and outcomes to measure the impact of analytics. The targets should also be feasible, realistic, and actionable for the analytical teams;

5) Analysts: This dimension measures the skills, competencies, and roles of the people who perform analytics. The analysts should have a high level of analytical expertise and proficiency in using various methods, techniques, and tools for data analysis. The analysts should also have a good understanding of the business context and domain knowledge, as well as communication and presentation skills to convey the analytical insights and recommendations;
6) Technology: This dimension measures the infrastructure and tools that support analytics. The technology should be agile, scalable, and flexible, and enable fast and easy access to data and analytics. The technology should also be secure, reliable, and cost-effective, and comply with the legal and ethical standards;
7) Analytical Techniques: This dimension measures the methods and techniques that are used for data analysis. The analytical techniques should be appropriate, effective, and efficient for the business problems and opportunities. The analytical techniques should also be diverse, innovative, and advanced for the analytical goals.

The framework provides 5 maturity levels:

1) Stage 1: Analytically Impaired. No idea what to do with data, no analytical questions asked by management;
2) Stage 2: Localized Analytics. Silos analytics, mostly individual analytical enthusiasts, no analytical structure, no collaboration between enthusiasts;
3) Stage 3: Analytical Aspirations. Recognise and understand importance of analytics however are far from advanced analytics;
4) Stage 4: Analytical Companies. Data-oriented, have analytical tools, have some coordination between analytical functions or resources however not fully used from strategic perspective;
5) Stage 5: Analytical Competitors. Strategical approach to analytics, widely used, data-driven decisioning.

10. **Analytics Maturity Model by Logi Analytics (2017):** A framework that provides a guideline for assessing and improving the analytics capabilities of an organization.

The framework defines five levels of analytics maturity: Standalone Analytics, Bolt-On Analytics, Inline Analytics, Infused Analytics, Genius Analytics, based on four dimensions: data, analytics, users, and value. Here is a brief overview of each level:

1) Standalone Analytics. This is the most basic level, where the primary application shares data with a standalone analytics application. The user has to switch between the two applications to access dashboards and reports. There is no security integration or context sharing between the applications;
2) Bolt-On Analytics. Secure Analytics level adds single sign-on security integration between the primary and analytics applications, so the user does not have to log in twice. However, the user still has to switch between the applications to view analytics content;
3) Inline Analytics. This level embeds analytics content within the primary application, so the user can view dashboards and reports without leaving the application. The analytics content is co-presented with other application content, but not integrated into the workflow or logic of the application;
4) Infused Analytics. This level integrates analytics content into the workflow and logic of the primary application, so the user can interact with analytics content as part of their tasks. The analytics content is tailored to the user's role and context, and can trigger actions or events in the application;
5) Genius Analytics. This is the most advanced level, where the primary application offers self-service data exploration and analysis capabilities to the end users. The users can create their own dashboards and reports, access data from multiple sources, and perform advanced analytics such as predictive and prescriptive analytics**.**

11. **Online Analytics Maturity Model (OAMM) by Cardinal Path** (2020): A framework that describes how an organization can develop and improve its online analytics capabilities over time. The OAMM consists of six areas of maturity, namely Management, Objectives, Scope, Team, Process, and Methodology. Each area has six levels of maturity, from Inexistent to Optimized. The OAMM covers the following dimensions of online analytics maturity:
    1) Management: This dimension measures the level of support and involvement of senior executives and managers in online analytics. The management should have a clear vision and strategy for online analytics and communicate its value and benefits to the organization. The management should also

provide guidance, direction, and support for the online analytics initiatives and projects;

2) Objectives: This dimension measures the alignment and prioritization of the online analytics objectives with the business goals and strategies. The objectives should be specific, measurable, achievable, relevant, and timely (SMART). The objectives should also be communicated and shared with the relevant stakeholders;
3) Scope: This dimension measures the breadth and depth of the online analytics scope. The scope should cover the entire online ecosystem, including websites, mobile apps, social media, email marketing, etc. The scope should also include different types of online analytics, such as descriptive, diagnostic, predictive, and prescriptive;
4) Team: This dimension measures the skills, competencies, and roles of the people who perform online analytics. The team should have a high level of analytical expertise and proficiency in using various methods, techniques, and tools for data analysis. The team should also have a good understanding of the business context and domain knowledge, as well as communication and presentation skills to convey the analytical insights and recommendations;
5) Process: This dimension measures the efficiency and effectiveness of the online analytics process. The process should be systematic, structured, and transparent, and involve relevant stakeholders from different functions and levels. The process should also be agile, iterative, and adaptive, and incorporate feedback loops and learning mechanisms;
6) Methodology: This dimension measures the appropriateness and rigor of the online analytics methodology. The methodology should follow the best practices and standards for online analytics development and maintenance. The methodology should also be diverse, innovative, and advanced for the online analytics goals.

12. **SAS Analytics Maturity Model by SAS** (2014): A framework that helps organizations assess and improve their analytics capabilities and performance. The framework defines five stages of analytics maturity, from Analytically Unaware to Explorative, based on four dimensions: Culture, Internal Process Readiness, Analytical Capabilities and Data Environment. Here is a brief overview of each stage:

1) Analytically Unaware: Decision makers rely on perceptions, historical decisions, and unvalidated beliefs. They have no defined data management or analytic processes to support insight development or business decisions. Organization lacks analytics skills or executive interest and considers historical reporting to be analytics. Furthermore, some projects have defined scope and objectives, but there is inconsistency and duplication of software;
2) Analytically Aware: Decision makers recognize the benefits of analytics in supporting decision-making but do not leverage analytics consistently. The full benefits of analytics are poorly understood, and analytics activities are siloed and ad hoc, yet obtaining reasonable results;
3) Analytically Astute: Decision-makers adopt analytics for all decisions. The organization is characterized by common data management processes in place, and the use of data sets and analytics is established for decision-making. Analytics capabilities evolve slowly, and analytics development is constrained, yet departments have their own experts and plans in place;
4) Empowered: Decision makers leverage analytics across the organization to support business decisions. Widely deployed data processes support specific business insights. Management supports analytics to bring business units into alignment;
5) Explorative: Decision makers search for new ways to use advanced analytics to support business decisions. Processes around data enhancement and analytic methods to optimize resources are continually refining. Analytical Capabilities: Commits to innovative analytic use for future growth and draws on advanced analytics and advances in new techniques.

13. **TDWI Analytics Maturity Model by Halper** (2020): A framework that describes how an organization can measure and improve its analytics capabilities and performance over time. The model defines five stages of analytics maturity – Nascent, Early, Established, Mature, Visionary, and is based on four dimensions: organization, resources, data infrastructure, analytics, governance. The model covers the following dimensions of analytics maturity:
    1) Data infrastructure: This dimension measures the quality, availability, and integration of data that is used for analytics. The data should be consistent, accurate, accessible, and relevant for the business objectives and analytical

needs. The data should also be integrated across different sources and systems, and stored in a centralized data warehouse or a distributed data lake;

2) Organization: This dimension measures the organizational structure, culture, and processes that support analytics. The enterprise should have a clear vision and strategy for analytics and align its resources and capabilities with its analytical goals. The enterprise should also foster a culture of data-driven decision-making, collaboration, and innovation among its stakeholders;
3) Resources: Skills and budget. Execution of the resource usage, talent acquisition, building skills. Obtain modern analytics including data literacy, model building and deployment, and data engineering talents and skills.
4) Analytics: Scope of your analytics. The complexity of analytics utilized (e.g., machine learning, real-time analytics, etc.) and how analytics results are delivered in the organization. Access to analytics. Ability to perform own analytics. Analytics into business processes. Data-driven automated decision-making in production. Innovations in analytics;
5) Governance: Coherence of the company's data governance strategy to support analytics. Collaboration between business and IT. Ability to use and access the organization's data properly. The governance of advanced models – deployment, maintenance, versioning. Data catalogues. Right tools. Security and privacy measures deployed.

14. **Web Analytics Maturity Model – WAMM by Hamel, Cardinal path** (2009): A framework that describes how an organization can develop and improve its web analytics capabilities over time. The model defines six areas of maturity, namely Management, Objectives, Scope, Team, Process, and Methodology. Each area has six levels of maturity: 0 – Analytically impaired, 1- Initiated, 2 – Operational, 3 – Integrated, 4 – Competitor, 5 – Analytically addicted. The model covers the following dimensions of web analytics maturity:
    1) Management: This dimension measures the level of support and involvement of senior executives and managers in web analytics. The management should have a clear vision and strategy for web analytics and communicate its value and benefits to the organization. The management should also provide guidance, direction, and support for the web analytics initiatives and projects;
    2) Objectives: This dimension measures the alignment and prioritization of the web analytics objectives with the business goals and strategies. The objectives

should be specific, measurable, achievable, relevant, and timely (SMART). The objectives should also be communicated and shared with the relevant stakeholders;

3) Scope: This dimension measures the breadth and depth of the web analytics scope. The scope should cover the entire online ecosystem, including websites, mobile apps, social media, email marketing, etc. The scope should also include different types of web analytics, such as descriptive, diagnostic, predictive, and prescriptive;
4) Team: This dimension measures the skills, competencies, and roles of the people who perform web analytics. The team should have a high level of analytical expertise and proficiency in using various methods, techniques, and tools for data analysis. The team should also have a good understanding of the business context and domain knowledge, as well as communication and presentation skills to convey the analytical insights and recommendations;
5) Process: This dimension measures the efficiency and effectiveness of the web analytics process. The process should be systematic, structured, and transparent, and involve relevant stakeholders from different functions and levels. The process should also be agile, iterative, and adaptive, and incorporate feedback loops and learning mechanisms;
6) Methodology: This dimension measures the appropriateness and rigor of the web analytics methodology. The methodology should follow the best practices and standards for web analytics development and maintenance. The methodology should also be diverse, innovative, and advanced for the web analytics goals.

15. **Defining Analytics Maturity Indicators (DAMI) by Lismonta et al**. (2017): A framework that defines five aspects of analytics maturity: data, enterprise, leadership, targets, and analysts. The model defines five levels of maturity, namely 1 - no analytics, 2 - analytics bootstrappers, 3 - sustainable analytics adopters, 4 - disruptive analytics innovators.

Each model provides a structured approach for organizations to assess their analytical capabilities and chart a path towards becoming data-driven organizations that can effectively leverage advanced analytics for business success. To summarize and analyse all the above descriptions, the author created 3 tables, which can be found in the appendices: Appendix A -

a summary of all models and their maturity levels, Appendix B - a summary of all models and their domains and sub-domains/factors, and Appendix C - all models with the 3 characteristics (important for building a new model) used to select a few models for more in-depth analyses.

Traditionally, 5 levels of maturity are widely used, and sometimes a zero level is created to categorise those who haven't implemented or developed anything in a specific area. Becker at al. (2009) identified and developed 5 levels of maturity. In case of Comuzzi & Patel (2016), an additional zero level was created to accommodate companies that needed to be sorted as the zero level in a specific domain or subdomain. Appendix A shows all 15 models, including the year of development, the number of maturity levels and the names of maturity levels.

Analysing the models in Appendix A, it is observed that 9 models have 5 levels of maturity, 2 models have 6 levels, 2 models have 4 levels, 1 model 3 levels and 1 model does not disclose the levels. All models describe level 1 as beginner/weak analytics/not data-driven, while the highest level is described as advanced/visionary/innovator/leading. The author noticed that the older the models are, the fewer maturity levels are used. Starting from 2017, all the analysed models use 5 levels, with 2 cases adding an additional level to describe the state of 'no analytics at all' or a specific stage between 2 levels. Consequently, the 5-level maturity assessment will be used to determine the maturity level of analytics in Latvian organizations with the newly created assessment and recommendation tool.

Appendix B shows all 15 models along with the year of development, the number of domains, and the names of domains (if disclosed, factors behind the domains are provided). Usually, at least 3 domains are used to assess analytics maturity. After analysing the models and their domains, it was observed that 2 models have only 3 domains, and these are the oldest models. 6 models have 4 domains, 3 models have 5 domains and 3 models have 6 domains, 1 model has 7 domains. The number of domains in a model impacts the precision of maturity detection and allows for more specific recommendations to address why an organization has not achieved a higher maturity level. Most models include domains characterizing Data, Analytics, Technology, and people-driven factors such as skills, culture, and values. Domains that describe processes within organizations are also widely used. Consequently, the model for assessing analytics maturity will utilise the following 6 domains: Data, Analytics, Technology, People, Culture, and Organization.

The author's conclusion is that all models have maturity levels as an outcome of the assessment and domains as dimensions that characterise the analytics maturity level. These domains help provide a deeper understanding of the drivers behind a specific level of maturity.

From Appendix C where all 15 models are compared based on 3 characteristics, the author selected 4 models with some disclosure of the methodology to detect specific levels of maturity. The major goal is to build a new model for use in Latvia, and a detailed methodology is necessary for developing, replicating, or adjusting the model for specific industries, countries, segments, or organizations. The best-described models with the most explicit approach, including questions and methodology, were chosen. The 3 characteristics used for comparison of models with purpose of providing a framework for the new model are: disclosure of the survey questionnaire, availability of an online tool, and disclosure of the methodology for detecting maturity levels. 7 models disclose the survey questionnaire or have an online tool, and 4 models disclose the methodology for determining maturity levels to some extent. Based on the information disclosed, the author selected 4 models from the previous analyses with the most information to be used for developing the new model. These 4 models were then analysed based on the following characteristics: Maturity levels, Types of maturity levels, Number of domains, Type of domains, Number of factors, Assessment, Maturity level assessment describer, Maturity level detection, Model development, Survey questionnaire disclosed, Maturity level description, Recommendations, Reproducibility, Interpretation.

These are the Analytics Maturity Quotient Framework (AMQ) (Priyanka, 2019), DELTA Plus Model (Davenport, 2017), Defining analytics maturity indicators (DAMI) (Lismonta et al., 2017), and TDWI Analytics maturity model (Halper, 2020). These models were described in terms of domains, factors, interpretation of the results (maturity level), recommendations, and any other supportive information that increases the ability to replicate or build the model. The summary of characteristics for the 4 models is provided in Table 2.1. In addition, the author's own ranking of the following characteristics, namely, Maturity level description, Recommendations, Reproducibility, Interpretation, and Relevance to the purpose of assessing the maturity level of the advanced analytics ecosystem, was used to indicate how helpful model could be for replicating or developing an analytics maturity model. A 5-point ranking system was used, where 1 signifies a slightly helpful characteristic with minimal description, and 5 signifies a very helpful characteristic with very detailed description.

Analytics Maturity Quotient Framework (AMQ) (Priyanka, 2019)

The Analytics Maturity Quotient (AMQ) Framework is based on 4 domains: Data Maturity, Leadership, Analytics Talent, Decision-making process. The domains contain 2-4 factors, assessed on a 10-point scale, with a final score ranging from 0 to 10. A publicly available simple DIY survey for assessing the Analytics Maturity Quotient (AMQ) was developed by Priyanka in 2019, allowing organizations to assess their AMQ. The model was developed based on detailed stakeholder interviews, auditing, and quantitative surveys. For the comprehensive approach, a detailed and prioritized set of recommendations to increase analytics maturity is provided. The analytics maturity assessment model is continuously developed and updated.

DELTA Plus Model (Davenport & Harris, 2017)

The DELTA Plus Model is adapted from the work of Davenport and Harris (Davenport et al., 2010; Davenport & Harris, 2007; Davenport & Harris, 2017) and is a tool developed by the International Institute for Analytics (IIA). It is built upon Davenport & Harris's analytics maturity assessment model from 2007, which is frequently cited ones and serves as a foundation. This model identifies 3 domains: 1) Organization with subdomains Analytical objectives, Analytical processes; 2) Human with subdomains Skills, Sponsorship, and Culture, and 3) Technology (Davenport & Harris, 2007). In 2010, the base model was enhanced with the DELTA framework (Davenport et al., 2010), and in 2017, the DELTA Plus model was introduced, which contains 7 domains: Data (breadth, integration, quality), Enterprise (approach to managing analytics), Leadership (passion and commitment), Targets (first deep, then broad), Analysts (professionals and amateurs), Technology (approach, orientation, velocity), Analytics techniques (sophistication, diversity). A publicly available version of the DELTA Plus Model (International Institute for Analytics, 2018) provides one factor with five statements for each domain. Analytics maturity stages are categorized as: 1) Analytically Impaired, 2) Localized Analytics, 3) Analytical Aspirations, 4) Analytical Companies, 5) Analytical Competitors. It also offers comparisons to industry benchmarks and digital native companies. While the algorithm for determining the maturity level is not disclosed, an explanation of each maturity stage is provided to those making assessments, and an action list to move from one stage to another is shared. The model has been developed over many years of research, interviews, and quantitative surveys.

Defining analytics maturity indicators (DAMI) (Lismonta et al., 2017)

Defining analytics maturity indicators: The survey approach paper model is based on 5 domains: Data, Organization, Leadership, Techniques and applications, and Analysts. 4 stages of the analytics maturity were found out with clustering based on 28 factors. 1 – No analytics, 2 – analytics bootstrappers, 3 – sustainable analytics adopters, 4 – disruptive analytics innovators. The research provides key characteristics of each stage and recommendations to improve analytics maturity. The model was developed based on interviews as a pre-test for the quantitative survey conducted in 2 rounds with a 1-year interval. The results were validated by experts, and a full questionnaire with 67 questions is available.

TDWI Analytics Maturity Model (Halper, 2020)

TDWI Analytics maturity model is based on 5 domains: Organization, Resource, Data Infrastructure, Analytics, Governance. Maturity consists of 5 stages plus 1 stage (chasm) between the third and the fourth stage. The maturity stages are 1 – Nascent, 2 – Early, 3 – Established, 4 – Mature, 5 – Advanced/Visionary. The Chasm represents the most challenging stage to overcome on the path to reaching the next level of maturity. The research provides a wide set of characteristics of each stage and a solid outlook of recommendations to improve analytics. The model was developed based on extensive research, surveys, and interviews for many years. A full questionnaire is available with 52 questions as an online assessment tool. An application is required to access the full questionnaire (TDWI assessment, 2020).

Table 2.1.1.

4 Analytics Maturity Models - Summary by 14 Characteristics

Characteristics	AMQ	DELTA Plus	DAMI	TDWI
Maturity levels	-	5	4	5+1
Types of maturity levels	-	1 - Analytically Impaired 2 - Localized Analytics 3 - Analytical Aspirations 4 - Analytical Companies 5 - Analytical Competitors	1 – No analytics 2 – analytics bootstrappers 3 – sustainable analytics adopters 4 – disruptive analytics innovators	1 – Nascent 2 – Early 3 – Established 4 – Mature 5 – Advanced/ Visionary Chasm
Number of Domains	4	7	5	5
Types of domains	Data Maturity Leadership Analytics Talent Decision-making process	Data Enterprise Leadership Targets Analysts Technology Analytics	Data Organization Leadership Techniques and applications Analysts	Organization Resource Data Infrastructure Analytics Governance

		techniques		
Number of factors	11	7	28	22
Assessment	10-point scale	Statements	Scale, Statements	Scale, Statements
Maturity level describer	AMQ score 0-10	DELTA Score 1-5	Cluster 1-4	Score 1-20
Maturity level detection	Not disclosed	Not disclosed	Clustering	Weighted score by domains and average total score
Model development	Interviews, auditing, and survey	Research, surveys, interviews	Interviews, survey, validation by experts	Research, surveys, interviews
Survey questionnaire disclosed	Short DIY version only, 11 questions	Only 7 statements and domains	67 questions, full survey	52 questions, full survey
Maturity level description	1	5	5	5
Recommendations	1	5	3	1
Reproducibility	3	4	5	5
Interpretation	1	2	4	4

Source: Created by the author (2021)

Based on a detailed analysis of the 4 models using the 14 characteristics, as summarized in Table 2.1, the author’s conclusion is as follows: none of the models fully discloses the methodology for detecting maturity levels. However, having a clear algorithm is crucial for building a model capable of determining an organization’s maturity level. The DAMI model is the most transparent in this regard. On the one hand, questionnaires are disclosed by all models. On the other hand, publicly available versions for 2 models consist of very short questionnaires that could help provide an initial estimation of where an organization stands overall but would not be very helpful for developing a new model.

The author acknowledges that DAMI and TDWI models are the most appropriate to use as the base for developing a new model. These models could be the most helpful if a person who aims to build their own model does not have very extensive experience in a wide range of analytics. These models provide full questionnaires and provide hints to analyse the survey data, ensuring some reproducibility of these models to use them in other countries or industries and afterward allows comparing results.

Data, analytics, related tools, and the overall analytics ecosystem are becoming increasingly crucial in any organization due to the high demand for digitization. Consequently, an organization's analytics maturity assessment has become critical for sustaining successful business operations. Many analytics service providers and consulting companies have developed analytics maturity assessments as part of their commercial services. It's worth noting that there are more analytics maturity assessment models available than those mentioned in this doctoral thesis. However, publicly available versions often come with limited options, such as fewer questions, undisclosed maturity level detection methodologies, and high-level assessments of maturity levels that do not address specific details, such as how, when, and what resources are needed to advance in analytics maturity.

The ability to build or replicate one's own analytics maturity assessment model can be appealing to various entities, including large organizations, those with existing analytical teams aiming to promote analytical culture throughout the organization, analytical teams themselves, researchers, consultants, and experts in the analytics sector. Furthermore, the rapid development of technologies and analytical platforms, along with the increase of data volumes and data accessibility for a wider audience, introduces the risk of publicly available (non-commercial) analytics maturity assessment models becoming outdated or partly outdated. However, models available in the market can still serve for comparisons within the industry, among similar segments, and to gauge the overall maturity level.

All 15 models that were reviewed provide a foundation for the independent development of an analytics maturity model. However, those responsible for building or replicating such a model should ideally come from the analytics or related industry, being experts and/or practitioners. This is crucial not only for the replication or development of the model itself, but also for creating relevant questionnaires, conducting audits, performing interviews, understanding, using and interpreting the outcomes to provide a precise assessment of the overall maturity level, both holistically and by individual domains. Additionally, they should be able to develop a set of recommendations to improve the existing level or progress to the next stage. All the models that were reviewed disclose domains, to some extent sub-domains or factors, and at least provide a high-level description of analytics maturity levels. However, none of them fully reveal the methodology for detecting specific maturity levels. In some cases, more information was provided regarding the model's development process, such as surveys, interviews with experts, audits, and back-testing over time with the same pool of data. Among the 4 models analysed in-depth, 2 of them disclose the full survey questionnaire, 1 provides insights into the data analysis and maturity level indicators, and 2 offer some explanations on how maturity levels are detected.

Developing an analytics maturity assessment model or replicating an existing one, based on the models reviewed in this section, is indeed feasible. However, several challenges need to be addressed. The primary challenge is defining a methodology to detect the level of maturity. Another challenge is interpreting the results to provide explanations for the detected analytics maturity level and recommendations for the next steps to improve the overall analytics maturity level. One more challenge is monetizing the transition to a higher maturity level. In addition, time and the rapid development of technologies plays a significant role because the model should include the latest developments in analytics ecosystems and not become outdated shortly after its creation. It should be able to assess the maturity level effectively in the present and over the mid-term future, enabling organizations to align their analytics ecosystem with the most current and applicable solutions. Thus, there is a growing need for new analytics maturity ecosystem assessment models.

2.2. Advanced Analytics Maturity Assessment Tools

Advanced Analytics maturity assessment tools are software or frameworks designed to evaluate and assess an organization's level of maturity in implementing advanced analytics practices. These tools help organizations understand their current analytical capabilities, identify strengths and weaknesses, and create a roadmap for improving their analytical maturity. These tools are a type of visualization or summary of the advanced analytics ecosystem maturity assessment models. The Appendix C from the Subsection 2.1 showed that only 6 models have their tools, but author believe that some of the models have tools on top of the model as a commercial version, thus not available for public use for free. The tools usually consist of surveys, interviews, or scorecards that evaluate the organization's capabilities across various dimensions, such as data, technology, culture, process, and people. They also provide recommendations and roadmaps for advancing to higher levels of analytics maturity and achieving business goals. The analysis performed in Subsection 2.1 indicates the key features and functionalities of advanced analytics maturity assessment tools:

- **Questionnaires and Surveys**: Most maturity assessment tools use questionnaires or surveys to collect relevant data from different departments and stakeholders within the organization. These questions cover a wide range of topics related to data management, analytics capabilities, technology infrastructure, talent, and business alignment;

- **Maturity Level Scoring**: The assessment tool typically assigns a numerical score to each response provided in the questionnaire. These scores are aggregated and used to determine the organization's overall maturity level in different aspects of advanced analytics;
- **Visualization and Reporting**: Assessment tools often provide visualization and reporting features to present the results in a clear and concise manner. Dashboards and charts help stakeholders understand the organization's current state, benchmark against industry standards, and identify areas that require improvement;
- **Benchmarking**: Some assessment tools offer benchmarking capabilities, allowing organizations to compare their maturity level with industry peers or best-in-class organizations. Benchmarking can provide valuable insights and motivate organizations to strive for higher levels of analytical maturity;
- **Recommendations and Action Plans**: Based on the assessment results, these tools may generate recommendations and action plans to help organizations address their weaknesses and advance to higher maturity levels. These action plans may include suggested training programs, technology upgrades, or process improvements;
- **Customizable Assessments**: Advanced analytics maturity assessment tools may offer flexibility in tailoring the assessment to the specific needs and goals of an organization. Customizable assessments ensure that the evaluation aligns with the organization's unique business context and objectives;
- **Data Security and Privacy**: Since these tools involve collecting sensitive data, data security and privacy are essential considerations. Reputable assessment tools adhere to data protection standards and ensure that the information collected remains secure;
- **Iterative Assessments**: Some tools support iterative assessments, enabling organizations to periodically reassess their maturity as they implement improvement initiatives. This allows organizations to track progress over time and measure the impact of their efforts;

- **Time to complete**: One of the issues is to make the tools advanced enough to assess with precision the organizations AA maturity level, another important factor - not to make the tool so complicated and time consuming to use it, to avoid drop - offs where users do not complete the assessment due to its length.

Such Advanced Analytics maturity assessment tools include proprietary software developed by consulting firms or analytics vendors, as well as open-source frameworks that organizations can customize to fit their specific needs. These tools play a crucial role in guiding organizations on their analytics journey, fostering data-driven decision-making, and achieving a competitive advantage through advanced analytics capabilities.

The review and analysis of the advanced analytics maturity assessment tools is based on the models mentioned in the Subsection 2.1. There are many different advanced analytics maturity assessment tools available from various researchers, consultants, and vendors. These tools come in various forms: some are, while others offer short versions of more advanced tools. Some tools are available for assessment at a specific price. In some cases, it is possible to make an assessment, but not receive the results unless the user subscribes or provides contact information. As a result, ideas for visualization, outcome presentation, and improvements for business users were collected during the inspection of these tools.

Not all advanced analytics maturity models described in Subsection 2.1 have their tools publicly available on the Internet. The author conducted experiments and completed all assessment tools available from the list of models described in the previous section (see Appendix C) and one more from a significant market player, Alteryx.

A list of explored tools will be provided below with link and the date when the author last successfully accessed the specific tool. Over time, the tools are updated, and after some time tools may become inaccessible or only the latest version is available, which is not described in this doctoral thesis.

1. **DELTA Plus** Maturity Model by Davenport & Harris
   a. Access location: https://iianalytics.com/services/analytics-assessments
   b. Access date: 18 August, 2023
2. **Analytics Maturity Quotient Framework (AMQ)** by Piyanka
   a. Access location: https://www.aryng.com/whitepaper/bgft/Aryng_AnalyticsMaturityQuotient_Whitepaper.pdf
   b. Access date: 20 March, 2021
3. **TDWI** Analytics Maturity Model by Halper

    a. Access location: https://tdwi.org/pages/assessments/adv-all-tdwi-analytics-maturity-model-assessment.aspx
    b. Access date: 18 August, 2023
4. **Analytics Maturity Assessment Framework** by Blast Analytics & Marketing
    a. Access location: https://www.blastanalytics.com/analytics-maturity-assessment
    b. Access date: 20 March, 2021
5. **Data Analytics Maturity Model (DAMM)** by Association Analytics
    a. Access location: https://associationanalytics.ratemydata.com/s/damm-assessment
    b. Access date: 18 August, 2023
6. **Analytics Maturity Model** by Logi Analytics
    a. Access location: https://logianalytics.com/analytics-maturity-assessment
    b. Access date: 20 March, 2021
7. **Analytics Maturity Assessment** by Alteryx
    a. Access location: https://www.alteryx.com/resources/analytics-maturity
    b. Access date: 18 August, 2023

The author provides a brief description and analysis of each tool based on the experiment conducted. Step-by-step visualizations were obtained during the experiment, offering graphical illustrations of the existing AA ecosystem maturity assessment tools. The visualizations and analyses will be used as examples for the newly created tool by the author.

1. **DELTA Plus** tool: This tool typically takes about 5 minutes to complete. It assesses 7 domains. For each domain, it presents 1 statement to assess on a scale from 1 to 5. The tool generates summary reports indicating where the organization stands compared to others in the same industry and Digital Leaders. No recommendations are provided. It is possible to contact the organization for further support. It does not allow users to download or receive results via email, only general information is provided for the interpretation of the results. Appendix D provides the visualizations as 'print screens' for all the described steps.
    1) **Step 1.** Access the tool: https://iianalytics.com/services/analytics-assessments or https://iianalytics.com/ama-widget. To start using it, you are required to provide your full name, organization, job role, email, and region.

2) **Step 2**. Assessment involves answering a few general questions about the organization and evaluating specific domains.
3) **Step 3.** The overall assessment is provided, along with a comparison to peers in the same industry and digital leaders. Specific organization reports cannot be downloaded, only a general industry-based report is available if an email is provided.

2. **AMQ** tool: Available as a downloadable document for performing a 'do-it-yourself' assessment. 10 questions must be answered and the outcome calculated manually using a provided formula. The time required to answer the questions is 5 minutes, with a few additional minutes needed for calculations. Appendix E provides the visualizations as 'print screens' for all the described steps.
   1) **Step 1.** Access the tool: https://www.aryng.com/whitepaper/bgft/Aryng_AnalyticsMaturityQuotient_Whitepaper.pdf or https://docplayer.net/37704650-The-analytics-maturity-quotient-framework.html. To start to use it, you need to open or download the DIY assessment document. It is not possible to compare to peers or others. The ability is provided to contact organizations to get a more in-depth assessment and explanations. A new version of the tool is available, but it lacks an explanation to determine the overall score of the analytics level (https://aryng.com/download/consulting-downloads/Aryng_-_Data_Culture_Assessment.pdf).
   2) **Step 2**. Assessment of the advanced analytics ecosystem involves self-assessment based on 10 questions. All questions are to be ranked from 0 to 10 points.
   3) **Step 3**. The overall assessment score must be calculated manually with the help of the provided formula. No explanation on how to interpret the outcome is provided. There is no comparison to peers (in the same industry) or to digital leaders. It is not possible to download the specific organization's report. Only an invitation is extended to arrange a meeting to discuss results and what could be done in the future.
3. **TDWI** tool: Requires the organization's information including an email address and a phone number, to start the assessment. It takes around 20 minutes to complete, contains 6 domains, with a couple of questions or statements provided for each domain, to assess on a scale from 1 to 5. The tool provides summary reports to show

where the organization stands in each domain. There is no comparison to peers or digital leaders. An explicit explanation how to interpret the results is provided in the guide, which can be downloaded from the website. No recommendations are provided. Users have the ability to contact the organization for further support. It is possible to download the guide and receive the assessment results via email. Appendix F provides the visualizations in the form of 'print screens' for all the described steps.

1) **Step 1.** Access the tool: https://tdwi.org/pages/assessments/adv-all-tdwi-analytics-maturity-model-assessment.aspx . To begin using you are required to provide your full name, organization, job role, email, region, revenue of the organization, postal address, and phone numbers.
2) **Step 2**. A very detailed assessment of the advanced analytics ecosystem, considering various domains and several factors that describe each specific domain.
3) **Step 3**. The overall assessment score is provided along with the score for each domain, indicating at what level the organization is rated. The explanation and some potential next steps are provided through "Learn How to Improve" TDWI Analytics Maturity Model Assessment Guide, available for download to everyone (https://tdwi.org/pages/assessments/adv-all-tdwi-analytics-maturity-model-assessment.aspx). The guide provides an explanation of the maturity model, the phases of maturity in analytics. It helps to interpret the specific score, and provides recommendations for how to progress. While there is no comparison to peers in the same industry or digital leaders, it is possible to download the specific organization's report.

4. **Blast Analytics** tool: To access it, you may encounter technical issues or security warnings on the website. This tool evaluates the organization's capabilities across five dimensions: culture, capability, technology, data, and process. It provides a summary of where the organization stands in each domain but does not offer comparisons to peers or digital leaders. While some explanation is provided, there are no recommendations. Users have the ability to contact the organization for further support. Appendix G provides visualizations in the form of 'print screens' for all the described steps.

1) **Step 1.** Access the tool: https://www.blastanalytics.com/analytics-maturity-assessment. To begin using it, you are required to provide your full name, organization, job role, email, and industry.
2) **Step 2**. Assessment of the advanced analytics ecosystem - across 5 domains, with each domain further broken down into 5 sub-factors that describe the specific domain.
3) **Step 3**. The overall assessment score is provided, along with score for each domain, indicating at which level the organization is rated. Explanations and potential next steps are provided for each domain. However, there is no comparison to peers in the same industry or digital leaders. It is not possible to download the specific organization's report.

5. **DAMM** tool: Stands for Data Analytics Maturity Model, a tool developed by Association Analytics, a company that provides data analytics solutions for associations and nonprofits. The tool is based on the Gartner's Maturity Model for Analytics and Data Analytics, a framework that describes the stages of analytics development and adoption within an organization (Gartner's Analytics maturity assessment tool is not available publicly). The outcome provides one of the 5 stages of Data Analytics Maturity where an organization is positioned. The DAMM tool enables users to answer a set of questions related to each level and receive a score that reflects their current analytics maturity level. The score ranges from 1 (lowest) to 5 (highest) and corresponds to one of the five stages of analytics maturity. The tool also provides users with a personalized report that includes recommendations, best practices and resources to help them advance to the next level of analytics maturity. The assessment only takes about 10 minutes. Furthermore, users receive a more in-depth report via email, containing a thorough explanation of the 5 stages, along with actionable steps to advance to the next stage. Appendix H provides visualizations in the form of 'print screens' for all the described steps.
   1) **Step 1.** Access the tool: https://associationanalytics.ratemydata.com/s/damm-assessment. To begin using it, you are required to provide your full name, organization, email, and number of employees.
   2) **Step 2**. Assessment of the advanced analytics ecosystem based on 55 questions, the majority of which is assessed on a 5-point scale, ranging from "strongly agree" to "strongly disagree".

3) **Step 3**. The overall assessment score is provided, along with a score for each domain, indicating the organization's rating at each level. Explanations and potential next steps are provided for each domain. A comparison is made with peers who have similar characteristics. It is possible to download, share, or print the specific organization's report.

6. **Logi Analytics** tool: - Accessing it, technical issues may be encountered, as well as security warnings of the website. It was successfully used on 20.03.2021. Logi Analytics provides more of a quiz-like experience than a serious self-assessment tool. It consists of only 6 questions and asks very general questions. A brief summary is provided to indicate where the organization stands. There is some limited comparison to peers. Some explanation of the maturity level is also provided. The option to contact the organization for further support is available. Appendix I provides visualizations in the form of 'print screens' for all the described steps.
   1) **Step 1.** Access the tool: https://www.blastanalytics.com/analytics-maturity-assessment. To begin using it, you are not required to provide any personal information.
   2) **Step 2**. Assessment of the advanced analytics ecosystem – very brief, just few general questions.
   2) **Step 3**. The overall assessment, including the maturity level at which the organization stands, is provided. The tool offers explanations and potential next steps for each domain. It does not include a comparison to peers in the same industry or to digital leaders. Additionally, it does not allow users to download the specific organization's report.
7. **Alteryx** tool: This tool consists of a scorecard that measures the organization's capabilities across eight dimensions: data, organizations, leadership, organizational alignment, analytics people & technology, and strategy. This tool is available in 6 languages: English, German, Spanish, France, Portuguese for Brazil, and Chinese. This tool provides explicit explanations about the current stage and what should be done to move to the next stage. It provides many materials on use cases for each domain, which can serve as a valuable source for generating ideas on how to improve existing processes or solve issues. Comparison to peers is provided, to some extent. Appendix J provides the visualizations in the form of 'print screens' for all the described steps.

1) **Step 1.** Access the tool: https://www.alteryx.com/resources/analytics-maturity. To begin using it, you are not required to provide any personal information.
2) **Step 2**. Assessment of the advanced analytics ecosystem is carried out in 8 domains. For each domain, there is 1 or more questions.
3) **Step 3**. To receive something more than an overall score, you must provided your full name, email, the name of your organization, phone mumber, and country. If such information is provided, the overall assessment score is provided, along with the score for each domain, indicating at what level the organization is rated. The explanation and some potential next steps are provided for each domain. There is a comparison to peers. It is possible to download the specific organization's report.

Table 2.2.1. summarizes the analysis of the tools. The main goal of exploring these tools was to obtain the framework for the online tool to be created by the author. All tools are based on questionnaires and ask to assess different statements, mostly using a 5-point Likert scale. All tools provide an overall score/level of advanced analytics ecosystem maturity. All tools provide an option to make repetitive assessments. All tools, except AMQ and Logi Analytics tools, provide visualizations and some reporting on assessment results. The benchmarking or comparison to peers (the same segment – industry, size, country or other) or Analytics Leaders is provided only by three tools, namely, Delta Plus, DAMM, and Alteryx. This is an important factor that indicates whether a competitive advantage exists or not in comparison to competitors. Recommendations and Action Plans are provided by four tools: TDWI, Blast, DAMM, and Alteryx, but only two of them, namely, TDWI and Alteryx, provide detailed and valuable recommendations, a plan for the next steps and even some business cases for better interpretation of how and where improvements could be implemented, and an indication of the expected impact. None of tools, at least in their publicly available free versions, provides customizable assessments. The author believes that commercial versions may offer customization for specific needs or segments. Regarding data security and privacy, there is only one tool that raises suspicion – Blast Analytics tool. All tools ensure iterative assessments. The time required to complete the questionnaire should be taken into account to ensure that the assessment tool is user-friendly. With help of two tools (Delta Plus and Logi Analytics), the assessment could be completed in only 5 minutes, while for another two tools (TDWI and Alteryx), it took at least 20 minutes. Summing up the 'Yes'

answers from the summary table, the author identified 4 tools that could be used as a framework for building a new tool. However, two tools - TDWI and Alteryx – are recognised as the most complete because they provide the most explicit and detailed disclosure of important factors, such as recommendations and action plans, and fulfil all other factors (answer ‘Yes’). TDWI and Alteryx will be used as benchmarks for the new tool. These tools are the most time-consuming to complete. Thus, the author will need to make the new tool shorter and/or simpler for end-users.

Table 2.2.1.

Summary of the Tools by 8 Characteristics and Time to Complete.

N.	Characteristics	AMQ	DELTA Plus	TDWI	Blast Analytics	DAMM	Logi Analytics	Alteryx
1	Questionnaires and/or Surveys	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2	Maturity Level Scoring	Yes	Yes	Yes	Yes	Yes	Yes	Yes
3	Visualization and Reporting	No	Yes	Yes	Yes	Yes	No	Yes
4	Benchmarking	No	Yes	No	No	Yes	No	Yes
5	Recommendations and Action Plans	No	No	Yes	Yes	Yes	No	Yes
6	Customizable Assessments	No	No	No	No	No	No	No
7	Data Security and Privacy	Yes	Yes	Yes	No	Yes	Yes	Yes
8	Iterative Assessments	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Time to complete (minutes)	10	5	25	10	15	5	20
	Total count of ‘YES’	**4**	**6**	**6**	**5**	**7**	**4**	**7**

Source: Created by the author

2.3. Localization for Latvia

Subsections 2.1 and 2.2 reveal advanced analytics assessment models and tools available globally in English. One tool (Alteryx) is available in a few other widely-used large languages. The tools available in English are not forbidden to be used by organizations in Latvia. However, due to language barriers and specific terminology, the assessment and outcomes could be heavily influenced and potentially misleading. One of the most important factors for localization is language and adapting the tools for regional usage and behaviour. Consequently, the author explored whether such models or tools have been customized and made available in Latvian. Additionally, the author looked into whether these tools are accessible to anyone interested in assessing the current state of a specific organization's advanced analytics maturity and whether a set of recommendations is available to implement or improve advanced analytics within the organization.

There are no reports, surveys, or research about the Baltic States or Latvia regarding the maturity of analytics, or advanced analytics and the usage of advanced analytics. Several studies have addressed related and more global areas under the Digital Economy and Society Index (DESI, 2022), but this only gives an idea whether there is a potential for analytics to be mature enough to adopt advanced analytics. Latvia is ranked as 17th from 27 Europe Union (EU) member states and even is below the average level of EU. The report on the Digital Economy and Society Index subdimension concerning the Integration of digital technology paints a picture in which Latvia is ranked only 23rd out of 27 countries (DESI Latvia, 2022). There has been research on digital maturity (Eremina et al., 2019) and digital transformation (Mavlutova et al., 2022) and their interaction with business performance, including factors such as revenue, sales growth, profitability, and sustainability, specifically for the Baltic states and Latvia. In the case of Eremina's research, two elements of digital maturity, namely data science and artificial intelligence, fall under the category of advanced analytics. However, during the research period (2013-2017), these two elements had limited presence in the real-life context of the segment explored, which included listed enterprises in Estonia, Latvia, and Lithuania. According to Mavlutova, where the financial sector digital transformation and its sustainable development were explored, the 2 core elements (4 in total) for successful digital transformation and sustainability are big data and advanced analytics, and artificial intelligence.

In conclusion, the author can affirm that while there have been several related research studies, they have not been specifically focused on advanced analytics. Nonetheless, it is worth noting that advanced analytics is widely recognised as one of the major factors that enables delivering on the global sustainability goals (Guandalini, 2022).

As of now, there are no tools available for assessing advanced analytics maturity in the Latvian language, however, there are 2 tools to assess digital maturity – overall and by some sub-directions. Digital maturity assessment tools cover a wider spectrum, including the existence of a website, the ability to see accounting data without the support of an accountant, if any analytical team or task management exists, while advanced analytics maturity assessment covers specific analytics-oriented questions, for example, data sources, storage, quality, analytical tools, and skills. The Latvian Information and communications technology association (LIKTA, https://likta.lv/en/home-en/) introduced the first digital maturity assessment tool in the Latvia market in 2019. This tool is called 'Digital maturity test' (https://www.gudralatvija.lv/), it is free for anyone and is in Latvian. It provides an overall assessment of digital maturity and of several subsections such as accounting, digital marketing, customer relationship management (CRM), data security, and others. In only one subsection that focuses on future development areas within the next 2-3 years, a question related to advanced analytics implementation has been included.

Another digital maturity assessment tool is provided by the European Digital Innovation Centre (Eiropas Digitālās inovācijas centrs, EDIC, https://dih.lv/lv) which is a part of the Digital Europe programme (DIGITAL). It is a new EU funding programme focused on bringing digital technology to businesses, citizens and public administrations (DIGITAL, https://digital-strategy.ec.europa.eu/en/activities/digital-programme). This programme is planned with an overall budget of 7.5 billion EUR (in current prices) for EU, with a focus on small and medium-sized enterprises. Funding is available through other EU programmes, such as the Horizon Europe programme for research and innovation, the Connecting Europe Facility for digital infrastructure, the Recovery and Resilience Facility, and the Structural funds. It is a part of the next long-term EU budget, the Multiannual Financial Framework 2021-2027. The organizations must provide full information about themselves and submit applications to obtain access to the digital maturity assessment tool provided by EDIC. During application, organizations must provide information about their specific needs, issues, and development plans and specify the EU funds category to which they are applying: below 5,000 EUR, 5,000-100,000 EUR, or up to 7,000,000 EUR. When all this information is provided, the organization is promised to be contacted by representatives of the EDIC and granted access to the assessment tool. At the same time, their website states that the digital maturity tests are currently unavailable. Instead, they recommend taking digital transformation training offered by another company https://www.kickstart.lv/, and these trainings are not free. However, it is possible to use the tool and take a digital maturity test in Latvian from http://dma.innocape.eu/lv, which is the original owner of the digital maturity tool. The tool is developed very closely based on the sub-dimensions of the Digital Economy and Society Index. It is a part of the EU project INNOCAPE https://innocape.eu/ in the Baltic Sea Region, and the tool is available in 7 languages, including Latvian.

Considering that an advanced analytics maturity assessment tool is not available in Latvian and that Latvia’s DESI index is below the EU average, the development of a locally customized tool is highly warranted. This implies that such tool needs to be created specifically for Latvia.

The topic of localization is multi-faceted and can be studied in various academic fields, including linguistics, computer science, economics, marketing, and cultural studies. According to Dunne (2023), localization is the process of adapting a product or service, or content to a specific market or culture. It involves translating and modifying the content, design, functionality, and user experience to suit the local preferences, expectations, and regulations of the target audience. Localization can help increase the relevance, usability, and acceptance of a product, service, or content in a target market or culture.

Localizing the advanced analytics maturity assessment for a specific country involves tailoring the assessment process to the country's unique business environment, cultural factors, and regulatory landscape. The key steps to localize the advanced analytics maturity assessment are (Esselink, 2000):

1) Research Country-Specific Context: Understand the country's business environment, industry trends, and data regulations. Research cultural aspects that may influence data usage and analytics adoption. This knowledge will help adapt the assessment to the country's specific needs;
2) Customize Questionnaires and Metrics: Modify the assessment questionnaires and metrics to align with the country's industry practices, language, and data-related regulations. Ensure that the questions reflect the country's business challenges and opportunities;
3) Consider Local Data Privacy Laws: Take into account the country's data privacy laws and regulations. Ensure that the assessment respects data protection and privacy requirements, and address any concerns related to data security;

4) Adapt Benchmarking Data: If the assessment includes benchmarking against industry peers or global standards, ensure that relevant local benchmarks are used to compare the organization's maturity level within the country's context;
5) Account for Industry Specifics: Consider the country's dominant industries and their specific analytics requirements. Customizing the assessment to address industry-specific needs will provide more accurate insights;
6) Engage Local Experts: Involve local experts or consultants who have a deep understanding of the country's business landscape and analytics adoption. Their input can help ensure the assessment's relevance and accuracy;
7) Pilot Test the Assessment: Before full-scale implementation, conduct pilot tests with a representative sample of organizations in the country. Use feedback from the pilot to fine-tune and validate the localized assessment;
8) Provide Localized Support and Documentation: Offer localized support and guidance for organizations participating in the assessment. Provide documentation and resources in the local language to facilitate better understanding and participation;
9) Analyse and Interpret Results in Local Context: While analysing the assessment results, interpret them in the context of the country's unique characteristics, business challenges, and opportunities. This will help in providing actionable insights and recommendations;
10) Continuously Update the Assessment: Regularly review and update the localized assessment to reflect changes in the country's business landscape, regulations, and technological advancements. Keep the assessment up-to-date with emerging analytics trends.

These steps could be called as best practice and will be taken into account where it is relevant developing the questionnaire.

By following these steps, it is possible to ensure that the advanced analytics maturity assessment is relevant, meaningful, and aligned with the specific needs of the organization in the specific country. It will enable the organization to better understand their analytics capabilities, chart a path towards becoming more data-driven and provide business with a competitive advantage by tailoring products, services, and marketing efforts.

In conclusion, for Latvia, the preparation of a survey or questionnaire must be in the Latvian language. From the author’s point of view, it is a quite serious issue driven by the challenge to translate certain terms from English into Latvian due to the absence of relevant terminology in the Latvian language. Additionally, the specificity of the topic may render this technical terminology unfamiliar to individuals outside the industry. Another challenge in localizing the tool is ensuring its relevance to the region and Latvia. For example, the assessment should not include tools, software, solutions, or techniques that have not yet been introduced to the region. In terms of data security and privacy, only one tool raised concerns, which was the Blast Analytics tool. All the tools support iterative assessments. To ensure user-friendliness, it's essential to consider the time it takes to complete the questionnaire. Notably, two tools, Delta Plus and Logi Analytics, enabled assessments to be completed in just 5 minutes, while the other two, TDWI and Alteryx, required a minimum of 20 minutes.

From the summary table, the author identified four tools suitable as a framework for building a new assessment tool. However, TDWI and Alteryx stand out as the most comprehensive due to their explicit and detailed disclosure of critical factors, recommendations, and action plans. Both tools received almost maximum 'Yes' by all criteria. Therefore, TDWI and Alteryx will serve as benchmarks for the new tool. It's worth noting that these tools are the most time-consuming to complete. Consequently, the author aims to create a new tool that is shorter and simpler for end-users.

3. APPROACH TO BUILDING THE ADVANCED ANALYTICS ECOSYSTEM MATURITY ASSESSMENT AND RECOMMENDATION TOOL

This section describes the approach used to ensure the research goal, which is the development of an advanced analytics ecosystem assessment and recommendation tool. First of all, the author explored and analysed publicly described analytics assessment models (as detailed in Subsection 2.1) with purpose of building a model tailored for Latvia. These models served as the primary source for questionnaire design and provided valuable insights on how to build the assessment model. Secondly, publicly available assessment and recommendations tools were examined and analysed (as detailed in Subsection 2.2) with the purpose of developing a tool specifically tailored for Latvia. These tools served as the primary source for the assessment and recommendations tool. Thirdly, best practices were explored for considerations in localizing approaches, processes, solutions, or tools (as described in Subsection 2.3).

Based on the experiences explored in Section 2, the author uses a series of steps to ensure the research goal. These steps involve developing the questionnaire in Latvian, specifying the target audience and formulating a data collection strategy. Localization aspects, including the use of the local language and consideration of data protection, are taken into account. Subsequently, data analysis is conducted, leading to the development of the assessment model, which detects the overall advanced analytics maturity level and maturity level within different domains. Descriptions are then prepared for each overall maturity level, along with recommendations for each level of maturity within each domain. The final phase involves the development of the tool, which is subsequently made available on the author's website at http://www.raaconsulting.eu/.

3.1. Quantitative Survey Design

The design of the quantitative survey questionnaire is the most significant step in building the assessment model. It allows for the collection of core data, which forms the initial model for assessing advanced analytics maturity. Based on the experiences explored in Section 2.1, where quantitative surveys were consistently used as the foundation behind the models, the author uses the quantitative survey as the main data source for building the model. The author's developed questionnaire is inspired by and based on the models and tools reviewed and analysed in sections 2.1 and 2.2, as well as the author's professional experience in the advanced analytics industry. The questionnaire design is primarily developed based on 4 models with disclosed or semi-disclosed information to obtain data for modelling: 1) AMQ – Analytics Maturity Quotient Framework (Piyanka, 2019); 2) DELTA Plus Model (Davenport & Harris, 2017); 3) DAMI – Defining analytics maturity indicators (Lismonta et al., 2017; 4) TDWI Analytics Maturity Model (Halper, 2020). The author developed a new questionnaire, adapting it for 2022 and customising it for use in Latvia.

The result is a questionnaire comprising 40 questions, with Appendix K presenting the full questionnaire in Latvian and Appendix L providing the full questionnaire in English. The questionnaire includes various question types, such as single choice, multiple choice, text entry, matrix table, and constant sum questions, allowing for the collection of a wide range of structured information. The questionnaire can be divided into 6 blocks of questions: the default question block with an introduction about the topic of the survey and a metadata browser, the demography block (11 questions) with questions like age, gender, and organization size, the maturity assessment block (23 questions), the challenges block (1 multiple choice question), the solutions block (1 multiple choice question), and the block about the impact on business (4 questions). The questionnaire contains only a few questions that were directly adopted from previous researches for this survey. Most of the questions and statements are newly created, drawing on the background and ideas from the sources mentioned in the Sections 1 and 2.

The maturity assessment block, consisting of 23 questions, has been structured to encompass all 6 domains selected by the author based on analysis of previous models and tools (refer to Subsections 2.1 and 2.2) and author's professional experience in the advanced analytics industry. Author named 6 domains as follows: Organization, People, Culture, Data, Analytics, and Technology. The aim of each domain is to assess its impact on the advanced analytics ecosystem in the organization. Each domain is characterized by a set of questions. For example, the 'Data' domain contains questions like what are the sources of data in the organization, how the data is stored, is data accessible by anyone, and how easy it is to access data. Following, each domain consists of factors, and each factor can be described by several statements assessable on a 5-point Likert scale. In other words, questions ask respondents to assess specific statements, for example, they are asked to assess how easy it is to access data in the organization. The maturity assessment block comprises 36 statements that are to be assessed on a 5-point Likert scale. The majority of questions in the assessment employ this scale to gauge the analytics maturity level. Specifically, a 5-point scale is used, with 1 indicating ‘strongly disagree’ and 5 representing ‘strongly agree’.

Appendix M shows all domains, factors, and the statements derived from the model through data analysis and modelling, as described in Subsection 4.2.

Each domain can be described as follows, based on the questions generated to explore domains as factors in order to detect the overall Advanced Analytics maturity level:

Organization – organizational factors such as the overall process of how functions interact with each other, the presence and execution of an analytics strategy, the alignment and interaction between the organization’s strategy and analytics strategy, the prevalence of data-driven decision-making within the organization, and the demonstration of executive support, all of which determine and indicate the maturity level of this domain;

People – this domain encompasses analytical resource sufficiency, ranging from basic to advanced analytics capabilities, skill development, investment in analytical talent, and collaboration between analytics and operations-related functions within the organization;

Culture – indicates a commitment to becoming or evolving into an analytics-driven organization. It reflects strong leadership in data and analytics functions, investments in data literacy, and the prioritization of analytics within the organization;

Data – represents the raw material, a fundamental element that provides the opportunity to implement and develop analytics strategies at any level. Data characteristics, including sources, quality, volumes, frequency, accessibility, integrity, and architecture, determine the maturity of the data domain;

Analytics – encompasses the entire analytics process, the applications, and techniques used, serving as the internal platform to derive value from data and ensure the organization’s ability to make data-driven decisions;

Technology – serves as the foundation for becoming a data-driven organization, encompassing the infrastructure, data storage methods, including data management systems, the presence of analytical platforms, and the tools for analytics, as well as their connectivity to the organization’s internal systems.

The challenges or barriers block includes 1 multiple choice question presenting 25 predefined potential barriers in random order. Respondents are required to select at least 3 answers, and there is also an option for respondents to submit their own named barrier.

The success drivers or solutions block consists of 1 multiple-choice question containing 25 predefined potential solutions presented in random order. Respondents are required to choose at least 3 answers, and there is also an option for respondents to submit their own named solution.

The block about the impact on business comprises 4 questions, with 1 being a multiple-choice question offering 21 predefined potential benefits to business in random order, requiring the selection of at least 3 answers, and providing an option for respondents to submit their own named benefits; there is also 1 question to indicate how quickly return on investments in analytics is observed, and 2 questions related to the organization's investments in analytics.

The online survey platform Qualtrics was used to construct and conduct the survey. The randomized response method was used, providing a list of numerous potential answers to ensure reliable results, free from the influence of their order. The adaptable and flexible screen solution was used to enhance response reliability. 2 pilot interviews were held with potential respondents before launching the survey, and their feedback was gathered to improve the questionnaire.

Taking into account that the questionnaire is the most significant instrument for building the analytics maturity assessment model for organizations in Latvia, it is crucial to have the questionnaire in Latvian to ensure maximum comprehensibility for the majority of people. Creating a questionnaire in Latvian was challenging due to the absence of relevant terminology in the language and the inherent difficulty of the topic for the majority of people. This led to the identification of potential new terminology to be developed and implemented in Latvian. The primary terminology, 'advanced analytics', was introduced by the author in Latvian as 'augstākā analītika' (see Subsection 1.5).

3.2. Data Collection

According to explored models in the Subsection 2.1, the survey is a main source of data to build the model. The target audience is senior executives, executives, managers, persons responsible for analytics management, experts. They were attracted through email data bases, professional networks, online surveys on websites. The author conducts an experiment to collect data with the help of the survey. The survey is the main source of data to be used to achieve the research goal – to develop an advanced analytics ecosystem assessment and recommendation tool – and answer research questions such as the advanced analytics ecosystem's maturity level in Latvian organizations. A representative set of responses has to be collected to provide a trustworthy source for modelling and to answer sub-questions. Therefore, to estimate the sample size for a research study that represents a population, data from the Central Statistical Bureau of the Republic of Latvia (2021a) is used.

The target audience consists of representatives from any organization in Latvia who bear responsibility or decision-making authority in the context of strategy, development, planning, result delivery, and function management. The representatives include owners, senior executives, directors, heads of departments or functions, experts, and business users who represent the analytics community. According to the Central Statistical Bureau of the Republic of Latvia, an organization is defined as an economically active enterprise with either turnover or employment. These economically active enterprises can be located anywhere in Latvia. Latvia can be divided into 6 areas: Riga city, Riga surrounding, and 4 regions – Vidzeme, Latgale, Zemgale and Kurzeme (Legal Acts of the Republic of Latvia, Order of the Cabinet of Ministers no. 911, 2021). Thus, the respondents must be proportionally represented by all 6 areas. Organizations of varying sizes and from different industries must be represented. In the case of this study, the population size represents the approximate number of organizations to be researched, and the sample size is the number of organizations within the target group to be researched. Each organization may have at least one respondent, but considering the survey's anonymity, it is possible that some organizations could be represented by more than one respondent, particularly large organizations. To minimize this possibility, a control question is introduced. To increase the response rate, any interested respondent receives compensation from the author upon completing the questionnaire.

The confidence level - statistical probability that the value of a parameter falls within a specified range of values, must be chosen to obtain statistically significant results. The most commonly used confidence levels are 90%, 95%, and 99%. A higher confidence level indicates a higher probability that results are accurate, but increasing it can dramatically increase the required sample size. Finding a balance between the confidence level and an achievable research goal is crucial. Each confidence level is translated to a z-score. A z-score is a statistical method for rescaling data that helps researchers draw comparisons easier. The Margin of Error is the maximum acceptable difference in results between the population and the sample. The smaller the margin of error, the more representative the results are of the total population. However, decreasing the margin of error will also result in a sharp increase in the sample size. It is usually recommended to use a 5% margin of error as the standard, which should never be increased above 10%.

The sample size is calculated using the following formula (Cohran, 1977):

$$S = P * \frac{\frac{z^2 * d * (1-d)}{e^2}}{P - 1 + \frac{z^2 * d * (1-d)}{e^2}} \qquad (3.2.1.),$$

where S - sample size, P - population size, z - z-score, e - margin of error, d - standard deviation. Assumption on a standard deviation is 0.5.

The following Table 3.2.1 was created by the author, and sample sizes were calculated under specific criteria:

Table 3.2.1

Sample Size Detection for Survey.

	Population size	181511		
	Standart deviation	0.5		
z-score	Confidence level	Margin of error		
		1%	5%	10%
2.576	99%	15200	661	166
1.960	95%	9121	383	96
1.645	90%	6522	270	68

Source: Created by the author

According to the Central Statistical Bureau of the Republic of Latvia data (2021a), there were 181511 organizations in Latvia in 2020. As a result, the sample size can be determined. Determining the appropriate sample size is one of the most important factors in statistical analysis. If the sample size is too small, it will not provide valid results or adequately represent the realities of the studied population. On the other hand, while larger sample sizes provide smaller margins of error and are more representative, a sample size that is too large may significantly increase the cost and time needed to conduct the research. The author has chosen a confidence level of 95% and a margin of error of 5%. Under these conditions, it is necessary to collect at least 383 responses to provide statistically significant results. Choosing a confidence level of 90% and a margin of error of 10% to provide statistically significant results requires collecting only 68 responses. It means that collecting at least 383 responses will allow to make statistically significant analysis even by a couple of groups like regions, size of organizations or other segments. Based on the exploration of models in Section 2.1, data analysis was observed by regions, size of organization, industry, often comparing the final outcome (AA maturity level) based on size and/or industry. Keeping in mind the research goal of building an advanced analytics maturity assessment model that can be used by any type of organization, it is important to ensure analysis by size and industry. From an organizational demographic perspective, the performance of the region depends on organizations located in that region – their industry, size, and whether they are local or international. Thus, any analysis performed by regions will mirror the performance of the industry, size, and other factors, rather than the region itself. As a result, the analyses by segments will be conducted based on the primary influencers: industry and the size of the organization. 6 regions – Riga, the surrounding area of Riga, Vidzeme, Latgale, Zemgale, and Kurzeme – according to Latvia's statistical regions and administrative units (Legal Acts of the Republic of Latvia, Order of the Cabinet of Ministers no. 911, 2021) will be used to assess the coverage of Latvia based on the actual responses collected. The size of organization will be used as one of the segments for analyses. The type of industry will be used as another segment for analysis of results. The size of organization will be determined by the number of employees in the organization. Table 3.2.2 shows the grouping that has been used, and it is comparable to the grouping used by the number of employees according to the Central Statistical Bureau of the Republic of Latvia (2021b).

Table 3.2.2.

Definition of Groups to be Used for Analyses by Number of Employees.

Group	Employees
Micro	<10
Small	<50
Medium	<250
Large	250+

Source: Created by the author

The Statistical Classification of Economic Activities in the European Community, Revision 2 (NACE2), offers a layered classification of economic activities. It consists of 21 sections labelled with alphabetical letters A to U, 88 sub-divisions identified by two-digit numerical codes (01 to 99), 272 sub-groups identified by three-digit numerical codes (01.1 to 99.0), and 615 sub-classes identified by four-digit numerical codes (01.11 to 99.00) (Central Statistical Bureau of the Republic of Latvia, 2021c). This classification is used to identify the industry represented by respondents. Given its highly granular classification, specific industry groupings will be detected during data analysis for further examination. The number of responses within each group will be determined, and homogeneous groups (e.g., NACE2 in any production industry) will be merged to ensure a sufficient amount of data in those groups.

The data for this study were collected using the online survey platform Qualtrics (Qualtrics, 2023). The questionnaire was built by author. Two distribution channels were used: the professional online panel company Intra research (https://intraresearch.com) and a digital marketing campaign created by the author with help of Google Ads and the author's website http://www.raaconsulting.eu/.

3.3. Maturity Assessment Model Development (Overall and by Domains)

The model development process can be described as follows: data source identification, setting the target variable, data sampling, variable construction and data transformation, correlation analysis, model development, scaling, and performance analysis.

The data source for modelling is the data collected during the quantitative survey. There are various mathematical methods available for assessing model development, ranging for different types of regressions such as logistic regression to algorithms like decision trees, neural networks, random forest, support vector machine, and more. The author uses the Generalized Linear Model (GLM) technique, which is widely used in the finance industry. The author has extensive experience in building assessment and prediction models for data-driven automated decision-making, with over 100 models implemented in production worldwide. This technique is appropriate for the specific task of detecting a specific level based on various factors, and the results obtained are easily interpretable. The GLM approach requires the setting of a target variable. To ensure this, a question is included in the questionnaire, which, during the modelling phase, is used as the target variable. This question asks respondents to assess their overall impressions of the advanced analytics level in their organization on a 5-point Likert scale. Scores of 4 and 5 are used as the target for modelling to determine how much each domain influences the overall advanced analytics maturity level in the organization. However, in practical situations, there may be instances where the planned variable does not function as the target and it has to be substituted with another variable.

Data sampling: All the responses provided are included into the modelling process. Answers such as "Not Applicable", "Do not know", or "Hard to say" will be substituted with valid values suitable for modelling. In production, the model can provide assessment for users of the assessment tool who respond to certain statements with "Not applicable" or "Do not know". There are several approaches to substituting these values are substituted with valid ones for modelling purposes. One option is to use the average or 0, depending on relevance.

The next stage for model development is variable construction. An initial statistical analysis is performed to explore results and trends. Variables are constructed based on statements under each domain, with each domain containing a couple of statements. In the end, there are 6 variables, each corresponding to a domain. After variable construction, all calculations are reviewed, to make sure that the variables are calculated exactly as specified, and any unexpected cases or inconsistencies in logic are addressed. Any outliers and inconsistencies are investigated, rectified, excluded, or noted and accounted for during the modelling process.

Correlation analysis is used to assess the statements within each factor and domain, as well as their correlation with one another. This analysis allows for the exploration of unexpected correlations between variables that may appear unrelated. Additionally, it can help identify highly correlated variables that may need to be excluded from the analysis.

Logistic linear regression is used as the primary method for developing the assessment model. The author uses a logit link function (binomial) to facilitate more direct result interpretation. Logistic regression is a specialised form of binomial regression models, which falls under the umbrella of generalized regressions models (GLM). GLMs allow to express the relationship between influencing variables (x) and the target variable (y) in a linear and additive manner, even when the underlying relationships may not be linear or additive. In other words, logistic regression, like most other predictive modelling methods, uses a set of predictor characteristics to estimate the probability of a specific outcome (the target). The formula for the logit transformation of the probability of an event is:

$$\text{Logit}\ (p_i) = \beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k \qquad (3.3.1.),$$

where p = posterior probability of "event," given inputs x = input variables, β_0 = intercept of the regression line, β_k = parameters (Siddiqi, 2006, p.90). It is possible to rewrite the formula (3.3.1) as follows:

$$\log(p_i/(1-p_i)) = \beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k \qquad (3.3.2.),$$

The goal of modelling is to establish a statistically validated relationship between all domains that assess the overall advanced analytics maturity level of a particular organization. In other words, it is about determining the significance of each domain in assessing the organization's advanced analytics maturity level. The modelling can reveal the irrelevance of some domains or factors and highlight the most important domains or factors.

During the modelling process, it is important to follow statistical measures that describe the model and indicate the adequacy and performance of generalized linear models. Deviance residuals are a concept often used in the context of generalized linear models (GLMs), particularly in logistic regression. They are a measure of how well a GLM fits the data and can be used for diagnostic purposes. Deviance residuals are similar to other types of residuals, but they are based on the concept of deviance, which is a measure of the goodness of fit for GLMs. Summary statistics of the deviance residuals include: Min, 1Q, Median, 3Q, Max. Min represents the smallest value among the deviance residuals. It represents the most negative or under-predicted residual in the model. 1Q is the first quartile, equivalent to the 25th percentile of the deviance residuals, signifying the value below which 25% of the residuals fall. It provides a measure of the spread within the lower 25% of the residuals. The Median denotes the median, or the 50th percentile, of the deviance residuals. It represents the middle value when all the residuals are sorted in ascending order and serves as a measure of central tendency for the residuals. 3Q is the third quartile, that corresponds to the 75th percentile of the deviance residuals, indicating the value below which 75% of the residuals fall. It provides insight into the spread of the lower 75% of the residuals. Max is the maximum value of the deviance residuals and represents the most positive or over-predicted residual in the model. For example, when the median of the deviance residuals is close to zero, it suggests that, on average, the model is fitting the data well. However, if the minimum and maximum values are very large in magnitude, it may indicate that there are outliers in the data. The quartiles provide information about the spread of the residuals, which can be useful for understanding the variability in the model's predictions.

In the context of the logistic regression or GLMs, the following values are crucial for assessing the significance of each predictor variable (independent variable) in the model: standard error, z value (z-score) and Pr(>|z|) (p-value for the z value). The standard error is a measure of the variability or uncertainty associated with the estimated coefficients of the model. It quantifies the expected variation of the estimated coefficients from one sample to another. Smaller standard errors indicate more precise coefficient estimates. The z value is a standardized measure that indicates how many standard errors a coefficient estimates deviates from zero. It is calculated by dividing the coefficient estimate by its standard error. It helps assess whether a coefficient is statistically different from zero. If the absolute value of the z value is large, it suggests that the coefficient is significantly different from zero. The p-value associated with the z value is used to test the null hypothesis that the corresponding coefficient is equal to zero (i.e., it has no effect). A small p-value (typically less than 0.05 or another chosen significance level) suggests that the coefficient is statistically significant, meaning it has an effect. A large p-value suggests that the coefficient is not statistically significant.

Through logistic regression, a probability is derived for being in the highest level of advanced analytics maturity. Thus, the scaling is needed to obtain the weighted overall advanced analytics maturity level. According to Siddiqi (2006), the scaling can be performed in the following way:

$$\text{Score} = \text{Offset} + \text{Factor} * \ln(\text{Odds}) \qquad (3.3.3.),$$

where Score is rescaled probability to numerical values, Offset is a constant adjustment, Factor is a multiplicative scaling factor.

The Offset and Factor determine the transformation of the natural logarithm of the odds into the desired score range. Offset is a constant adjustment term that shifts the scaled scores obtained from the natural logarithm of the odds (ln(Odds)) and the scaling factor (Factor). It determines the baseline score that corresponds to a specific value of ln(Odds). In other words, it sets the lower bound or starting point for the scores calculated using the formula (3.3.3). In practical terms, you can think of the Offset as an adjustment that allows to control where the scaled scores start on the numeric scale. It helps to define the minimum score to be assigned for a specific value of ln(Odds) and to adjust the overall positioning of scores within a given range. On the other hand, the Factor serves as a multiplicative scaling factor that regulates the extent to which the natural logarithm of the odds (ln(Odds)) affects the resulting score. It controls the steepness or slope of the relationship between ln(Odds) and the calculated score. In other words, the Factor allows to control the degree of transformation applied to ln(Odds) to achieve the desired scaling effect. A higher Factor amplifies the impact of ln(Odds), potentially creating steeper score changes, while a lower Factor dampens the impact, resulting in more gradual score changes. Adjusting the Factor allows to fine-tune how odds are transformed into scores to meet the specific requirements of the application or analysis.

$$\text{Offset} = \text{Score} - \text{Factor} * \ln(\text{Odds}) \qquad (3.3.4.),$$

Therefore, to determine the Range of the Natural Logarithm, it is necessary to calculate the natural logarithm (ln) of the odds for the entire dataset or the range of odds values being worked with. As for the Factor, it scales the ln(Odds) values to fit within the desired score range. The Factor can be determined using the following formula:

Factor = (Maximum Score - Minimum Score) / (ln(Maximum ln(Odds)) - ln(Minimum ln(Odds)))   (3.3.5.),

When all measures are calculated, the Score is calculated using formula 3.3.4. In the case of the author's research, the calculated score provides the advanced analytics maturity level based on the assessment of 6 domains.

To assess the model's predictive power, stability, accuracy and goodness of fit, various statistical tests are performed, including ROC curve analysis, AUROC, GINI coefficient, ANOVA (analysis of variance) test, and the Hosmer-Lemishow test. According to Siddiqi (2006) and the author's professional expertise, the most powerful nonparametric two-sample test is the C-statistic. The C-statistic, also known as the Concordance statistic or the Area Under the Receiver Operating Characteristic Curve (AUROC), is a measure of the discriminatory power of a binary classification model. It is commonly used in statistics and machine learning to evaluate the performance of models that predict binary outcomes, such as logistic regression models or machine learning classifiers. The C-statistic is closely related to the ROC (Receiver Operating Characteristic) curve and the GINI coefficient. It quantifies the model's ability to distinguish between the two classes (positive and negative) by measuring the area under the ROC curve. It works within the context of binary classification, where a model predicts one of two possible outcomes, typically labelled as positive and negative. The ROC curve is a graphical representation of a binary classification model's performance. It plots the true positive rate (Sensitivity) against the false positive rate (1 - Specificity) at various decision thresholds. Each point on the ROC curve represents a different threshold for classifying the positive and negative classes. The C-statistic is calculated by finding the area under the ROC curve. It quantifies the overall ability of the model to distinguish between the positive and negative classes across all possible threshold values. The C-statistic score ranges from 0 to 1.0, with a higher value indicating better model performance. For example, if the C-statistic is 0.5, it means that the model's performance is equivalent to a random chance (no discrimination). The C-statistic is widely used in fields such as medicine (for evaluating diagnostic tests), credit scoring (for assessing credit risk models), and machine learning (for model evaluation). The AUROC (Area Under the Receiver Operating Characteristic) curve is a graphical representation of the performance of a binary classifier across different decision thresholds. The AUROC is calculated as the area under the ROC curve, which plots the True Positive Rate (Sensitivity) against the False Positive Rate (1 - Specificity) at various threshold values. The AUROC can be interpreted as the probability that a randomly chosen positive example will have a higher predicted score than a randomly chosen negative example.

The AUROC can be calculated by the following formula (Bradley, 1997):

$$\text{AUROC} = \frac{1}{n_{+} * n_{-}} \sum_{i=1}^{n_{+}} \sum_{j=1}^{n_{-}} II(s_i > s_j) \qquad (3.3.6), \text{ where}$$

n_+ - number of positive samples

n_- - number of negative samples

s_i - the score associated with the s_i-th positive sample,

s_j - the score associated with the s_j-th negative sample,

$\sum_{i=1}^{n_{+}}$ represents the summation over all positive samples,

$\sum_{j=1}^{n_{-}}$ represents the summation over all negative samples,

II ($s_i > s_j$) is an indicator function that equals 1 if ($s_i > s_j$) and 0 otherwise.

The GINI coefficient can be calculated by the following formula:

$$\text{GINI} = 2*\text{AUROC}-1 \qquad (3.3.7.),$$

An alternative approach to determining the overall advanced analytics maturity level involves assuming equal weights for all domains, such as a weight of 1. As a result, the overall advanced analytics maturity level is determined based on the average values across all domains.

The description and explanation of each maturity level must be developed, both in the overall context and for each domain, based on the analysis of the survey data and author's the professional expertise. Additionally, a set of recommendations should be provided, based on the analysis of the survey data and the author's professional expertise.

3.4. Online Assessment Tool

The tool will be published on author's website: http://www.raaconsulting.eu/

Here it is publicly available for free for anyone who is interested in to assess the advanced analytics ecosystem maturity level in specific organization of Latvia, following the principle of Open Science.

The tool must include all questions, statements which are used by model to assess the maturity level.

JotForm (https://www.jotform.com/) is used to build the advanced analytics assessment tool. It provides an immediate overall assessment of the maturity level, maturity level by domains, and a set of recommendations on how to improve the existing state of advanced analytics. The data collected during the assessment is automatically stored on Google Cloud-linked storage owned by the author. The tool provides data privacy and security in accordance with the General Data Protection Regulation (European Union, 2016).

4. DEVELOPMENT OF AN ADVANCED ANALYTICS ECOSYSTEM MATURITY ASSESSMENT AND RECOMMNDATION TOOL

This section describes the practical outcome and results of the approach described in the previous section to ensure the research goal, namely, to develop an advanced analytics ecosystem assessment and recommendation tool.

The data collection, as a part of experiment, was performed from 20 December 2021 to 31 March 2022. The data of this survey was obtained using an online survey platform Qualtrics. A total of 1164 unique questionnaires were initiated through both channels, including the Intra Research online panel and the RAA Consulting website via Google Ads. Out of these, 555 completed questionnaires were received, resulting in a response rate of 48%. An anonymous link was used for distribution of the survey to ensure confidentiality. The invitation to participate in this survey was sent only to the target audience: any level managers registered on the Intra research online panel and distributed across Latvia. The screening question “What is your role in the organization?” was used to filter out those who are not target audience. The survey consisted of 40 questions in Latvian, and average completion time was 14 minutes. The target group, represented by individuals in roles such as senior executives, executives, directors, managers, responsible persons for analytics, experts, decision makers, and owners of organizations in Latvia, was distributed as follows: C-level and Owners of the organization - 31%, Heads of departments and Senior experts – 56%, Other -13%. Thus, ensuring responses collected from the strategy developers and implementors and decision makers in the organizations, the aim of the author was to obtain opinions of the decision makers in the area of business development. Qualtrics analytical platform, MS Excel and R software were used for data transformation, processing, visualization, and analytics. To increase response rate, any respondent receives points convertible to euros by Intra research and the option to receive the research outcome and free-of-charge consultations from the author.

The data collected are representative and can be used to describe and characterize the entirety of Latvia and specific segments, such as the size of the organization and industry. It was planned to collect at least 383 responses (see Section 3) to ensure a dataset with a confidence level of 95% and margin of error of 5%. The completed number of questionnaires (555) allows for the comparison of a few segments with a statistically acceptable confidence level.

The dataset used for analysis and modelling is available in Appendix N.

RStudio is used to perform data transformation, analysis, modelling, and reporting. The scripts are provided in the appendices (Appendix O and Appendix P). The visualizations are created using MS Excel.

Table 4.1 shows a comparison of the distribution by region: actual survey data vs. data from the Central Statistical Bureau of the Republic of Latvia (Central Statistical Bureau Republic of Latvia, 2022a). Responses are distributed across all regions and can be used to describe the overall situation in Latvia.

Table 4.1.

Number of Representatives of Organizations, Number of Organizations by Regions.

Region	Survey data, 2022		CSB data, 2021	
	N	%	N	%
Kurzeme	51	9%	19983	12%
Latgale	53	10%	17342	10%
Riga & Surrounding	355	64%	104124	60%
Vidzeme	58	10%	16098	9%
Zemgale	38	7%	16018	9%
Total	**555**	**100%**	**173565**	**100%**

Source: created by the author, Survey 2022 data and CSB 2021 data.

Table 4.2 shows a comparison of distribution by the size of the organization: actual survey data vs. data from the Central Statistical Bureau of the Republic of Latvia (2022b). The observed split of actual responses collected, and the actual distribution of organizations drives implications for the detection of the overall advanced analytics maturity level in Latvia. However, to make a comparable analysis by the size of organizations, responses by size groups are sufficient to provide statistically confident analysis and conclusions. Thus, a weighted average approach will be used to detect the overall maturity level of advanced analytics in Latvia, with 92.8% of the impact coming from micro-organizations’ advanced analytics maturity level. The comparable analysis by the size of organizations can be performed, and the advanced analytics maturity level detected with a confidence level of 95% and a margin of error ranging from 4.4% to 10%.

Table 4.2.

Number of Representatives of Organizations, Number of Organizations by Size and Actual Data Confidence Level and Margin of Error.

Number of Employees	Survey data, 2022		CSB data, 2021		Survey data 2022 representativeness	
	N	%	N	%	Conf.int.	Error
1-9	157	30%	151562	92.8%	95%	7.8%
10-49	92	17%	9 898	6.1%	95%	10.0%
50-249	125	24%	1 611	1.0%	95%	8.5%
250+	153	29%	221	0.1%	95%	4.4%
NA	28					
Total	**555**	**100%**	**163292**	**100%**	**95%**	**4.15%**

Source: Created by the author. Survey 2022 data, CSB 2021 data and calculation of collected data representativeness (calculated using the formula provided in Section 3.2).

Table 4.3.

Number of Representatives of Organizations, Number of Organizations by Size.

Industry according to NACE2 classification	Survey data, 2022		CSB data, 2020	
	N	%	N	%
A Agriculture, forestry and fishing	41	7%	25526	14%
B Mining and quarrying	11	2%	339	0.2%
C Manufacturing	25	5%	10968	6%
D Electricity, gas, steam and air conditioning supply	15	3%	506	0.3%
E Water supply, sewerage, waste management and remediation activities	7	1%	327	0.2%
F Construction	51	9%	11518	6%
G Wholesale and retail trade, repair of motor vehicles and motorcycles	41	7%	25192	14%
H Transportation and storage	26	5%	8335	5%
I Accommodation and food service activities	17	3%	4158	2%
J Information and communication	52	9%	7740	4%
K Financial and insurance activities	21	4%	2378	1%
L Real estate activities	7	1%	14790	8%
M Professional, scientific and technical activities	16	3%	20226	11%
N Administrative and support service activities	7	1%	7573	4%
O Public administration and defence, compulsory social security	57	10%	446	0.2%
P Education	55	10%	4893	3%
Q Human health and social work activities	31	6%	6293	3%
R Arts, entertainment and recreation	15	3%	8133	4%
S Other service activities	60	11%	21821	12%
Total	**555**	**100%**	**181162**	**100%**

Source: created by the author, Survey 2022 data, CSB 2021 data.

Table 4.3 shows a comparison of the distribution by industry: actual survey data vs. data from the Central Statistical Bureau of the Republic of Latvia (2020). Table 4.3 shows that the survey data covers all NACE2 classification groups, each with a minimum of 7 responses. Consequently, a detailed breakdown is not suitable for industry analysis. Thus, to overcome these issues, NACE2 groups are merged according to the grouping used by the Central Statistical Bureau of the Republic of Latvia (except for Finance which is treated separately due to unweighted data indicating the highest advanced analytics maturity level by industries, and based on Section 1.2. Finance industry is in the leading positions regarding AA application): A Agriculture, forestry and fishing; B-E Production; F Construction; G Wholesale and retail trade, repair of motor vehicles and motorcycles; H-J, L-N, P-R, S Services; O Public administration and defence, compulsory social security; K Finance.

Table 4.4. shows a comparison of the distribution by merged industries according to the CSB methodology: actual survey data vs. data from the Central Statistical Bureau of the Republic of Latvia.

Table 4.4.

Number of Representatives of Organizations, Number of Organizations by Industry and Actual Data Confidence Level and Margin of Error.

Merged Industries NACE2	Survey data, 2022		CSB data, 2020		Survey data 2022 representativeness	
	N	%	N	%	Conf.int.	Error
A Agriculture, forestry and fishing	41	7%	25526	14%	81%	10%
B-E Production	58	10%	12140	7%	88%	10%
F Construction	51	9%	11518	6%	85%	10%
G Wholesale and retail trade, repair of motor vehicles and motorcycles	41	7%	25192	14%	81%	10%
H-J,L-N, P-R, S Services	286	52%	103962	57%	95%	6%
O Public administration and defence, compulsory social security	57	10%	446	0%	90%	10%
K Finance	21	4%	2378	1%		
Total	**555**	**100%**	**181162**	**100%**	**95%**	**4.15%**

Source: created by the author, Survey 2022 data, CSB 2020 data and calculation of collected data representativeness (calculated by formula provided in Section 3.2.).

Table 4.5.

Distribution by Industry by Size of Organization.

Industry	Number of employees					
	1-9	10-49	50-249	250+	NA	Total
A Agriculture, forestry and fishing	24	3	5	6	3	41
B-E Production	12	11	16	19		58
F Construction	16	14	17	3	1	51
G Wholesale and retail trade, repair of motor vehicles and motorcycles	14	10	6	10	1	41
H-J,L-N, P-R, S Services	85	50	64	65	22	286
K Finance	5	1	4	11		21
O Public administration and defence, compulsory social security	1	3	13	39	1	57
Total	**157**	**92**	**125**	**153**	**28**	**555**

Source: created by the author, Survey 2022

Subsection 4.1 provides initial data analysis by target variable Q21, size of organization, and industry of the organization.

Subsection 4.2 describes the modelling process and the outcome, which model is used to be integrated into the assessment tool. The model indicates how important each domain is in assessing the overall advanced analytics ecosystem maturity level.

Subsection 4.3 provides assessment of advanced analytics based on the model.

Subsection 4.4 provides an overview of the stages of advanced analytics, and subsection 4.5 provides an overview of recommendations for the specific level to progress to the next level.

Subsection 4.6 provides the link where you can find the model online and an example for a specific organization that provided responses for the survey.

4.1. Survey Data Analysis

The raw dataset contains 1164 responses, of which 555 are fully completed and used for further analysis and modelling. Comprehensive data analysis was performed using descriptive statistics to obtain an overview of the data, identify patterns and relationships, validate data quality, ensure consistency within the target group, assess distribution by segments, gain an initial understanding of results, observe differences between segments, generate ideas and understanding for modelling, and identify and clean extreme values. Based on this analysis, it is possible to draw conclusions, identify new research areas, and provide suggestions. Appendix O provides the R code for data transformation and preparation for analysis, code for descriptive statistics, and code to print/export the results in MS Word format. Appendix Q provides an overview of the survey results using descriptive statistics. Appendix R provides an overview of the survey results using descriptive statistics for the target variable Q21. Appendix S provides an overview of the survey results using descriptive statistics by the size of the organization. Appendix T provides an overview of the survey results using descriptive statistics by industry. It is recommended to use Appendix K (full questionnaire in Latvian) or Appendix L (full questionnaire in English) to access the complete set of questions, statements, answers, and assessment scales for a comprehensive understanding of the quantitative survey results. Each question is accompanied by a count of specific answers and a distribution of answers. In cases where it is relevant (questions with 5-point Likert scale), the minimal and maximal values, mean, standard deviation, and variance are provided.

The survey was completed by 59% females and 41% males. The age structure indicates that 63% of respondents fell into the age group 30-50, while 26% were in the age group 51-60. The remaining participants were either under the age of 30 or over 60. 34% of respondents held a Master's degree, and 32% had a Bachelor's degree. Regarding job positions, 16% were chief executive officers, board members, or owners, 29% were directors and heads of departments, and 41% were senior experts with decision-making authority. The remaining respondents included self-employed individuals, farmers, or specialists. All regions of Latvia were represented, with Riga and its surrounding areas accounting for 64% of respondents, while Vidzeme, Latgale, Zemgale, and Kurzeme made up the remaining 36%. The survey included a diverse range of organization sizes, with micro, small, medium, and large enterprises all being represented. Additionally, all industries, based on the NACE classification, were represented.

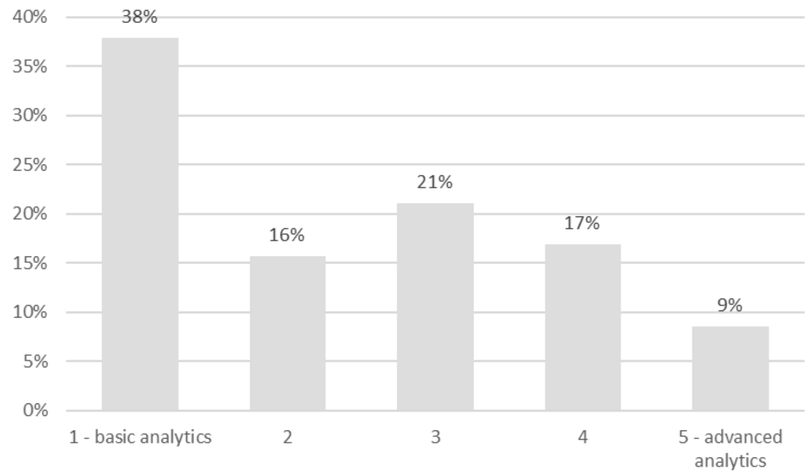
There is a question, Q21, which asks "How would you characterize the analytical development in the organization from the point of view of applied analytical solutions/methods? Are simple, basic descriptive analytical methods (descriptive analytics) used, or are in-depth, event and behaviour predicting and action recommending analytical methods (predictions, prescriptions analytics) used? Rate on a scale of 1-5, where 1 - simple methods, 5 - advanced analytical methods". This scale provides a simplified approach to assess the overall advanced analytics maturity level in the organizations of Latvia. The author uses this question as the target variable in the modelling process to understand the influence of different domains on the advanced analytics maturity level. Additionally, the author uses this question for detecting the advanced analytics maturity level in the organizations of Latvia and within specific segments.

4.1.1. Overall Readiness of Latvia's Organizations for Advanced Analytics Based on Target Variable

The survey includes a comprehensive block of questions designed to assess the overall level of advancement in analytics – is it closer to basic analytics or advanced analytics and where exactly it stands. The block includes questions and statements to assess the level of development in specific areas such as data, governance, people, and culture in terms of analytics, tools, and employed techniques. A 5–point scale was used to find out the respondents' level of agreement or disagreement with the statements.

The readiness for advanced analytics is described using 5 levels. Beginner (level 1): Organizations at this level have weak analytical capabilities, primarily relying on spreadsheets. They face challenges with data gathering and quality, often dealing with missing or low-quality data, and there is no support from management. Intermediate (level 2): Organizations at this level have analytical activities operating in silos, better data accessibility, autonomous activities, no coordination, no data owners. Specialist (level 3): Organizations at this level have achieved wide operational usage, with some coordination between the analytical community. They may have existing data warehouses, repositories, or data lakes in place. Expert (level 4): Organizations at this level are considered analytical companies, with high quality data, that have integrated analytics into many processes and decision-making. Analytics serves as a competitive advantage. Visionary (level 5): Visionary advanced companies exhibit a strong analytics culture and mindset. They are at the forefront of testing and adopting cutting-edge tools, techniques, and solutions, giving them a highly competitive advantage.

Based on the simplified approach using question Q21 as the target variable, the overall analytics maturity level in Latvia falls between the 2nd and 3rd stages, reaching a level of 2.4. Figure 4.1.1.1 shows the distribution of organizations in Latvia across different analytics maturity levels.



Source: created by the author, survey 2022, N=555

Figure 4.1.1.1.

Advancement Level of Analytics Based on Target Variable Q21.

54% of organizations in Latvia fall below the 3rd level, indicating relatively weak analytical capability. These organizations primarily rely on spreadsheets, face issues with data gathering and quality, lack coordination in their analytical processes, lack data owners, and receive weak support from management. However, about 26% of organizations show a very strong readiness for advanced analytics. They possess high quality data, integrate analytics into various processes and decision-making, have existing data warehouses, repositories, and data lakes, foster a strong analytical culture and mindset, adopt new solutions and technologies, and already use analytics as a competitive advantage.

Most of organizations lack an analytics strategy, with the majority relying on spreadsheet-based analytical tools. Additionally, half of the organizations primarily use only internal data, and more than a third of organizations do not possess any analytical resources.

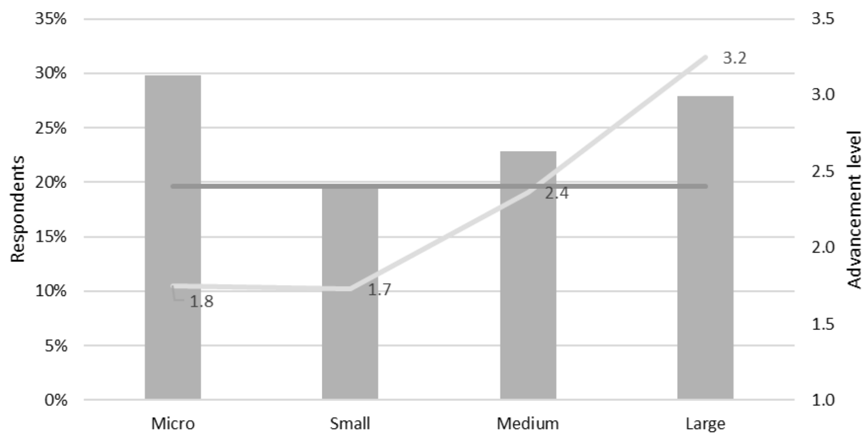
4.1.2. Readiness of Latvia's Organizations for Advanced Analytics Based on Target Variable by Segments

The advancement level of analytics was explored across several segments, including regions, organization size, and industry.

Size

Organizations were divided into 4 size segments in Latvia: micro, small, medium, and large. The lowest level of analytics advancement of analytics is 1.8 in micro-sized organizations, while small organizations are at 1.7, indicating a nearly basic analytics level. In contrast, large organizations have the highest level at 3.2, signifying a solid specialist to expert level with the ability to use the benefits of advanced analytics, while small and medium-sized organizations both demonstrate an average level of 2.4 in analytics maturity. The standard deviation falls within a range from 1.0 to 1.3.

Figure 4.1.2.1 depicts the analytics maturity level by organization size in Latvia. The light line represents the analytics maturity level, while the dark line shows the simple average level across all organizations in Latvia.



Source: created by the author, survey 2022, N=555

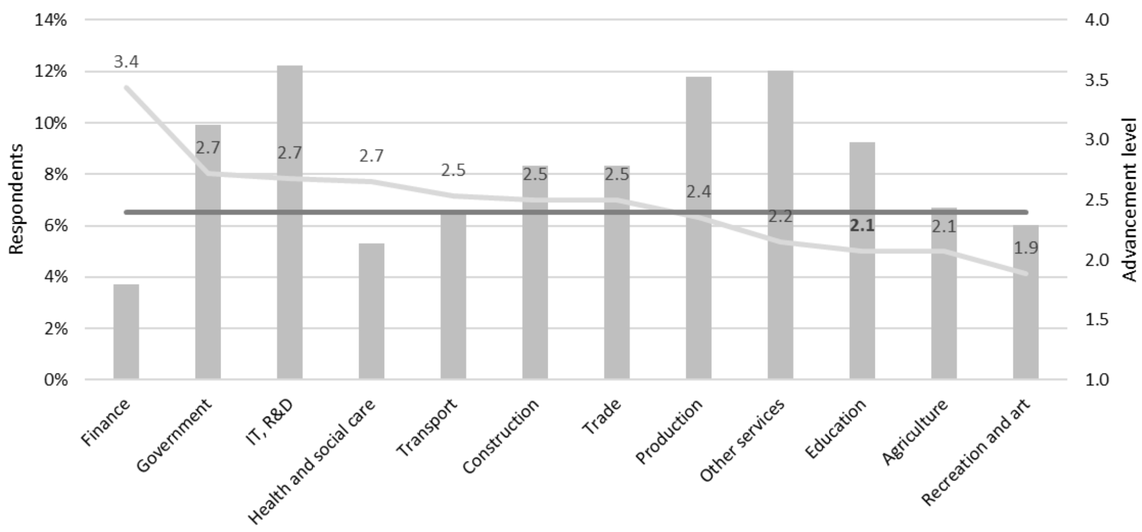
Figure 4.1.2.1.

Advancement Level of Analytics by Size.

Industry

There were 12 segments used for the initial analysis to differentiate organizations by industry in Latvia, based on the NACE2 classification. The lowest level of analytics advancement is 1.9 in the Recreation and Art industry, while the highest level was seen in the Finance industry, reaching 3.4. Information Technologies and Government also demonstrated higher than average advancement levels, with ratings of 2.7.

Figure 4.1.2.2 shows the distribution and analytics maturity level of organizations in Latvia.



Source: created by the author, survey 2022, N=555

Figure 4.1.2.2.

Advancement Level of Analytics by Industry.

The split by industries reveals that industries with a historical reliance on data and analytics, such as Finance, tend to have a higher level of analytics readiness. At the same time, the lowest level of readiness to adopt advanced analytics is in the Agriculture, Education, Recreation and Art sectors. The Education industry together with the Agriculture, Recreation and Art sectors should concentrate substantial efforts to reach at least an average level of advancement of analytics maturity. Education, being a cornerstone of human resource development and science, must not fall behind, as it would undermine its fundamental purpose.

To understand why some industries fall below the average level, the barriers (question Q46 “What are the main barriers to apply/implement/develop more advanced analytical approaches and solutions in the organization?”, see Appendix K or Appendix L) were analysed and compared to organizations above or on average level. Two segments were created based on the target variable Q21: Basic analytics (Q21 ratings of 1 or 2) and Advanced analytics (Q21 rating of 3, 4, or 5).

Barriers to implement advanced analytics

There were 25 unique potential barriers provided to respondents in random order, and an option to provide other barriers in an open-text format, if they were not mentioned in the list.

The barriers represented several various issues related to funding, skills, human resources, technology, or organizational processes. Figure 4.1.2.3 shows the top 10 barriers for the 2 segments, and the barriers are coloured by direction of barrier. Orange represents funding-related barriers, light blue represents skills and experience-related barriers, light yellow represents analytical solutions and technology-related barriers, light green represents data management, light pink represents human resource-related barriers, and light brown represents organizational barriers.

TOP 10 barriers						
Q21 Basic analytics (1 or 2)				Q21 Advanced analytics (3, 4 or 5)		
1	Needed investments (EUR, HR infrastructure)	30%		1	Data security	14%
2	Not clear if investments will give expected return	28%		2	Data quality	14%
3	No technical skills	27%		3	Data accessibility	13%
4	Not enough people with technical skills	22%		4	Needed investments (EUR, HR infrastructure)	13%
5	Not sure how to use the result	17%		5	Data privacy	13%
6	Not known best practice	13%		6	Not clear if investments will give expected return	12%
7	Structure of the organization's analytical function	11%		7	No barriers	12%
8	Difficult to find appropriate tools	10%		8	Not enough people with technical skills	11%
9	Accessibility of the relevant analytical tools	9%		9	Challenge to attract and keep analytical talents	11%
10	Not enough support form the organization's top management	9%		10	Issues to implement automated analytical solutions in the production	10%

Source: created by the author, survey 2022, N=555

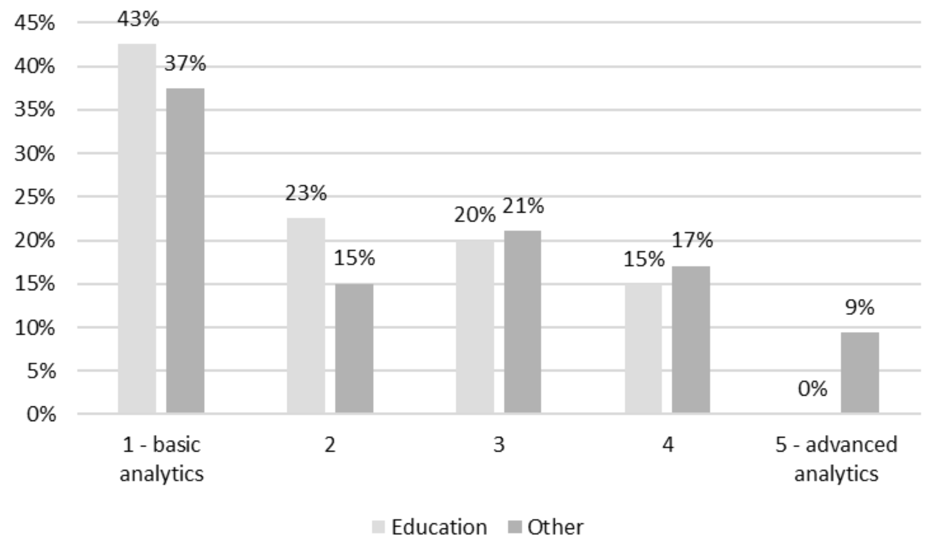
Figure 4.1.2.3.
Top 10 Barriers for Organizations Within Basic Analytics and Advanced Analytics Segments.

Comparing these 2 segments, it is clear that for those who are below average, certain barriers dominate. These barriers include not having enough skills and experience to implement or develop analytics at a solid level, as well as investment-related issues such as human resources, IT infrastructure, financial resources, and uncertainty about whether investments in analytics will yield returns. To summarize, the key challenges involve a lack of experience and knowledge in implementing or developing analytics. Those who are at an average or above-average level in advanced analytics, the barriers are significantly different. They are primarily focused on solving practical and production-related issues, as well as prioritization within the organization. All data-related barriers are related to production, while investment-related challenges are tied to the organization’s priorities. However, there are also some barriers related to skills and experience. In summary, the segment that is below average requires the most support to make progress. The segment that is already in some state of advanced analytics is on its, and they key factor is how quickly and effectively they can continue to move forward to maintain their competitiveness.

The educations industry must make a significant contribution to improving or removing these barriers. However, based on survey data, the education industry itself faces challenges, as its advanced analytics level is below the average in Latvia. As a result, it may struggle to provide the expected contribution to the Latvia's economy, which includes providing the necessary related to technology awareness, usage, application, analytical skills, data structures and flows, the ability to use the newest analytical platforms, data science, data engineering, data translation, automated data-driven decision-making, automated everyday operations monitoring, and the ability to create technology-based products and services. Thus, the education industry needs to be explored in more detail.

Education industry

The overall analytics maturity level for the Education industry is 2.1, while other industries have an average advancement level of analytics at 2.4. Figure 4.1.2.4 shows the distribution of analytics maturity levels in organizations in Latvia, comparing the Education industry to other industries. Unfortunately, the Education industry is dominant in lower maturity levels, while other industries are more advanced. The most concerning fact is that none of the organizations in the Education industry falls into the advanced analytics category, while 10% of organizations in other industries are represented at the most developed level of analytics.



Source: created by the author, survey 2022, N=555

Figure 4.1.2.4.

Advancement Level of Analytics in Education vs. Other Industries.

In the Education industry, 65% of organizations in Latvia and 52% of organizations in other industries are below the 3rd level of analytics maturity. This suggests weak analytical capabilities, heavy reliance on spreadsheets, issues with data gathering and quality, lack of coordinated analytical processes, no designated data owners, and limited support from management. However, 15% of organizations in the Education industry and 26% of organizations in other industries have demonstrated a high level of readiness for advanced analytics. These organizations have high-quality data, integrated analytics in their processes and decision-making, existing data warehouses, repositories, and data lakes, a strong analytical culture and mindset, and are adopting new solutions and technologies, with analytics already providing a competitive advantage.

In the Education industry, the lack of an analytics strategy, reliance on basic analytical tools, predominantly using internal data sources, and limited availability of analytical resources are factors contributing to the lower level of analytics maturity. To understand why the Education industry faces these challenges in implementing advanced analytics, an analysis of barriers was conducted. A total of 24 unique barriers were identified. One-quarter of the respondents recognised the lack of technical skills as a barrier to implementing and developing advanced analytics in their organizations. 8 unique barriers were acknowledged by more than 10% of the respondents. These include the lack of technical skills, insufficient personnel with technical skills, lack of knowledge regarding best practices, difficulties in finding appropriate tools, the need for investments (both financial and in terms of human resources and infrastructure), concerns related to data privacy, uncertainty about whether investments will yield the expected return, a lack of understanding how to apply the results, and concerns related to data security.

Figure 4.1.2.5 shows the 5 most frequently mentioned barriers in the Education industry and in the Other industries. It is evident that the Education industry recognises barriers that could be described as initial prerequisites for commencing the application of advanced analytics – the lack of technical skills and an insufficient number of individuals with technical skills. At the same time, the Other industries are already discussing how to assess or understand whether investments in advanced analytics will yield the expected returns, or even stating that there are no barriers to adopting advanced analytics.

TOP 5 barriers						
Education				Other		
1	No technical skills	25.00%		1	Not clear if investments will give expected return	19.50%
2	Not enough people with technical skills	22.92%		2	Needed investments (EUR, HR infrastructure)	19.29%
3	Not known best practice	18.75%		3	No barriers	16.98%
4	Difficult to find appropriate tools	14.58%		4	No technical skills	16.77%
5	Needed investments (EUR, HR infrastructure)	14.58%		5	Not enough people with technical skills	15.09%

Source: created by the author, survey 2022, N=555

Figure 4.1.2.5.
Top 5 Barriers in Education vs. Other Industries.

Another finding that supports the points made earlier is that 51% of organizations in the Education industry do not have any analytical resources, or if they do, there are very few individuals who engage in analytics. This situation contributes to the absence of an analytics strategy, the lack of advanced analytics, and a shortage of technical skills and analytics professionals. In terms of the analytical tools used, the Education industry primarily relies on MS Excel (52%), with limited access to predictive analytics tools (17%). Other industries also use MS Excel (40%) but have more widespread access to predictive analytics tools (33%). Thus, it appears that organizations in other industries are better equipped for advanced analytics.

4.2. Maturity Assessment Model

The goal of developing the maturity assessment model is to determine the advanced analytics overall maturity level and the maturity level by domains. The overall level results from interaction between the domains and provides an explanation of what underlies the specific advanced analytics maturity level. The model will be integrated in the assessment tool to calculate the advanced analytics maturity level for the specific organization.

The first step in any modelling process is to become familiar with data set to be used for modelling – data quality, content covered, identification of outliers, observed trends, any interactions noticed. This step is covered in the previous Section 4.1. This section covers the development of the advanced analytics maturity assessment model. The author uses R as a tool for modelling. Appendix P contains the R code utilised for the modelling process. The code is organized according to modelling steps, and comments are used within the code to document, separate, and indicate each step.

The methodology and steps involved in modelling are described in Section 3.3. The author will follow these steps: data source identification, target variable setting, data sampling, variable construction and data transformation, correlation analysis, model development, scaling, and performance analysis. Question Q21 “How would you characterize the analytical development in the organization from the point of view of applied analytical solutions/methods? Are simple, basic descriptive analytical methods (descriptive analytics) used, or are in-depth, event and behaviour predicting and action recommending analytical methods (predictions, prescriptions analytics) used? Rate on a scale of 1-5, where 1 indicates simple methods, and 5 represents advanced analytical methods” was included in the questionnaire to be used as simple detector of advanced analytics maturity level and as a main potential target variable for the modelling. Throughout the modelling process, the author examines the interaction between the target variable and all 6 domains (Organization, People, Culture, Analytics, Data, Technology) to identify the specific advanced analytics maturity level in the organization and assess the impact of each domain on that level. By detecting the maturity level of each domain and assessing the impact of each domain, it is possible to determine a more precise advanced analytics maturity level. This, in turn, reveals what is missing, what needs improvement, and identifies the strengths and weaknesses within the organization’s advanced analytics ecosystem.

The modelling question and the target variable question aim to determine the probability of an organization reaching a certain advanced analytics maturity level based on the specific interaction between 6 domains. After the model is obtained, scaling is used to calculate the specific advanced analytics maturity level within a range of 1 to 5.

The target variable is set on question Q21 “How would you characterize the analytical development in the organization from the point of view of applied analytical solutions/methods? Are simple, basic descriptive analytical methods (descriptive analytics) used, or are in-depth, event and behaviour predicting and action recommending analytical methods (predictions, prescriptions analytics) used? Rate on a scale of 1-5, where 1 indicates simple methods, and 5 represents advanced analytical methods”. 4 potential target variables have been constructed, referred to as TARGET_1 in the R code where an answer of 1 signifies basic analytics, TARGET_12 in the R code where answers of 1 and 2 indicate a low advanced analytics level, TARGET_45 in the R code where answers of 4 and 5 represent a high advanced analytics level, and TARGET_5 in the R code where an answer of 5 is signifies advanced analytics. The modelling process involves the use of all 4 target variables, and the final model chosen for integration into the tool is the one that demonstrates the highest predictive capability.

The modelling dataset includes all completed responses. The approach of dividing the data into training and test datasets due to the limited number of completed responses, which amounts to only 555. If the training/test dataset approach were used, the dataset would be divided into 2 parts, where 70-80% of the entries would be used as the training dataset (the model is built using this set) and the remaining portion would be designated as the test dataset (after the model is completed, the test dataset would be used in production to assess the model's performance by trying to predict the results and validating them against actual data). When designing the questionnaire, the author constructed questions to comprehensively cover the 6 domains established by the author. These domains were derived from the analysis of previous models in Section 2.1 and Section 2.2. The author defined 6 domains: Organization (sub-factors: Strategy and Process), People, Culture, Analytics (sub-factors: Process and Usage), Data (sub-factors: Sources, Quality and Governance), Technology (sub-factors: Big data and IT Infrastructure), which were described with 36 statements to be assessed by respondents. All 36 statements, except Q35, Q29, Q28, Q31, Q32, Q39, and Q42 (see Appendices K or L) were presented for assessment using a 5-point Likert scale. and an option was provided to choose "Do not know" as a response. Responses indicating "Do not know" were substituted with the average numerical value of responses for modelling purposes. The statements with categorical answers (Q35, Q29, Q28, Q31, Q32, Q39, Q42) were transformed into numerical values to enable the calculation of average values. At the end, the average maturity level for each domain was calculated (see the following Section 4.3 for a discussion of the results of advanced analytics maturity levels by domains).

Correlation analysis is used to assess the correlations between the domains (Table 4.2.2) and factors (Table 4.2.1) to avoid situations where highly correlated factors exist within one domain. While such situations do not adversely impact the final outcome, they also do not provide any additional value in explaining the data within the model. The highest correlations are observed between factors describing the domains of Organization, People, and Culture. Although there is a high correlation between the "process_org" factor within the Organization domain and the "process_anal" factor within the Analytics domain, this is not surprising. Such a correlation is expected because there should not be a situation in an organization where the overall process of how the organization's functions interact is excellent, while a specific functional process is very poor. The factor that describes the current stage of Big data within the organization exhibits the lowest correlation with all of the other factors.

Table 4.2.1.

Correlation Between Factors.

FACTORS	strategy	process_org	people	culture	process_anal	usage	governance	quality	sources	BigData	Infrastructure
strategy	100%	86%	64%	71%	79%	60%	41%	53%	35%	17%	65%
process_org	86%	100%	67%	71%	81%	58%	43%	54%	34%	20%	66%
people	64%	67%	100%	76%	68%	57%	38%	43%	25%	16%	64%
culture	71%	71%	76%	100%	71%	65%	42%	48%	35%	20%	67%
process_anal	79%	81%	68%	71%	100%	63%	44%	53%	31%	15%	70%
usage	60%	58%	57%	65%	63%	100%	40%	46%	34%	17%	60%
governance	41%	43%	38%	42%	44%	40%	100%	60%	45%	19%	50%
quality	53%	54%	43%	48%	53%	46%	60%	100%	56%	25%	64%
sources	35%	34%	25%	35%	31%	34%	45%	56%	100%	27%	42%
BigData	17%	20%	16%	20%	15%	17%	19%	25%	27%	100%	27%
Infrastructure	65%	66%	64%	67%	70%	60%	50%	64%	42%	27%	100%

Source: Created by the author, survey 2022, N=555

Table 4.2.2.

Correlation Between Domains.

DOMAINS	Dom_organization	Dom_people	Dom_culture	Dom_analytics	Dom_data	Dom_technologies
Dom_organization	100%	68%	74%	81%	54%	49%
Dom_people	68%	100%	76%	69%	43%	44%
Dom_culture	74%	76%	100%	75%	50%	49%
Dom_analytics	81%	69%	75%	100%	56%	51%
Dom_data	54%	43%	50%	56%	100%	53%
Dom_technologies	49%	44%	49%	51%	53%	100%

Source: Created by the author, survey 2022, N=555

4 models, each with a different target variable, are built using the logistic regression approach. The glm function with a binomial family is used in R (see Appendix P with R code). All 6 domains are used as independent variables in all models. The interpretation of logistic regression model measures and outcomes is described in Section 3.3.

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.9779	-0.7007	-0.3532	0.6842	2.7219

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	5.52038	0.65036	8.488	< 2e-16	***
Dom_organization	0.06143	0.18639	0.33	0.74172	
Dom_people	0.15006	0.16452	0.912	0.3617	
Dom_culture	-0.1415	0.1985	-0.713	0.47594	
Dom_analytics	-0.01397	0.23747	-0.059	0.9531	
Dom_data	-0.70072	0.22694	-3.088	0.00202	**
Dom_technology	-1.89774	0.27199	-6.977	3.01E-12	***

AUROC: 84.71

Gini: 69.42

Source: Created by the author, survey 2022, N=555

Figure 4.2.1.

Model_1 Outcome with Target Variable TARGET_1.

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.2105	-0.7907	-0.3153	0.8090	2.4825

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	5.833239	0.633402	9.209	< 2e-16	***
Dom_organization	0.188338	0.174312	1.08	0.27993	
Dom_people	-0.07808	0.151759	-0.514	0.60691	
Dom_culture	0.071044	0.186152	0.382	0.70272	
Dom_analytics	-0.00486	0.23121	-0.021	0.98324	
Dom_data	-0.66555	0.218543	-3.045	0.00232	**
Dom_technology	-1.89838	0.245186	-7.743	9.74E-15	***

AUROC: 84.4

Gini: 68.8

Source: Created by the author, survey 2022, N=555

Figure 4.2.2.

Model_12 Outcome with Target Variable TARGET_12.

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.81105	-0.49170	-0.26333	-0.09525	3.07190

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-9.6838	0.9984	-9.699	< 2e-16	***
Dom_organization	0.4075	0.2292	1.778	0.0754	.
Dom_people	0.2693	0.1937	1.39	0.1645	
Dom_culture	-0.2431	0.2314	-1.05	0.2935	
Dom_analytics	0.6395	0.3121	2.049	0.0404	*
Dom_data	0.285	0.2921	0.976	0.3291	
Dom_technology	1.2556	0.2414	5.201	1.98E-07	***

AUROC: 87.37
Gini: 74.74

Source: Created by the author, survey 2022, N=555
Figure 4.2.3.
Model_45 Outcome with Target Variable TARGET_45.

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.3550	-0.2672	-0.1164	-0.0462	3.9688

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-15.1296	2.0974	-7.213	5.46E-13	***
Dom_organization	0.6665	0.385	1.731	0.0834	.
Dom_people	0.16	0.2786	0.574	0.5658	
Dom_culture	-0.112	0.3246	-0.345	0.73	
Dom_analytics	0.5325	0.464	1.148	0.2511	
Dom_data	1.2836	0.5175	2.48	0.0131	*
Dom_technology	0.9388	0.3225	2.911	0.0036	**

AUROC: 86.59
Gini: 73.18

Source: Created by the author, survey 2022, N=555
Figure 4.2.4.
Model_5 Outcome with Target Variable TARGET_5.

The primary measure for detecting whether the model has a sufficiently high predictive power is the GINI coefficient and AUROC. The higher the GINI and AUROC, the better the model predicts the outcome (see Section 3.3). Based on these values, the author chooses Model_45 as the final model to be used in the assessment tool.

All 4 models demonstrate a sufficiently high prediction power, with an AUROC above 80%. In other words, in the case of Model_45, it will be possible to correctly assess the advanced analytics maturity level in 87.37% cases.

There are 3 parameters that are statistically significant in Model_45, namely, Technology, Analytics, and Organization. With a confidence level of at least 90%, they have an impact on the dependent variable. Thus, these 3 domains have the highest impact on the final result – the advanced analytics maturity level in the organization. All 4 models found the domain Technology to be statistically significant in detecting the advanced analytics maturity level. 3 models found the domain data to be statistically significant in detecting the advanced analytics maturity level. 2 models found the domain Organization to be statistically significant in detecting the advanced analytics maturity level.

The Model_45 can also be expressed in the form of an equation:

$$\log(p_{45}/(1-p_{45})) = -9.6838 + 0.4075 * Dom\_organization + 0.2693 * Dom\_people - 0.2431*Dom\_culture + 0.6395 * Dom\_analytics + 0.2850 * Dom\_data + 1.2556 * Dom\_technology \quad (4.2.1.),$$

where Dom_organization is the average assessment of the domain Organization, Dom_people is the average assessment of the domain People, Dom_culture is the average assessment of the domain Culture, Dom_analytics is the average assessment of the domain Analytics, Dom_data is the average assessment of the domain People, Dom_ data is the average assessment of the domain Data, Dom_technology is the average assessment of the domain People, and Dom_data is the average assessment of the domain Technology.

With the help of the model, the author calculated the probability of being in the highest level of analytics. Scaling is used to obtain the overall advanced analytics maturity level. The obtained probabilities are scaled to the interval from 1 to 5, where the minimum value is set to 1 and interpretable as basic analytics, while the maximum value of 5 is interpretable as advanced analytics. Based on the approach described in Section 3.3, the scaling for the final model is:

$$Score = 3.70487 + 0.38258*LN(p/(1-p)) \quad (4.2.2.),$$

where p is probability obtained by the model for the specific response, and Score is the advanced analytics maturity level for that specific respondent.

4.2.1. Comparison of the Models

The author created Table 4.2.1.1 to analyse the differences between the model created by the author and the 15 models analysed in Subsection 2.1., described in Appendix A, Appendix B, Appendix C. The models are compared based on 6 characteristics.

Table 4.2.1.1.

Comparison: Author's Model vs 15 Models Analysed in Section 2.1.

Comparison characteristics	Author's model	15 models analysed in Section 2.1 (Appendix A, Appendix B, Appendix C)
Maturity levels	5	3-6 levels Oldest model from 2002 - 3 levels 2 newest from 2020 – 6 levels, including 0 level
Domains	6 Organization, People, Culture, Data, Analytics, Technology	3-7 Majority has: Organization, People, Data, Analytics/Processes, Technology
Factors	11	Partly disclosed, 3-16
Maturity level detection	Weighted domains and average score	Mostly not disclosed
Online tool	Yes	6 from 15
Recommendations	Yes	4 from 6

Source: Created by the author

The author's newly created model employs 5 levels of maturity. While the majority of the analysed models also use 5 levels, the oldest model features only 3 levels, while the two newest encompass 6 levels, including level 0.

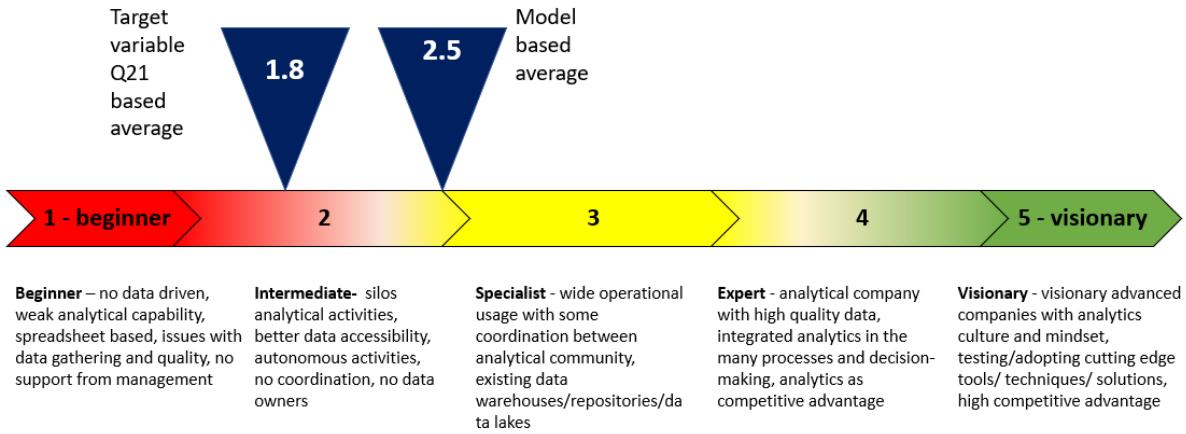
The author selected the most commonly used domains from the 15 analysed models, namely: Organization, People, Culture, Data, Analytics, and Technology. To describe these domains, the author created 11 new factors since these factors were rarely discussed in the literature by the authors of the 15 models analysed. Notably, none of the previously explored models disclosed the methodology for detecting the maturity level.

In response, the author devised a methodology for calculating the overall Advanced Analytics maturity level, as detailed in subsection 3.3. This newly created model features a visualization in the form of an online tool, a feature found in the minority of the 15 analysed models. In summary, the author's model facilitates a comprehensive assessment of Advanced Analytics maturity, bridging the gap left by the undisclosed factors and the undiscussed AA maturity level detection methods from the previous 15 models analysed.

4.3. Advanced Analytics Ecosystem Maturity Level Based on Model

Based on the model built and described in the previous Section 4.2, it is possible to assess the advanced analytics ecosystem maturity level in Latvian organizations overall and within each domain.

Based on the data collected during the experiment, the weighted average level of advanced analytics maturity in organizations of Latvia is 2.5 (see Figure 4.3.1). Latvia's average organization can be described as follows in terms of advanced analytics: Analytical activities are conducted in various departments or teams without coordination. Data is more accessible, but it may still be stored in department-specific repositories. The organization is starting to use specialized analytics software and tools. Teams conduct analytics autonomously without centralized coordination. There are no clear data owners responsible for data quality and governance. The weighted average based on target variable Q21 indicates an advanced analytics maturity of 1.8 (see Figure 4.3.1). Q21 does not provide insights into the factors influencing the specific assessment made from 1 to 5, while model-based assessment explains the outcome using 11 factors, highlighting both the weakest and strongest points.



Source: Created by the author, Survey 2022, N=555.

Figure 4.3.1.

Weighted Advanced Analytics Maturity Level in Organizations of Latvia.

Figure 4.3.2 illustrates the maturity of each domain, providing insights into the underlying factors that contribute to the average maturity level. When analysing these drivers of maturity, it's important to consider the model's outcome, which takes into account the interactions between all domains to detect the advanced analytics maturity level. The most significant domains were Technology, Analytics, and Organization. The simple averages indicate that the Technology domain is the weakest domain. Considering its substantial impact on detecting AA maturity levels, it is the primary factor contributing to why AA maturity in Latvian organizations is below level 3. The absolutely lowest factor is Big data usage and solutions based on Big data implementation. The strongest factor is Data, particularly the aspect of Governance. Analysing this further, it suggests that organizations in Latvia have implemented policies and have designated responsible persons for data security, privacy. This correlates with the level of the Analytics domain, which is the second highest factor.

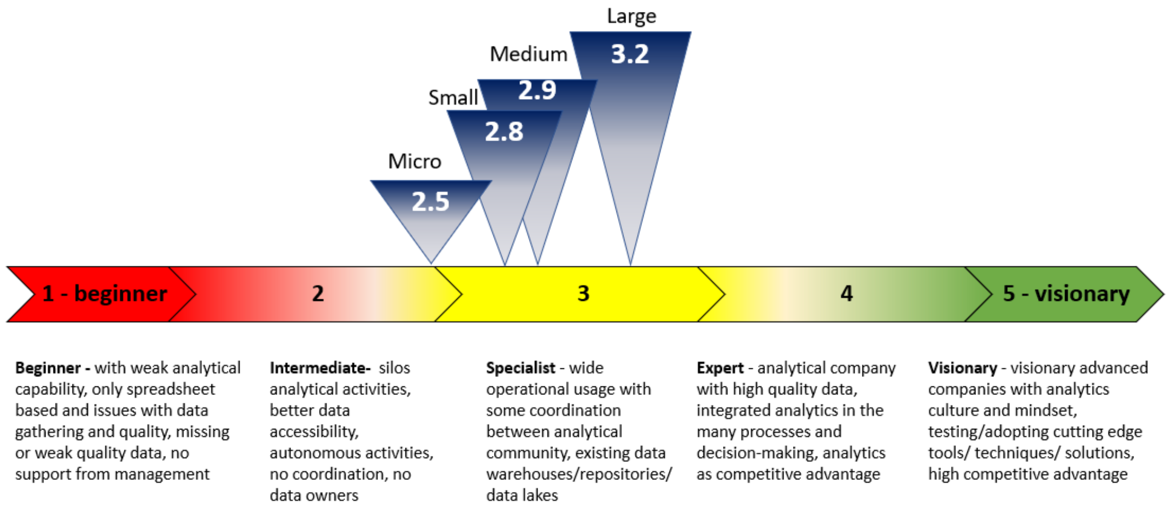
Domain	Factor	Maturity level	
Organization			**2.7**
	Strategy	2.7	
	Process	2.7	
People	Analysts	2.6	**2.6**
Culture	Analytics-driven	2.6	**2.6**
Analytics			**2.9**
	Process	2.8	
	Usage	3.0	
Data			**3.0**
	Governance	3.2	
	Quality	3.1	
	Sources	2.8	
Technology			**2.2**
	Big data	1.7	
	T Infrastructure	2.6	

Source: Created by the author, survey 2022, N=555

Figure 4.3.2.

Advanced Analytics Maturity Level by Domains and Factors.

Analysing data by the size of the organization (Figure 4.3.3), it is evident that organizations of all sizes fall within the range of 2.5 to 3.2 in terms of average maturity level. The larger an organization is, the higher the advanced analytics maturity level. This result clearly illustrates the significant impact on the overall advanced analytics maturity level, particularly from the segment of micro-organizations with less than 10 employees, which represents 93% of all organizations in Latvia. Furthermore, if the aim is to determine the overall advanced analytics level, only the Micro segment could be included in the research. However, from the author’s perspective, 2 different questions can be researched. One question pertains to the overall advanced analytics maturity level in Latvian organizations, while the other concerns the percentage of people working in data-driven environments. This involves multiplying the number of organizations by the people working in organizations of specific sizes. Thus, there is a higher probability of individuals having a data-driven and analytics-driven mindset. In the author’s opinion, having more individuals from data-driven organizations, and likely with such a mindset, is more valuable. This could help better forecast Latvia’s competitiveness in the global market. In other words, having more people with a data, analytics, and technology-driven mindset is beneficial for Latvia’s economy and its global competitiveness. But this is a research question that is not covered in the author’s work but could be subject of future investigations regarding its correlation with the value brought to Latvia’s economy.



Source: Created by the author, Survey 2022. N=555.

Figure 4.3.3.

Advanced Analytics Maturity Level by the Size of the Organization.

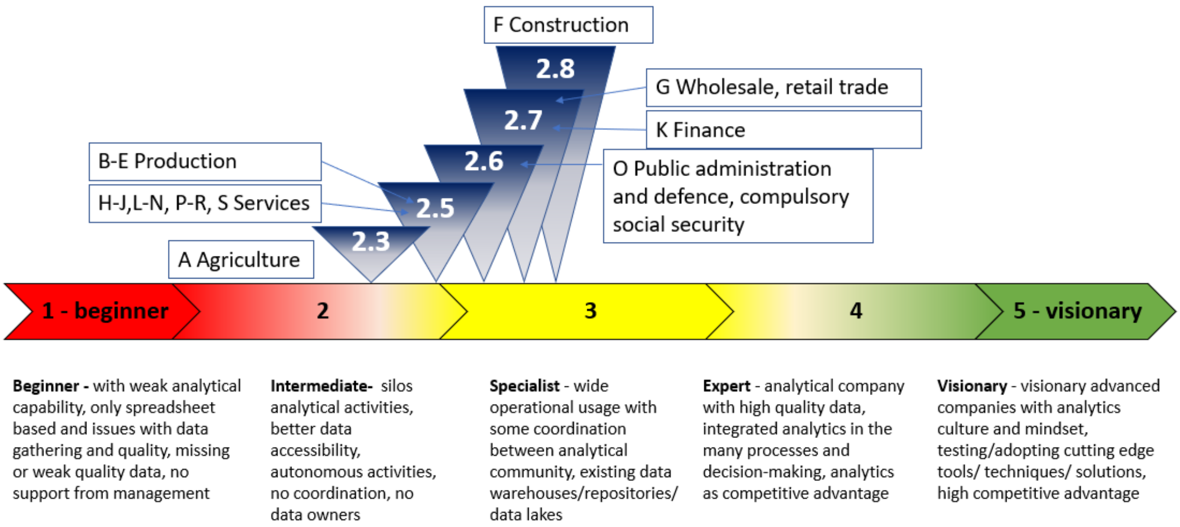
Figure 4.3.4 shows the maturity of each domain according to the size of the organization. In each domain, the pattern is consistent: larger organizations exhibit higher levels of maturity. The most interesting finding for the author is that the difference between Micro and Large organizations is nearly 1 maturity level. In practical terms, this translates to a gap of 5 to 10 years. Taking into account the considerably faster pace of technology development, this gap is expected to widen. This situation is particularly concerning in Latvia, where 93% of organizations fall into the Micro category. If it were only found that the majority of employees in Latvia possess a data, analytics, and technology-oriented mindset. However, this research cannot provide an answer to this crucial question.

Domain	Factor	Maturity level							
		Micro		Small		Medium		Large	
Organization			**2.7**		**3.1**		**3.2**		**3.6**
	Strategy	2.7		3.1		3.2		3.6	
	Process	2.7		3.1		3.1		3.5	
People	Analysts	2.6	**2.6**	2.9	**2.9**	2.9	**2.9**	3.4	**3.4**
Culture	Analytics-driven	2.5	**2.5**	3.0	**3.0**	3.1	**3.1**	3.4	**3.4**
Analytics			**2.8**		**3.1**		**3.2**		**3.5**
	Process	2.7		3.0		3.1		3.5	
	Usage	3.0		3.3		3.2		3.6	
Data			**3.0**		**3.3**		**3.4**		**3.8**
	Governance	3.1		3.5		4.0		4.4	
	Quality	3.1		3.2		3.3		3.8	
	Sources	2.7		3.0		2.9		3.2	
Technology			**2.1**		**2.5**		**2.5**		**2.8**
	Big data	1.7		2.0		2.1		2.3	
	IT Infrastructure	2.6		2.9		2.9		3.3	

Source: Created by the author, survey 2022, N=555
Figure 4.3.4

Maturity by Domain and Factors by Size of the Organization.

Analysing data by industry of the organization (Figure 4.3.5), all industries fall between a 2.3 and 2.8 weighted average maturity level. The lowest level is demonstrated in Agriculture, which can be explained by some factors such as being a digitally disconnected industry, where the majority of work is performed manually without the assistance of any devices, and there is little need or even feasibility to conduct operations differently. Naturally, this decreases the need for advanced analytics. The Construction industry leads with a weighted average advanced analytics level of 2.8, even slightly ahead of the Finance industry. It may seem surprising that the Construction industry has the highest level, but taking into account that data-driven processes are essential for building even the smallest structure, it is no longer a surprise; in fact, the opposite would be surprising.



Source: Created by the author, Survey 2022. N=555.

Figure 4.3.5.

Weighted Advanced Analytics Maturity Level by the Industry of the Organization.

Figure 4.3.6 shows the maturity of each domain by industry of the organization. The lowest level of maturity is in the Technology domain for all industries. The highest level of maturity is in the Data domain for all industries except Construction.

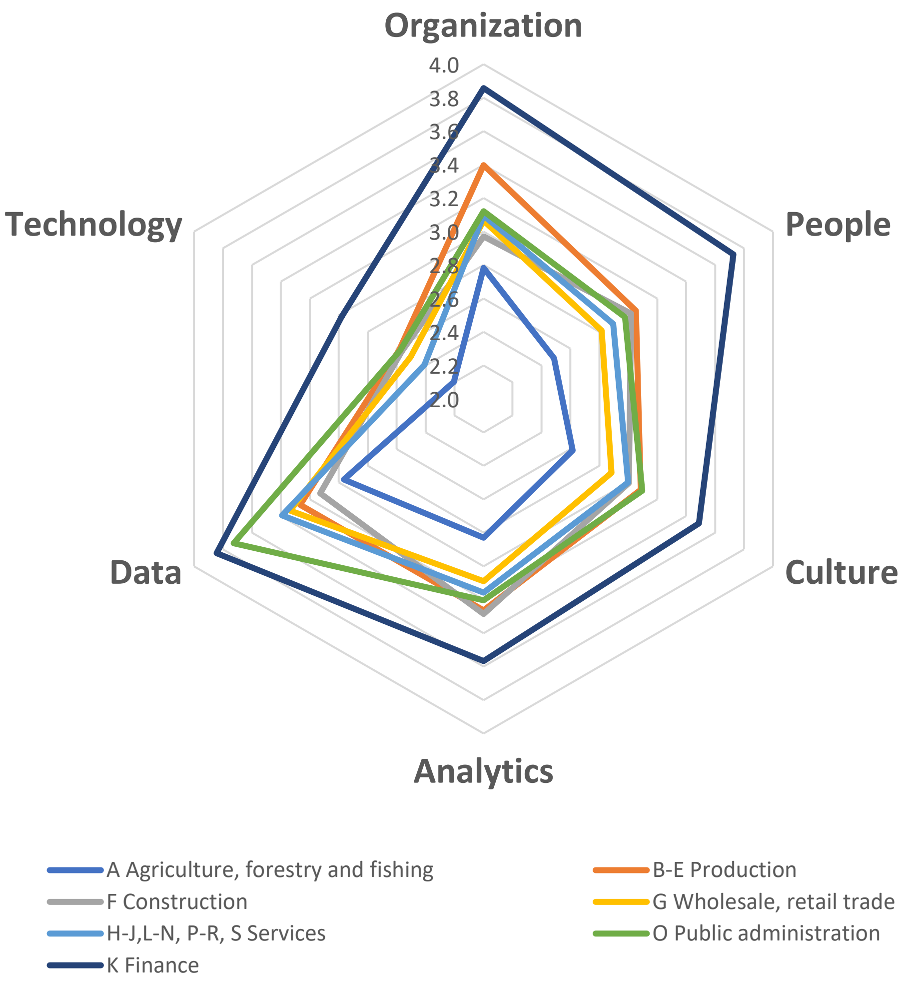
Domain	Factor	Maturity level													
		A Agriculture, forestry and fishing		B-E Production		F Construction		G Wholesale, retail trade		H-J,L-N, P-R, S Services		O Public administration		K Finance	
Organization			**2.8**		**3.4**		**3.0**		**3.1**		**3.1**		**3.1**		**3.9**
	Strategy	2.8		3.3		2.9		3.0		3.1		3.1		3.9	
	Process	2.7		3.4		3.0		3.2		3.1		3.2		3.9	
People	Analysts	2.5	**2.5**	3.1	**3.1**	3.0	**3.0**	2.8	**2.8**	2.9	**2.9**	3.0	**3.0**	3.7	**3.7**
Culture	Analytics-driven	2.6	**2.6**	3.1	**3.1**	3.0	**3.0**	2.9	**2.9**	3.0	**3.0**	3.1	**3.1**	3.5	**3.5**
Analytics			**2.8**		**3.3**		**3.3**		**3.1**		**3.2**		**3.2**		**3.6**
	Process	2.7		3.2		3.1		3.0		3.1		3.1		3.6	
	Usage	3.0		3.4		3.4		3.2		3.2		3.3		3.5	
Data			**3.0**		**3.3**		**3.1**		**3.3**		**3.4**		**3.7**		**3.8**
	Governance	3.3		3.7		3.4		3.8		3.8		4.3		4.3	
	Quality	3.0		3.2		3.2		3.4		3.4		3.6		4.0	
	Sources	2.6		2.9		2.8		2.8		3.0		3.2		3.3	
Technology			**2.2**		**2.6**		**2.6**		**2.5**		**2.4**		**2.6**		**3.0**
	Big data	1.8		2.2		2.1		2.1		1.9		2.2		2.5	
	IT Infrastructure	2.6		2.9		3.0		2.9		2.9		3.0		3.5	

Source: Created by the author, survey 2022, N=555

Figure 4.3.6

Maturity by Domain and Factors by Industry of the Organization.

The author created a visualization of the maturity of each domain by industries (Figure 4.3.7). In Figure 4.3.7, the Finance industry leads in all domains, while Agriculture has the lowest maturity in all domains. The weighted average (Figure 4.3.5) shows the overall advanced analytics maturity level by industries. Finance lost its leading position because of the weighting based on the size of organizations, with micro-organizations operating in the Finance industry not being as advanced as larger ones. Consequently, the overall result for Finance is significantly influenced by the performance of micro finance organizations. A similar explanation applies to construction organizations, where a notably different distribution of micro, small, medium, and large organizations is observed within the construction industry.



Source: Created by the author, Survey 2022, N=555

Figure 4.3.7.

Maturity Level of Domains (Simple Average) by Industry.

4.4. Overview of the Advanced Analytics Ecosystem Maturity Levels

The description of each level is prepared based on the questionnaire (see Section 3.1., Appendix K and Appendix L), data analysis performed in Section 4.1, the developed assessment model (see Section 4.2), analysis by domains' impact on overall AA maturity level based on the newly developed model (see Section 4.3), and explored models and tools in Sections 2.1 and 2.2. This description, serving as an explanation of the current stage of the assessment for specific organizations, will be incorporated into the tool to the advanced analytics maturity level of individual organizations.

Level 1. Beginner (not data-driven)

Spreadsheet reliance, where analysis is primarily conducted using basic spreadsheet tools like Excel. Data quality issues, where data gathering is challenging and there are issues with data accuracy and completeness. Limited data support where there is little to no support from management for analytics initiatives. Ad Hoc Analysis where analytical activities are sporadic and lack structure.

Domain: Organization

There is limited experience with advanced analytics, and organizations are just beginning to explore its potential. The organization lacks an existing analytics strategy and has limited awareness of the benefits of advanced analytics. Challenges related to data quality, access, and integration are prevalent. Occasional, ad hoc analytics initiatives occur with no formal structure, and there is lack of leadership buy-in, with little to no support from top management for analytics projects.

Domain: People

There is a deficiency in analytics skills among the workforce. The organization has low awareness of advanced analytics and its potential, with basic skills in data analysis and statistical methods. A significant skills gap exists in advanced analytics, and there is a lack of training or limited training opportunities in analytics. Furthermore, there is no dedicated leadership for analytics initiatives.

Domain: Culture

There is limited experience with fostering an analytical culture within the organization. Awareness of the role of data and analytics in decision-making is lacking, leading to resistance to adopting data-driven approaches. Data and analytics activities are fragmented and exist in departmental silos. Formal training or education on analytics is limited, and there is minimal Collaboration between teams for data and analytics initiatives.

Domain: Analytics

The organization has just started to explore the potential of advanced analytics. There is either no understanding or limited understanding of advanced analytics concepts and techniques. Challenges are faced in data collection, quality, and management. Analytics activities are irregular and are often conducted using basic tools. There is little to no organizational support or investment in analytics initiatives, and insights are typically generated on an ad hoc basis.

Domain: Data

The organization has limited experience in using data for advanced analytics. It often relies on internal data sources due to limited external data sources. Common data quality issues affect the reliability of insights. Data is stored in departmental silos, making integration challenging. There is also weak awareness of the potential of data in decision-making.

Domain: Technology

The organization has limited technology adoption in the field of advanced analytics. It relies on basic IT infrastructure and tools for data storage and processing. There is either no or limited usage of Big data, and the organization primarily deals with relatively small datasets, typically from internal sources.

Level 2. Intermediate (Siloed Analytics)

There is progress, but the organization still operates in silos. Analytical activities are conducted independently in various departments or teams without coordination. Data is more accessible, but it may still be stored in department-specific repositories. Teams conduct analytics autonomously without centralized coordination, and there are no clear data owners responsible for data quality and governance.

Domain: Organization

The organization recognizes the importance of advanced analytics. It is in the process of developing a team with improving analytical skills. There are initiatives to integrate data from various sources for analysis. The organization has adopted specialized analytics software and tools. Support and recognition from management are on the rise. The organization generates structured insights used for decision support.

Domain: People

Initiatives have been started to provide training in analytics and data science. Employees are gaining skills in data analysis and visualization. Small analytics teams or roles have been established, and there is an increasing awareness of the value of analytics.

Domain: Culture

There are initiatives in place to raise awareness about the value of analytics. The organization provides basic training in data and analytics to everyone through Training and Education. Data sharing and cross-functional collaboration are encouraged. Some individuals within the organization champion data-driven decision-making, and pilot analytics projects are beginning to be initiated.

Domain: Analytics

The organization recognizes the importance of analytics and is making progress. It is in the process of building a talent pool with improving analytical skills. The organization has started to use specialized analytics software and tools. There is some recognition and support from management for analytics efforts, and analytical insights are becoming more structured and are used for decision support.

Domain: Data

The organization has expanded data usage and improved data quality. It has expanded data sources to include external and unstructured data. Efforts have been made to improve data quality and governance. Initiatives are in place to integrate data from various sources for analytics. The organization has adopted specialized analytics software and tools, and there is an increasing awareness of the value of data in decision-making.

Domain: Technology

The organization has made investments in more advanced IT infrastructure, including cloud solutions. It deals with larger datasets, which include some external data sources. Specialized analytics software and tools have been adopted. The organization has also implemented data warehousing solutions, and it possesses basic data processing and transformation capabilities.

Level 3: Specialist (Coordinated Operational Analytics)

The organization has achieved wide operational usage of analytics with some coordination between analytical teams. Data warehouses, repositories, or data lakes may have been established. Analytics are integrated into many operational processes and decision-making. There is coordination between analytical teams, sharing of best practices, and some central oversight. Data is stored in data warehouses, repositories, or data lakes for better access and management. Emerging data governance practices are in place, with some data ownership.

Domain: Organization

Analytics are integrated into daily operations. It is a key component of decision-making and processes. Analytics is fully integrated into core business processes and decision-making. Dedicated analytics and data science teams are in place. The organization has a robust data warehousing and data management infrastructure. Well-defined data governance practices and data ownership are established. The organization engages in proactive decision-making where analytics is used to optimize processes and outcomes.

Domain: People

The organization has an analytics-centric workforce that is well-prepared for advanced analytics. Analytics expertise is on the rise, with an increasing number of employees with knowledge in advanced analytics. Dedicated analytics teams or roles have been established within various departments. Access to advanced training and development programs is available. There is improved data literacy across the organization, and analytics ambassadors have emerged, advocating for analytics within the organization.

Domain: Culture

The organization has a data-driven decision-making culture in place. An increasing number of employees are data literate and use data in their roles. Dedicated analytics teams support various business units. Leadership actively advocates for data-driven decision-making. Key performance indicators (KPIs) align with data-driven goals, and formalized governance practices for analytics are established.

Domain: Analytics

Operational analytics capabilities have been established. Analytics is integrated into daily operations and is a fundamental part of core business processes and decision-making. Specialized teams dedicated to analytics and data science are in place. The organization actively uses analytics to proactively generate insights and optimize processes and outcomes.

Domain: Data

Integrated data-driven decision-making is firmly established within the organization. Data is stored in data warehouses, facilitating efficient access and analysis. A wide range of data sources, including real-time and big data, is utilized. The organization maintains high data quality standards and robust governance practices. Data is strategically used to drive business goals and outcomes, and there is a cultural emphasis on data as a critical asset in decision-making.

Domain: Technology

The organization has adopted big data technologies and frameworks such as Hadoop and Spark. A robust IT ecosystem is in place, supporting data storage, processing, and analysis. The utilization of advanced analytics and machine learning software is prevalent. There is comprehensive data integration across various sources, and effective collaboration between IT and analytics teams.

Level 4. Expert (Analytics as a Competitive Advantage)

Analytics is deeply integrated into processes and decision-making, providing a competitive advantage. It is fully integrated into core business processes and decision-making. Data quality is consistently high, with robust data governance practices in place. The organization has embraced a data-driven culture and mindset. Analytics is a core competitive advantage, driving innovation and efficiency.

Domain: Organization

The organization possesses analytics capabilities that consistently deliver actionable insights. It is recognized as an industry leader in analytics and data-driven decision-making. The organization actively utilizes advanced analytics techniques, machine learning, and AI. Analytics plays a significant role in innovation and business growth, indicating a strategic impact. There is a culture of continuous improvement in analytics.

Domain: People

The organization has fostered a culture of analytics excellence. Leadership actively champions data-driven decision-making. The organization boasts highly skilled analytics teams with expertise in machine learning and AI. There is a culture of continuous learning and improvement in analytics, and innovation and experimentation with data are actively encouraged.

Domain: Culture

The organization has successfully cultivated a culture of analytics excellence. Data and analytics are integral to decision-making processes. Many employees champion data-driven approaches at all levels. A data-first mindset is evident across the organization, making data the starting point for strategic decisions. There is a continuous culture of learning and improvement in analytics. Additionally, innovation and experimentation with data are actively encouraged.

Domain: Analytics

The organization consistently delivers actionable insights. It is recognized as an industry leader in analytics and data-driven decision-making. The organization actively utilizes advanced analytics techniques, machine learning, and AI. Analytics plays a strategic role in innovation and business growth. There is an ongoing commitment to continuous improvement in analytics.

Domain: Data

The organization has achieved data excellence and leverages it as a competitive advantage. It maintains a mature data ecosystem that includes data lakes, AI, and machine learning. The organization has well-defined data governance practices and clear data ownership. Advanced predictive and prescriptive analytics are effectively utilized. Data serves as a driver for innovation and product development. There is a culture of continuous improvement in data usage.

Domain: Technology

The organization excels in technology adoption and uses it to drive advanced analytics excellence. It has adopted cutting-edge technologies like AI and IoT for analytics. The organization maintains a highly scalable and flexible IT infrastructure, enabling real-time data processing and analytics capabilities. Robust data security and privacy measures are in place. Technology enables innovation and new product development.

Level 5: Visionary Innovator (State-of-the-art Analytics ecosystem)

The organization has a clear vision of analytics innovation. Advanced analytics is integrated in every function within the organization. There is active usage and adoption of cutting-edge tools, techniques, and solutions. A culture of continuous learning and improvement in analytics is deeply ingrained. Analytics serves as a source of sustained competitive advantage, and the organization is a market leader in its industry. The organization plays a pivotal role in shaping the future of analytics, technology, and data ethics on a global scale. Achieving this level represents an organization's commitment to pushing the boundaries of what's possible and harnessing analytics for the betterment of society.

Domain: Organization

The organization's leadership in analytics is widely recognized, not only within its industry but across sectors. Government agencies seek its expertise for data-driven policymaking. The organization actively invests in advanced research and development centres, fostering innovation and driving societal impact. The organization serves as a global benchmark for data-driven excellence.

Domain: People

The organization boasts an elite team of data scientists, machine learning experts, and AI researchers with expertise in cutting-edge analytics technologies and methodologies. These individuals are globally recognized for their contributions to the field and are regularly invited to speak at conferences and collaborate on ground-breaking research. The organization actively participates in shaping the education and training of future data scientists and AI professionals by partnering with leading universities and institutions.

Domain: Culture

The organization has transformed into a culture where analytics is at the forefront of innovation and strategy. Visionary leadership actively drives data and analytics initiatives. A data-centric mindset is deeply ingrained across the organization, fostering an environment that encourages innovation and the testing of cutting-edge analytics solutions. Data is treated as a strategic asset, and its value is maximized. A culture of data ethics and responsible AI permeates the organization, ensuring that all innovations align with ethical principles. The organization leads industry forums and discussions on the responsible use of data and AI.

Domain: Analytics

The organization is setting trends and pushing the boundaries of what is possible with analytics. Analytics is deeply integrated into every facet of the organization's operations and has become synonymous with innovation and competitiveness. The organization is at the forefront of developing and applying emerging analytics techniques and technologies, such as quantum machine learning or neuromorphic computing. It leverages AI to create entirely new industries and transform existing ones.

Domain: Data

The organization’s executives drive data and analytics initiatives with a clear vision. They actively experiment with and adopt cutting-edge data technologies. Data at this level extends far beyond traditional sources. The organization taps into unconventional data streams, such as data from space missions, cutting-edge scientific research, and the forefront of technological advancements. It leads global initiatives for open data sharing, contributing valuable insights and resources to the broader data community. Data governance practices are highly sophisticated, ensuring both privacy and data quality at the highest levels.

Domain: Technology

The organization is actively experimenting with emerging technologies like quantum computing. It maintains an advanced data ecosystem that includes AI, machine learning, and advanced analytics. The organization operates at the bleeding edge of IT infrastructure, with the capacity to process massive datasets in real-time. Technology is not a constraint but a catalyst for innovation, and the organization actively shapes the development of new technologies through research collaborations and investments.

4.5. Recommendations /Next Steps to Improve Maturity Level

The recommendations provided for each domain are prepared to guide the organization in taking the next steps to enhance its existing stage of advanced analytics ecosystem maturity based on the findings from the questionnaire (see Section 3.1, Appendices K or L), data analysis performed in Section 4.1, the developed assessment model (see Section 4.2), the analysis of each domain's impact on the overall advanced analytics maturity level using the newly developed model (see Section 4.3), as well as the exploration of models and tools in Sections 2.1 and 2.2. This set of recommendations will be implemented in the tool to provide the next steps to be taken by specific organization to improve the existing maturity level.

Recommendations are provided to facilitate the progression from one maturity level to the next within each domain: from Beginner level to Intermediate, from Intermediate to Specialist, from Specialist to Expert, and from Expert to Visionary Innovator.

From Beginner to Intermediate

To move from the Beginner level to the Intermediate level in each of the advanced analytics domains (Organization, People, Culture, Analytics, Data, Technology), organizations should focus on building a foundation for advanced analytics capabilities.

Domain: Organization

Create Analytics Roles: Start by creating roles responsible for analytics, such as data analysts or data scientists.

Analytics Strategy: Develop a basic analytics strategy outlining the goals and objectives for using analytics.

Invest in Tools: Begin investing in basic analytics tools and software for data analysis.

Data Access: Work on improving data access and storage, even if it is limited to internal data.

Data Governance: Establish basic data governance practices to ensure data quality and security.

Domain: People

Basic Training: Provide basic training in data analysis and statistics to employees.

Data Awareness: Raise awareness among employees about the potential of data and analytics.

Skills Development: Encourage employees to develop their analytical skills through online courses or workshops.

Champion Analytics: Identify individuals who show an interest in analytics and encourage them to champion analytics initiatives.

Management Support: Seek support from management to allocate resources for training and skills development.

Domain: Culture

Promote Data Awareness: Create initiatives to promote data awareness and its importance in decision-making.

Encourage Experimentation: Foster a culture of experimentation, where employees are encouraged to explore data and generate insights.

Reward Analytics Use: Recognize and reward employees who actively use analytics for decision-making.

Data-Driven Discussions: Encourage data-driven discussions and decision-making in meetings and projects.

Begin Analytics Advocacy: Begin advocating for analytics as a valuable tool for improving processes and outcomes.

Domain: Analytics

Basic Analytics Tools: Invest in basic analytics tools and software for data analysis.

Ad Hoc Analysis: Start conducting ad hoc analyses using available data.

Structured Insights: Begin structuring insights generated from data analysis.

Data Reporting: Develop basic data reporting capabilities to communicate insights.

Analytics Roadmap: Create a roadmap for the adoption of more advanced analytics techniques in the future.

Domain: Data

Data Collection: Address data collection challenges and work on improving data collection methods.

Data Quality: Begin efforts to improve data quality, especially for the data you already have.

Basic Data Storage: Invest in basic data storage solutions, such as databases or data warehouses.

Data Integration: Start integrating data from various internal sources, even if it is a manual process.

Data Awareness: Raise awareness among employees about the importance of data quality and data management.

Domain: Technology

Basic IT Infrastructure: Invest in basic IT infrastructure to support data storage and analysis.

Analytics Tools: Start adopting basic analytics software and tools for data analysis.

Data Access: Improve data accessibility for analysts and decision-makers.

Data Processing: Begin basic data processing and transformation capabilities.

Data Security: Address basic data security concerns, especially if sensitive data is involved.

It is essential to prioritize initiatives based on the organization's goals and available resources while continuously assessing progress and adjusting the strategy as needed.

From Intermediate to Specialist

To progress to the next level, organization should focus on enhancing and optimizing their existing capabilities.

Domain: Organization

Cross-Functional Collaboration: Foster stronger collaboration between analytics teams and other departments to ensure analytics insights are integrated into decision-making processes.

Data Governance Maturity: Further mature data governance practices, including data quality management and data ownership.

Data-Driven Strategy: Align the analytics strategy closely with the overall business strategy to ensure analytics initiatives support broader organizational goals.

Resource Allocation: Allocate more resources and budget for analytics initiatives, including advanced analytics tools and talent.

Executive Engagement: Engage top executives more actively in analytics efforts to secure their ongoing support and commitment.

Domain: People

Advanced Training: Offer advanced training programs in data science, machine learning, and AI to upskill the analytics team and other relevant staff.

Talent Acquisition: Attract and hire top analytics talent with specialized skills in advanced techniques and technologies.

Data Literacy: Continue to promote data literacy across the organization by providing targeted training and resources.

Analytics Champions: Identify and empower analytics champions within various departments to promote data-driven decision-making.

Leadership Development: Invest in leadership development programs that focus on data and analytics leadership skills.

Domain: Culture

Innovation Culture: Foster an innovation culture where employees are encouraged to experiment with data and analytics to drive innovation.

Data-Driven Decision-Making: Reinforce the culture of data-driven decision-making by making it a core part of the organizational DNA.

Analytics Recognition: Recognize and reward employees who contribute significantly to analytics initiatives.

Data Transparency: Promote data transparency by making data and analytics insights accessible to a broader range of employees.

Analytics Advocacy: Encourage employees at all levels to advocate for analytics and its value in their respective areas.

Domain: Analytics

Advanced Analytics Adoption: Begin adopting advanced analytics techniques, including predictive and prescriptive analytics, and explore machine learning and AI.

Advanced Tools: Invest in advanced analytics software and tools that support complex modelling and analysis.

Data-Driven Products: Explore opportunities to create data-driven products and services that generate additional value.

Innovation Initiatives: Launch innovation initiatives that leverage analytics to drive product and process innovation.

Analytics Centre of Excellence: Consider establishing an Analytics Centre of Excellence (CoE) to centralize expertise and best practices.

Domain: Data

External Data Sources: Expand data sources to include external data, such as third-party data or data from industry sources.

Big Data Infrastructure: Invest in big data infrastructure and technologies for handling larger volumes of data and real-time processing.

Data Lakes: Implement data lakes or similar solutions for more flexible and scalable data storage.

Data Integration Excellence: Continue to enhance data integration capabilities for seamless access to data from various sources.

Data Quality Automation: Automate data quality checks and improve data quality management practices.

Domain: Technology

Advanced Technology Stack: Adopt advanced technology stacks that support big data processing, AI, and machine learning.

Real-Time Analytics: Invest in real-time analytics capabilities to enable more responsive decision-making.

Data Security Enhancement: Strengthen data security measures to protect sensitive information in line with regulatory requirements.

Advanced Data Processing: Implement advanced data processing and transformation capabilities, such as data pipelines and ETL automation.

Experimentation with Emerging Tech: Actively experiment with emerging technologies like quantum computing or blockchain for analytics applications.

Advancing to the Specialist level requires a deliberate strategy that involves both enhancing existing capabilities and exploring more advanced techniques and technologies. Continuous learning and a commitment to staying at the forefront of analytics developments are essential for success at this stage.

From Specialist to Expert

At this level, strong operational analytics capabilities have been established. To advance to the next level (Expert), organizations should focus on achieving excellence in analytics and further integrating it into their strategic decision-making processes.

Domain: Organization

Strategic Alignment: Ensure that analytics initiatives are fully aligned with the organization's strategic goals and objectives.

Data-Driven Leadership: Promote a culture of data-driven leadership throughout the organization, with senior executives actively championing analytics.

Analytics Governance: Implement advanced analytics governance practices to ensure ethical and compliant data use.

Cross-Functional Collaboration: Strengthen collaboration between analytics teams and business units to ensure analytics insights are applied in all areas.

Investment in Innovation: Allocate resources for innovative analytics projects that can drive competitive advantage.

Domain: People

Advanced Skill Development: Provide advanced training in specialized analytics areas, such as deep learning, natural language processing, or reinforcement learning.

Data Science Excellence: Continue to attract top data science talent and develop in-house data science expertise.

Data Leadership Development: Develop data leadership programs to prepare leaders who understand the strategic role of data and analytics.

Analytics Centres of Excellence: Consider establishing multiple Analytics Centres of Excellence (CoE) in different business units.

Data Literacy Across Functions: Promote data literacy not only among analytics teams but also across all business functions.

Domain: Culture

Innovation Ecosystem: Foster an innovation ecosystem where analytics-driven innovation is actively encouraged and supported.

Data-Driven Decision-Making: Ensure that data-driven decision-making is a norm, and that employees at all levels are comfortable using data to inform their choices.

Innovation Recognition: Recognize and reward employees who contribute to innovative analytics projects.

Data Transparency: Enhance data transparency by making data and insights easily accessible to all employees.

Analytics Advocacy Across Departments: Encourage departments and teams to advocate for analytics as a means to improve their operations.

Domain: Analytics

Advanced Modelling: Expand the use of advanced analytics techniques, including machine learning, deep learning, and artificial intelligence, across various functions.

AI Integration: Integrate AI technologies, such as chatbots or recommendation systems, into customer-facing applications or services.

Data-Driven Product Development: Drive product development and innovation through data-driven insights and customer feedback.

Advanced Reporting and Visualization: Implement advanced reporting and visualization tools that provide actionable insights.

Innovation Labs: Establish innovation labs or centres dedicated to exploring cutting-edge analytics solutions and technologies.

Domain: Data

Data Ecosystem Expansion: Extend the data ecosystem to incorporate a wider range of external and unstructured data sources, such as social media data or IoT data.

Big Data and Real-Time Analytics: Enhance big data and real-time analytics capabilities to support faster decision-making.

Data Governance Maturity: Further mature data governance practices, especially if dealing with sensitive data or expanding data sources significantly.

Data Quality Automation: Automate data quality checks and implement advanced data quality management practices.

Data Monetization: Explore opportunities to monetize data through partnerships, data marketplaces, or data-as-a-service offerings.

Domain: Technology

Advanced Technology Stacks: Invest in advanced technology stacks that support AI and machine learning at scale.

AI Integration: Implement AI and machine learning platforms that enable automation and intelligence in various processes.

Advanced Data Processing: Develop advanced data processing capabilities to support complex analytics workloads.

Data Security Excellence: Enhance data security measures to ensure the protection of sensitive data.

Innovation with Emerging Tech: Experiment with emerging technologies such as quantum computing or blockchain to discover new possibilities for analytics.

Moving to the Expert level requires a comprehensive strategy that focuses on innovation, leadership, and a deep commitment to data-driven decision-making. Organizations at this stage should continuously evaluate the impact of their analytics efforts on business outcomes and be prepared to adapt to evolving analytics trends and technologies.

From Expert to Visionary Innovator

At this level, organizations have achieved a high level of analytics excellence. To advance to the next level (Visionary Innovator), organizations should focus on becoming pioneers and visionaries in the field of advanced analytics.

Domain: Organization

Industry Leadership: Strengthen the organization's position as a thought leader and industry influencer in the application of advanced analytics.

Continuous Reinvention: Foster a culture of continuous reinvention, where analytics strategies are re-evaluated and evolved proactively.

Strategic Partnerships: Form strategic partnerships with leading technology companies, academia, and research institutions for innovation.

Market Expansion: Explore opportunities for market expansion and diversification through analytics-driven initiatives.

Ethical AI: Lead in ethical AI practices and transparency, setting industry standards.

Domain: People

Innovation Champions: Identify and empower innovation champions who can push the boundaries of what's possible with analytics.

Advanced Skill Ecosystem: Develop an ecosystem of advanced skills, including AI ethics, quantum computing, and frontier technologies.

Global Talent: Attract top global talent in data science, machine learning, and emerging fields from diverse backgrounds.

Data Leadership: Cultivate data leadership that drives innovation and fosters collaboration across functions.

Academic Partnerships: Collaborate with universities and research institutions to stay at the forefront of analytics knowledge.

Domain: Culture

Culture of Disruption: Establish a culture of disruption, where innovation is embraced, and employees are encouraged to challenge the status quo.

Data-First Mindset: Embed a data-first mindset at all levels, ensuring that data and analytics are integral to decision-making and culture.

Innovation Recognition: Recognize and reward innovation across the organization, promoting a culture of experimentation.

Data Transparency and Privacy: Balance data transparency with privacy and security, ensuring ethical data practices.

Cross-Industry Collaboration: Collaborate with organizations beyond your industry to drive cross-industry innovation through data sharing.

Domain: Analytics

Cutting-Edge Technologies: Actively explore and adopt cutting-edge analytics technologies, such as quantum computing and explainable AI.

Innovation Labs: Establish dedicated innovation labs or centres focused on exploring the next frontier of analytics.

Open-Source Contributions: Contribute to open-source analytics projects and communities to share knowledge and drive innovation.

AI-Powered Products: Develop AI-powered products and services that disrupt traditional business models.

Data-Driven Research: Lead in data-driven research, setting the agenda for research in your industry.

Domain: Data

Data Ecosystem Expansion: Expand the data ecosystem to include unconventional data sources, such as space data, genomics, or environmental data.

AI in Data Management: Implement AI-driven data management solutions that automate data collection, processing, and quality control.

Monetization Strategies: Develop advanced data monetization strategies, creating new revenue streams.

Data Sharing Consortia: Lead or participate in data sharing consortia and ecosystems to drive collective innovation.

Privacy-Centric Data Practices: Implement advanced privacy-centric data practices, adhering to the highest ethical standards.

Domain: Technology

Emerging Tech Adoption: Embrace emerging technologies beyond analytics, such as blockchain, to create synergies with analytics capabilities.

AI at Scale: Implement AI at scale, automating decision-making processes and leveraging AI-driven insights across the organization.

Data Ecosystem Integration: Achieve seamless integration of data across the entire data ecosystem, supporting data agility and scalability.

Data Security Excellence: Continue to enhance data security and privacy measures in alignment with evolving regulations.

Innovation Sandbox: Create an innovation sandbox environment for rapid prototyping and testing of analytics solutions.

Moving to the Visionary Innovator level requires a fearless commitment to pushing the boundaries of analytics and continuously innovating. Organizations at this level play a leading role in shaping the future of analytics in their industry and beyond.

Visionary Innovator level

Keep pushing the boundaries of analytics through cutting-edge research. Collaborate with universities, research institutions, and industry peers to drive forward the field's knowledge. Invest in R&D to explore their potential applications in analytics. Encourage employees to challenge conventions and explore unconventional ideas. Develop innovation labs or centres dedicated to experimentation. Collaborate globally with organizations, governments, and academia to address global challenges through analytics. Explore partnerships beyond your industry to apply analytics expertise to new sectors, uncovering fresh opportunities for innovation and impact. Continuously explore data monetization strategies to create new revenue streams and maximize the value of data assets. Develop AI-powered products and services that disrupt traditional business models or create entirely new markets. Maintain a strong presence as a thought leader in the analytics industry. Publish research, speak at conferences, and contribute to discussions on the future of analytics. Continue to recognize and reward innovation within the organization, fostering a culture of experimentation and creativity. Ensure that data-driven decision-making remains integral to the organization's culture and operations. Forge strategic alliances with leading technology companies and research institutions to access resources and stay at the forefront of analytics capabilities.

4.6. Online Assessment Tool

The online advanced analytics ecosystem maturity assessment tool originally developed by the author is seamlessly integrated into the author's website http://www.raaconsulting.eu/ which is built using the Mozello website builder platform.

The questionnaire and the model for assessment are built using the https://www.jotform.com/ solution, which facilitates the creation of extensive conditional scenarios, report generation, and workflow automation.

The example, based on a specific respondent from the experimental survey, is described below to demonstrate how the advanced analytics ecosystem assessment and recommendation tool works for a particular organization. It demonstrates how the results, as described in Section 4, are applied in a real case scenario.

The respondent was randomly chosen from the micro-organizations (93% of Latvia's organizations), and they belong to the auditor's industry. The owner of the organization provided answers for the survey. Based on the target variable Q21, the simple average advanced analytics maturity level is 1, as outlined in subsection 4.1. The maturity levels by domains are: Organization – 2.9, People – 2.3, Culture – 3.5, Analytics – 2.7, Data – 3.7, Technology – 2, which results in a weighted average advanced analytics maturity level of 2.4, as detailed in subsection 4.2. To summarize the detailed explanations of the existing state and recommendations provided in the following paragraphs, in more business-oriented language: The organization is currently in a favourable position to begin reaping the benefits of advanced analytics. There is little need for significant investments in data management. The management fully understands the importance of analytics, and if a specific analytics-related initiative aligns with the organization's strategy or specific strategical goals for a given period, there should not be any obstacles in prioritizing a specific analytics-related initiative or project and allocating resources (EUR, HR, IT) as needed. The organization should focus on essential investments, primarily in developing existing analytical resources, such as training, tools, experience sharing, and motivational schemes. In the technology domain, it should ensure that its IT infrastructure aligns with the analytical needs to support a technical environment capable of handling a variety of analytical tasks and initiatives. This positions the organization to transition to a level where it can begin to realize the benefits and returns from advanced analytics.

According to subsection 4.4, the specific overall advanced analytics maturity level and the level of domains can be described as intermediate level or siloed analytics. Analytical activities are conducted in various departments or teams without coordination. Data is more accessible, but it may still be stored in department-specific repositories. Teams conduct analytics autonomously without centralized coordination. There are no clear data owners responsible for data quality and governance. Domains can be characterized as follows: Organization - Analytics are integrated into daily operations. Analytics is a key component of decision-making and processes. Analytics is fully integrated into core business processes and decision-making. Dedicated analytics and data science teams are in place. There is a robust data warehousing and data management infrastructure. Well-defined data governance practices and data ownership have been established. Proactive decision-making is in place, where analytics is used to optimize processes and outcomes. People - initiatives have been started to provide training in analytics and data science. Employees are gaining skills in data analysis and visualization. Small analytics teams or roles are formed. There is an increasing awareness of the value of analytics. Culture – there is a culture of analytics excellence. Data and analytics are core to decision-making processes. Many employees champion data-driven approaches at all levels. There is a data-first mindset across the organization, and data is the starting point for strategic decisions. A culture of continuous learning and improvement in analytics is fostered. Innovation and Experimentation: Encouragement of innovation and experimentation with data. Analytics – there are established operational analytics capabilities. Analytics is integrated into daily operations. Analytics is part of core business processes and decision-making. Specialized teams dedicated to analytics and data science are in place. Proactive insights are generated using analytics to optimize processes and outcomes. Data - data excellence has been achieved and is leveraged as a competitive advantage. A mature data ecosystem that includes data lakes, AI, and machine learning is in place. Well-defined data governance practices and data ownership are established. Advanced predictive and prescriptive analytics are actively utilized. Data plays a pivotal role in driving innovation and product development. There is a culture of continuous improvement in data usage. Technology – there is an investment in more advanced IT infrastructure, including cloud solutions. The organization deals with larger datasets, including some external data sources. Specialized analytics software and tools have been adopted. Data warehousing solutions have been implemented. Basic data processing and transformation capabilities are in place. The recommendations for the specific organization are as follows:

From Specialist to Expert - Domain: Organization

Strategic Alignment: Ensure that analytics initiatives are fully aligned with the organization's strategic goals and objectives.

Data-Driven Leadership: Promote a culture of data-driven leadership throughout the organization, with senior executives actively championing analytics.

Analytics Governance: Implement advanced analytics governance practices to ensure ethical and compliant data use.

Cross-Functional Collaboration: Strengthen collaboration between analytics teams and business units to ensure analytics insights are applied in all areas.

Investment in Innovation: Allocate resources for innovative analytics projects that can drive competitive advantage.

From Intermediate to Specialist – Domain: People

Advanced Training: Offer advanced training programs in data science, machine learning, and AI to upskill the analytics team and other relevant staff.

Talent Acquisition: Attract and hire top analytics talent with specialized skills in advanced techniques and technologies.

Data Literacy: Continue to promote data literacy across the organization by providing targeted training and resources.

Analytics Champions: Identify and empower analytics champions within various departments to promote data-driven decision-making.

Leadership Development: Invest in leadership development programs that focus on data and analytics leadership skills.

From Expert to Visionary Innovator - Domain: Culture

Culture of Disruption: Establish a culture of disruption, where innovation is embraced, and employees are encouraged to challenge the status quo.

Data-First Mindset: Embed a data-first mindset at all levels, ensuring that data and analytics are integral to decision-making and culture.

Innovation Recognition: Recognize and reward innovation across the organization, promoting a culture of experimentation.

Data Transparency and Privacy: Balance data transparency with privacy and security, ensuring ethical data practices.

Cross-Industry Collaboration: Collaborate with organizations beyond your industry to drive cross-industry innovation through data sharing.

From Specialist to Expert - Domain: Analytics

Advanced Modelling: Expand the use of advanced analytics techniques, including machine learning, deep learning, and artificial intelligence, across various functions.

AI Integration: Integrate AI technologies, such as chatbots or recommendation systems, into customer-facing applications or services.

Data-Driven Product Development: Drive product development and innovation through data-driven insights and customer feedback.

Advanced Reporting and Visualization: Implement advanced reporting and visualization tools that provide actionable insights.

Innovation Labs: Establish innovation labs or centres dedicated to exploring cutting-edge analytics solutions and technologies.

From Expert to Visionary Innovator - Domain: Data

Data Ecosystem Expansion: Expand the data ecosystem to include unconventional data sources, such as space data, genomics, or environmental data.

AI in Data Management: Implement AI-driven data management solutions that automate data collection, processing, and quality control.

Monetization Strategies: Develop advanced data monetization strategies, creating new revenue streams.

Data Sharing Consortia: Lead or participate in data sharing consortia and ecosystems to drive collective innovation.

Privacy-Centric Data Practices: Implement advanced privacy-centric data practices, adhering to the highest ethical standards.

From Intermediate to Specialist - Domain: Technology

Advanced Technology Stack: Adopt advanced technology stacks that support big data processing, AI, and machine learning.

Real-Time Analytics: Invest in real-time analytics capabilities to enable more responsive decision-making.

Data Security Enhancement: Strengthen data security measures to protect sensitive information in line with regulatory requirements.

Advanced Data Processing: Implement advanced data processing and transformation capabilities, such as data pipelines and ETL automation.

Experimentation with Emerging Tech: Actively experiment with emerging technologies like quantum computing or blockchain for analytics applications.

Moving to the Specialist level requires a deliberate strategy that involves both enhancing existing capabilities and exploring more advanced techniques and technologies. Continuous learning and a commitment to staying at the forefront of analytics developments are essential for success at this stage.

Based on the assessment and the provided recommendations, a specific organization can create an action plan to improve its advanced analytics maturity level.

CONCLUSIONS

The research goal of the doctoral thesis has been successfully accomplished. The advanced analytics ecosystem assessment and recommendations tool has been developed, published online, and is readily available to the public at no cost, following the principle of Open Science. By conducting in-depth analyses of theoretical literature, the author has summarized the essence of advanced analytics and has introduced the corresponding terminology and definition in Latvian, contributing to the development of the scientific language for advanced analytics in Latvian.

Based on the findings of international research, the author has developed a new methodology for evaluating advanced analytics. This methodology serves to assess the overall level of advanced analytics maturity, as well as the domain-specific maturity level, with adjustments made to align it with the Latvian context. As an integral component of her doctoral thesis, the author has designed and validated an advanced analytics ecosystem assessment and recommendation tool specifically tailored for Latvian organizations.

Utilizing the advanced analytics assessment methodology and assessment tool she developed, the author conducted an experimental survey of representatives from Latvian organizations responsible for making decisions related to strategy, development, planning, performance achievement, functional management, and the analysis of advanced analytics maturity within Latvian companies. This analysis encompassed industry groups and company size classifications based on the number of employees.

Summarizing the survey results, the author identified several dimensions of data quality that require attention, including the methodology for data collection and processing, data completeness, and data representativeness. The objectivity of the data may be impaired due to varying of insufficient understanding of terminology among the respondents. The author also explored avenues for improving the company's advanced analytics in the future and provided suggestions.

The model developed for assessing the maturity level of advanced analytics will be patented in Latvia. The approach for assessing the maturity level of advanced analytics will also be patented in Latvia and internationally. Likewise, the online assessment and recommendation tool developed for assessing the maturity level of advanced analytics will be patented in Latvia and internationally

To achieve the goal, a set of tasks has been completed within the framework of the doctoral thesis:

1) Review and analysis of academic and industry publications, research, surveys, books, and leading practitioners and organizations' insights on advanced analytics, analytics maturity assessment models and tools, and their impact on business performance:
    a. Historical evolution;
    b. Advanced analytics in the organizations of Latvia;
    c. Existing models and tools.
2) Development of the overall approach to build the model and tool based on the literature review;
3) Development of the analytics maturity assessment model for Latvia;
4) Development of the analytics maturity assessment and recommendations tool for Latvia;
5) A set of recommendations to improve the current state of advanced analytics or set up advanced analytics within the organization, including specific segments.

As a result of the study, scientifically based answers to the research questions were provided:

1) What is the overall level of advanced analytics ecosystem maturity in Latvia?
2) What are the existing models and approaches to assess advanced analytics maturity?
3) How to the best practices from existing practices be adapted to build a new advanced analytics ecosystem assessment model for Latvia?
4) What are the challenges of adopting advanced analytics in organizations in Latvia and what actions and initiatives can be taken to overcome them?

Conclusions:

1) In scientific literature and previous research, comprehensive models and tools for assessing the maturity of advanced analytics are available. However, existing research lacks an operational principle applicable to local conditions. They cannot be directly applied and adopted in Latvia due to language, regional specifications, and the rapid development of technologies. The literature has reported the impact of advanced analytics on organizational

performance, but there is limited literature on the challenges to be faced and the steps to be taken to leverage the capabilities of advanced analytics.

2) There is no methodology available in the scientific literature for model development and tool creation. While there are free tools, they typically offer limited functionality, often involving only a few questions or statements asked to fill out. Therefore, they do not provide the organization with full opportunities to better understand its analytics capabilities, chart a course to become more data-driven, and offer the company a competitive advantage by adapting products, services, and marketing activities.
3) All 15 of the reviewed models provide a framework for the independent development of the analytics maturity model. All the reviewed models disclose domains, to some extent sub-domains or factors, and at least a high-level description of analytics maturity levels. However, they do not provide details of the methodology for detecting a specific maturity level. In some cases, more information is provided about what underlies the model and how it was developed. This includes methods such as surveys, interviews with experts, audits, and back tests over time using the same data pool.
4) It is possible to develop a new model or replicate to some extent an analytics maturity assessment model based on the models reviewed in this doctoral thesis. The challenging part is the methodology for detecting the level of maturity. The author overcame this challenge and created a new methodology to assess the maturity level of the advanced analytics ecosystem. Another challenge is to interpret the results in order to provide an explanation of the detected analytics maturity level and recommendations for the next steps to improve the overall analytics maturity level. The author has created a set of recommendations to progress from one level to a higher level. One more challenge is to monetize the transition to a higher maturity level. In addition, time and the rapid development of technologies play a significant role because the model should include the latest trends in the analytics ecosystem to avoid becoming outdated shortly after its creation. It should be capable of assessing the maturity level accurately both today and in the mid-term future, enabling it to provide organizations with appropriate recommendations for developing the analytics ecosystem in line with the newest and most applicable solutions.

Thus, this drives the need for new and updated analytics maturity assessment models.

5) The results of the analysis of the scientific literature show that the following dimensions can be used for the model – People, Culture, IT, Data, and Analytics. Such dimensions are adaptable for localized solutions, as they are characteristic of any business environment, therefore, the author proposes to use the following dimensions for assessing the maturity level of Latvian organizations: Organization, People, Culture, Analytics, Data, and Technology.
6) Considering that the explored 15 models did not offer a specific methodology for detecting the maturity level of an advanced analytics ecosystem, the author developed a new methodology. This novel approach is founded on logistic regression, which furnishes numerical expressions (weights) for the interactions among all six domains influencing the maturity level of the advanced analytics ecosystem. Consequently, it enables a more precise assessment of the maturity level and the identification of both strengths and weaknesses. As a result, organizations can formulate action plans to enhance weaknesses and sustain or improve their strengths. Collectively, these measures facilitate a more effective adoption and utilization of the benefits of advanced analytics.
7) As all the models reviewed in the scientific literature are in English, and the terms used are specific and sometimes not easily translatable or self-explanatory in the business context, the challenge was to create a questionnaire in Latvian due to the absence of relevant terminology. This process led to the identification of potential new terminology that needs to be developed and implemented in Latvian. As a result, new terminology has been introduced by the author in Latvian where ‘Advanced analytics’ is represented as ‘Augstākā analītika’ in Latvian.
8) The quality of the data collection and processing methodology plays a pivotal role in the accuracy and reliability of the maturity level assessment. It is not an exaggeration to say that the entire foundation of the assessment hinges on the precision of data gathering and processing. To obtain trustworthy results, it's imperative that data validation processes are in place. This includes checks

and measures to ensure that the data collected is accurate, consistent, and free from errors or biases.

9) The author's proposed methodology includes weighting various factors or components within the data to account for their relative importance. Weighting is a critical step in ensuring that the assessment reflects the true significance of different variables in the context of maturity evaluation, therefor, the model developed by the author has the potential to be adopted/used in any country. Only minimal localization, such as translating it into the local language, is required to initiate testing in other countries.
10) The ability to build or replicate one's own analytics maturity assessment model is likely to be appealing to large organizations, those with existing analytical teams, and organizations determined to promote an analytical culture across the entire organization. It's also of interest to analytical teams, researchers, consultants, and experts in the analytics sector. Another reason is the rapid development of technologies, analytical platforms, the increase of data volumes, data accessibility to a wider audience. This poses a risk since publicly available (non-commercial) analytics maturity assessment models are outdated or partly outdated. However, models available in the market can provide comparisons within the industry, with similar segments, and on an overall level.
11) Summarizing the results of the experimental survey, the author found that the overall maturity level of advanced analytics in Latvian organizations is 1.8 based on a simple weighted average and 2.5 based on a weighted model outcome. This signifies the absence of an analytics strategy. In most cases, analytics operates in isolation, with analytical activities conducted in different departments or teams without coordination. There is also an insufficient number or analytical resources, and the skills may not be adequate. While data is more accessible, it may still be stored in department-specific repositories. Teams conduct analytics autonomously without centralized coordination. There are no clearly defined data owners responsible for data quality and governance. All this leads to the conclusion that the majority of Latvia's organizations are far from being able to improve productivity, maximize the potential of the digital environment, exploit data for data-driven and

automated decisions, and are distant from the digital opportunities of the 21st century. This situation places the sustainability of these organizations at risk.

12) Large organizations demonstrate a high readiness level for advanced analytics, with some reaching as high as 3.2. Similarly, the finance industry, construction sector, and, to some extent, the Information Technologies sector, also exhibit a strong readiness level, reaching as high as 2.8. In these cases, most of the required infrastructure and cultural elements within the organization are already in place. On the other hand, the Education sector has one of the lowest readiness levels, with a rating of only 2.1. This situation poses a risk to Latvia's ability to develop a workforce adequately skilled for the digital century.
13) Micro organizations demonstrate a readiness for advanced analytics almost one level lower (1.8 based on the simple Q21 target variable and 2.5 at the model-based level) than Large organizations. This represents a significant gap, especially when considering the considerably faster pace of technological development, which is expected to further widen this gap. This situation is particularly concerning in Latvia, where 93% of organizations fall into the Micro category.
14) Ability to assess the maturity level of analytics could be attractive to any organization striving to use the full range of opportunities offered by technologies, data, and digital solutions that are most suitable for their needs. Another reason is the rapid development of technologies and analytical platforms, the increase of data volumes, and increased data accessibility to a wider audience. These factors pose a risk to the competitive advantage of organizations.
15) The state of advanced analytics implementation can vary significantly based on factors such as the organization's size, budget, data maturity, and the availability of skilled data professionals. The cultural factors dominate as the most significant obstacle to delivering business value from data investments.
16) Main barriers to implementing and using advanced analytics include: a lack of technical skills, a shortage of people with technical skills, a lack of knowledge about best practices, difficulties in finding appropriate tools, required investments (in terms of euros, human resources, and infrastructure), concerns about data privacy, uncertainty about whether investments will yield the

expected returns, a lack of understanding about how to apply the results, and data security.

17) It is possible to run such surveys regularly, not only as an experiment to build the tool. Survey of this type can be used to develop country level policies and strategies for specific industries or segments. The challenge is to bring organizations that are below the specialist level (3) to at least an analytics maturity level of 3 – strong specialist level. This level would enable them to adopt and implement many advanced analytics features or, at the very least, prepare them for the next steps to optimize the usage of advanced analytics.
18) Considering the rapid development of technologies, the increasing volume of data, and the availability of more user-friendly analytical platforms, it would be necessary to conduct such a survey annually to monitor the readiness of Latvia’s organizations for advanced analytics. The Baltic region and annual surveys should be conducted to enhance the credibility of this research and its outcomes.

The research carried out in the doctoral thesis corresponds to the problem to be addressed, and the applied methods ensure the implementation of the tasks and the achievement of the goal.

SUGGESTIONS

To responsible state institutions, municipalities, non-governmental organizations:

1. Increase awareness about advanced analytics and its impact on business through educational campaigns and public information efforts. These initiatives should inform people about what advanced analytics is (similarly to digital transformation, as it is a part of digitization) and how it can be beneficial in everyday life. Utilize real examples and success stories. The data collected during the online survey performed by the author can be used to provide reliable information regarding the most beneficial impacts of advanced analytics implementation in the organization and the time it took to observe a return on investment.

To responsible state institutions, experts from industries, educators:

1. Introduce missing advanced analytics terminology in Latvian, such as advanced analytics ecosystem, predictive modelling and/or analytics, prescriptive modelling and/or analytics, data dictionary, and other relevant terms. It will help inform, educate, and reach any Latvian-speaking audience about advanced analytics and its beneficial effects on business processes and everyday life, using the most understandable language for them.
2. Use the experimental survey as a foundation and enhance it for regular conduct (at least every second year) to assess the advanced analytics maturity in Latvian organizations. Use the obtained data to develop national-level policies and strategies for specific industries or segments. Regular monitoring of the maturity of advanced analytics in Latvian organizations can be used to evaluate the effectiveness of state digital transformation-related initiatives and programs, improve digital transformation guidelines, and compare the impact of digital transformation by segments (e.g., organization size).

To state institutions and any other interested parties:

1. Conduct similar research at the Baltic states level to facilitate comparisons, mutual learning, and the exchange of success stories among these countries.
2. Conduct research specific to particular industries or sizes of organizations.
3. Conduct research with an adjusted data collection strategy to assess the proportion of Latvia's population that possesses a data-driven mindset.

4. Utilize the advanced analytics ecosystem maturity assessment tool developed in this doctoral thesis (http://www.raaconsulting.lv/home-1/) to assess the advanced analytics maturity of individual organizations and obtain recommendations for the next steps.

To any organization or interested party (stakeholder):

Begin to perceive data as valuable assets of the organization. Here is a step by step guide: 1) identify an experienced analytics representative who can assess the existing state of analytics and provide an independent view on how to establish or adopt advanced analytics in the organization (a one-year plan), or use the assessment tool developed in this doctoral thesis, 2) appoint or hire an analytics leader, or hire an outsourced expert to develop an analytics strategy and establish analytics within the organization, 3) develop an action plan for the 1st year, including milestones, quick wins, and long-term goals, 4) explore and identify all available data sources, 5) make all identified data available for basic descriptive analytics in an automated way using any of the widely available analytical platforms, 6) provide access and training to users of dashboards, 7) identify areas of analytics or decision-making that could be automated. If all of these steps are covered, the organization is prepared for advanced analytics based on its specific needs.

To responsible state institutions, municipalities, educators:

1. Consider the development of a Centre of Excellence concept for advanced analytics that could serve the state or municipality institutions at the national, regional or municipal level. For example, analytical teams could be established to serve specific sets of institutions, such as those in education, health, or law enforcement.
2. Consider engaging universities, especially regional ones, as an 'outsourced' resource in analytics on a regular basis. This may involve the obligation to provide internships for education programmes where needed. Such an approach strengthens the connection to specific regions or municipalities and fosters a sense of engagement and direct contribution. For example, regional universities already have significant interaction with local municipalities and contribute to research or various supportive functions. Regional universities could serve as centres of excellence to implement, develop, and maintain analytics strategies and related activities for organizations in the region, providing comprehensive support to institutions in that specific region. This form of cooperation could lead to sustainability of the region and help retain

residents, preventing them from relocating. For example, this collaboration could be structured with a lead analysts or analytics leader employed by the municipality, while the remaining team members are provided by universities, consisting of experts and junior analysts, including students participating in internships. Such an approach could increase synergy between the municipality and the regional university.

To the author:

Considering that the created model has the potential for international use, the existing tool should be translated into the language of the target region. It is recommended to translate it into English and test it on an international scale. To validate the model's appropriateness for the international environment, the assessment tool should request the names of the countries from international users.

Several research directions have been identified for future exploration:

1. Enhance the experimental survey, conduct it regularly (at least biennially), to evaluate the maturity of advanced analytics in Latvian organizations and monitor trends in relation to state initiatives in the advanced analytics industry. The data obtained could be used to develop national-level policies and industry-specific strategies.
2. Conduct new research to assess the level of advanced analytics proficiency among the workforce in Latvia. This involves determining the proportion of Latvia's population already engaged in, or possessing a data-driven and technology-oriented mindset.
3. Conduct an adapted survey in the Baltic region or across Europe to evaluate the maturity level of advanced analytics. Leading countries can share their experiences that contribute to their prominent positions.
4. Develop a new advanced analytics maturity assessment model that incorporates more advanced machine learning algorithms for real-time data assessment.
5. Create specific assessment models tailored to different segments, based on size and industry.
6. The model developed for Latvia could be tested in Estonia and Lithuania, new research should be run in these countries to gather data and validate the hypothesis –

if originally designed models for Latvia using Latvian data, can effectively assess the maturity level of advanced analytics in Estonia and Lithuania.

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Appendices

Appendix A. Summary of analytics maturity levels of 15 models

No.	Model name	Year	Number of maturity levels	Names of maturity levels
1	**Watson's data warehousing** maturity model	2002	3	1 - Initiation, 2 - Growth, 3 - Maturity
2	**Comuzzi's & Patel's Big Data** maturity model	2016	5	1 - Initial, 2 - Developing, 3 - Defined, 4 - Managed, 5 - Optimized
3	**Early DELTA maturity mode**l by Davenport & Harris	2007	5	1 - Analytically Impaired (Not Data-Driven), 2 - Localized Analytics (Use Reporting), 3 - Analytical Aspirations (See the Value of Analytics), 4 - Analytical Companies (Good at Analytics), 5 - Analytical Competitors (Analytical Nirvana)
4	**Business Analytics Capability Maturity Model (BACMM)** by Cosic	2012	4	0: non existing; 1 - Initial: the capability exists but is poorly developed; 2 - Intermediate: the capability is well developed but there is much room for improvement; 3 - Advanced: the capability is very well developed but there is still a little room for improvement; 4 - Optimised: the capability is so highly developed that it is difficult to envision how it could be further enhanced. At this point the capability is considered to be fully mature.
5	**Analytic Processes Maturity Model (APMM)** by Grossman	2018	5	1 - Building reports, 2 - Building and deploying models, 3 - Building and deploying analytics, 4 - Enterprise-wide processes for analytics, 5 - Analytics is strategy driven
6	**Analytics Maturity Quotient Framework (AMQ)** by Piyanka	2012	NA	Not disclosed
7	**Analytics Maturity Assessment Framework** by Blast Analytics & Marketing	2021	5	1 - Laggard, 2 - Follower, 3 - Competitor, 4 - Leader, 5 - Innovator

8	**Data Analytics Maturity Model (DAMM)** by Association Analytics	2017	5	1 - Learning, 2 - Planning, 3 - Building, 4 - Applying, 5 - Leading
9	**DELTA Plus** maturity model by Davenport	2017	5	1 - Analytically Impaired (Not Data-Driven), 2 - Localized Analytics (Use Reporting), 3 - Analytical Aspirations (See the Value of Analytics), 4 - Analytical Companies (Good at Analytics), 5 - Analytical Competitors (Analytical Nirvana)
10	**Analytics Maturity Model by Logi Analytics**	2017	5	1 - Standalone Analytics, 2 - Bolt-On Analytics, 3 - Inline Analytics, 4 - Infused Analytics, 5 - Genius Analytics
11	**Online Analytics Maturity Model (OAMM)** by Cardinal Path	2020	6	0 - Inexistent, 1 - Initial, 2 - Repeatable, 3 - Defined, 4 - Managed, 5 - Optimized
12	**SAS Analytics Maturity Model** by SAS	2014	5	1 - Analytically Unaware, 2 - Analytically Aware, 3 - Analytically Astute, 4 - Empowered, 5 - Explorative
13	**TDWI Analytics Maturity Model** by Halper	2020	5+1	1 – Nascent, 2 – Early, 3 – Established, 4 – Mature, 5 – Advanced/ Visionary and the Chasm – the most difficult stage to overcome to reach the next level.
14	**Web Analytics Maturity Model (WAMM)** by Hamel, Cardinal path	2009	5	1 - Analytically impaired to 5 - Analytically Addicted
15	**Defining analytics maturity indicators (DAMI)** by Lismonta et al.	2017	4	1 – No analytics, 2 – analytics bootstrappers, 3 – sustainable analytics adopters, 4 – disruptive analytics innovators.

Appendix B. Summary by domains of maturity (with factors)

No.	Model name	Year	Number of domains	Domains of maturity (with factors)
1	**Watson's data warehousing** maturity model	2002	3	People, Processes, Technology
2	**Comuzzi's & Patel's Big Data** maturity model	2016	4	Business strategy, Information management, Analytics, Governance
3	**Early DELTA maturity mode**l by Davenport & Harris	2007	3	Organization, Human, Technology
4	**Business Analytics Capability Maturity Model (BACMM)** by Cosic	2012	4	**Governance** (Decision Rights, Strategic Alignment, Dynamic BA Capabilities, Change Management) **Culture** (Evidence-based Management, Embeddedness, Executive Leadership and Support, Flexibility and Agility) **Technology** (Data Management, Systems Integration, Reporting and Visualisation BA Technology, Discovery BA Technology) **People** (Technology Skills and Knowledge, Business Skills and Knowledge, Management Skills and Knowledge, Entrepreneurship and Innovation)
5	**Analytic Processes Maturity Model (APMM)** by Grossman	2018	6	**Building** analytic models, **Deploying** analytic models, **Managing and operating** analytic infrastructure, **Protecting** analytic assets through appropriate policies and procedures, **Operating** an analytic governance structure, **Identifying** analytic opportunities, making decisions, and allocating resources based upon an analytic strategy
6	**Analytics Maturity Quotient Framework (AMQ)** by Piyanka	2012	4	Data Maturity, Leadership, Analytics Talent, Decision making process

7	**Analytics Maturity Assessment Framework** by Blast Analytics & Marketing	2021	5	Culture, Capability, Technology, Data and Process
8	**Data Analytics Maturity Model (DAMM)** by Association Analytics	2017	4	Organization and Culture, Architecture/Technology, Data governance, Strategic alignment
9	**DELTA Plus** maturity model by Davenport	2017	7	Data, Enterprise, Leadership, Targets, Analysts, Technology, Analytics techniques
10	**Analytics Maturity Model by Logi Analytics**	2017	4	Data, Analytics, Users, Value
11	**Online Analytics Maturity Model (OAMM)** by Cardinal Path	2020	6	**Management, governance, and adoption**; **Objectives definition** (What is the primary objective of your current online analytics program?); **Scoping** (the scope defines the size of the playing field); **Analytics team and expertise** (How is your online analytics team structured?); **Continuous improvement process and analysis methodology** (How do you develop a hypothesis, define problems and opportunities, analyse and provide insight?); **Tools, technology and data integration**
12	**SAS Analytics Maturity Model** by SAS	2014	4	**Culture:** Decision-Makers Use of Data and Analysis; **Internal Process Readiness**; **Analytical Capabilities;** **Data Environment:** Infrastructure and Software
13	**TDWI Analytics Maturity Model** by Halper	2020	5	Organization, Resource, Data Infrastructure, Analytics, Governance
14	**Web Analytics Maturity Model (WAMM)** by Hamel, Cardinal path	2009	6	Management, governance, and adoption; Objectives definition; Scoping; Analytics team and expertise; Continuous improvement process and analysis methodology; Tools, technology, and data integration
15	**Defining analytics maturity indicators (DAMI)** by Lismonta et al.	2017	5	Data, Organization, Leadership, Techniques and applications, Analysts

Appendix C. Comparison of 15 models by 3 main characteristics disclosing the most how the models built and maturity detected

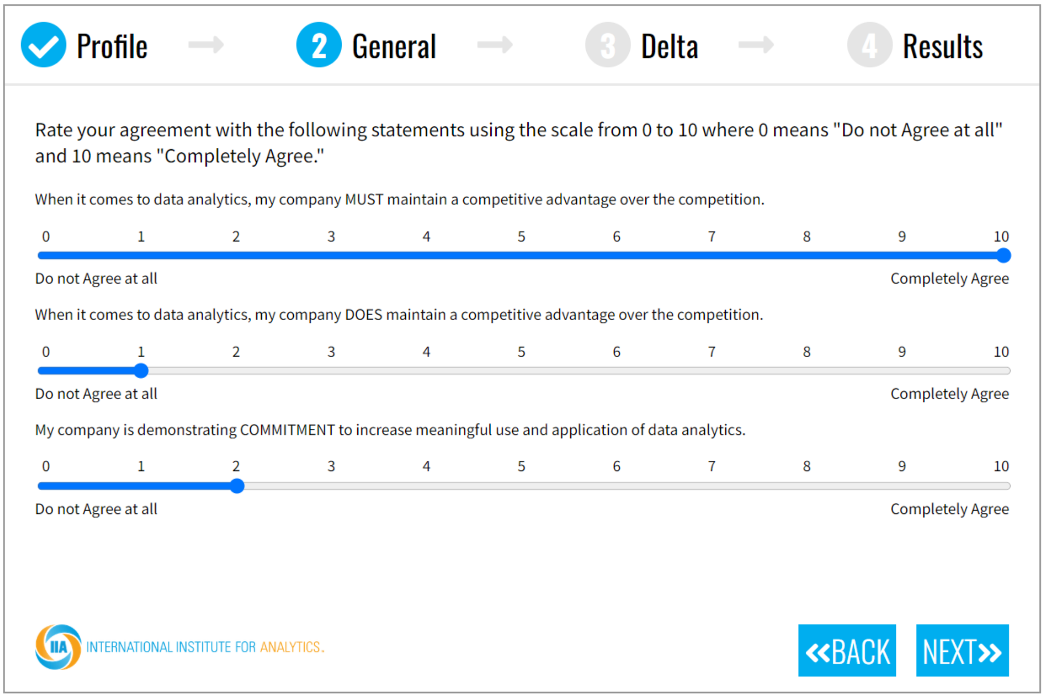
No.	Model name	Year	Survey questionnaire disclosed	Online tool	Maturity level detection (methodology)
1	**Watson's data warehousing** maturity model	2002	No	No	Not disclosed
2	**Comuzzi's & Patel's Big Data** maturity model	2016	No	No	Not disclosed
3	**Early DELTA maturity mode**l by Davenport & Harris	2007	No	No	Not disclosed
4	**Business Analytics Capability Maturity Model (BACMM)** by Cosic	2012	No	No	Not disclosed
5	**Analytic Processes Maturity Model (APMM)** by Grossman	2018	No	No	Not disclosed
6	**Analytics Maturity Quotient Framework (AMQ)** by Piyanka	2012	11 questions from short DIY version	Yes	Formula provided
7	**Analytics Maturity Assessment Framework** by Blast Analytics & Marketing	2021	Questions from the online tool	Yes	Not disclosed
8	**Data Analytics Maturity Model (DAMM)** by Association Analytics	2017	Questions from the online tool	Yes	Not disclosed
9	**DELTA Plus** maturity model by Davenport	2017	7 questions (1 for each domain) from the online tool	Yes	Partly
10	**Analytics Maturity Model by Logi Analytics**	2017	Questions from the online tool	Yes	Not disclosed
11	**Online Analytics Maturity Model (OAMM)** by Cardinal Path	2020	No	No	Not disclosed
12	**SAS Analytics Maturity Model** by SAS	2014	No	No	Not disclosed
13	**TDWI Analytics Maturity Model** by Halper	2020	52 questions, full survey	Yes	Weighted score by domains and average total score
14	**Web Analytics Maturity Model (WAMM)** by Hamel, Cardinal path	2009	No	No	Not disclosed

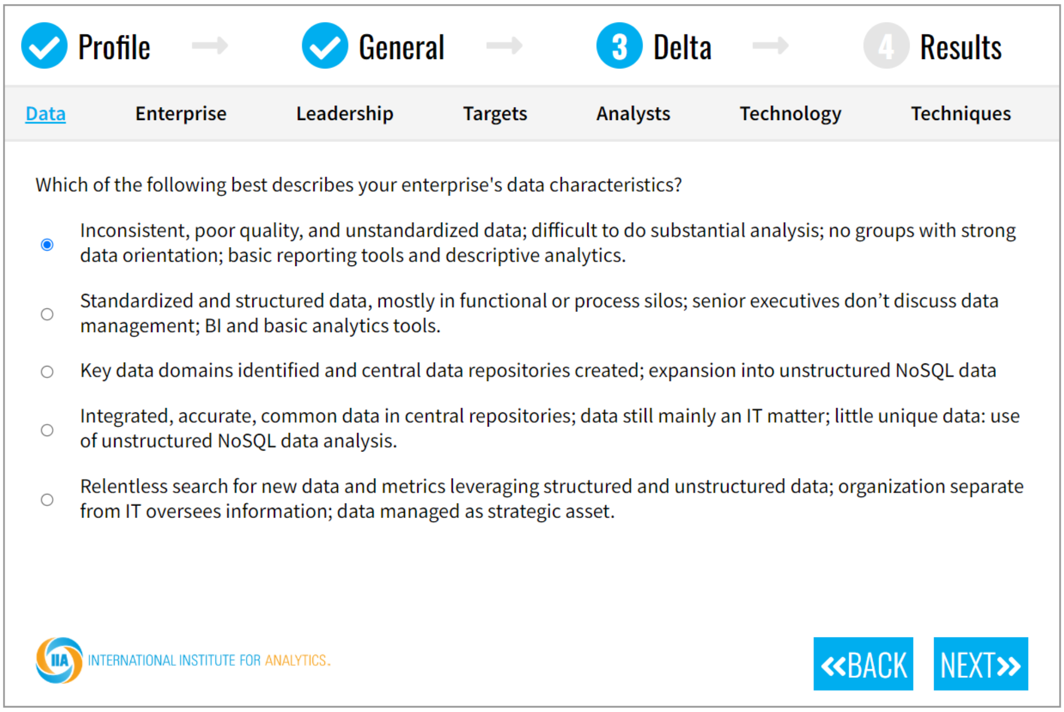
15	**Defining analytics maturity indicators (DAMI)** by Lismonta et al.	2017	67 questions, full survey	No	Clustering

Appendix D. DELTA Plus tool

1) **Step1.** Access the tool: https://iianalytics.com/services/analytics-assessments or https://iianalytics.com/ama-widget . To start to use it, it is required to provide full name, organization, job role, email and region.

2) **Step 2**. Assessment by the few general questions about the organization and assessment of the specific domains.


Profile
2 General
3 Delta
4 Results
Rate your agreement with the following statements using the scale from 0 to 10 where 0 means "Do not Agree at all" and 10 means "Completely Agree."
When it comes to data analytics, my company MUST maintain a competitive advantage over the competition.
0 1 2 3 4 5 6 7 8 9 10
Do not Agree at all
Completely Agree
When it comes to data analytics, my company DOES maintain a competitive advantage over the competition.
0 1 2 3 4 5 6 7 8 9 10
Do not Agree at all
Completely Agree
My company is demonstrating COMMITMENT to increase meaningful use and application of data analytics.
0 1 2 3 4 5 6 7 8 9 10
Do not Agree at all
Completely Agree
IIA INTERNATIONAL INSTITUTE FOR ANALYTICS.
«BACK
NEXT»


Profile
General
3 Delta
4 Results
Data
Enterprise
Leadership
Targets
Analysts
Technology
Techniques
Which of the following best describes your enterprise's data characteristics?
Inconsistent, poor quality, and unstandardized data; difficult to do substantial analysis; no groups with strong data orientation; basic reporting tools and descriptive analytics.
Standardized and structured data, mostly in functional or process silos; senior executives don't discuss data management; BI and basic analytics tools.
Key data domains identified and central data repositories created; expansion into unstructured NoSQL data
Integrated, accurate, common data in central repositories; data still mainly an IT matter; little unique data: use of unstructured NoSQL data analysis.
Relentless search for new data and metrics leveraging structured and unstructured data; organization separate from IT oversees information; data managed as strategic asset.
IIA INTERNATIONAL INSTITUTE FOR ANALYTICS.
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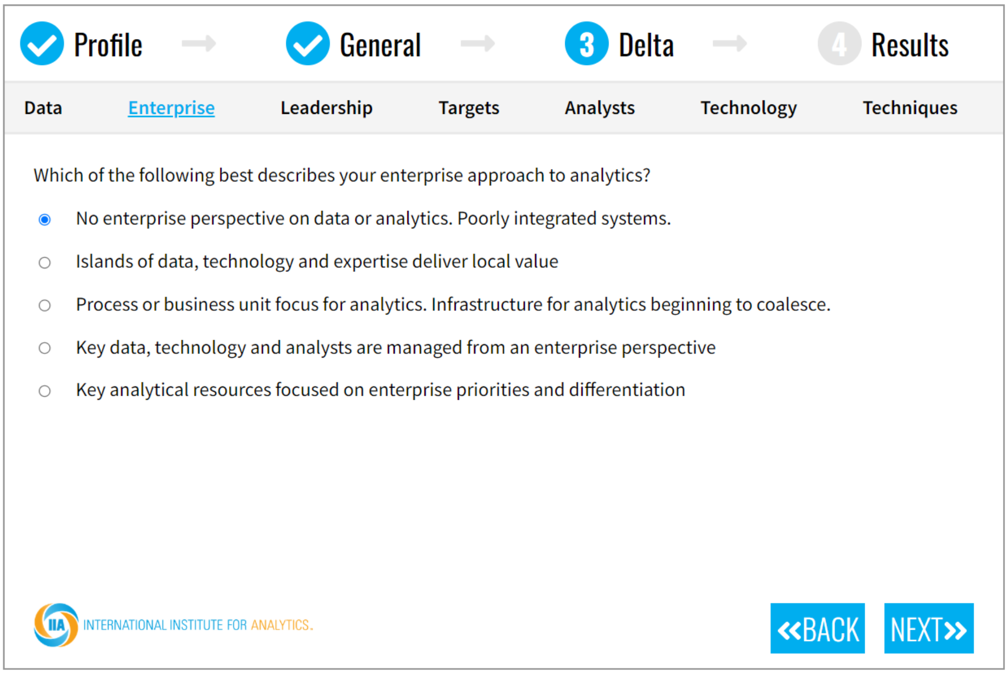
Profile
General
3 Delta
4 Results
Data
Enterprise
Leadership
Targets
Analysts
Technology
Techniques
Which of the following best describes your enterprise approach to analytics?
No enterprise perspective on data or analytics. Poorly integrated systems.
Islands of data, technology and expertise deliver local value
Process or business unit focus for analytics. Infrastructure for analytics beginning to coalesce.
Key data, technology and analysts are managed from an enterprise perspective
Key analytical resources focused on enterprise priorities and differentiation
IIA INTERNATIONAL INSTITUTE FOR ANALYTICS.
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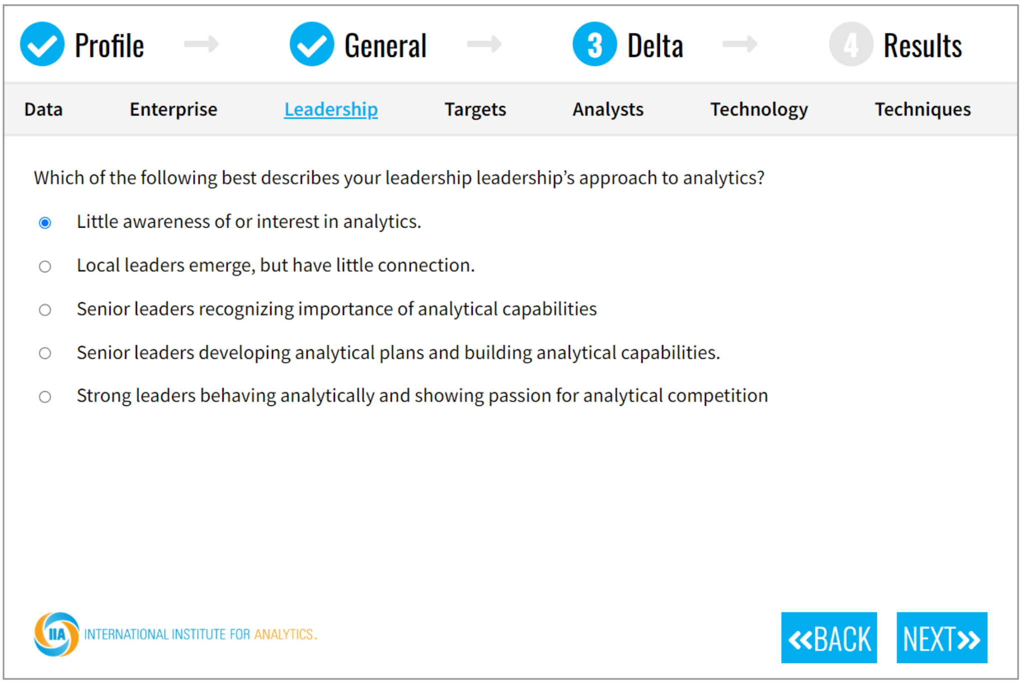
Profile
General
3 Delta
4 Results
Data
Enterprise
Leadership
Targets
Analysts
Technology
Techniques
Which of the following best describes your leadership leadership's approach to analytics?
Little awareness of or interest in analytics.
Local leaders emerge, but have little connection.
Senior leaders recognizing importance of analytical capabilities
Senior leaders developing analytical plans and building analytical capabilities.
Strong leaders behaving analytically and showing passion for analytical competition
IIA INTERNATIONAL INSTITUTE FOR ANALYTICS.
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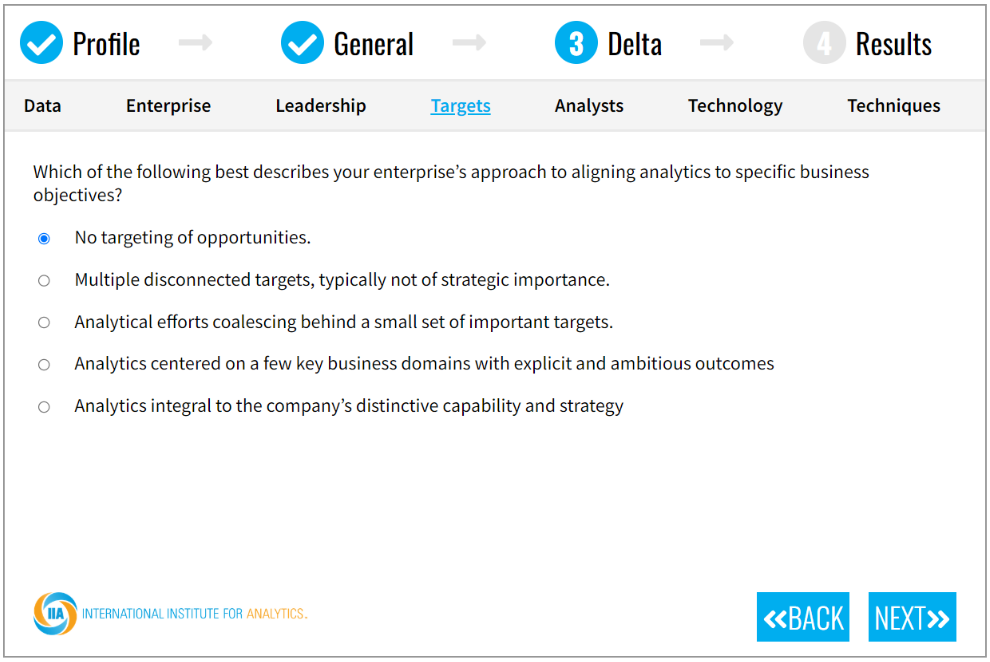
Profile
General
3 Delta
4 Results
Data
Enterprise
Leadership
Targets
Analysts
Technology
Techniques
Which of the following best describes your enterprise's approach to aligning analytics to specific business objectives?
No targeting of opportunities.
Multiple disconnected targets, typically not of strategic importance.
Analytical efforts coalescing behind a small set of important targets.
Analytics centered on a few key business domains with explicit and ambitious outcomes
Analytics integral to the company's distinctive capability and strategy
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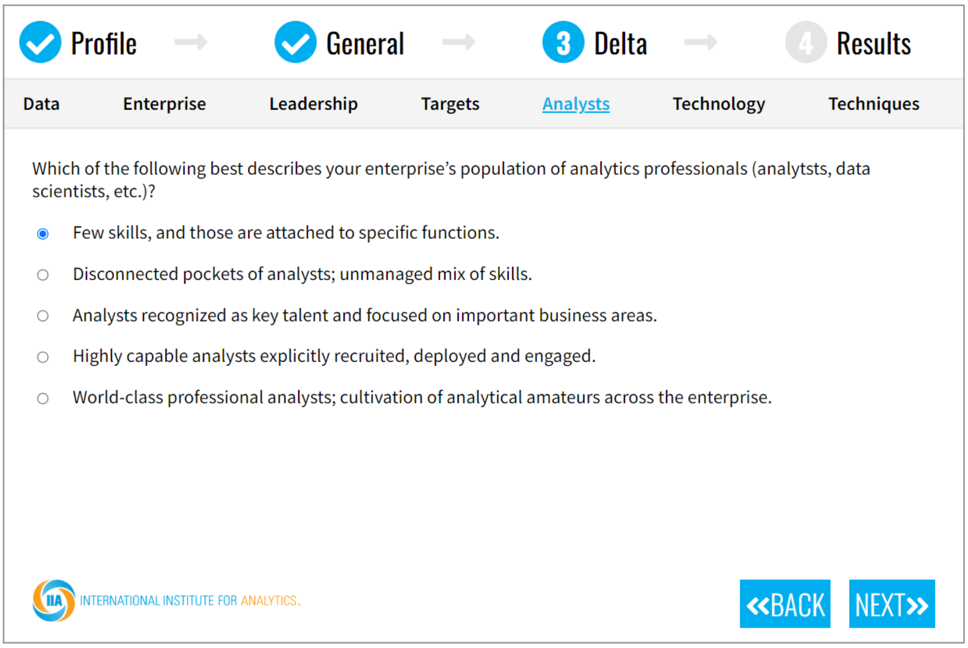
Profile
General
3 Delta
4 Results
Data
Enterprise
Leadership
Targets
Analysts
Technology
Techniques
Which of the following best describes your enterprise's population of analytics professionals (analytsts, data scientists, etc.)?
Few skills, and those are attached to specific functions.
Disconnected pockets of analysts; unmanaged mix of skills.
Analysts recognized as key talent and focused on important business areas.
Highly capable analysts explicitly recruited, deployed and engaged.
World-class professional analysts; cultivation of analytical amateurs across the enterprise.
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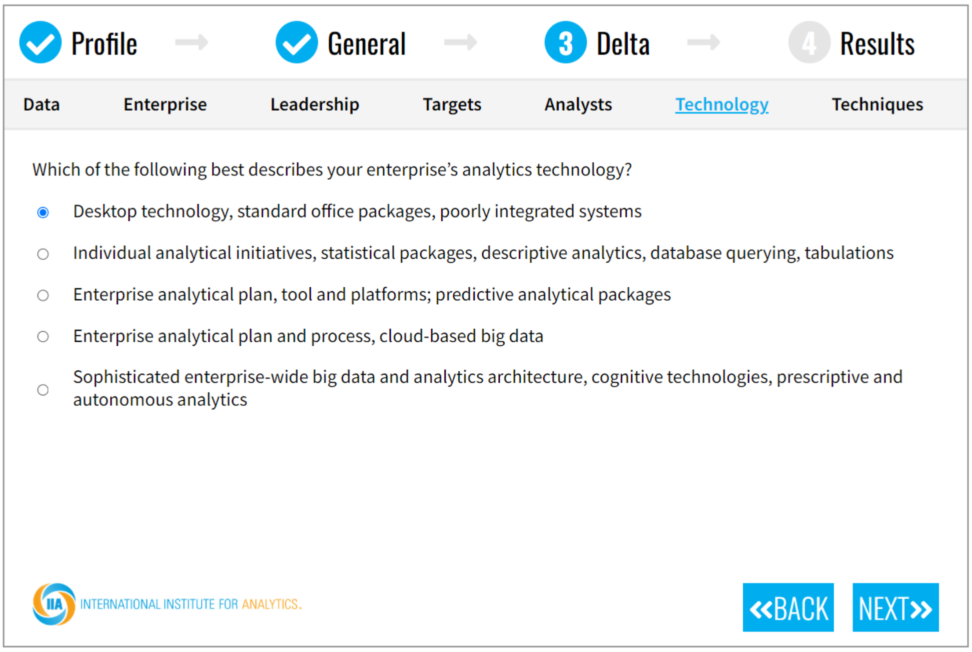
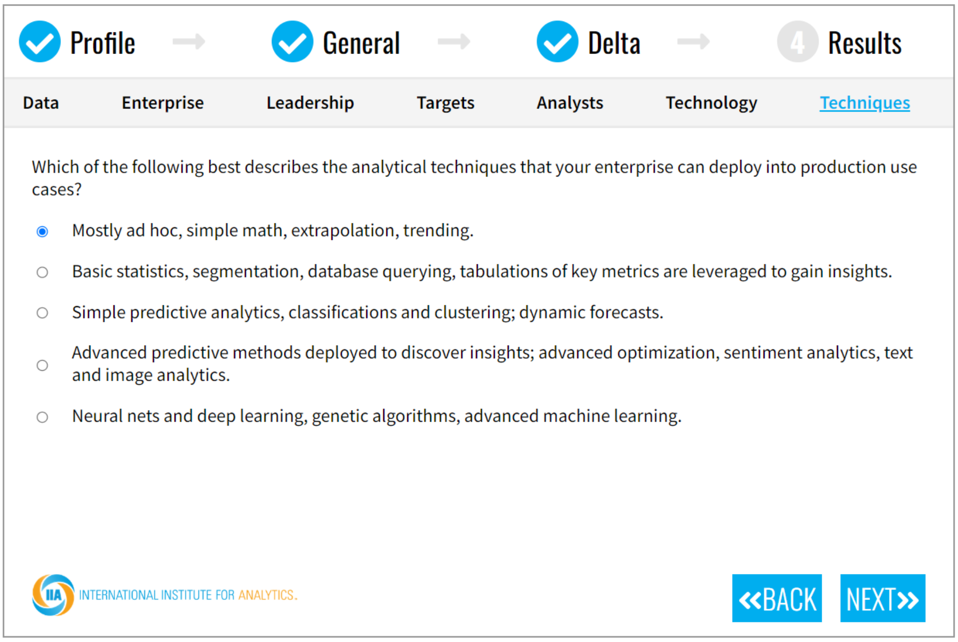
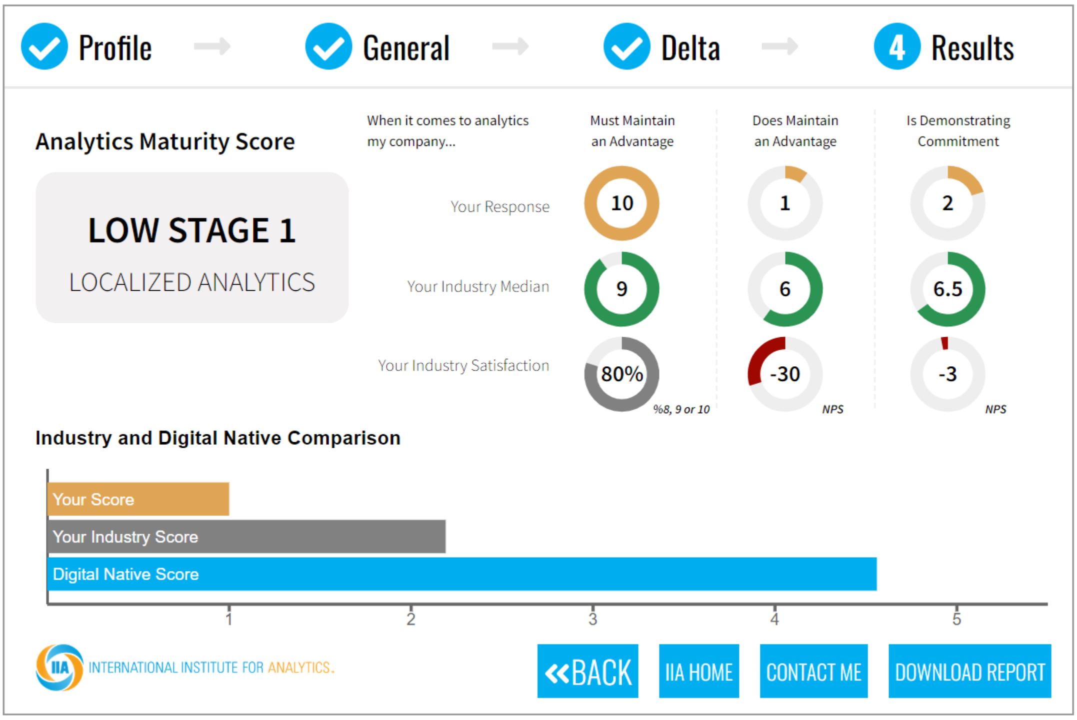




3) **Step 3.** The overall assessment is provided, comparison to peers (the same industry) and to the digital leaders. It is not possible to download the specific organization's report, only general industry based report, if an email again is provided.


Profile
General
Delta
4 Results
Analytics Maturity Score
LOW STAGE 1
LOCALIZED ANALYTICS
When it comes to analytics my company...
Must Maintain an Advantage
Does Maintain an Advantage
Is Demonstrating Commitment
Your Response
10
1
2
Your Industry Median
9
6
6.5
Your Industry Satisfaction
80%
-30
-3
%8, 9 or 10
NPS
NPS
Industry and Digital Native Comparison
Your Score
Your Industry Score
Digital Native Score
1
2
3
4
5
INTERNATIONAL INSTITUTE FOR ANALYTICS.
«BACK
IIA HOME
CONTACT ME
DOWNLOAD REPORT

Appendix E. AMQ tool

1) **Step1.** Access the tool: https://www.aryng.com/whitepaper/bgft/Aryng_AnalyticsMaturityQuotient_Whitepaper.pdf . To start to use it, it is required to open it or download the document with DIY assessment. It is not possible to compare to peers or others. Ability to contact organizations to get much deeper assessment and explanations. New version available, but without explanation to get at least overall score of the analytics level (https://aryng.com/download/consulting-downloads/Aryng_-_Data_Culture_Assessment.pdf) .

Speaking in mathematical terms,

AMQ = DQ x (0.4 x L + 0.3 x P + 0.2 x D + 0.1 x I)

Where

DQ represents data quality with value between 0 and 10. Sufficiently accurate data is foundational to analytics and poor data quality would handicap any organization wanting to leverage data for decision-making (Zynga and Redbox both would be close to 10. Netflix and Electronic Arts, I assume would be both close to 9 in their data quality).

L stands for the degree to which the leadership is data driven and has a value between 0 and10. 0 being organizations where there are no leaders who believe in leveraging data for decision making and 10 for organizations where all the leaders are data-driven (Per my estimate, L for Zynga = 9, Redbox = 8, Netflix = 4 and EA = 6).

P is the degree to which organization has people with right analytics skills. The analytics professionals use structured process for delivering efficient analysis with actionable recommendation to drive business impact. This too, takes value between 0 and10 (P, for Zynga = 7, Redbox = 7, Netflix = 6, Electronic Arts = 4).

D represents the degree to which the organization has data inserted within decision making process and takes on values from 0 to10. As an example, how does marketing budget gets allocated within your organization? Is it zero-sum based and dollars allocated based on expected ROI or is it status quo per last year and some incremental? The former would be more common for organization with D closer to 10 and latter would be the case for organizations with D tending towards 0; (D, for Zynga = 10, Redbox = 8, Netflix = 4, Electronic Arts = 4)

I, represents the organization's readiness to instrument quickly and takes on value from 0 to10. Organizations with mature BI department, with process to take requests for previously unavailable data and make it available fairly quickly would have I closer to 10. (I, for Zynga = 10, Redbox = 8, Netflix = 7, Electronic Arts = 7)

Hence, per the AMQ method, Zynga's AMQ = 87, Redbox's AMQ = 77, EA's AMQ= 46 and Netflix's AMQ =44

So, what's your organization's AMQ? Follow the below DIY process to find out.

2) **Step 2**. Assessment of the advanced analytics ecosystem – self-assessment based on 10 questions. All questions to be ranked from 0 to 10 points.

DIY: Analytics Maturity Quotient

At Aryng, we have a comprehensive method for AMQ calculation based on detailed stake-holder interviews and auditing. Short of that, here is a quick way to estimate your own organizations AMQ by taking this survey. Have this survey be taken by all or as many decision makers in your organization as possible, and take the average answer to compute AMQ.

SURVEY

Estimating "DQ": Data quality is a measure of accuracy of data currently in production data base.

1. How likely is it, for a randomly pulled data set (from production environment), to be accurate?

Not at all likely — Very Likely

0	1	2	3	4	5	6	7	8	9	10
O	O	O	O	O	O	O	O	O	O	O

2. On an average, what percentage of an analytics project timeline gets spent on reconciling data from different sources?

>50% — <5%

0	1	2	3	4	5	6	7	8	9	10
O	O	O	O	O	O	O	O	O	O	O

DQ = Answers from (Q1*Q2)/10

Estimating "L": Data-driven leaders are those who use data to prove/disprove ideas and have structured, evidence based approach to decision making.

3. What percentage of leaders in your organization make decisions based on data at least sometimes?

0% — 100%

0	1	2	3	4	5	6	7	8	9	10
O	O	O	O	O	O	O	O	O	O	O

4. Of all the decisions those leaders make, what percentage of the decisions are data-driven?

0% — 100%

0	1	2	3	4	5	6	7	8	9	10
O	O	O	O	O	O	O	O	O	O	O

L = Answers from (Q3*Q4)/10

Estimating "P": People with appropriate analytical skills have structured approach to analysis: starting with identifying real business question, laying out hypothesis driven plan, collecting relevant data, analyzing with appropriate techniques and engaging presentation laden with actionable insights. In addition, they have the interpersonal and business skills to maintain alignment with stakeholders so those valuable insights can be converted to business impact.

5. What percentage of analytics people in your organization have required analytical skills (as laid above)?

0% — 100%

0	1	2	3	4	5	6	7	8	9	10
O	O	O	O	O	O	O	O	O	O	O

6. Of all the analytics projects undertaken in your organization, what percentage gets used towards making a business decision?

0% — 100%

0	1	2	3	4	5	6	7	8	9	10
O	O	O	O	O	O	O	O	O	O	O

P = Answers from (Q5*Q6)/10

Estimating "D": Data-driven decision making process involves a well-defined structured process of decision making based either on known facts or hypothesis driven learning. The process also has well defined accountability structure with clear definition of roles and responsibility. Organizations with mature data-driven decision making often lead to greater employee satisfaction due to transparency in decisions (i.e. employees can proudly tell you why they are doing - what they are doing, and can often cite evidence behind decisions)

7. What percentage of decisions made in your organization, has come about, from a well-defined process?

0% 100%

0	1	2	3	4	5	6	7	8	9	10
O	O	O	O	O	O	O	O	O	O	O

8. What percentage of those decisions, made via a well-defined process, was based on data? (truly based on data vs. data contorted to support a decision which was already made)

0% 100%

0	1	2	3	4	5	6	7	8	9	10
O	O	O	O	O	O	O	O	O	O	O

D = Answers from (Q7*Q8)/10

Estimating "I": Agile infrastructure for instrumentation involves a process by which data gaps discovered by analysis are quickly and efficiently instrumented to enable more complete analysis towards insight generation.

9. How likely is it, for an identified data field, which is currently not captured or stored or rendered, to be eventually made available for analysis in future?

Not at all likely Very Likely

0	1	2	3	4	5	6	7	8	9	10
O	O	O	O	O	O	O	O	O	O	O

10. On an average, how long does it take for the identified data field to be made available post a request?

1 year+ 2-3 weeks

0	1	2	3	4	5	6	7	8	9	10
O	O	O	O	O	O	O	O	O	O	O

I = Answers from (Q9*Q10)/10

Now use the average values from above survey, to compute AMQ using the formula
AMQ = DQ x (0.4 x L + 0.3 x P + 0.2 x D + 0.1 x I)

Summary

Before embarking on the analytics journey, it is very important for an organization to take stock of their current analytics maturity, identify the weakest links and start fixing it in the optimal order

3) **Step 3**. The overall assessment score must be calculated manually with the help of provided formula. No explanation how to interpret the outcome provided. There is no comparison to peers (the same industry) or to the digital leaders. It is not possible to download the specific organization's report. Only invitation to arrange a meeting to discuss results and what could be done in the future.

I = Answers from (Q9*Q10)/10

Now use the average values from above survey, to compute AMQ using the formula
AMQ = DQ x (0.4 x L + 0.3 x P + 0.2 x D + 0.1 x I)

Summary

Before embarking on the analytics journey, it is very important for an organization to take stock of their current analytics maturity, identify the weakest links and start fixing it in the optimal order

Aryng

(DQ, L, P, D, I). For most well scaled organizations today with strong BI teams, data quality issues are a thing of past. The biggest hurdle most of these organizations face today is cultivating a data-driven culture often brought about by data-driven leaders and followed through with hiring skilled analytics professionals (or training the current staff). More on tips for improving the AMQ in the next whitepaper, in the meantime use our AMQ framework to understand the analytics maturity of your organization.

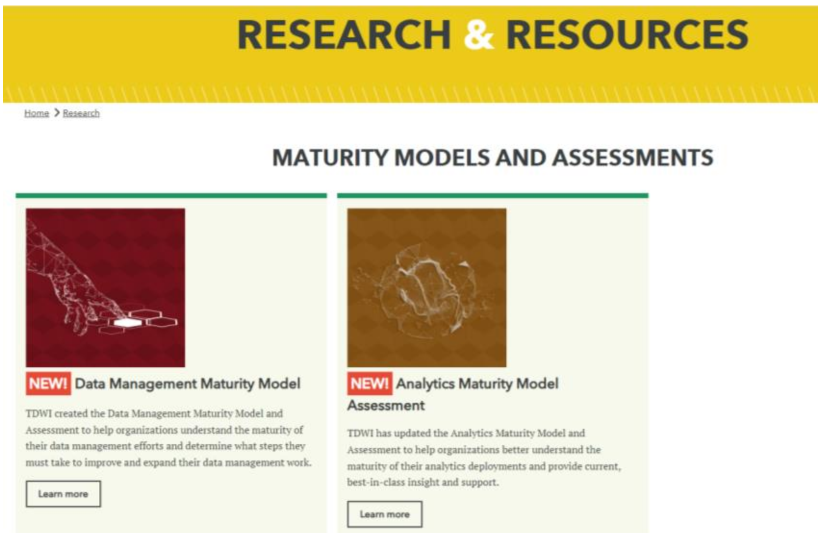
Comprehensive AMQ Assessment

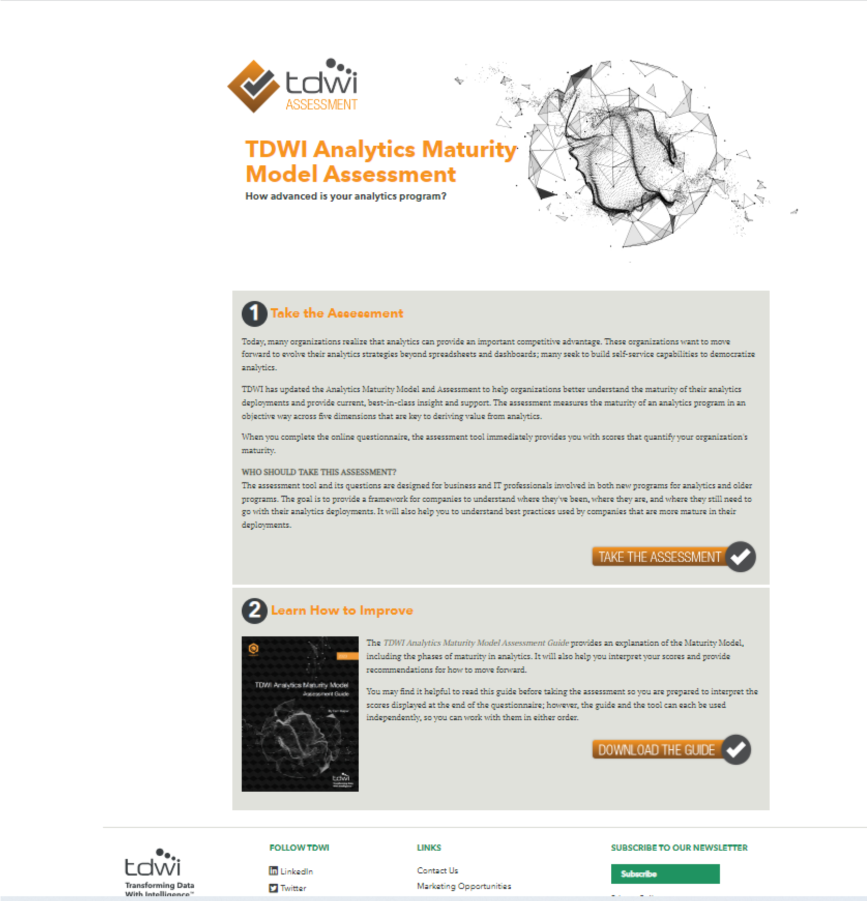
If you like what you see here and would like Aryng to conduct a comprehensive Analytics Maturity Assesment at your organization, please contact Piyanka directly at Piyanka@aryng.com.

On an average, **Comprehensive AMQ assessment** involves
1. 1 week of stake-holder interview with executives + interviews with business, analytics and IT/BI department heads.
2. About 2 week time-period for company-wide survey.
3. Last week: Heat map of findings; Prioritized list of recommendation for increasing analytics maturity.

Appendix F. TDWI tool

1) **Step1.** Access the tool: https://tdwi.org/pages/assessments/adv-all-tdwi-analytics-maturity-model-assessment.aspx . To start to use it, it is required to provide full name, organization, job role, email, region, revenue of the organization, postal address, phone numbers.





tdwi ASSESSMENT

TDWI Analytics Maturity Model Assessment

How advanced is your analytics program?

1 Take the Assessment

Today, many organizations realize that analytics can provide an important competitive advantage. These organizations want to move forward to evolve their analytics strategies beyond spreadsheets and dashboards; many seek to build self-service capabilities to democratize analytics.

TDWI has updated the Analytics Maturity Model and Assessment to help organizations better understand the maturity of their analytics deployments and provide current, best-in-class insight and support. The assessment measures the maturity of an analytics program in an objective way across five dimensions that are key to deriving value from analytics.

When you complete the online questionnaire, the assessment tool immediately provides you with scores that quantify your organization's maturity.

WHO SHOULD TAKE THIS ASSESSMENT?
The assessment tool and its questions are designed for business and IT professionals involved in both new programs for analytics and older programs. The goal is to provide a framework for companies to understand where they've been, where they are, and where they still need to go with their analytics deployments. It will also help you to understand best practices used by companies that are more mature in their deployments.

TAKE THE ASSESSMENT

2 Learn How to Improve

TDWI Analytics Maturity Model Assessment Guide

The *TDWI Analytics Maturity Model Assessment Guide* provides an explanation of the Maturity Model, including the phases of maturity in analytics. It will also help you interpret your scores and provide recommendations for how to move forward.

You may find it helpful to read this guide before taking the assessment so you are prepared to interpret the scores displayed at the end of the questionnaire; however, the guide and the tool can each be used independently, so you can work with them in either order.

DOWNLOAD THE GUIDE

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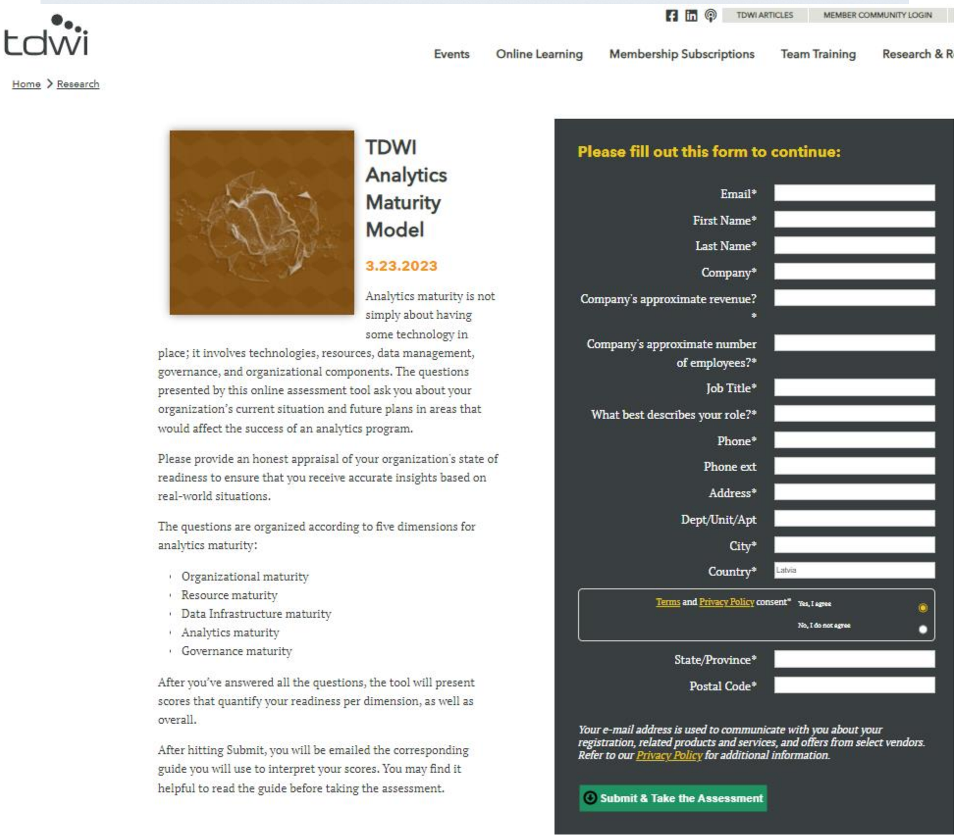

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TDWI Analytics Maturity Model

3.23.2023

Analytics maturity is not simply about having some technology in place; it involves technologies, resources, data management, governance, and organizational components. The questions presented by this online assessment tool ask you about your organization's current situation and future plans in areas that would affect the success of an analytics program.

Please provide an honest appraisal of your organization's state of readiness to ensure that you receive accurate insights based on real-world situations.

The questions are organized according to five dimensions for analytics maturity:

- Organizational maturity
- Resource maturity
- Data Infrastructure maturity
- Analytics maturity
- Governance maturity

After you've answered all the questions, the tool will present scores that quantify your readiness per dimension, as well as overall.

After hitting Submit, you will be emailed the corresponding guide you will use to interpret your scores. You may find it helpful to read the guide before taking the assessment.

Please fill out this form to continue:

Email*
First Name*
Last Name*
Company*
Company's approximate revenue?*
Company's approximate number of employees?*
Job Title*
What best describes your role?*
Phone*
Phone ext
Address*
Dept/Unit/Apt
City*
Country* Latvia
Terms and Privacy Policy consent* Yes, I agree / No, I do not agree
State/Province*
Postal Code*

Your e-mail address is used to communicate with you about your registration, related products and services, and offers from select vendors. Refer to our Privacy Policy for additional information.

Submit & Take the Assessment

TDWI ANALYTICS MATURITY MODEL ASSESSMENT

Thank you in advance for participating in this analytics maturity assessment. TDWI's goal is to help organizations learn from peers in order to gain new business advantages from analytics.

BACKGROUND: The assement asks questions about your organization's maturity in analytics across a number of dimensions including organizational maturity, data infrastructure maturity, analytics maturity, and governance maturity. It examines whether your organization has the resources to move it along its journey. Through participation in this assessment you will be able to benchmark where you are in your analytics journey relative to your peers. This can help you effectively plan for the future.

DEFINITIONS: In this assessment analytics includes technologies that find, explore, and display the results of data analysis as well as those that help users find meaningful insights and patterns in data using statistical, mathematical, and other algorithmic techniques.

PURPOSE: This 10-minute assessment asks a series of questions related to analytics. At the end of the survey, you will receive your score in each of these dimensions relative to your peers. **We ask that you provide an honest appraisal of your analytics progress. This will ensure that you and others taking the benchmark receive the best possible insight.**

GUIDE: Please make sure to read the Guide that accompanies this assessment for further insight.

WHO SHOULD TAKE THE SURVEY: This survey is geared to individuals who are involved in analytics. This includes business as well as IT. If you are a consultant, please answer these questions with your most recent client in mind.

Start

2) **Step 2**. Very detailed assessment of the advanced analytics ecosystem - by domains, by several factors what describes specific domain.

Organization

Leadership

* Your leadership supports and evangelizes analytics across the company.

- ◉ Not at all
- ○ They seem ambivalent about analytics, and they don't really evangelize it
- ○ They support analytics efforts and are starting to evangelize it
- ○ They firmly support analytics efforts, they use analytics to make decisions, and they evangelize it across the company

* Your company has a Chief Analytics Officer (CAO) who is in charge of your analytics efforts.

- ◉ We don't have anyone in charge of analytics in the organization
- ○ Analytics is controlled by IT in my company
- ○ We have a VP or Director of Analtyics in my company, who is in charge of analtyics
- ○ Yes, have a Chief Analytics Officer

Strategy

* Your company has a strong strategy in place to support its data and analytics efforts.

- ◉ No and we have no plans to do so
- ○ No, but we plan to do so in the next year
- ○ Yes, we are in the process of putting a strategy together
- ○ Yes, we have a solid strategy in place for analytics

* Analytics is an important part of your company's digital transformation strategy

- ◉ No, we do not have an digital transformation strategy
- ○ Yes, we are in the process of putting our digital transformation strategy in place and analytics will play an important role
- ○ Yes, analytics is an important part of my company's digital transformation strategy

Impact

* What % of business units in your company use analytics for day to day decision making

- (●) less than 25%
- ( ) 26-40%
- ( ) 41-55%
- ( ) 56-70%
- ( ) Greater than 70%

* Your organization has measured an impact with its analytics

- ( ) No
- (●) No, but I think we've gained value
- ( ) Yes, we've measured a top or bottom line impact

Culture

* Your organization uses analytics to take action.

- ( ) Strongly disagree
- (•) Disagree
- ( ) Neutral
- ( ) Agree
- ( ) Strongly agree

* There is a culture of trust in analytics across your company.

- ( ) Strongly disagree
- (•) Disagree
- ( ) Neutral
- ( ) Agree
- ( ) Strongly agree

* There is strong collaboration on analytics in your organization.

- (•) No, we don't perform analytics
- ( ) No, we don't collaborate on analytics - IT is in charge
- ( ) Not yet, but we are moving in that direction
- ( ) Yes, business and IT regularly work together as they need to
- ( ) Yes, business, IT, and others work together because they want to and see their collaboration as helpful for success

* There is a culture of innovation in your company that extends to analtyics

- ( ) Strongly disagree
- (•) Disagree
- ( ) Neutral
- ( ) Agree
- ( ) Strongly agree

* There is a strong ethical foundation in your organization that extends to analytics.

- ( ) Completely disagree
- (•) Disagree
- ( ) Neutral -- neither agree nor disagree
- ( ) Agree
- ( ) Completely agree

Data Infrastructure

Diversity, Volume, Speed

* Your organization currently collects and manage what types of data as part of its analytics efforts?

- ○ Structured data (i.e., tables, records)
- ● Structured data as well as demographic data such as age, location, etc.
- ○ All of the above including semistructured data (XML and similar)
- ○ All of the above including 1-2 of the following: internally generated text data (e.g., emails, call interaction notes, survey verbatim), social media data (blogs, tweets), machine-generated data, geospatial data, real-time event data, audio, video, weblogs, clickstreams, scientific data, demographic data
- ○ All of the above, as well as 3+ of the following: internally generated text data (e.g., emails, call interaction notes, survey verbatim), social media data (blogs, tweets), machine-generated data, geospatial data, real-time event data, audio, video, weblogs, clickstreams, scientific data, demographic data

Data Access

* Employees can access data as needed, including structured and unstructured data, through a well-defined unified access platform and governance process.

- ● Not at all
- ○ Only if they go through IT
- ○ Yes, if they meet certain access criteria
- ○ Yes, mostly business analysts and data scientists can access and make use of the data, although sometimes it is a struggle
- ○ Yes, we use technology such as a data catalog to help organize and access data

* Your organization has an extensive data sharing model and a wide range of sources in place for analytics.

- ● Data access is limited to the enterprise warehouse and ad hoc sharing through spreadsheets
- ○ Additionally, data is shared across departments in a data lake
- ○ Additionally, data is collected from external third-party partners through web services APIs and placed in a cloud data warehouse or equivalent

Data Integration

* Your organization often makes use of multiple data sources for an analytics effort.

- ○ No
- ● Yes, with structured data
- ○ Yes, with different kinds of data including unstructured data and other nontraditional data
- ○ Yes, with different kinds of data, and we do a good job integrating it
- ○ Yes, with both structured and unstructured data -- it's all just data to us and essential that we use it all to get the full picture

* Your organization has a trusted data foundation in place for analtyics

- ○ Strongly disagree
- ● Disagree
- ○ Neutral
- ○ Agree
- ○ Strongly agree

Resources

Funding

* Your organization has a well-established funding process in place for technology for analytics. It is both business- and IT-driven.

- ○ Strongly disagree
- ● Disagree
- ○ Neutral
- ○ Agree
- ○ Strongly agree

* Your organization's analytics strategy includes an organizational component that allows us to execute on analytics. This might include funding a center of excellence, innovation teams, and the like.

- ○ No and I'm not sure we know what that is
- ● No, but we realize this is important and some of us want this
- ○ Yes, we are in the process of putting this in place
- ○ Yes, we have one in place and are also working to expand it
- ○ Yes, we have a significant one in place which includes training and support for analytics initiatives

* Your company invests in change management initiatives.

- ○ No and we have no plans to do so
- ● No, but we plan to do so in the next year
- ○ Yes, we are in the process of doing that now
- ○ Yes, we have that in place to provide change management training - but it is only for executives
- ○ Yes, we have it in place across the organization

Roles and Responsibilities

* Your team is struggling to maintain its data infrastructure

- ● Yes, it is a struggle. We have too few resources
- ○ We are trying to work smarter and use technology to help boost productivity, along with hiring more people
- ○ We are working smarter and have the resources we need

* Your company has hired data scientists as part of its analytics efforts.

- ● No
- ○ No, but we plan to do this soon
- ○ Yes, we have a few data scientists
- ○ Yes, our data scientists are part of the analytics team
- ○ Yes, data scientists are part of the analytics team and they collaborate with the business

* Aside from data scientists, your organization employs a range of staff to deal with different aspects of the analytics life cycle. This includes data engineers and operations teamsfor example, to deal with deal analtyics in production

Analytics

Scope

* Which of the following technologies does your organization use to analyze its data?

- ◉ We use spreadsheets
- ○ We use reports, dashboards, and visualizations
- ○ We use the above and self-service data discovery and we are starting with predictive analytics/ML
- ○ We use the above and predictive analytics/ML against multiple data types
- ○ We use the above as well as techniques such as NLP, deep learning, and IoT analytics and other facets of AI

* Your organization analyzes large amounts of data (e.g., more than 10 TB)

- ◉ No
- ○ Not yet, but we are rapidly moving in that direction
- ○ Yes, we utilize analytics against large volumes of data

* How many predictive analytics/machine learning models does your company have in production?

- ◉ None
- ○ 1
- ○ 2-10
- ○ Dozens
- ○ Hundreds

* What percent of people in your company have access to analytics?

- ◉ Less than 25%
- ○ 26-40%
- ○ 41-55%
- ○ 56-70%
- ○ Greater than 70%

Analytics Maturity

* Your organization is successful at articulating business problems that require analytics. It understands when to use specific techniques against specific business problems.

- ◉ Completely disagree
- ○ Disagree
- ○ Neutral — neither agree nor disagree
- ○ Agree
- ○ Completely agree

* Analytics is used by teams across the organization, where needed.

- ◉ No, it is mostly used in finance, operations, or IT

Governance

Data Governance

* Data is trusted for analytics across platforms in your organization

- No, we have a bunch of data silos that are not governed
- We trust the data that we use for reporting that comes from our DW, but not much else
- We are starting to put processes in place for data governance beyond just the DW or other sources of data that need to be compliant (e.g., HIPAA) so we can trust other key data sources
- We have a solid data governance plan that outlines key policies and processes. These are followed in the organization

* Your organization understands where data is sourced from and have the right policies in place to deal with different kinds of data.

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

* Users accept and are responsive to the need to adhere to data governance policies.

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

* Your organization uses tools such as data catalogs to help users access trusted data.

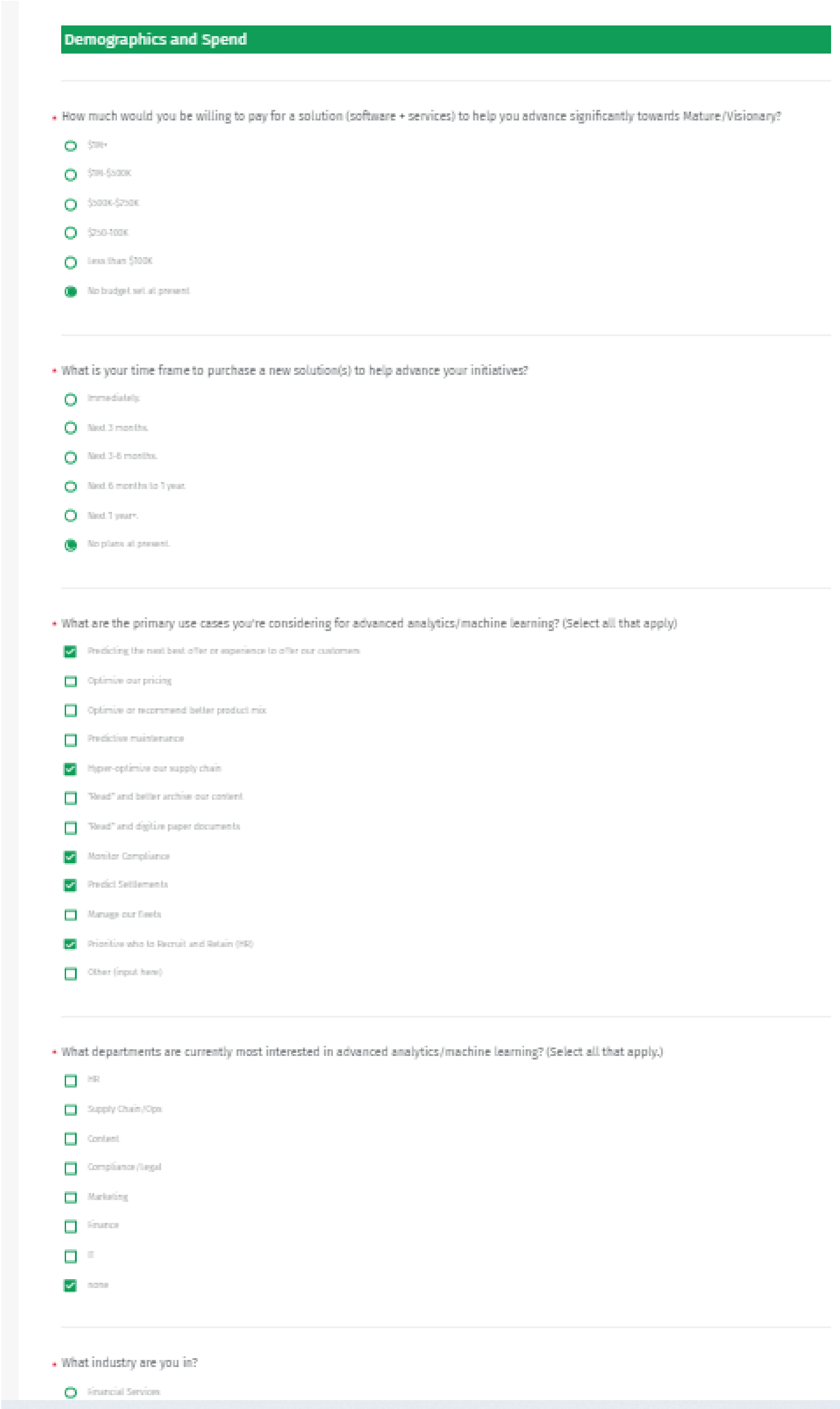
- No, and we have no plans to install a data catalog
- No, but we are thinking about it
- We are in the process of selecting a catalog vendor now
- Yes, we have a data catalog and people have bought into using it
- Yes, we have a data catalog, but not everyone uses it

Model Governance

* Model deployment processes are in place in your organization. For example, models must be checked so as not to be incorrect or unethical (e.g., have racial bias, etc.) before they are put into production.

- Not applicable/we don't have models in production in my organization
- We have models deployed, but we don't check if they are incorrect. We trust our data scientists
- We are putting controls in place over our models
- We have a strong model control process in place

* Model management policies are in place in your organization. Models must be version controlled and metadata captured for each model put into production.

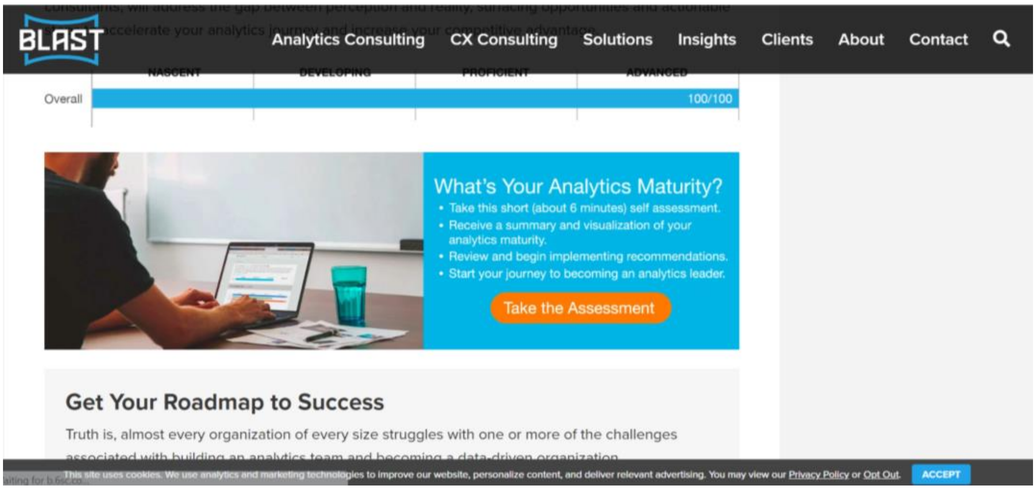


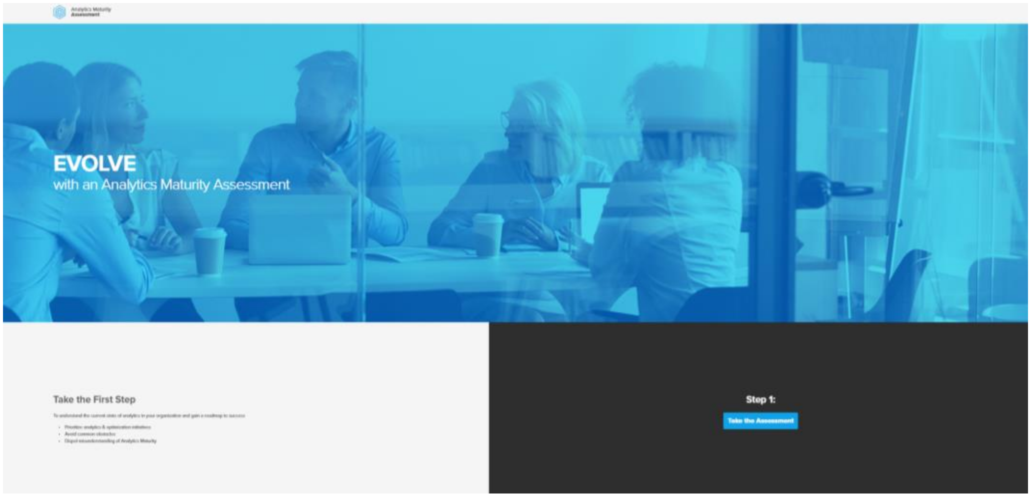
3) **Step 3**. The overall assessment score is provided and score by each domain, indicating at what level organization rated. The explanation and some potential next steps are provided through "Learn How to Improve" TDWI Analytics Maturity Model Assessment Guide what is available for

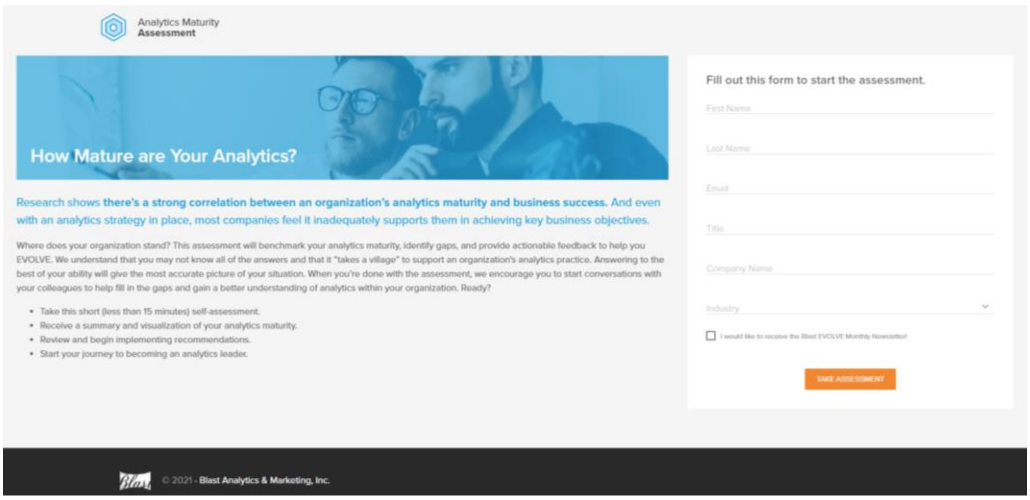
download for everyone (https://tdwi.org/pages/assessments/adv-all-tdwi-analytics-maturity-model-assessment.aspx). The guide provides an explanation of the Maturity Model, the phases of maturity in analytics, helps to interpret the specific score and provide recommendations for how to move forward. There is no comparison to peers (the same industry) or to the digital leaders. It is possible to download the specific organization's report.

Appendix G. Blast Analytics tool

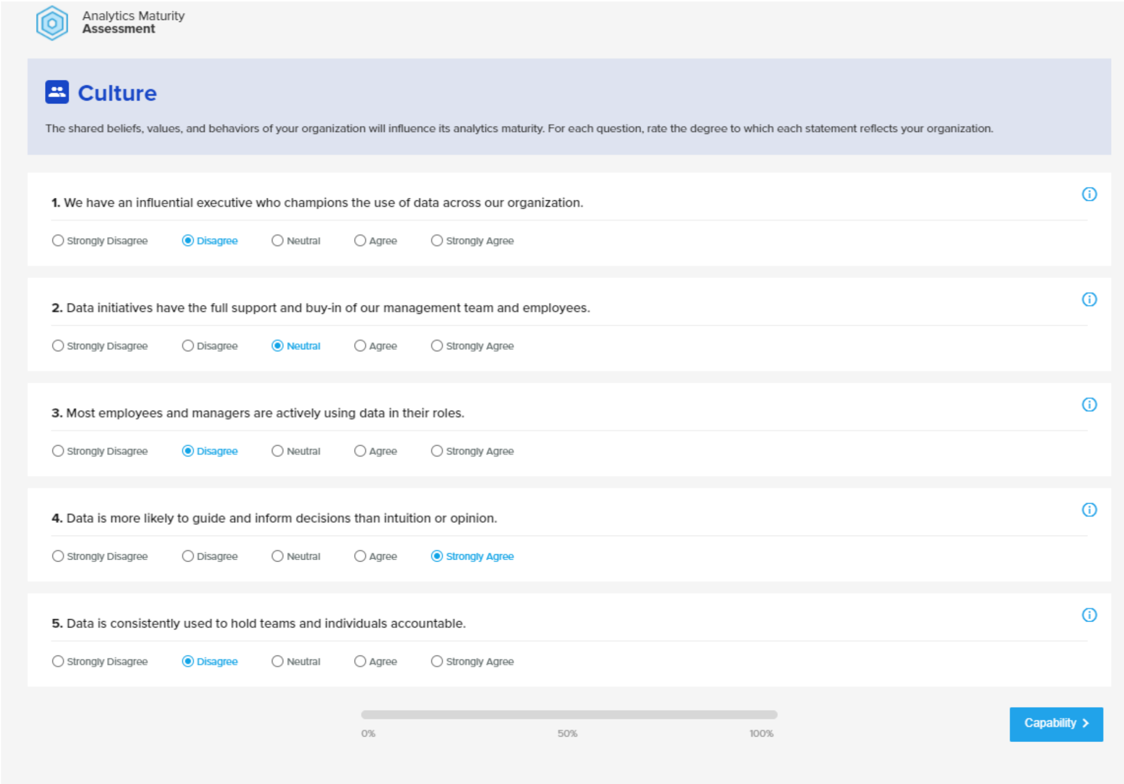
1) **Step1.** Access the tool: https://www.blastanalytics.com/analytics-maturity-assessment . To start to use it, it is required to provide full name, organization, job role, email, industry.

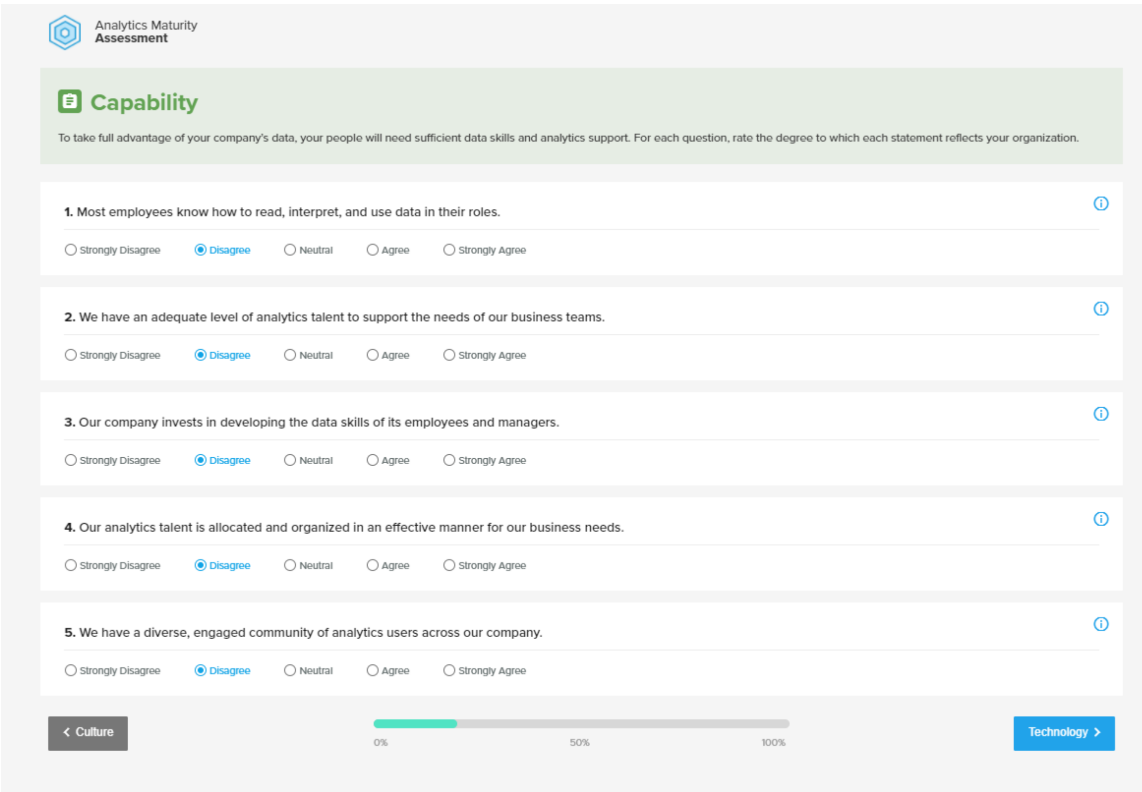


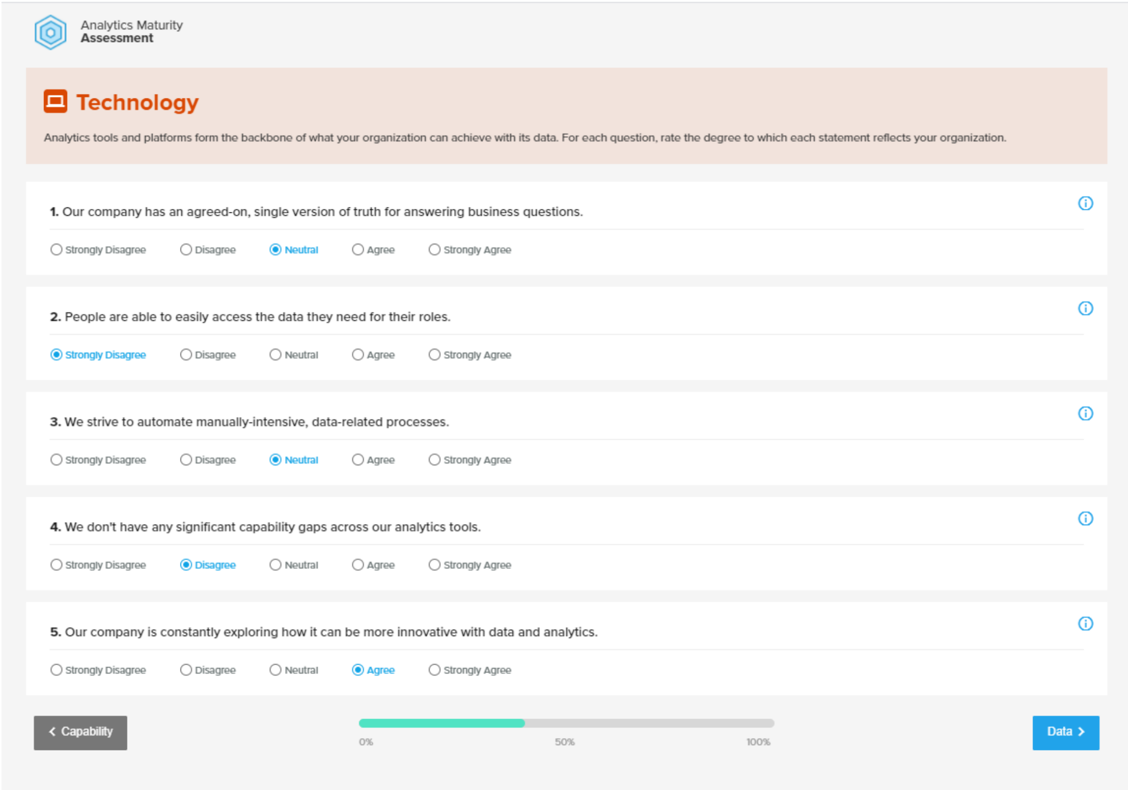




2) **Step 2**. Assessment of the advanced analytics ecosystem - by 5 domains, by 5 sub-factors what describes specific domain.






Analytics Maturity
Assessment

Technology

Analytics tools and platforms form the backbone of what your organization can achieve with its data. For each question, rate the degree to which each statement reflects your organization.

1. Our company has an agreed-on, single version of truth for answering business questions.

Strongly Disagree Disagree Neutral Agree Strongly Agree

2. People are able to easily access the data they need for their roles.

Strongly Disagree Disagree Neutral Agree Strongly Agree

3. We strive to automate manually-intensive, data-related processes.

Strongly Disagree Disagree Neutral Agree Strongly Agree

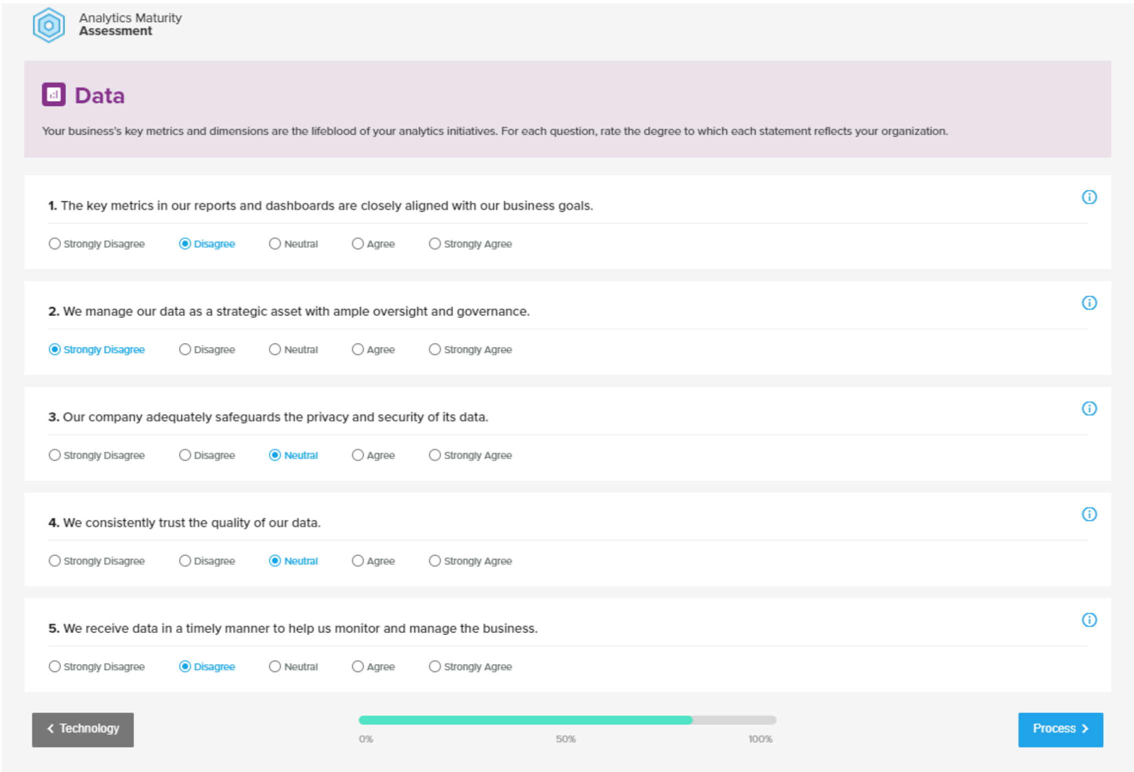
4. We don't have any significant capability gaps across our analytics tools.

Strongly Disagree Disagree Neutral Agree Strongly Agree

5. Our company is constantly exploring how it can be more innovative with data and analytics.

Strongly Disagree Disagree Neutral Agree Strongly Agree

< Capability 0% 50% 100% Data >


Analytics Maturity
Assessment

Data

Your business's key metrics and dimensions are the lifeblood of your analytics initiatives. For each question, rate the degree to which each statement reflects your organization.

1. The key metrics in our reports and dashboards are closely aligned with our business goals.

Strongly Disagree Disagree Neutral Agree Strongly Agree

2. We manage our data as a strategic asset with ample oversight and governance.

Strongly Disagree Disagree Neutral Agree Strongly Agree

3. Our company adequately safeguards the privacy and security of its data.

Strongly Disagree Disagree Neutral Agree Strongly Agree

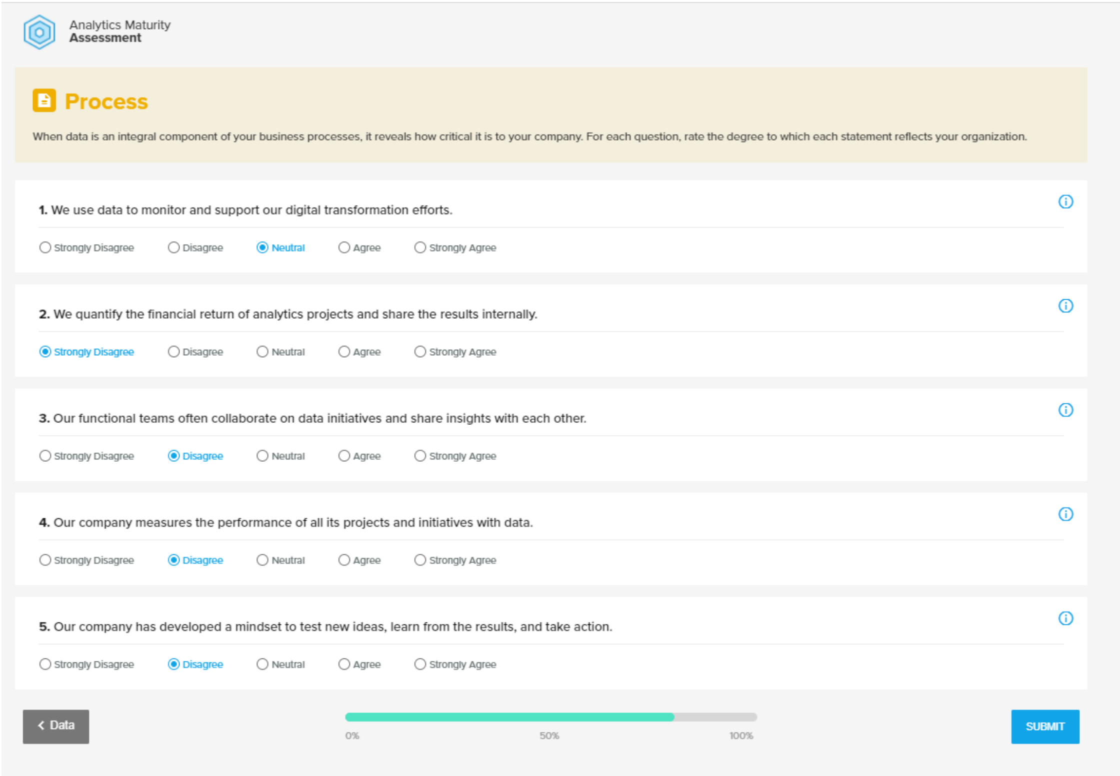
4. We consistently trust the quality of our data.

Strongly Disagree Disagree Neutral Agree Strongly Agree

5. We receive data in a timely manner to help us monitor and manage the business.

Strongly Disagree Disagree Neutral Agree Strongly Agree

< Technology 0% 50% 100% Process >



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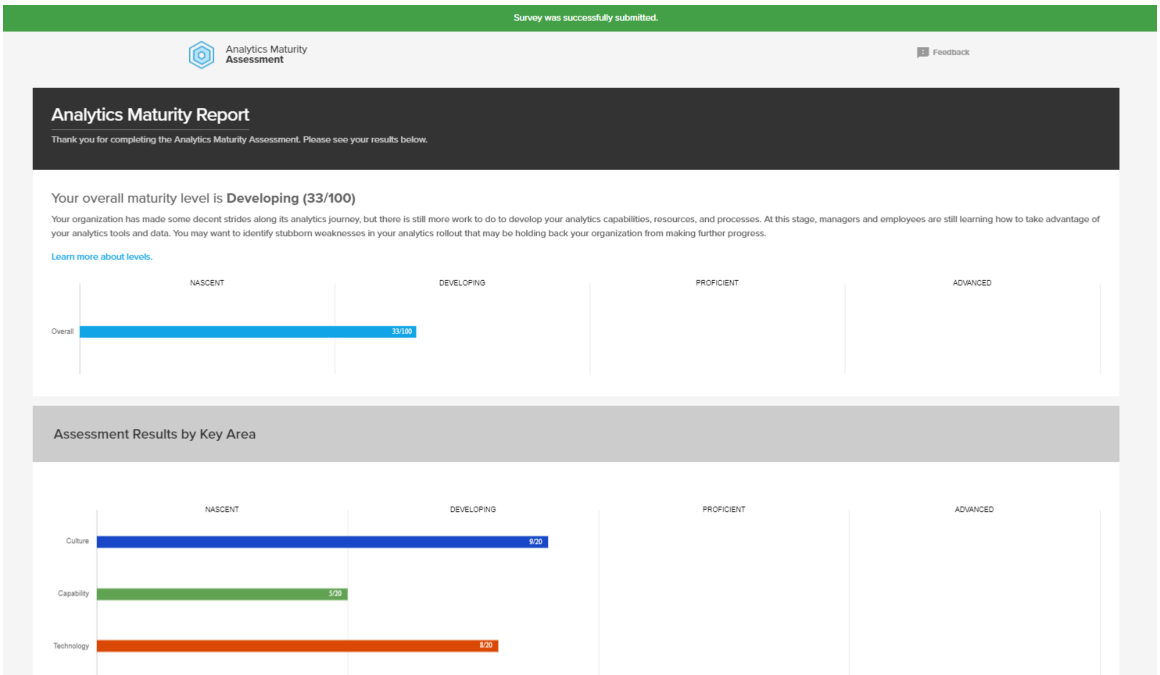
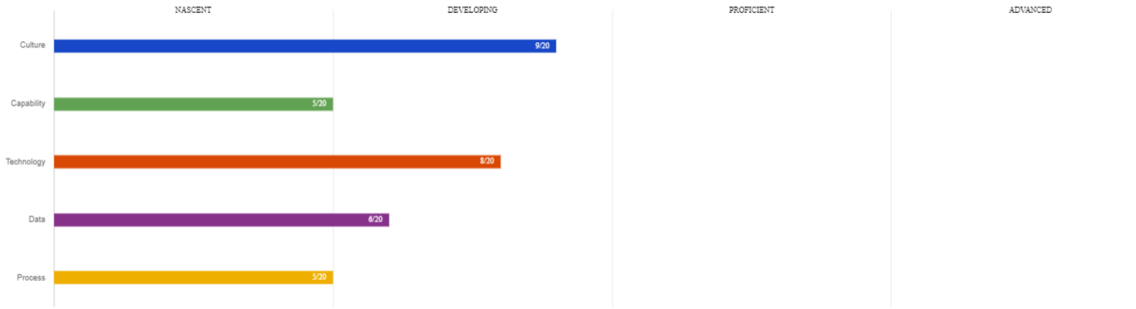


Assessment Results by Key Area



Developing
9/20

Culture

You're starting to see some progress in fostering a data culture but still struggle with:

- Limited involvement or commitment from executive sponsor for data initiatives
- Only pockets of the business have begun relying on data to run their areas of the business
- Still difficult to garner consistent interest from leadership for data-related projects
- Many decisions are still being made without any data to support them

Key Steps to EVOLVE:

- Verify you have the right executive sponsor to drive greater buy-in and sense of urgency
- Collaborate with the executive sponsor to identify ways to broaden the adoption of analytics
- Educate different leaders and teams on the wins that have been achieved with data

Nascent
5/20

Capability

Your organization is facing a number of challenges in building out its data capabilities:

- No or limited data skills among managers and employees
- Insufficient analytics talent to support more than basic data needs
- Limited analytics resources are dispersed and disconnected
- No training offered to improve employee data skills

Key Steps to EVOLVE:

- Evaluate current analytics talent and determine immediate hiring needs
- Assess key data skills gaps among employees
- Develop a hiring and training plan

Developing
8/20

Technology

You have an initial foundation of analytics technology in place, but you still have a ways to go, as evidenced by the following characteristics:

- Fragmented data silos without a single version of truth
- Limited, inconsistent data access across employee base
- Significant manual effort to maintain and update data
- Little effort is focused on innovating with data

Key Steps to EVOLVE:

- Work towards creating a single version of truth
- Identify areas where richer tool capabilities are needed
- Explore how data access can be expanded to more employees

Data

Developing

6/20

As data increasingly becomes a strategic priority for your organization, it's time to advance beyond your existing limitations:

- Some gaps in alignment between business goals and collected data
- Lingering data quality issues that impede how much your people trust your data
- Limited oversight or governance of key data systems
- Some delays in getting data to decision makers in a timely fashion

Key Steps to EVOLVE:

- Document key business goals and assess potential gaps in data collection
- Identify key data quality issues that must be addressed to improve data trust
- Assess areas where increased data oversight or governance could be beneficial

Process

Nascent

5/20

Up until this point, most of your data initiatives have been ad-hoc in nature as demonstrated by:

- Incomplete or poor data collection for key projects and initiatives
- Little effort or focus on leveraging data in project planning or execution phases
- Lack of visibility into the financial contributions of analytics projects
- No collaboration on data intiatives between functional teams

Key Steps to EVOLVE:

- Identify key process lapses in tracking projects and initiatives
- Try to quantify the value delivered by analytics projects
- Facilitate more communication between internal teams on data projects

Share with a Colleague

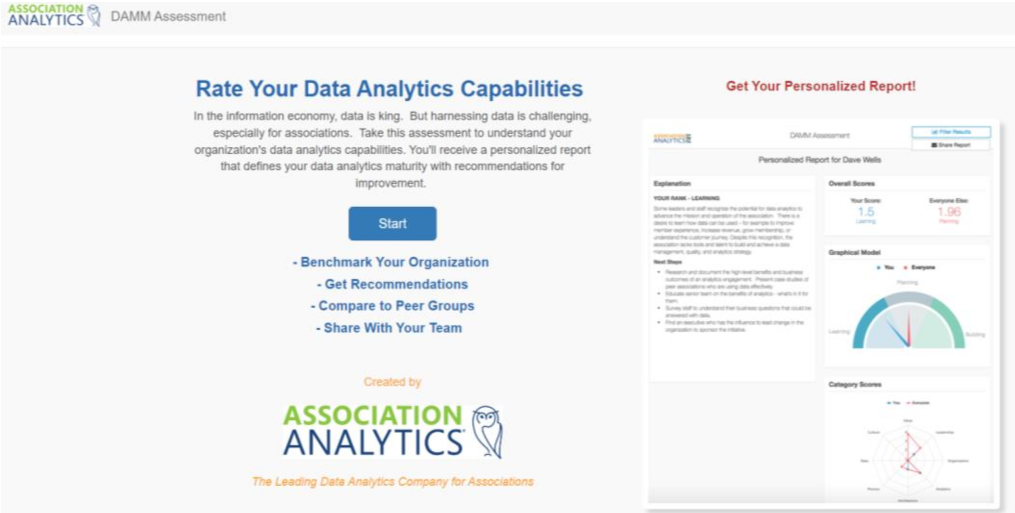
To build an even more complete picture, we recommend asking your colleagues to complete the assessment. Sharing your results can spark some productive conversations, and inspire you to take the next step as a team.

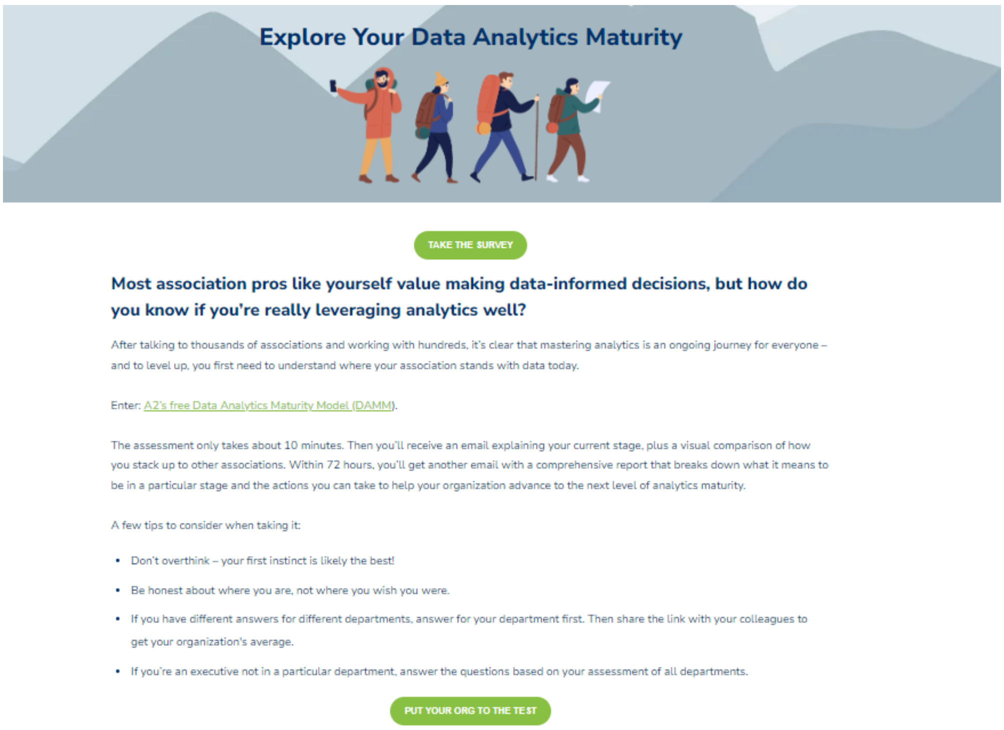
Share the Assessment

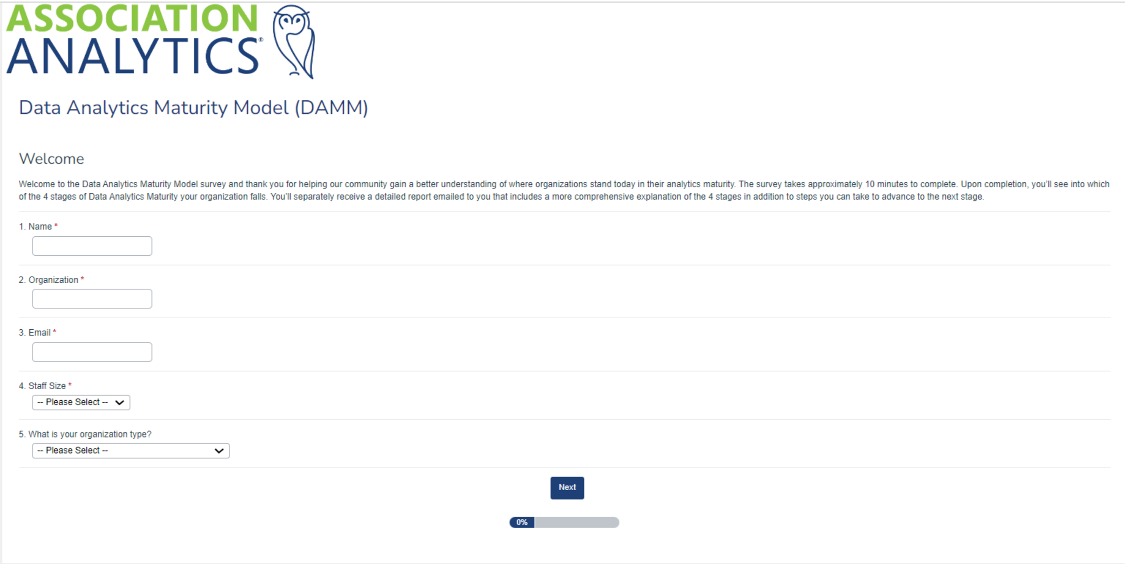
https://maturity.blastanalytics.com Copy

Appendix H. DAMM (Data Analytics Maturity Model) tool

1) **Step1.** Access the tool: https://associationanalytics.ratemydata.com/s/damm-assessment . To start to use it, it is required to provide full name, organization, email, number of employees.







2) **Step 2**. Assessment of the advanced analytics ecosystem based on 55 questions where majority is assessed in 5-point scale, from strongly agree to strongly disagree.

ASSOCIATION ANALYTICS®

Data Analytics Maturity Model (DAMM)

Take the Survey

6. We have a Core Team that regularly looks at data and analytics. *

- ○ Strongly disagree
- ○ Disagree
- ○ Neutral
- ○ Agree
- ○ Strongly agree

7. Our front line managers and directors use dashboards to manage performance *

- ○ Strongly disagree
- ○ Disagree
- ○ Neutral
- ○ Agree
- ○ Strongly agree

8. Our organization is guided by data *

- ○ Strongly disagree
- ○ Disagree
- ○ Neutral
- ○ Agree
- ○ Strongly agree

9. We use analytics to optimize our digital systems and experiences. *

- ○ Strongly disagree
- ○ Disagree
- ○ Neutral
- ○ Agree
- ○ Strongly agree

10. We schedule and dedicate time to discuss data within our Association. *

- ○ Strongly disagree
- ○ Disagree
- ○ Neutral
- ○ Agree
- ○ Strongly agree

11. My organization has a data retention policy *

- ○ Strongly disagree
- ○ Disagree
- ○ Neutral
- ○ Agree
- ○ Strongly agree

12. There are consistent views of data across all levels (executives, directors, managers, etc.) in our organization. *

- ○ Strongly disagree
- ○ Disagree
- ○ Neutral
- ○ Agree
- ○ Strongly agree

13. We have a unique identifier that is consistent across each of our systems in place. *

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neutral
- ◯ Agree
- ◯ Strongly agree

14. We are collecting all of the data we need to do analysis across all of our systems *

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neutral
- ◯ Agree
- ◯ Strongly agree

15. Digital experiences are segmented according to demographics, transaction history, and behaviors. *

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neutral
- ◯ Agree
- ◯ Strongly agree

16. We have a consistent process for getting reliable data from our key systems *

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neutral
- ◯ Agree
- ◯ Strongly agree

17. We have a standard tool/process (shared drive, web dashboard, collaboration tool) for sharing important data between departments. *

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neutral
- ◯ Agree
- ◯ Strongly agree

18. We review our data collection methods regularly *

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neutral
- ◯ Agree
- ◯ Strongly agree

19. There are documented roles and responsibilities for data management. *

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neutral
- ◯ Agree
- ◯ Strongly agree

20. We have a process to clean our data regularly. *

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neutral
- ◯ Agree
- ◯ Strongly agree

21. Our KPIs are tracked and used for strategic planning. *

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neutral
- ◯ Agree
- ◯ Strongly agree

23. Reporting and analysis is a critical part of our budgeting process. *

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

24. New opportunities for the organization are evaluated based on data. *

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

25. Each departments has a goal to be more data-driven or have KPIs and metrics. *

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

26. Our key systems are integrated. *

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

27. Key data is updated in real-time. *

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

28. Our systems collect and share data without a lot of manual intervention. *

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

29. We have a central location for shared data for the purpose of analysis. *

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

30. We rarely encounter conflicting data between systems. *

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

31. Key business staff generally know where data is. *

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

32. Leadership recognize the need for analytics. *

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neutral
- ◯ Agree
- ◯ Strongly agree

33. We have the framework of a general analytics strategy. *

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neutral
- ◯ Agree
- ◯ Strongly agree

34. Staff in my department have the skills to find the information they need. *

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neutral
- ◯ Agree
- ◯ Strongly agree

35. I use data in my daily job.

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neutral
- ◯ Agree
- ◯ Strongly agree

36. We have a business glossary providing a shared understanding of our Association's data. *

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neutral
- ◯ Agree
- ◯ Strongly agree

37. I trust my association data. *

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neutral
- ◯ Agree
- ◯ Strongly agree

38. Our data records are accurate and complete. *

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neutral
- ◯ Agree
- ◯ Strongly agree

39. Data is accessible to me as needed. *

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neutral
- ◯ Agree
- ◯ Strongly agree

40. Most of our staff have an understanding of the business need for any data that is collected. *

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neutral
- ◯ Agree
- ◯ Strongly agree

41. When new software is purchased, we have a process to manage the new data we acquire. *

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

42. Data is refreshed on a regular schedule.

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

43. We have documented procedures for using data and analytics in our business. *

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

44. We have a data retention policy for all of our critical data. *

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

45. There are roled-based permissions for access to data. *

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

46. We use our visualizations in our executive team meetings. *

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

47. There is a strong desire to learn how to use data in our organization. *

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

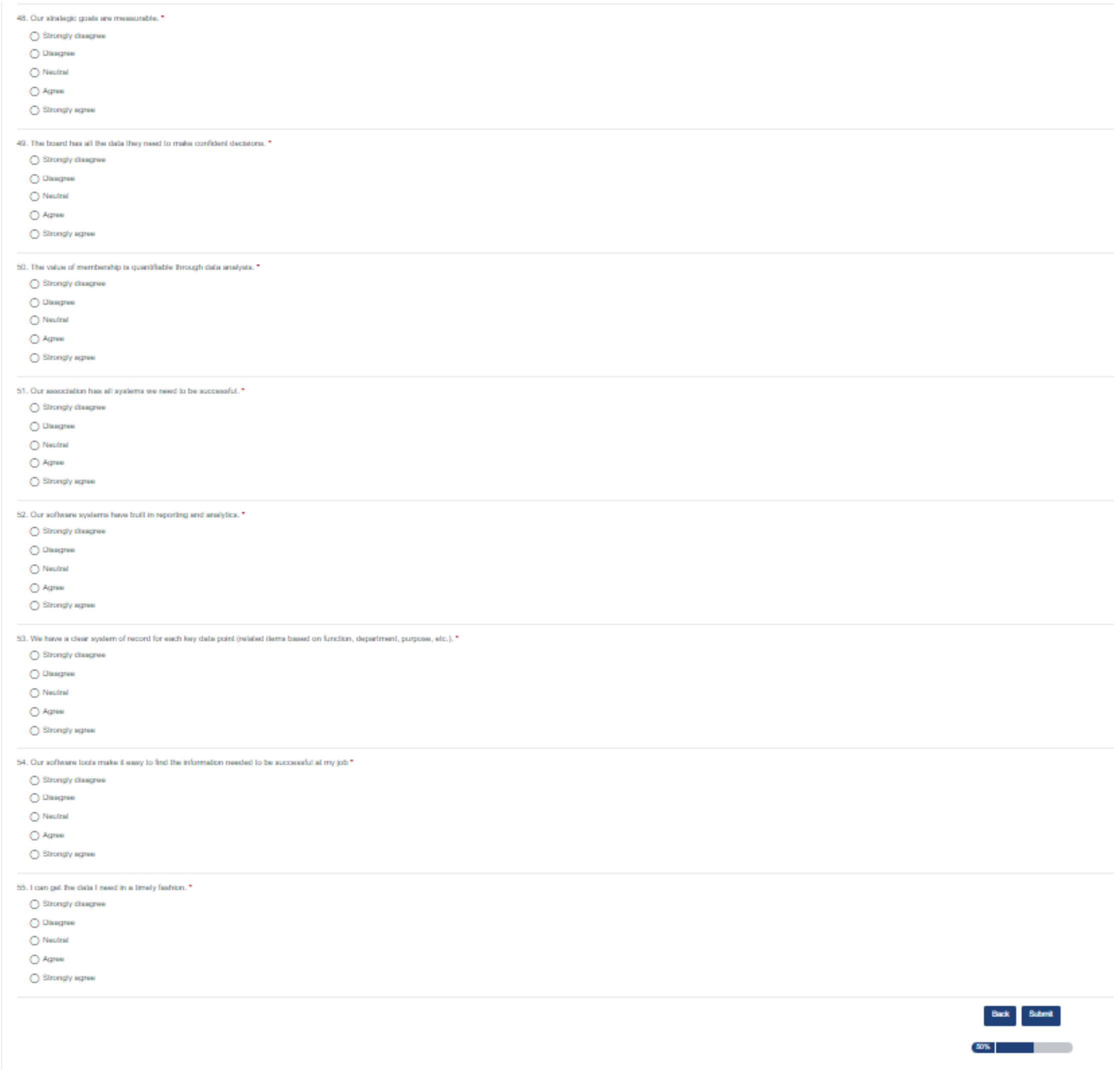
48. Our strategic goals are measurable. *

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

49. The board has all the data they need to make confident decisions. *

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

50. The value of membership is quantifiable through data analysis. *



48. Our strategic goals are measurable. *
- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

49. The board has all the data they need to make confident decisions. *
- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

50. The value of membership is quantifiable through data analysis. *
- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

51. Our association has all systems we need to be successful. *
- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

52. Our software systems have built in reporting and analytics. *
- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

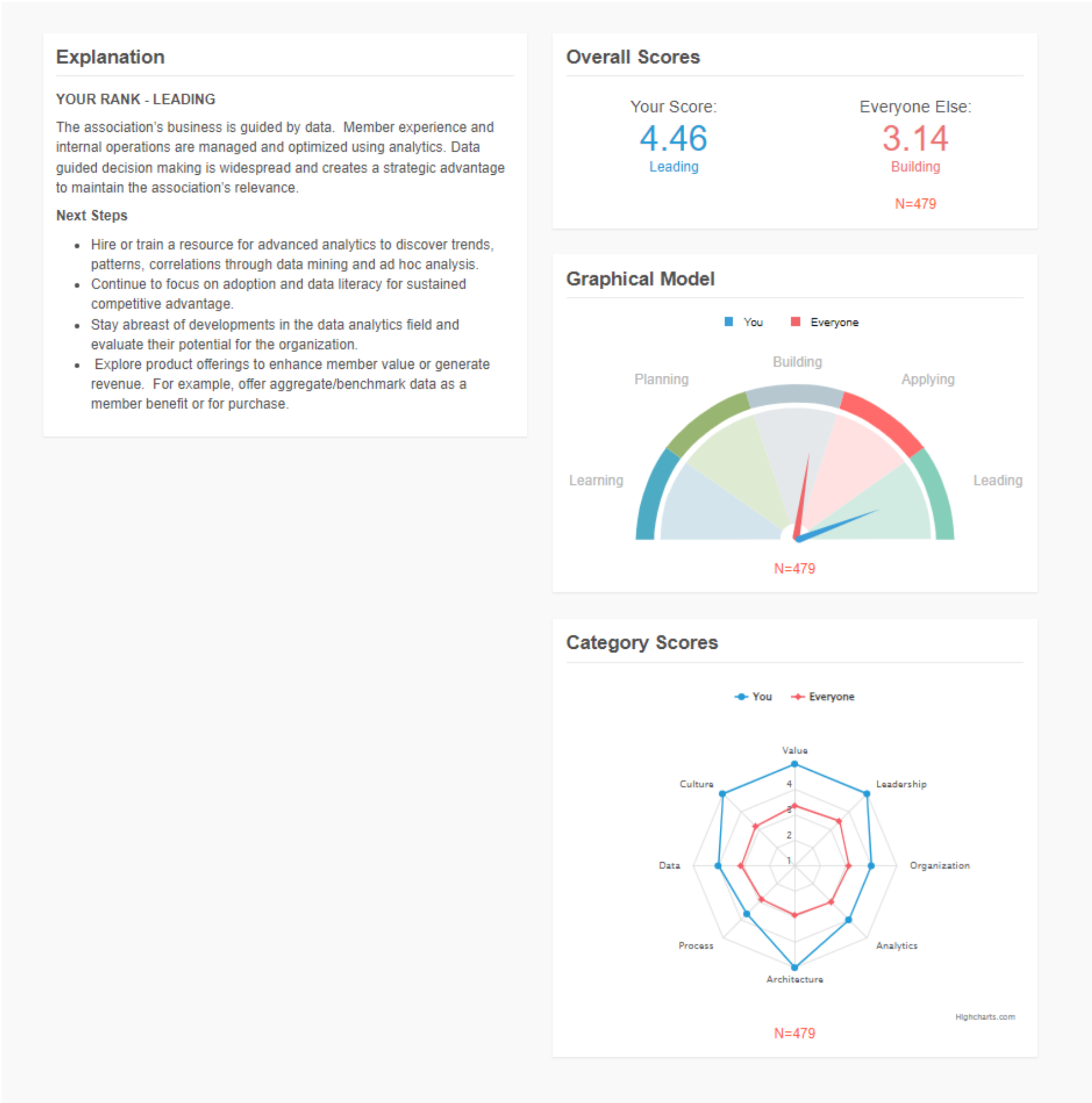
53. We have a clear system of record for each key data point (related items based on function, department, purpose, etc.). *
- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

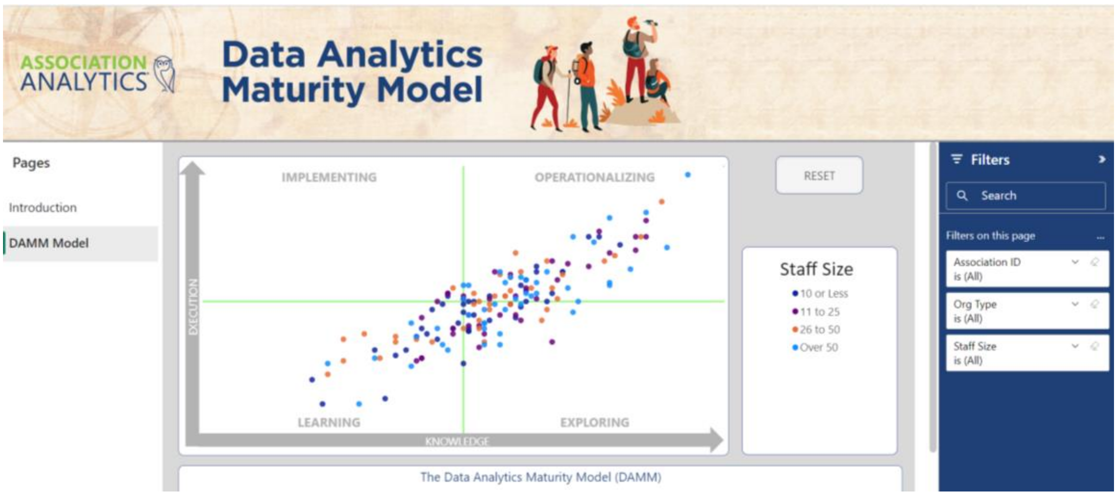
54. Our software tools make it easy to find the information needed to be successful at my job *
- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

55. I can get the data I need in a timely fashion. *
- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

Back Submit

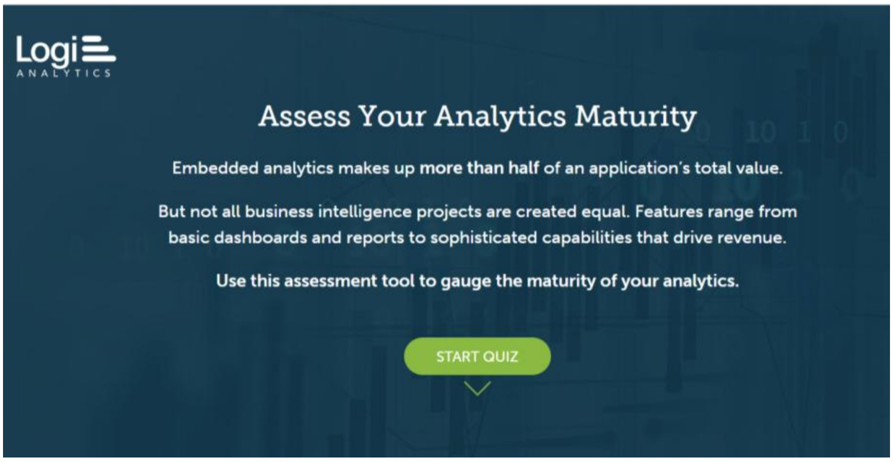
3) **Step 3**. The overall assessment score is provided and score by each domain, indicating at what level organization rated. The explanation and some potential next steps are provided for each domain. There is some comparison to peers (have the same characteristics). It is possible to download, share, print the specific organization's report.


Explanation
YOUR RANK - LEADING
The association's business is guided by data. Member experience and internal operations are managed and optimized using analytics. Data guided decision making is widespread and creates a strategic advantage to maintain the association's relevance.
Next Steps
• Hire or train a resource for advanced analytics to discover trends, patterns, correlations through data mining and ad hoc analysis.
• Continue to focus on adoption and data literacy for sustained competitive advantage.
• Stay abreast of developments in the data analytics field and evaluate their potential for the organization.
• Explore product offerings to enhance member value or generate revenue. For example, offer aggregate/benchmark data as a member benefit or for purchase.
Overall Scores
Your Score:
4.46
Leading
Everyone Else:
3.14
Building
N=479
Graphical Model
You
Everyone
Building
Planning
Applying
Learning
Leading
N=479
Category Scores
You
Everyone
Value
Culture
Leadership
Data
Organization
Process
Analytics
Architecture
Highcharts.com
N=479

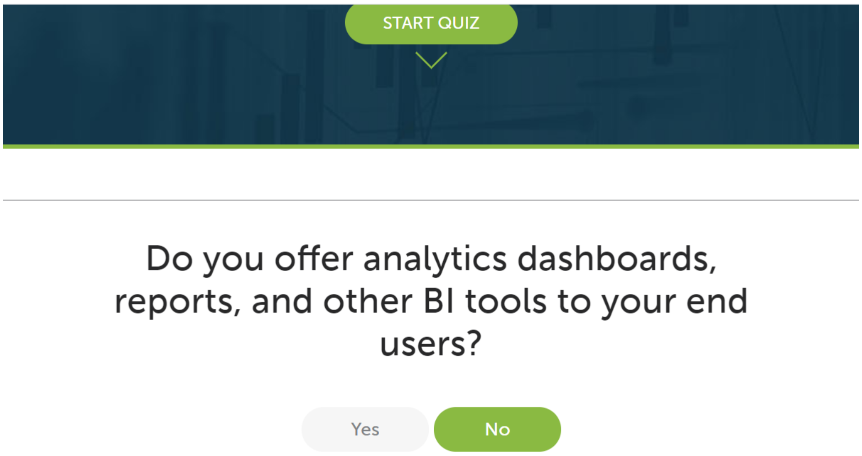

ASSOCIATION ANALYTICS
Data Analytics Maturity Model
Pages
Introduction
DAMM Model
IMPLEMENTING
OPERATIONALIZING
LEARNING
EXPLORING
EXECUTION
KNOWLEDGE
RESET
Staff Size
10 or Less
11 to 25
26 to 50
Over 50
Filters
Search
Filters on this page
Association ID is (All)
Org Type is (All)
Staff Size is (All)
The Data Analytics Maturity Model (DAMM)

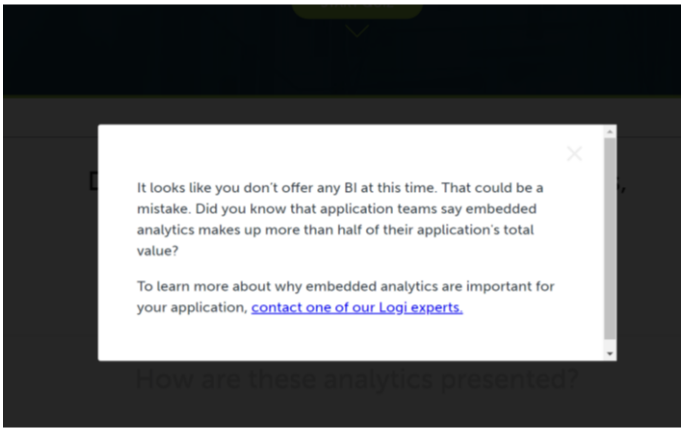
Appendix I. Logi Analytics tool

4) **Step1.** Access the tool: https://www.blastanalytics.com/analytics-maturity-assessment . To start to use it, it was not required to provide any personal information.



5) **Step 2**. Assessment of the advanced analytics ecosystem – very short, just few general questions.





How are these analytics presented?

- As a standalone portal, separate tab, or different application from the rest of our users' workflows
- Embedded as part of a larger application

To what extent is your team able to customize the look and feel of your BI offering?

Click and drag slider

No Customization — Total Customization Control

How would you describe the security integration of your analytics solution?

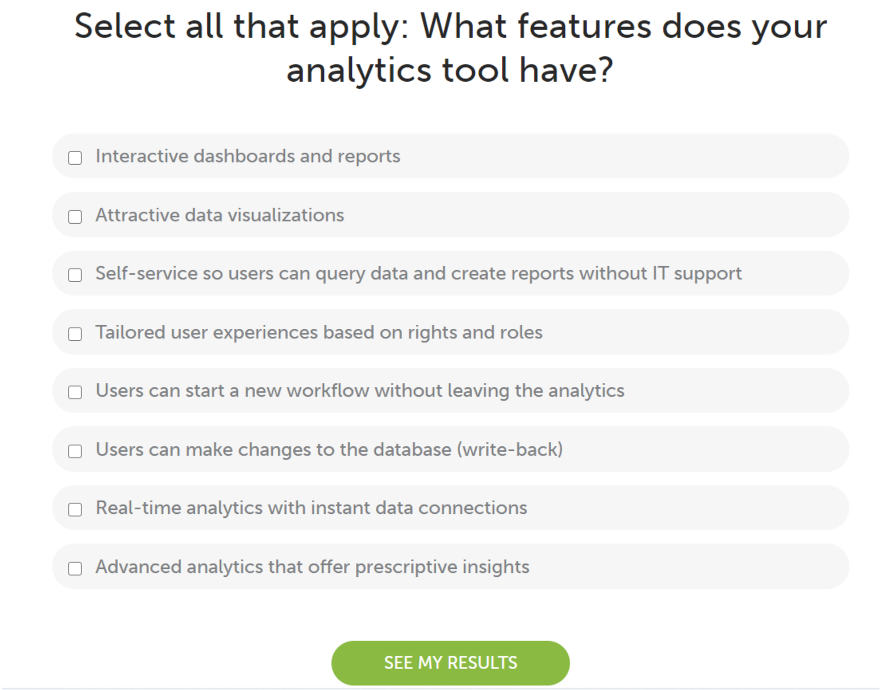
Click and drag slider

Separate from the rest of our application — Completely integrated with our application

Is your analytics solution mobile responsive?

Click and drag slider

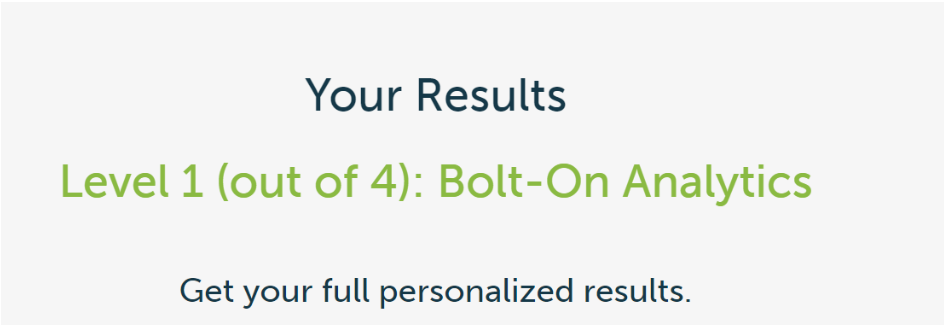
Not at all — Yes, completely


Select all that apply: What features does your analytics tool have?

- ☐ Interactive dashboards and reports
- ☐ Attractive data visualizations
- ☐ Self-service so users can query data and create reports without IT support
- ☐ Tailored user experiences based on rights and roles
- ☐ Users can start a new workflow without leaving the analytics
- ☐ Users can make changes to the database (write-back)
- ☐ Real-time analytics with instant data connections
- ☐ Advanced analytics that offer prescriptive insights

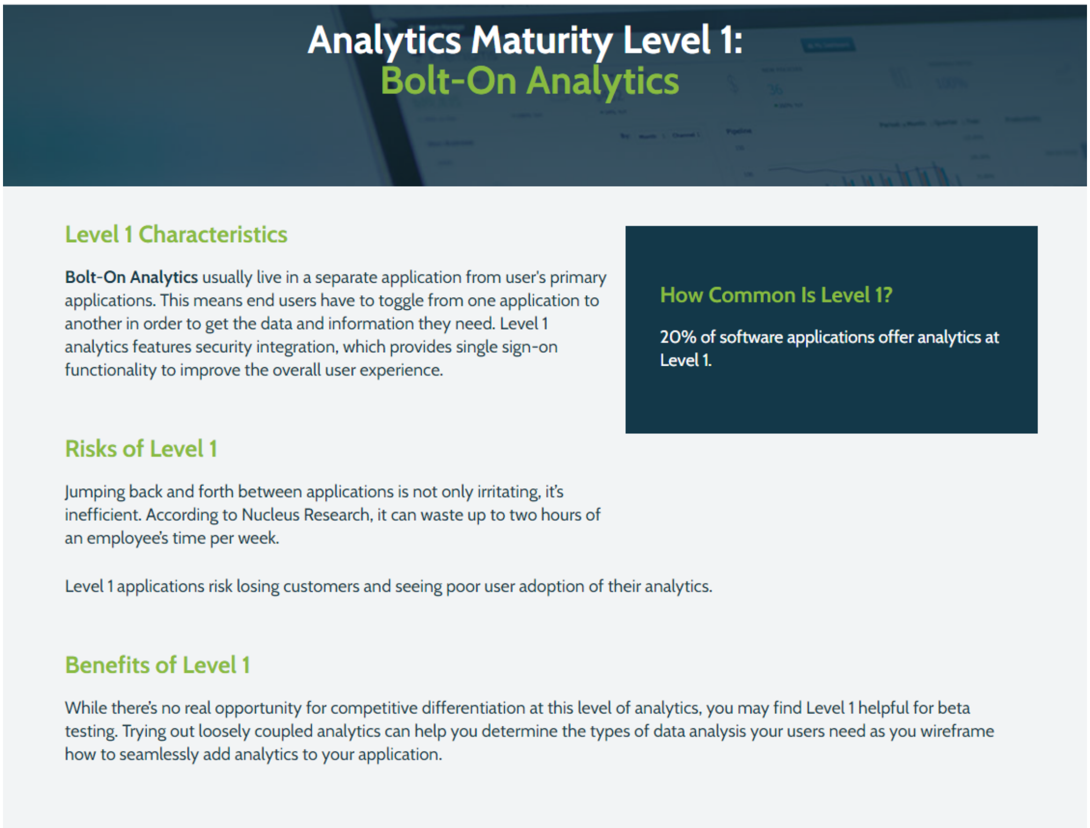
SEE MY RESULTS

3) **Step 3**. The overall assessment in which maturity level organization stands is provided. The explanation and some potential next steps are provided for each domain. There is no comparison to peers (the same industry) or to the digital leaders. It is not possible to download the specific organization's report.


Your Results

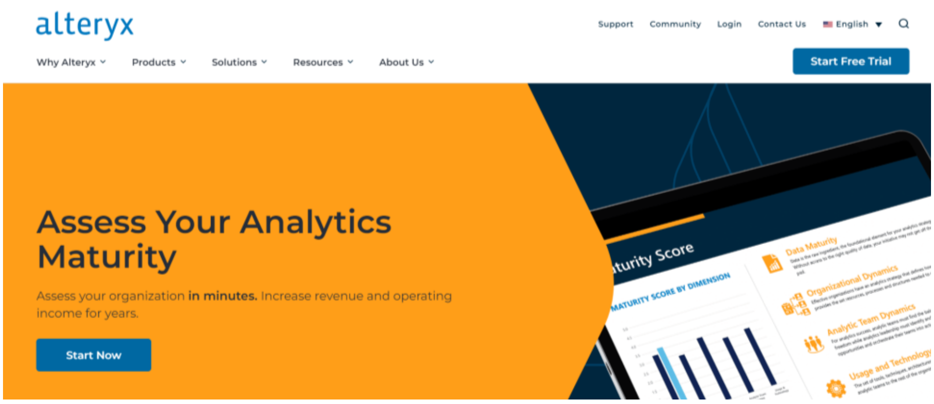
Level 1 (out of 4): Bolt-On Analytics

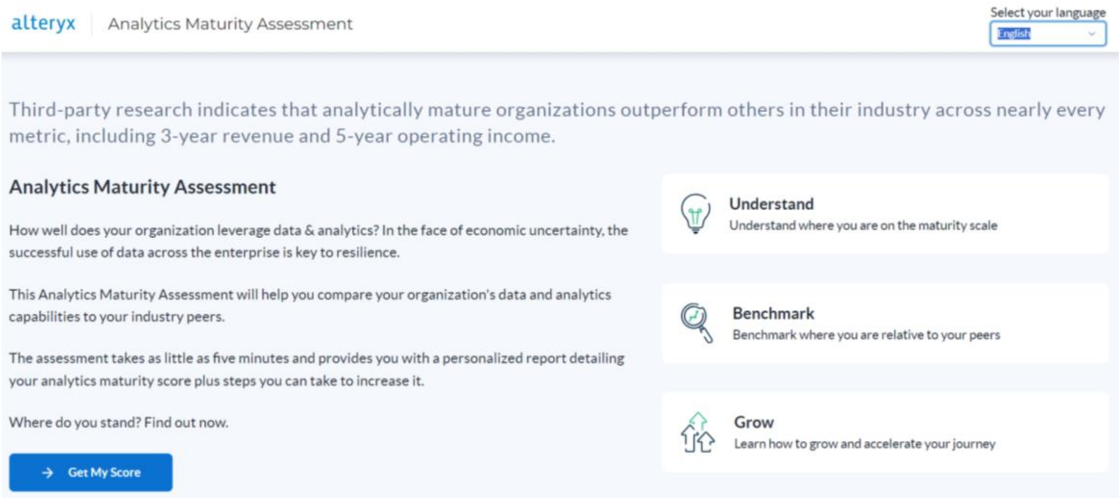
Get your full personalized results.



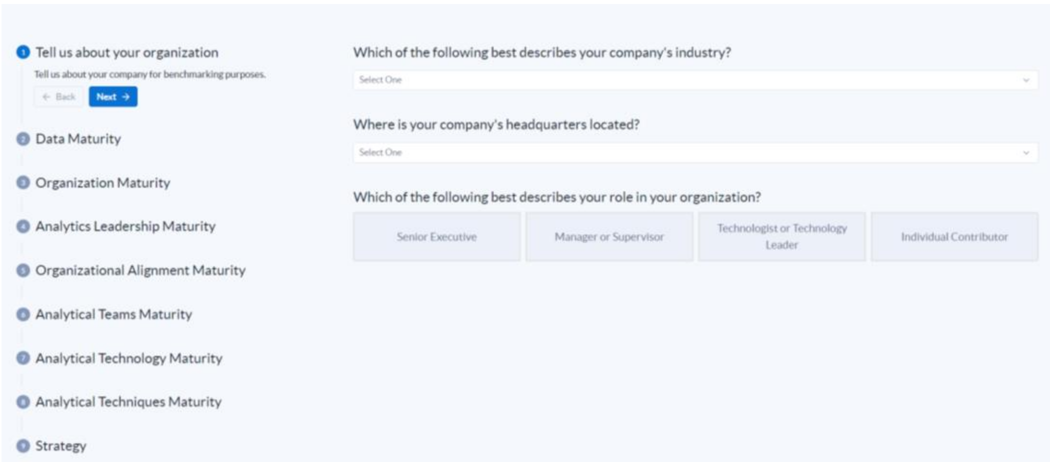
Appendix J. Alteryx tool

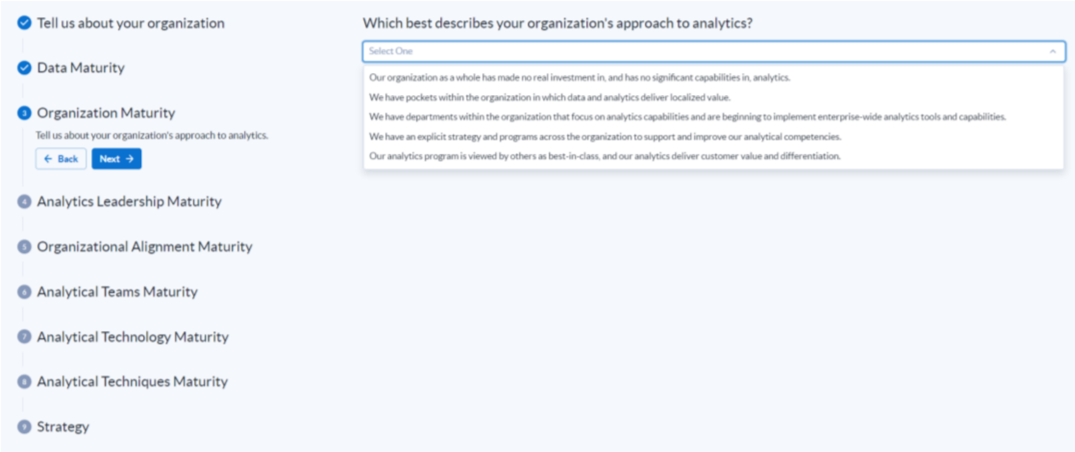
1) **Step1.** Access the tool: https://www.alteryx.com/resources/analytics-maturity . To start to use it, it is not required to provide any personal information.

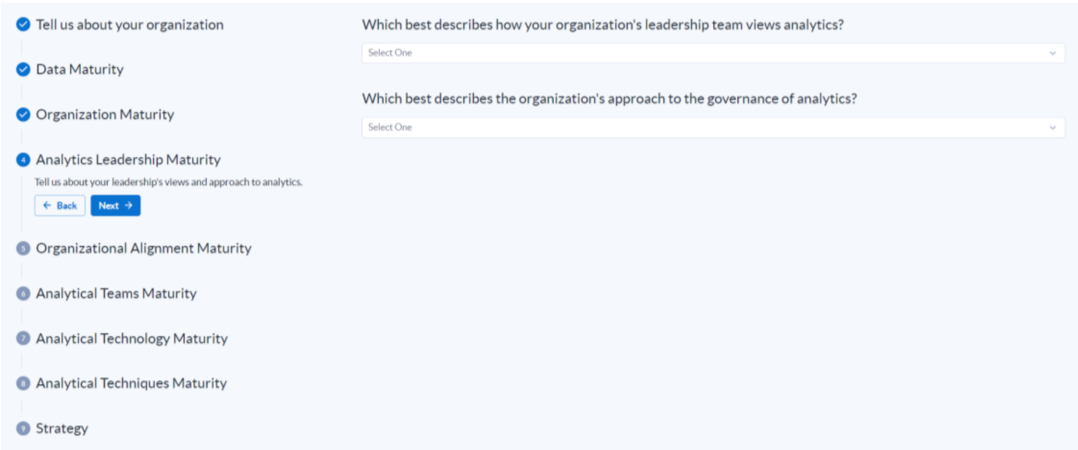


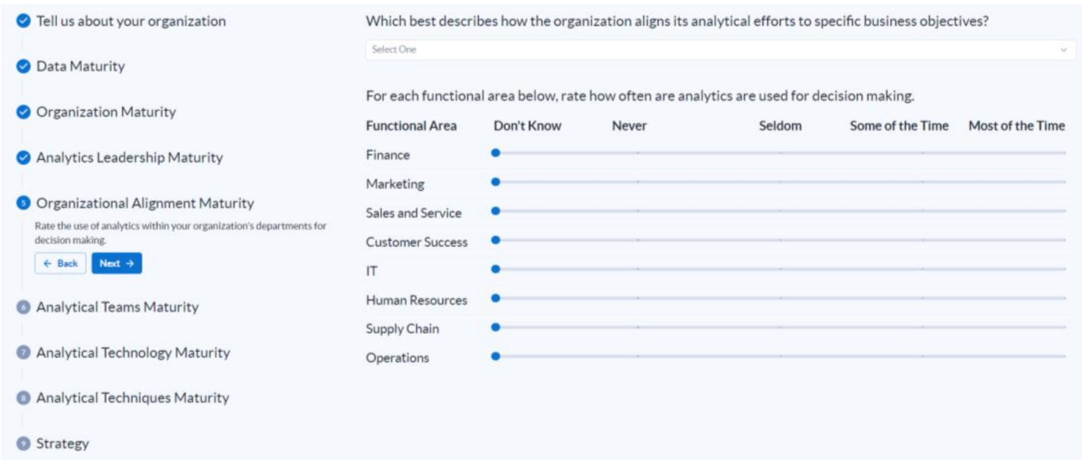


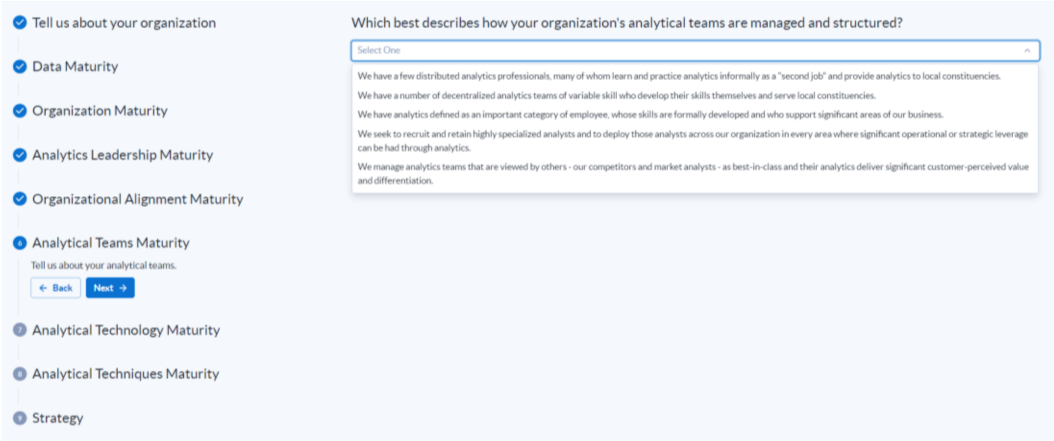
2) **Step 2**. Assessment of the advanced analytics ecosystem - by 8 domains. For each domain there are 1 or more questions.

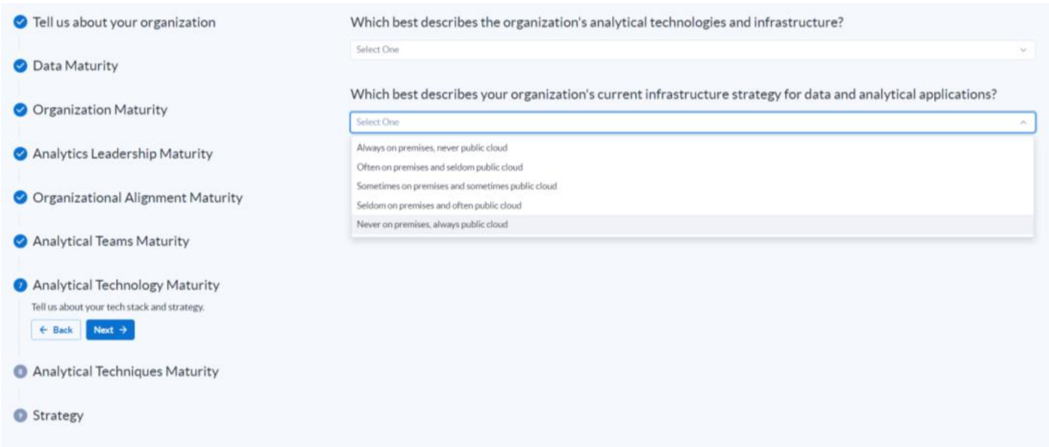


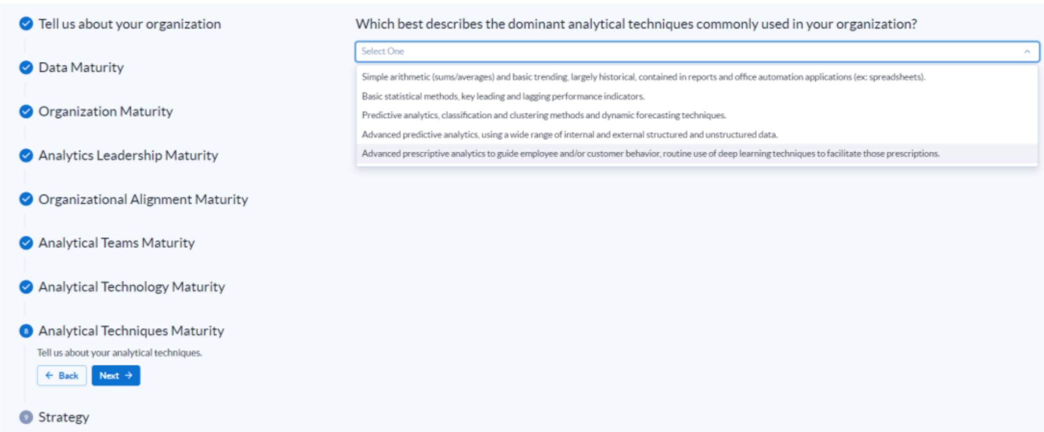

Tell us about your organization
Data Maturity
Organization Maturity
Tell us about your organization's approach to analytics.
Back
Next
Analytics Leadership Maturity
Organizational Alignment Maturity
Analytical Teams Maturity
Analytical Technology Maturity
Analytical Techniques Maturity
Strategy
Which best describes your organization's approach to analytics?
Select One
Our organization as a whole has made no real investment in, and has no significant capabilities in, analytics.
We have pockets within the organization in which data and analytics deliver localized value.
We have departments within the organization that focus on analytics capabilities and are beginning to implement enterprise-wide analytics tools and capabilities.
We have an explicit strategy and programs across the organization to support and improve our analytical competencies.
Our analytics program is viewed by others as best-in-class, and our analytics deliver customer value and differentiation.


Tell us about your organization
Data Maturity
Organization Maturity
Analytics Leadership Maturity
Tell us about your leadership's views and approach to analytics.
Back
Next
Organizational Alignment Maturity
Analytical Teams Maturity
Analytical Technology Maturity
Analytical Techniques Maturity
Strategy
Which best describes how your organization's leadership team views analytics?
Select One
Which best describes the organization's approach to the governance of analytics?
Select One

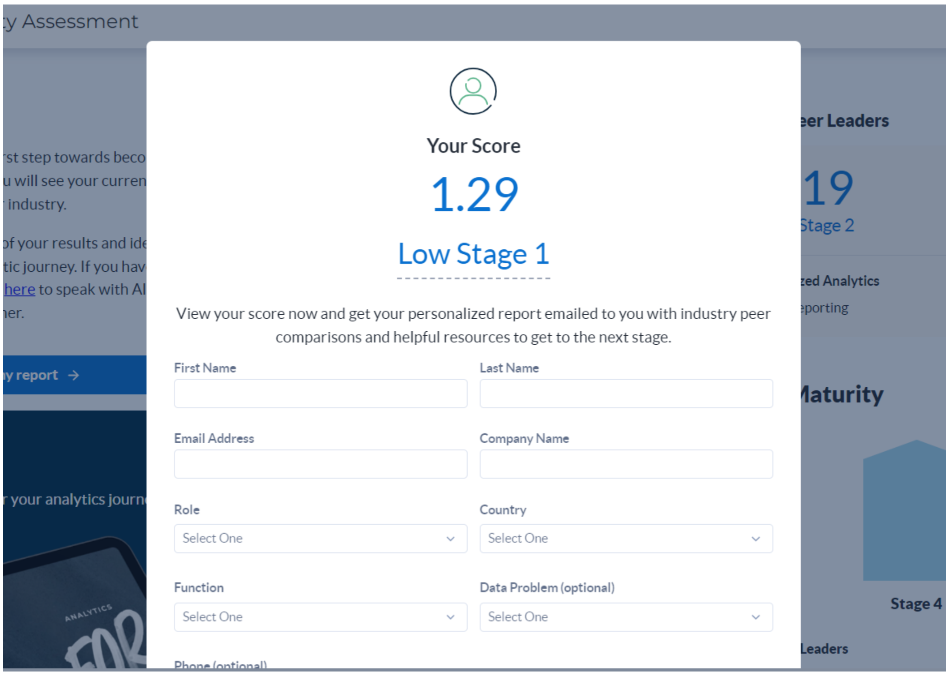

Tell us about your organization
Data Maturity
Organization Maturity
Analytics Leadership Maturity
Organizational Alignment Maturity
Rate the use of analytics within your organization's departments for decision making.
Back
Next
Analytical Teams Maturity
Analytical Technology Maturity
Analytical Techniques Maturity
Strategy
Which best describes how the organization aligns its analytical efforts to specific business objectives?
Select One
For each functional area below, rate how often are analytics are used for decision making.
Functional Area
Don't Know
Never
Seldom
Some of the Time
Most of the Time
Finance
Marketing
Sales and Service
Customer Success
IT
Human Resources
Supply Chain
Operations


Tell us about your organization
Data Maturity
Organization Maturity
Analytics Leadership Maturity
Organizational Alignment Maturity
Analytical Teams Maturity
Tell us about your analytical teams.
Back
Next
Analytical Technology Maturity
Analytical Techniques Maturity
Strategy
Which best describes how your organization's analytical teams are managed and structured?
Select One
We have a few distributed analytics professionals, many of whom learn and practice analytics informally as a "second job" and provide analytics to local constituencies.
We have a number of decentralized analytics teams of variable skill who develop their skills themselves and serve local constituencies.
We have analytics defined as an important category of employee, whose skills are formally developed and who support significant areas of our business.
We seek to recruit and retain highly specialized analysts and to deploy those analysts across our organization in every area where significant operational or strategic leverage can be had through analytics.
We manage analytics teams that are viewed by others - our competitors and market analysts - as best-in-class and their analytics deliver significant customer-perceived value and differentiation.

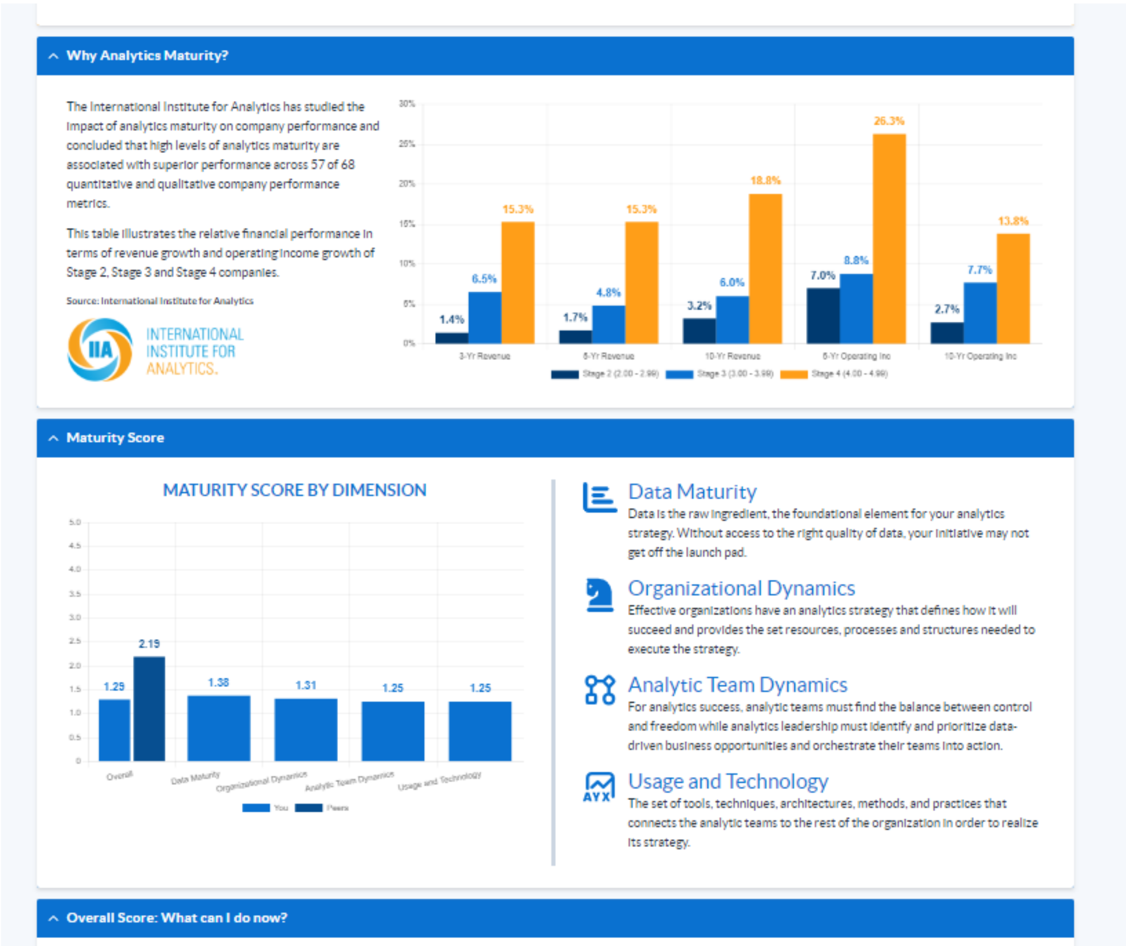

Tell us about your organization
Data Maturity
Organization Maturity
Analytics Leadership Maturity
Organizational Alignment Maturity
Analytical Teams Maturity
Analytical Technology Maturity
Tell us about your tech stack and strategy.
Back
Next
Analytical Techniques Maturity
Strategy
Which best describes the organization's analytical technologies and infrastructure?
Select One
Which best describes your organization's current infrastructure strategy for data and analytical applications?
Select One
Always on premises, never public cloud
Often on premises and seldom public cloud
Sometimes on premises and sometimes public cloud
Seldom on premises and often public cloud
Never on premises, always public cloud

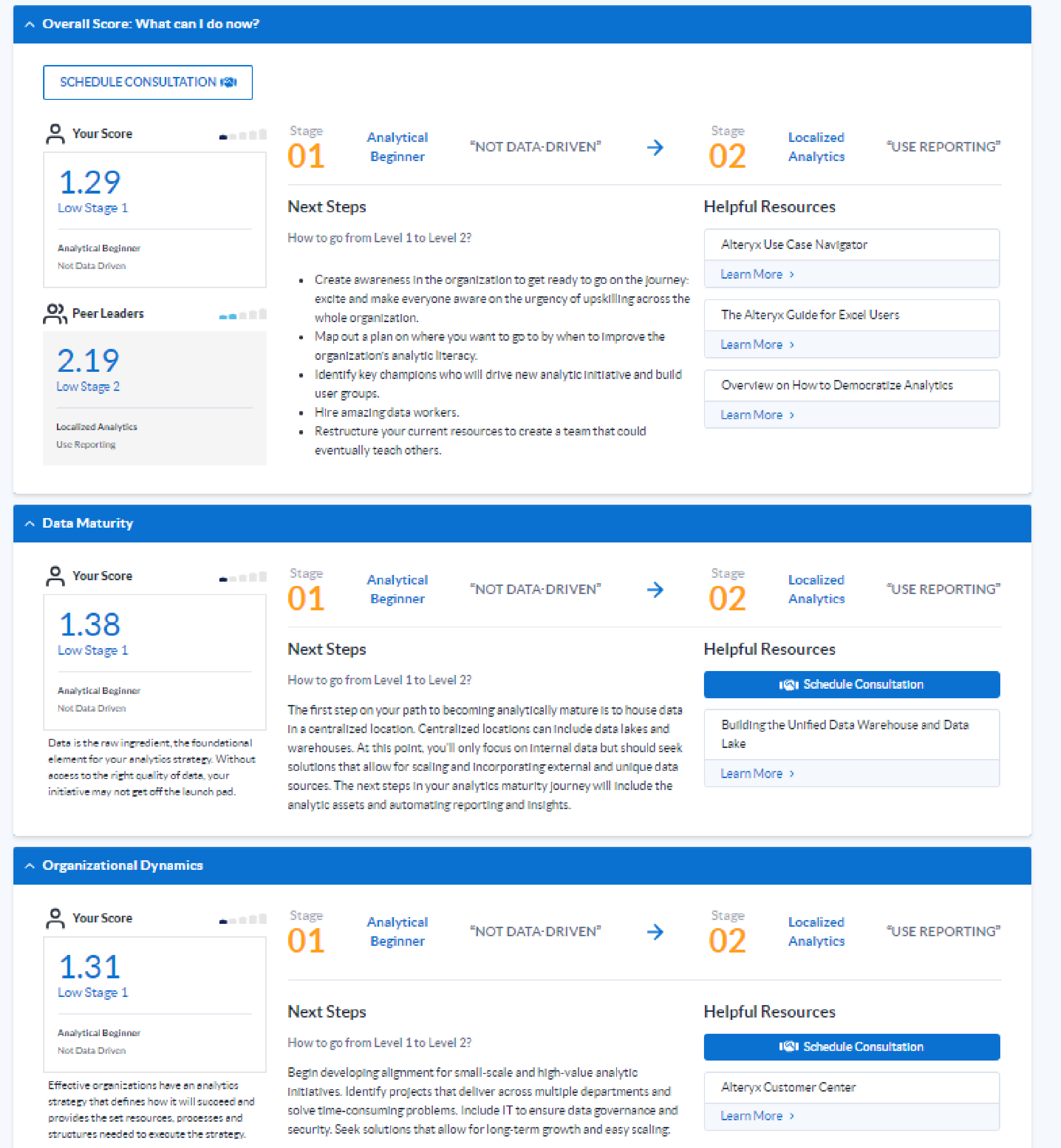

Tell us about your organization
Data Maturity
Organization Maturity
Analytics Leadership Maturity
Organizational Alignment Maturity
Analytical Teams Maturity
Analytical Technology Maturity
Analytical Techniques Maturity
Tell us about your analytical techniques.
Back
Next
Strategy
Which best describes the dominant analytical techniques commonly used in your organization?
Select One
Simple arithmetic (sums/averages) and basic trending, largely historical, contained in reports and office automation applications (ex: spreadsheets).
Basic statistical methods, key leading and lagging performance indicators.
Predictive analytics, classification and clustering methods and dynamic forecasting techniques.
Advanced predictive analytics, using a wide range of internal and external structured and unstructured data.
Advanced prescriptive analytics to guide employee and/or customer behavior, routine use of deep learning techniques to facilitate those prescriptions.

3) **Step 3**. To receive something more than overal score, must be provided full name, email, name of organization, phone mumber, country. If such information provided, the overall assessment score is provided and score by each domain, indicating at what level organization rated. The explanation and some potential next steps are provided for each domain. There is a comparison to peers. It is possible to download the specific organization's report.

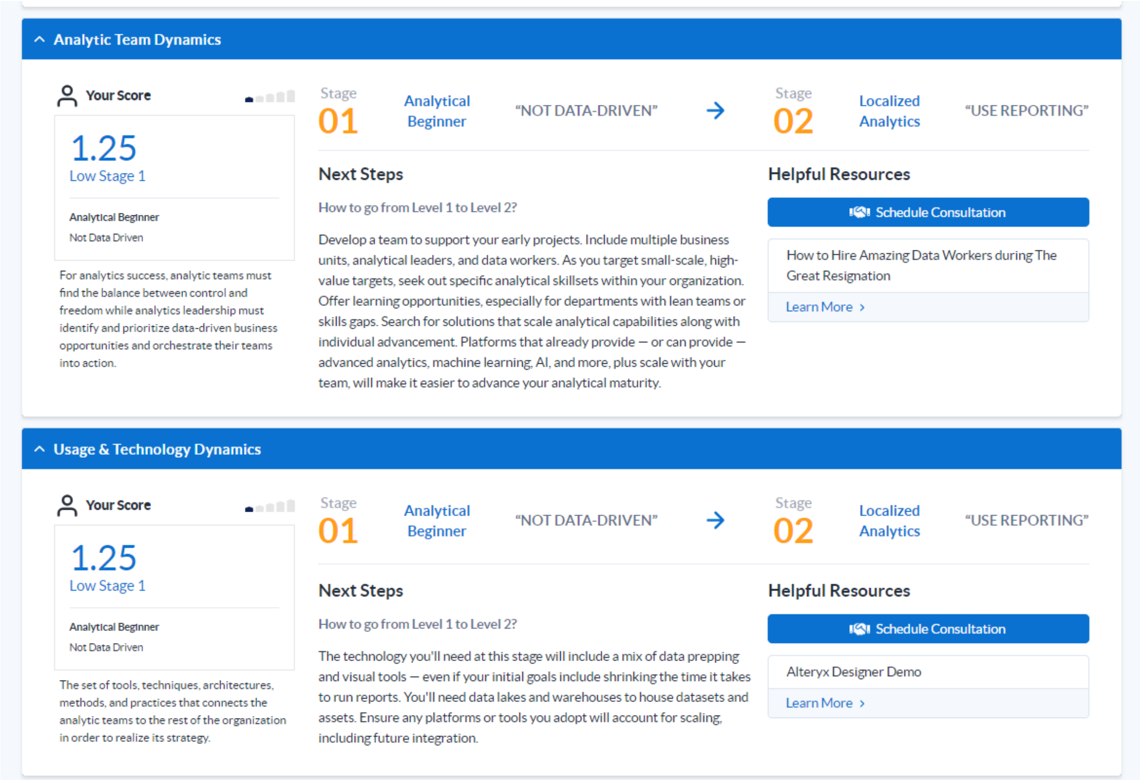



alteryx
Analytics Maturity Assessment
Congratulations!
16 August 2023
Organization Name
RAA Consulting
Industry
Other / All
Your Role
C-Level / EVP
Your Overall Score
Low Stage 1
Analytical Beginner
Your Overall Peers
Low Stage 2
Localized Analytics
Congratulations for taking the first step to democratizing analytics across your organization. The first step in any journey, is to understand your current situation. Research shows that although many organizations strive to become data-driven, many challenges remain. The assessment you just completed measured your maturity across 4 dimensions.
Stage 1
Analytical Beginner
Stage 2
Localized Analytics
Stage 3
Analytical Aspirations
Stage 4
Analytical Companies
Stage 5
Analytical Competitors
Your Score
Peer Leaders


Why Analytics Maturity?
The International Institute for Analytics has studied the impact of analytics maturity on company performance and concluded that high levels of analytics maturity are associated with superior performance across 57 of 68 quantitative and qualitative company performance metrics.
This table illustrates the relative financial performance in terms of revenue growth and operating income growth of Stage 2, Stage 3 and Stage 4 companies.
Source: International Institute for Analytics
INTERNATIONAL INSTITUTE FOR ANALYTICS.
1.4%
6.5%
15.3%
1.7%
4.8%
15.3%
3.2%
6.0%
18.8%
7.0%
8.8%
26.3%
2.7%
7.7%
13.8%
Maturity Score
MATURITY SCORE BY DIMENSION
1.29
2.19
1.38
1.31
1.25
1.25
Overall
Data Maturity
Organizational Dynamics
Analytic Team Dynamics
Usage and Technology
You
Peers
Data Maturity
Data is the raw ingredient, the foundational element for your analytics strategy. Without access to the right quality of data, your initiative may not get off the launch pad.
Organizational Dynamics
Effective organizations have an analytics strategy that defines how it will succeed and provides the set resources, processes and structures needed to execute the strategy.
Analytic Team Dynamics
For analytics success, analytic teams must find the balance between control and freedom while analytics leadership must identify and prioritize data-driven business opportunities and orchestrate their teams into action.
Usage and Technology
The set of tools, techniques, architectures, methods, and practices that connects the analytic teams to the rest of the organization in order to realize its strategy.
Overall Score: What can I do now?



Overall Score: What can I do now?
SCHEDULE CONSULTATION
Your Score
1.29
Low Stage 1
Analytical Beginner
Not Data Driven
Peer Leaders
2.19
Low Stage 2
Localized Analytics
Use Reporting
Stage 01
Analytical Beginner
"NOT DATA-DRIVEN"
Stage 02
Localized Analytics
"USE REPORTING"
Next Steps
How to go from Level 1 to Level 2?
Create awareness in the organization to get ready to go on the journey: excite and make everyone aware on the urgency of upskilling across the whole organization.
Map out a plan on where you want to go to by when to improve the organization's analytic literacy.
Identify key champions who will drive new analytic initiative and build user groups.
Hire amazing data workers.
Restructure your current resources to create a team that could eventually teach others.
Helpful Resources
Alteryx Use Case Navigator
Learn More
The Alteryx Guide for Excel Users
Learn More
Overview on How to Democratize Analytics
Learn More
Data Maturity
Your Score
1.38
Low Stage 1
Analytical Beginner
Not Data Driven
Data is the raw ingredient, the foundational element for your analytics strategy. Without access to the right quality of data, your initiative may not get off the launch pad.
Stage 01
Analytical Beginner
"NOT DATA-DRIVEN"
Stage 02
Localized Analytics
"USE REPORTING"
Next Steps
How to go from Level 1 to Level 2?
The first step on your path to becoming analytically mature is to house data in a centralized location. Centralized locations can include data lakes and warehouses. At this point, you'll only focus on internal data but should seek solutions that allow for scaling and incorporating external and unique data sources. The next steps in your analytics maturity journey will include the analytic assets and automating reporting and insights.
Helpful Resources
Schedule Consultation
Building the Unified Data Warehouse and Data Lake
Learn More
Organizational Dynamics
Your Score
1.31
Low Stage 1
Analytical Beginner
Not Data Driven
Effective organizations have an analytics strategy that defines how it will succeed and provides the set resources, processes and structures needed to execute the strategy.
Stage 01
Analytical Beginner
"NOT DATA-DRIVEN"
Stage 02
Localized Analytics
"USE REPORTING"
Next Steps
How to go from Level 1 to Level 2?
Begin developing alignment for small-scale and high-value analytic initiatives. Identify projects that deliver across multiple departments and solve time-consuming problems. Include IT to ensure data governance and security. Seek solutions that allow for long-term growth and easy scaling.
Helpful Resources
Schedule Consultation
Alteryx Customer Center
Learn More


Analytic Team Dynamics
Your Score
1.25
Low Stage 1
Analytical Beginner
Not Data Driven
For analytics success, analytic teams must find the balance between control and freedom while analytics leadership must identify and prioritize data-driven business opportunities and orchestrate their teams into action.
Stage 01
Analytical Beginner
"NOT DATA-DRIVEN"
Stage 02
Localized Analytics
"USE REPORTING"
Next Steps
How to go from Level 1 to Level 2?
Develop a team to support your early projects. Include multiple business units, analytical leaders, and data workers. As you target small-scale, high-value targets, seek out specific analytical skillsets within your organization. Offer learning opportunities, especially for departments with lean teams or skills gaps. Search for solutions that scale analytical capabilities along with individual advancement. Platforms that already provide — or can provide — advanced analytics, machine learning, AI, and more, plus scale with your team, will make it easier to advance your analytical maturity.
Helpful Resources
Schedule Consultation
How to Hire Amazing Data Workers during The Great Resignation
Learn More ›
Usage & Technology Dynamics
Your Score
1.25
Low Stage 1
Analytical Beginner
Not Data Driven
The set of tools, techniques, architectures, methods, and practices that connects the analytic teams to the rest of the organization in order to realize its strategy.
Stage 01
Analytical Beginner
"NOT DATA-DRIVEN"
Stage 02
Localized Analytics
"USE REPORTING"
Next Steps
How to go from Level 1 to Level 2?
The technology you'll need at this stage will include a mix of data prepping and visual tools — even if your initial goals include shrinking the time it takes to run reports. You'll need data lakes and warehouses to house datasets and assets. Ensure any platforms or tools you adopt will account for scaling, including future integration.
Helpful Resources
Schedule Consultation
Alteryx Designer Demo
Learn More ›

Appendix K. Questionnaire in Latvian

ViA prod INTRA 20220117

Start of Block: Intro

Q1 Šis pētījums tiek veikts sadarbojoties Vidzemes Augstskolai un RAA Consulting**.** Pētījuma mērķis ir izstrādāt publiski pieejamu **digitālās ekosistēmas** (ar fokusu uz komplekso analītiku) **novērtēšanas un rekomendācijas sniedzošu rīku**, lai jebkura organizācija varētu nodrošināt laikmetam atbilstošu digitālo transformāciju, kas ļautu uzlabot organizācijas darbības rezultātus saskaņā ar stratēģiskajiem mērķiem. Jūsu atbildes ir anonīmas un nevajadzētu aizņemt vairāk kā 15 minūtes Jūsu laika. Jūs varat pārtraukt aizpildīšanu un to turpināt vēlāk no vietas, kur apstājāties. **Kā kompensāciju par dalību pētījumā, jebkurš dalībnieks iegūst 1,5h bezmaksas konsultāciju par viņu interesējošiem digitālās ekosistēmas attīstīšanas jautājumiem.** Pētījuma dalībniekiem ir iespēja pieteikties uz dalību **nākošajā pētījuma etapā**, kas ietvers organizācijas digitālās ekosistēmas **detalizētu novērtējumu, ieteicamos nākošos soļus un to izmaksu novērtējumu**.

Q53 Browser Meta Info
Browser (1)

Version (2)

Operating System (3)

Screen Resolution (4)

Flash Version (5)

Java Support (6)

User Agent (7)

End of Block: Intro

Start of Block: Demo Fiz/Jur

Q54 **Kā Jūs raksturotu savu lomu organizācijā?**

- ❍ Organizācijas vadītājs (CEO) (1)
- ❍ Finanšu direktors (CFO) (2)
- ❍ IT direktors (CIO/CTO) (3)
- ❍ Datu/Analītikas direktors (CDO/CAO) vai ekvivalenta loma (4)
- ❍ Mārketinga direktors (CMO) (5)
- ❍ Pārdošanas direktors (30)
- ❍ Citi Direktoru līmeņa pārstāvji (6)
- ❍ Organziācijas Valde, Īpašnieks (7)
- ❍ Struktūrvienības, Nodaļas, Biznesa vienības, departamenta vadītājs vai vietnieks (8)
- ❍ Vecākais eksperts, vadošais speciālists (11)
- ❍ Grāmatvedis, Finanšu speciālists vai līdzīga loma (31)
- ❍ Pašnodarbinātais vai Zemnieku saimniecības pārstāvis (32)
- ❍ Cits (ierakstiet) (13) ____
- ❍ Neviens no iepriekšminētajiem (33)

Page Break

*

Q2 **Jūsu vecums:**

____

X→

Q3 **Dzimums:**

- ❍ Sieviete (1)
- ❍ Vīrietis (2)

Page Break

X→

Q4 **Augstākais iegūtais izglītības līmenis:**

- ❍ Pamatizglītība (7)
- ❍ Profesionālā izglītība (6)
- ❍ Vidējā izglītība (1)
- ❍ Koledžas izglītība (10)
- ❍ Bakalaura grāds (2)
- ❍ Maģistra grāds (3)
- ❍ Doktora grāds (4)
- ❍ Cits (9)

Q7 **Kuru/- as mācību iestādi/-es Jūs esat absolvējis?** *(Norādiet visas pabeigtās iestādes)*

- ❑ LU (1)
- ❑ RTU (5)
- ❑ RSU (6)
- ❑ LLU (11)
- ❑ Biznesa augstskola "Turība" (12)
- ❑ Banku augstskola (9)
- ❑ Rīgas Ekonomikas augstskola (8)
- ❑ Cits (ierakstiet) (10) ________________

Page Break

Q13 **Kādā nozarē darbojas Jūsu pārstāvētā organizācija?** *(Atzīmējiet visus atbilstošos)*

- ❑ Lauksaimniecība, mežsaimniecība un zivsaimniecība (1)
- ❑ Ieguves rūpniecība un karjeru izstrāde (6)
- ❑ Apstrādes rūpniecība (7)
- ❑ Elektroenerģija, gāzes apgāde, siltumapgāde un gaisa kondicionēšana (8)
- ❑ Ūdens apgāde; notekūdeņu, atkritumu apsaimniekošana un sanācija (9)
- ❑ Būvniecība (10)
- ❑ Vairumtirdzniecība un mazumtirdzniecība; automobiļu un motociklu remonts (11)
- ❑ Transports un uzglabāšana (12)
- ❑ Izmitināšana un ēdināšanas pakalpojumi (13)
- ❑ Informācijas un komunikācijas pakalpojumi (14)
- ❑ Finanšu un apdrošināšanas darbības (15)
- ❑ Operācijas ar nekustamo īpašumu (16)
- ❑ Profesionālie, zinātniskie un tehniskie pakalpojumi (17)
- ❑ Administratīvo un apkalpojošo dienestu darbība (18)
- ❑ Valsts pārvalde un aizsardzība; obligātā sociālā apdrošināšana (19)
- ❑ Izglītība (20)
- ❑ Veselība un sociālā aprūpe (21)
- ❑ Māksla, izklaide un atpūta (22)
- ❑ Citi pakalpojumi (23)

Q44 **Ierakstiet konkrētu galveno darbības jomu.** *(Piem., veikals, banka, auto serviss, frizētava, skola, kafejnīca, galdnieka pakalpojumi utt)*

____

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Q57 **Kurā administratīvajā teritorijā atrodas Jūsu organizācija?**

▼ Rīga (1) ... Ventspils novads (48)

Page Break

Q14 **Vai tā ir starptautiska organizācija?**

- ❍ Jā (1)
- ❍ Nē (2)
- ❍ Nezinu (3)

Q15 **Cik darbinieku strādā organizācijā?**

	Darbinieku skaits					
	1-9 (1)	10-49 (2)	50-249 (3)	250-499 (4)	500+ (5)	Nav atbildes/Nezinu (6)
Latvijā (1)	❍	❍	❍	❍	❍	❍
Globāli (6)	❍	❍	❍	❍	❍	❍

Q16 **Cik liels ir organziācijas gada apgrozījums (pēdējai zināmais)?**

	Gada apgrozījums							
		0.5-1.99 milj. EUR (2)	2-5 milj. EUR (3)	6-10 milj. EUR (4)	11 - 20 milj. EUR (5)	20-49 milj. EUR (6)	50 + milj. EUR (7)	Nav atbildes/Nezinu (8)
Latvijā (1)	❍	❍	❍	❍	❍	❍	❍	❍
Globāli (2)	❍	❍	❍	❍	❍	❍	❍	❍

Page Break

End of Block: Demo Fiz/Jur

Start of Block: Block A

Q58 **Kādi datu apkopošanas un/vai analītiskie apskati tiek gatavoti Jūsu organizācijā?**

- ❑ Finanšu pārskati, ko pieprasa likumdošana (1)
- ❑ Organizācijas budžets un tā analīze (2)
- ❑ Mārketinga aktivitāšu atdeves/ izmaksu/mērķauditorijas sasniegšanas apkopojumi un analīzes (3)
- ❑ Produktu/ pakalpojumu pārdošanas apkopojumi un analīzes (4)
- ❑ Produktu/ pakalpojumu ražošanas apkopojumi un analīzes (5)
- ❑ Klientu uzvedības apkopojumi un analīzes (6)
- ❑ Cilvēkresursu vadības datiu apkopojumi un analīzes (7)
- ❑ Risku vadības datu apkopojumi un analīzes (8)
- ❑ Cits (Ierakstiet) (10) ____

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Q39 **Kurš no apgalvojumiem vislabāk atbilst organizācijas iekšējo un ārējo (publiskās datu bāzes, sociālo tīklu informācija utml.) datu lietošanai? Lietoti tiek:**

- ❍ Tikai iekšējie dati (1)
- ❍ Pārsvarā iekšējie dati, nedaudz ārējie (2)
- ❍ Iekšējie un ārējie dati aptuveni vienādi (3)
- ❍ Pārsvarā ārējie dati (4)
- ❍ Tikai ārējie dati (5)
- ❍ Nav atbildes/Nezinu (6)

Q40 **Kādus datu avotus lietojat organizācijā?**

- ❑ Iekšējie visu veida dati (1)
- ❑ Kredītreitinga/Kredītbiroju informācija (2)
- ❑ Dati no publiskajām/valsts datu bāzēm (3)
- ❑ Sociālo mediju dati (4)
- ❑ Trešo pušu mārketinga dati (5)
- ❑ Ģeogrāfiskās vietas dati (6)
- ❑ Telekomunikācijas (7)
- ❑ Epasti (8)
- ❑ Web uzvedība (digital footprint) (9)
- ❑ Cits (ierakstiet) (10) ____
- ❑ ⊗Nav atbildes/Nezinu (11)

Q31 **Kurš no apgalvojumiem vislabāk raksturo organizāciju attiecībā uz datu pārvaldību un kvalitāti?**

- ❍ Slikta - Slikta datu kvalitāte un pārvaldība, kas apgrūtina jebkādu analīzi. Nav funkciju/komandu ar stingru datu fokusu. (1)
- ❍ Nepietiekama - Datus var lietot, bet tie ir funkcionāli vai procesuāli izolēti. Datu pārvaldības jautājumus reti apspriež organizācijas vadības līmenī. (2)
- ❍ Apmierinoša - Ir identificēti galvenie datu apgabali un dati ir centralizēti repozitorijā/krātuvē. (3)
- ❍ Laba - Integrēti, akurāti, pamatdati ir pieejami centralizētā datu noliktavā. Dati ir IT pārziņā. Maz unikālu datu avotu. (4)
- ❍ Izcila – dati tiek uztverti kā stratēģisks aktīvs, ir atsevišķa komanda, kas pārvalda datus. Notiek nemitīga jaunu datu avotu apzināšana un piegāde biznesam. (5)
- ❍ Nav atbildes/Nezinu (6)

Page Break

Q17 **Kurš no apgalvojumiem vislabāk raksturo Jūsu organizācijas analītisko kopienu?**

- ❍ Nav analītiķu vispār (6)
- ❍ Nekoordinētas analītiskās aktivitātes (1 vai vairāki analītiķi, kuri darbojas atsevišķi) (1)
- ❍ Lokālas analītiskās komandas, kas ir iesākušas dalīšanos ar rīkiem, datiem un zināšanām (2)
- ❍ Centrāla analītiskā grupa, ar daļēju koordinēšanu par analītiskajām aktivitātēm visā organizācijā (3)
- ❍ Centrāla analītiskā grupa, kas cieši koordinē un attīsta analītiskās aktivitātes visā organizācijā (4)
- ❍ Cits (5)

Q18 **Kurš visbiežāk ir projektu iniciators datu un analītiskajām aktivitātēm organizācijā?**

- ❍ Pārsvarā organizācijas vadītājs (1)
- ❍ Pārsvarā kāds no Augstākās vadības (direktoru līmenis, ieskaitot organizācijas vadītāju) (2)
- ❍ Pārsvarā kāds Departamenta vadītājs (3)
- ❍ Nav tādu iniciatīvu, kuru projektu iniciators ir augstākā vadība (4)
- ❍ Nav atbildes/ Nezinu (5)

Page Break

Q19 **Cik lielā mērā organizācijai atbilst sekojoši apgalvojumi? Novērtējiet skalā no 1-5, kur 1 - pilnīgi nepiekrītu un 5 - pilnīgi piekrītu .**

	1 - pilnīgi nepiekrītu (1)	2 (2)	3 (3)	4 (4)	5 -pilnīgi piekrītu (5)
Organizācijas stratēģijas izveide ir balstīta uz datiem un paredzošo analītiku (predictive analytics) (1)	❍	❍	❍	❍	❍
Organizācijai ir ilgtermiņa Analītikas attīstības stratēģija (2)	❍	❍	❍	❍	❍
Analītikas attīstīšana ir organizācijas stratēģija konkurētspējas palielināšanai (3)	❍	❍	❍	❍	❍
Analītiskais process visā organizācijā ir sakārtots, skaidri definēts un caurspīdīgs (4)	❍	❍	❍	❍	❍
Analītika tiek lietota lielākajā daļā no organizācijas darbības un lēmumu pieņemšanas procesiem (5)	❍	❍	❍	❍	❍

Page Break

Q20 **Cik lielā mērā organizācijai atbilst sekojoši apgalvojumi? Novērtējiet skalā no 1-5, kur 1 - pilnīgi nepiekrītu un 5 - pilnīgi piekrītu .**

	1 - pilnīgi nepiekrītu (1)	2 (2)	3 (3)	4 (4)	5 - pilnīgi piekrītu (5)
Visa veida analītiskie rīki/platformas/programmatūras (aprakstošās/paredzošās, strukturētiem/nestrukturētiem un vēsturiskiem/'real-time' datiem, vizualizācijai) ir plaši un viendabīgi lietoti organizācijas ikdienas darbības un lēmumu pieņemšanas procesos (1)	❍	❍	❍	❍	❍
Organizācijas datu apstrādes process tiek veikts efektīvi (2)	❍	❍	❍	❍	❍

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Q42 **Kurš no apgalvojumiem vislabāk raksturo tehnoloģijas analītikas atbalstam organizācijā?**

❍ Neattīstītas, pamatā uz izklājlapām (Excel) un pamata pārskatu veidošanas rīki (1)

❍ Pamatā pārskatu veidošanas rīki ar ierobežotu paredzošās analītikas (predictive analytics) rīkiem (2)

❍ Pārskatu un paredzošās analītikas (predictive analytics) rīki ir plaši pieejami organizācijā (3)

❍ Pārskatu un paredzošās analītikas (predictive analytics) rīki ir plaši pieejami organizācijā, plus rīki, lai analizētu nestrukturētus datus (4)

❍ Pārskatu un paredzošās analītikas (predictive analytics) rīki ir plaši pieejami organizācijā, plus rīki, lai analizētu nestrukturētus datus (nav datu bāžu struktūras) ar iesakošās (prescriptive triggers/alerts) analītikas rezultātiem (5)

❍ Nav atbildes/Nezinu (6)

Page Break

Q26 **Kuri no uzskaitītajiem rīkiem/risinājumiem tiek lietoti Jūsu organizācijā datu apstrādes un analītikas nodrošināšanai?** *(Atzīmējiet visus atbilstošos)*

- ❑ MS Excel (4)
- ❑ SQL (6)
- ❑ R (1)
- ❑ Python (7)
- ❑ SAS (3)
- ❑ SPSS (2)
- ❑ MS Power BI (24)
- ❑ Tableau (8)
- ❑ MATLAB (11)
- ❑ KNIME (12)
- ❑ Alteryx (40)
- ❑ RapidMiner (13)
- ❑ Microsoft SQL Server (14)
- ❑ Qlik (20)
- ❑ WPS (43)
- ❑ SAP Business Objects (28)
- ❑ Teradata (33)
- ❑ H2O (45)
- ❑ TensorFlow (46)
- ❑ Torch (47)
- ❑ Hive (37)
- ❑ Caffe (44)
- ❑ Cits (ierakstiet) (41) ____

Page Break

Q21 **Kā Jūs raksturotu analītisko attīstību organizācijā no pielietoto analītisko risinājumu/metožu viedokļa?Vai tiek pielietotas vienkāršas, pamata aprakstošas analītiskās metodes (descriptive analytics), vai arī tiek pielietotas padziļinātas, notikumus un uzvedību paredzošas un darbību iesakošas analītiskās metodes (predictions, prescriptions analytics)? Novērtējiet skalā no 1-5, kur 1 - vienkāršas metodes, 5 - padziļinātas analītiskas metodes.**

- ❍ 1 - vienkāršas analītiskās metodes (basic analytics) (1)
- ❍ 2 (2)
- ❍ 3 (3)
- ❍ 4 (4)
- ❍ 5 - padziļinātas analītiskās metodes (advanced analytics) (5)
- ❍ Nezinu (6)

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Q23 **Cik daudz (%) no Jums zināmajām/ Jūsu atbildībā esošajām analītiskajām darbībām (datu apkopojumi, analīzes, apskati, pārskati, monitoringi utt.) tiek atkārtotas vai atjaunotas sekojošā biežumā?**
1 reizi gadā : _______ (1)

1 reizi mēnesī : _______ (2)

1 reizi nedēļā : _______ (3)

1 reizi dienā : _______ (4)

Ik pēc dažām stundām : _______ (5)

1 reizi stundā : _______ (6)

Reālā laikā atspoguļots : _______ (7)

Total : ________

Page Break

Q27 **Vai organizācijā ir atsevišķa funkcija/komanda/cilvēki, kuri strādā uz izpēti un attīstību, lai atbalstītu/ nodrošinātu analītikas attīstību un inovatīvu risinājumu pārbaudi un ieviešanu?**

- ❍ Jā (1)
- ❍ Nē (2)
- ❍ Nezinu (3)

Page Break

Q28 **Vai organizācijā ir konkrēts atbildīgais par sekojošām aktivitātēm?**

	Jā (1)	Nav, bet ir nolūks iecelt (2)	Nav un nav plānots (3)	Nezinu (4)
Vispārēja atbildība par datiem organizācijā (1)	❍	❍	❍	❍
Datu privātums (2)	❍	❍	❍	❍
Datu drošība (3)	❍	❍	❍	❍
Datu integrācija un vadība (4)	❍	❍	❍	❍
Datu pārvaldība (5)	❍	❍	❍	❍
Analītika un izpratne (6)	❍	❍	❍	❍

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Q29 **Kādas ar datu pārvaldību saistītas politikas ir jau ieviestas organizācijā?**

	Ir (1)	Nav (2)	Izstrādes procesā (3)	Nezinu (4)
Datu privātuma politika (1)	❍	❍	❍	❍
Datu drošības politika (2)	❍	❍	❍	❍
Sociālo mediju lietošanas politika organizācijā (3)	❍	❍	❍	❍
Politika, kas ierobežo kibernoziegumu risku organizācijā (4)	❍	❍	❍	❍
Datu pieejas politika (5)	❍	❍	❍	❍
Politikas, kas nosaka datu savākšanu, uzturēšanu, lietošanu, izplatīšanu un arhivēšanu (6)	❍	❍	❍	❍
Politikas, kas pārvalda darbinieku iekārtu lietošanu (7)	❍	❍	❍	❍
Datu uzskaites politika (8)	❍	❍	❍	❍

Page Break

Q30 **Kā Jūs novērtētu, cik liela uzmanība organizācijā tiek pievērsta datu kvalitātei? Novērtējiet skalā no 1-5, kur 1 - netiek pievērsta vispār, 5 - ļoti pievēršs uzmanību.**

- ❍ 1 - netiek pievērsta vispār (1)
- ❍ 2 (2)
- ❍ 3 (3)
- ❍ 4 (4)
- ❍ 5 - ļoti pievēršs (5)
- ❍ Nezinu (6)

Page Break

Q32 **Kurš no apgalvojumiem vislabāk raksturo organizāciju attiecībā uz 'big data' lietošanu?**

- ❍ Nav vajadzība pēc 'big data' (1)
- ❍ Šobrīd nav plānu attiecībā uz 'big data' (2)
- ❍ Ir interese par 'big data', bet vēl nav veikti ieguldījumi un nav plāna, kā to ieviest (3)
- ❍ Tiek veikta izpēte (4)
- ❍ Plāno ieviest/uzsākt ar 'big data' saistītus projektus (5)
- ❍ Aktīvi/noritoši pilotprojekti (6)
- ❍ Šobrīd ir procesā 'big data' risinājumu ieviešana (7)
- ❍ Ir ieviests viss un nodrošināts, lai lietotu/analizētu 'big data' (8)
- ❍ Nav atbildes/Nezinu (9)

Page Break

Q34 **Cik lielā mērā organizācijai atbilst sekojoši apgalvojumi? Novērtējiet skalā no 1-5, kur 1 - pilnīgi nepiekrītu un 5 - pilnīgi piekrītu.**

	1 - pilnīgi nepiekrītu (1)	2 (2)	3 (3)	4 (4)	5 -pilnīgi piekrītu (5)
Organizācijā ir pietiekami analītisko cilvēkresursu, lai veiktu pieprasītās analītiskās darbības (1)	❍	❍	❍	❍	❍
Esošo analītisko resursu vidū ir atbilstošas zināšanas/pieredze, lai pielietotu sarežģītākas analītiskās metodes (2)	❍	❍	❍	❍	❍
Organizācija atbalsta vajadzīgo zināšanu iegūšanu un attīstīšanu (apmācības, konferences, atbalsts jaunu analītisko tehniku un risinājumu testēšanai) (3)	❍	❍	❍	❍	❍
Organizācijas visas analītiskās funkcijas labi sadarbojas savā starpā (4)	❍	❍	❍	❍	❍

Page Break

Q35 **Kurš galvenokārt ir atbildīgs par datu un analītikas attīstību organizācijā?**

- ❍ Organizācijas vadītājs (CEO) (1)
- ❍ Finanšu direktors (CFO) (2)
- ❍ Risku direktors (CRO) (16)
- ❍ IT direktors (CIO/CTO) (3)
- ❍ Datu/Analītikas direktors (CDO/CAO) vai ekvivalenta loma (4)
- ❍ Mārketinga direktors (CMO) (5)
- ❍ Pārdošanas direktors (30)
- ❍ Ražošanas direktors (31)
- ❍ Citi Direktoru līmeņa pārstāvji (6)
- ❍ Organizācijas Valde (7)
- ❍ Biznesa vienības vai departamenta vadītājs (8)
- ❍ Dažādi iecelti datu pārvaldnieki (9)
- ❍ DWH vai BI komandas (10)
- ❍ Datu arhitektu komanda (11)
- ❍ Individuāli departamenti (12)
- ❍ Cits (ierakstiet) (13) ____
- ❍ Nav viena konkrēta atbildīgā (14)
- ❍ Nezinu (15)

Page Break

Q38 **Cik lielā mērā organizācijai atbilst sekojoši apgalvojumi? Novērtējiet skalā no 1-5, kur 1 - pilnīgi nepiekrītu un 5 - pilnīgi piekrītu.**

	1 - pilnīgi nepiekrītu (1)	2 (2)	3 (3)	4 (4)	5 -pilnīgi piekrītu (5)
Dati/informācija organizācijā tiek uzskatīti par organizācijas aktīviem/vērtību (1)	❍	❍	❍	❍	❍
Analītiskais pamatojums ņem virsroku pār vadības pieredzi, kad jārisina svarīgi biznesa jautājumi (2)	❍	❍	❍	❍	❍
Organizācijai iegulda analītiskajās tehnoloģijās, analītisko talantu piesaistē un apmācībā (3)	❍	❍	❍	❍	❍
Organizācijai ir svarīgi pastiprināt analītikas lietojumu, lai pieņemtu labākus lēmumus (4)	❍	❍	❍	❍	❍

Page Break

Q37 **Cik lielā mērā Jūs piekrītat apgalvojumam, ka IT un Bizness strādā kopā, lai definētu, kuri dati ir vajadzīgi un tiem jātiek saglabātiem, kā arī regulāri tiek pārskatītas un atjaunotas prasības to saglabāšanai un piekļuvei? Novērtējiet skalā no 1-5, kur 1 - pilnīgi nepiekrītu un 5 - pilnīgi piekrītu.**

- ❍ 1 - pilnīgi nepiekrītu (1)
- ❍ 2 (2)
- ❍ 3 (3)
- ❍ 4 (4)
- ❍ 5 - pilnīgi piekrītu (5)
- ❍ Nezinu (6)

Page Break

Q45 **Cik lielā mērā organizācijai atbilst sekojoši apgalvojumi? Novērtējiet skalā no 1-5, kur 1 - pilnīgi nepiekrītu un 5 - pilnīgi piekrītu.**

	1 - pilnīgi nepiekrītu (1)	2 (2)	3 (3)	4 (4)	5 -pilnīgi piekrītu (5)
Esošās tehnoloģijas un sistēmas ir atbilstošas organizācijas vajadzībām (1)	❍	❍	❍	❍	❍
Ir izveidota organizatoriska datu vadības struktūra (2)	❍	❍	❍	❍	❍

Page Break

Q56 **Kā Jūs raksturotu līdzsvaru starp intuīciju/pieņēmumiem un uz datiem balstītu analītikas izmantošanu organizācijā sekojošu jautājumu risināšanā? Novērtējiet skalā no 1-5, kur 1 - intuīcija un 5 - analītika.**

	1 - intuīcija (1)	2 (2)	3 (3)	4 (4)	5 - analītika (5)
Izmaksu samazināšana (1)	❍	❍	❍	❍	❍
Finanšu prognozēšana (2)	❍	❍	❍	❍	❍
Ikdienas darbības procesu optimizēšanā (3)	❍	❍	❍	❍	❍
Mērķa tirgus identificēšanā (4)	❍	❍	❍	❍	❍
Cenošanas modeļu izveide (5)	❍	❍	❍	❍	❍
Organizācijas stratēģisko mērķu nospraušana (6)	❍	❍	❍	❍	❍
Darbinieka snieguma novērtējums (7)	❍	❍	❍	❍	❍
Reālā laika lēmumu pieņemšana (8)	❍	❍	❍	❍	❍
Riska novērtēšanas modeļu izveide (9)	❍	❍	❍	❍	❍
Mārketinga kampaņas definēšana (10)	❍	❍	❍	❍	❍
Ieviešot/attīstot jaunus produktus un pakalpojumus (11)	❍	❍	❍	❍	❍

End of Block: Block A

Start of Block: Block - Issues

Q46 **Kādas ir galvenās problēmas/šķēršļi, kas kavē pielietot/ieviest/attīstīt advancētākas analītiskās pieejas un risinājumus uzņēmumā?** (Atzīmējiet vismaz 3 svarīgākos)

❑ Datu drošība (1)

❑ Datu privātums (2)

❑ Datu kvalitāte (3)

❑ Datu pieejamība/piekļuve (4)

❑ Atbilstošu analītisko rīku pieejamība (5)

❑ Biznesa prasību iegūšana (6)

❑ Organizācijas augstākās vadības nepietiekams atbalsts (7)

❑ Nav skaidrs, vai investīcijas atmaksāsies (8)

❑ Nav zināma labākā prakse (best practise) (9)

❑ Nav atbilstošu tehnisko zināšanu (10)

❑ Nav pārliecības, kā lietot rezultātus (11)

❑ Grūtības ar nestrukturēto datu pieejamību (12)

❑ Esošās datu bāžu sistēmas/programmatūras/risinājumi nespēj ātri apstrādāt/piegādāt liela apjoma un/vai nestrukturētus datus lietotājiem ērtā veidā (13)

❑ Nespēja izskaidrot sarežģītu analītisko risinājumu rezultātus biznesa lietotājiem saprotamā valodā (14)

❑ Nespēja manipulēt un integrēt dažādus datus (15)

❑ Nepietiekams analītisko cilvēku skaits un/vai nepietiekamas zināšanas/pieredze (16)

❑ Grūtības parādīt/novērtēt ietekmi uz biznesa rezultātiem monetārā veidā (ROI, business case) (17)

❑ Grūtības piesaistīt un noturēt analītiskos talantus (18)

❑ Organizācijas analītisko funkciju struktūra/organizācija (19)

❑ Grūtības atrast optimālos analītiskos rīkus (20)

❑ Uzraugošo iestāžu nostāja attiecībā uz datiem un analītisko metožu pielietojumu (21)

❑ Izmaksas/investīcijas saistītas ar attīstīšanu un ieviešanu (infrastruktūra, rīki, cilvēki) (22)

❑ Centralizētas/vienotas datu noliktavas (DWH, Data lake) trūkums/ sadrumstaloti datu avoti (23)

❑ Grūtības savākt un analizēt ‘big data’ (24)

❑ Grūtības ieviest produkcijā automātiskus analītisko risinājumus/modeļus (25)

❑ Cits (ierakstiet) (26)

____

❑ ⊗Nav šķēršļu (27)

End of Block: Block - Issues

Start of Block: Block - Solutions/Recommendations

Q51 **Kādi soļi būtu jāsper, lai analītiskās iniciatīvas būtu veiksmīgas un organziācija ieguldītu analītiskās funkcijas pilnvērtīgā attīstībā?** (Atzīmējiet vismaz 3 svarīgākos)

- ❑ Komandas ar atbilstošām zināšanām izveide (1)
- ❑ Analītikas centralizācija un/vai Analītiskā zināšanu centra izveide, kas virza visu analītisko funkciju organizācijā (2)
- ❑ Analītikas decentralizācija (3)
- ❑ Analītikas attīstības stratēģijas izveide (4)
- ❑ Analītisko rezultātu sasaiste ar lēmumu pieņemšanas procesu ieviešana (5)
- ❑ Jāveicina tāda organizācijas kultūra/uztvere, ka dati/informācija ir būtisks tās aktīvs (6)
- ❑ Atbilstošāko tehnoloģiju/programmatūru izvēle (7)
- ❑ Jānodrošina efektīva pieeja iekšējiem datiem (8)
- ❑ Jānodrošina efektīva pieeja ārējiem datiem (9)
- ❑ Jāpanāk aktīvs augstākās vadības atbalsts (10)
- ❑ Jāveicina analītisko speciālistu aktīva sadarbība ar biznesa pārstāvjiem (11)
- ❑ Jāierosina nelieli projekti reālajā dzīvē, kas parādā potenciālo pievienoto vērtību biznesa rezultātiem (12)
- ❑ Jāparāda taustāmi ieguvumi biznesam no analītiskās iniciatīvas, organizācijas darbības optimizēšanai un finansiāliem ieguvumiem (13)
- ❑ Uzskatāmi jāparāda kā analītika uzlabo konkurētspēju (14)
- ❑ Pareizo ‘data-driven’ iniciatīvu izvēle (15)
- ❑ Jānodrošina zināšanas un pacietība datu integrācijā (16)
- ❑ Jānodrošina plašāka analītikas lietošana mārketinga un ar klientu saskarsmi saistītos jautājumos (17)
- ❑ Jāidentificē potenciālās vērtības radīšanas iespējas un riski (18)
- ❑ Jāizveido iekšēja kapacitāte, lai veidotu ‘data-driven’ organizāciju (19)
- ❑ Jāievieš ar datu drošību, privātumu, kvalitāti saistītas politikas (20)
- ❑ Jānodrošina cilvēkkapacitāte ‘big data’ analītikā (21)
- ❑ Jāievieš motivācijas programmas, lai veicinātu dalīšanos ar datiem kopējā rezultāta uzlabošanai (22)
- ❑ Jāattīsta politikas, kas līdzsvaro organizācijas vēlmi izmantot datus un radīt pievienoto vērtību organizācijai, un klientu vēlmi pēc drošības un privātuma (23)
- ❑ Jāatrisina tehnoloģiskās barjeras un jāpaātrina izpētes un attīstības jautājumi mērķa apgabalos (24)
- ❑ Jānodrošina investīcijas informācijas tehnoloģiju infrastruktūrā (25)

- ❑ Cits (ierakstiet) (26)

____

- ❑ ⊗Nav atbildes/Nezinu (27)

End of Block: Block - Solutions/Recommendations

Start of Block: Block 5

Q52 **Kādi ir lielākie ieguvumi organizācijai no dažādām analītiskajam iniciatīvām?** (Atzīmējiet vismaz 3 svarīgākos)

- ❑ Konkurētspējas palielināšana (1)
- ❑ Samazinātas izmaksas (2)
- ❑ Jaunas biznesa iespējas (3)
- ❑ Gudrākā/labāka lēmumu pieņemšana (4)
- ❑ Palielināts ienākums/apgrozījums no esošiem klientiem/produktiem (5)
- ❑ Jauni, papildus klienti (6)
- ❑ Palielināta tirgus daļa (7)
- ❑ Uzlaboti ikdienas procesi (8)
- ❑ Palielināta klientu apmierinātība (9)
- ❑ Dziļāka tirgus un konkurentu izpratne (10)
- ❑ Risku un krāpniecības samazināšana (11)
- ❑ Automatizēti 'real-time' lēmumu pieņemšanas procesi (12)
- ❑ Klientu segmentācija (13)
- ❑ Dziļāka un precīzāka izpratne par biznesu (14)
- ❑ Labāka plānošana un prognozēšana (15)
- ❑ Labāka iespēju palielināšana no galvenajām stratēģiskajām iniciatīvām (16)
- ❑ Labākas attiecības ar klientiem un sadarbības partneriem (17)
- ❑ Labāka riska novērtēšana un spēja reaģēt uz ekonomiskās vides izmaiņām (18)
- ❑ Labāks organizācijas finanšu sniegums (19)
- ❑ Labāka spēja reaģēt uz izmaiņām tirgū (20)
- ❑ Jaunu produktu vai pakalpojumu radīšana, kas palielina ienākumu plūsmu (21)
- ❑ Cits (ierakstiet) (22)

____

- ❑ ⊗Nav atbildes/Nezinu (23)

Page Break

Q53 **Cik ilgā laikā ir novērojama atdeve organizācijai pēc ieguldījumu (rīki, cilvēki, platformas, datu avoti utml.) veikšanas datu ieguvē/pieejas nodrošināšanā/ analītikā?**

- ❍ < =6 mēneši (1)
- ❍ 7-12 mēneši (2)
- ❍ 13-18 mēneši (3)
- ❍ 19 -24 mēneši (4)
- ❍ 24+ mēneši (5)
- ❍ Nav pozitīvas atdeves (6)
- ❍ Nezinu (7)

Q54 **Kā Jūs raksturotu organizācijas ieguldījumus datu ieguvē/pieejas nodrošināšanā/ analītikā?**

- ❍ Palielinās (1)
- ❍ Paliek tādi paši (2)
- ❍ Samazinās (3)
- ❍ Nezinu (4)

Q55 **Kādos ar datu ieguvi/pieeju nodrošināšanu/ analītiku saistītos virzienos organizācija iegulda visvairāk?**

- ❑ Cilvēki (1)
- ❑ Rīki/platformas (2)
- ❑ Apmācības (3)
- ❑ Datu avoti (4)
- ❑ Datu privātums (5)
- ❑ Datu pārvaldība (6)
- ❑ Cits (ierakstiet) (7) ____
- ❑ ⊗Nekur neiegulda (8)

Page Break

Q43 **Liels paldies par Jūsu atbildēm un veltīto laiku!**

Ja vēlaties sazināties ar pētījuma autoru un RAA Consulting pārstāvi, kontaktinfomācija pieejama šeit: RAA Consulting.

Lai pabeigtu aptauju atzīmējiet visus atbilstošos un spiediet pogu ">>".

- ❑ Vēlos saņemt pētījuma rezultātus (norādiet saņēmēja e-pasta adresi) (1) ____
- ❑ Vēlos saņemt bezmaksas 1.5h konsultāciju (norādiet kontaktinformāciju: e-pasts, tel. num. u.c.) (2) ____
- ❑ Vēlos piedalīties nākošajā pētījuma etapā (norādiet kontaktinformāciju: e-pasts, tel. num. u.c.) (3) ____
- ❑ ⊗Neviens no augstākminētajiem (4)

End of Block: Block 5

Appendix L. Questionnaire in English

ViA prod INTRA 20220117

Start of Block: Intro

Q1 This research is carried out in cooperation between Vidzeme University and RAA Consulting. The aim of the study is to develop a publicly available digital ecosystem assessment and recommendation tool (with a focus on complex analytics) so that any organization can ensure a digital transformation appropriate to the era, which will allow improving the performance of the organization in accordance with the strategic goals. Your answers are anonymous and should not take more than 15 minutes of your time. You can stop filling and resume it later from where you left off. As compensation for participating in the study, any participant gets a 1.5-hour free consultation on issues of digital ecosystem development that interest them. Study participants have the opportunity to apply to participate in the next phase of the study, which will include a detailed assessment of the organization's digital ecosystem, recommended next steps and an assessment of their costs.

Q53 Browser Meta Info
Browser (1)

Version (2)

Operating System (3)

Screen Resolution (4)

Flash Version (5)

Java Support (6)

User Agent (7)

End of Block: Intro

Start of Block: Demo Fiz/Jur

Q54 How would you describe your role in the organization?

□ Head of organization (CEO) (1)

□ Chief Financial Officer (CFO) (2)

□ IT director (CIO/CTO) (3)

□ Chief Data/Analytics (CDO/CAO) or equivalent role (4)

□ Director of Marketing (CMO) (5)

□ Sales Director (30)

□ Other directors level representatives (6)

□ Organization Board, Owner (7)

□ Head or deputy of structural units, departments, business units, department (8)

□ Senior expert, leading specialist (11)

□ Accountant, Financial Specialist or similar role (31)

□ Self-employed or representative of a farm (32)

□ Other (write) (13) ____

□ None of the above (33)

Page Break

Q2 **Age:**

____

Q3 **Gender:**

- Female (1)
- Male (2)

Page Break

Q4 Highest level of education obtained:

□ Basic education (7)

□ Professional education (6)

□ Secondary education (1)

□ College education (10)

□ Bachelor's degree (2)

□ Master's degree (3)

□ Doctoral degree (4)

□ Other (9)

Q7 Which educational institution/s did you graduate from? (List all completed institutions)

❑ □ LU (1)

❑ □ RTU (5)

❑ □ RSU (6)

❑ □ LLU (11)

❑ □ University of Business "Turība" (12)

❑ □ BA School of Business and Finance (9)

❑ □ Stockholm School of Economics (8)

❑ □ Other (type) (10)____

Page Break

Q13 In which sector does the organization you represent operate? (Check all that apply)

□ Agriculture, forestry and fisheries (1)

□ Mining and quarrying (6)

□ Manufacturing industry (7)

□ Electricity, gas supply, heat supply and air conditioning (8)

□ Water supply; wastewater, waste management and rehabilitation (9)

□ Construction (10)

□ Wholesale and retail trade; car and motorcycle repair (11)

□ Transport and storage (12)

□ Accommodation and catering services (13)

□ Information and communication services (14)

□ Financial and insurance activities (15)

□ Operations with real estate (16)

□ Professional, scientific and technical services (17)

□ Operation of administrative and service services (18)

□ State administration and defense; compulsory social insurance (19)

□ Education (20)

□ Health and social care (21)

□ Arts, entertainment and recreation (22)

□ Other services (23)

*

Q44 Write a specific main area of activity. (E.g. shop, bank, car service, hairdresser, school, cafe, carpentry services, etc.)____

Page Break

Q57 In which administrative territory is your organization located?

▼ Rīga (1) ... Ventspils novads (48)

Page Break

Q14 Is it an international organization?

☐ Yes (1)
☐ No (2)
☐ Don't know (3)

Q15 How many employees work in the organization?

	Number of employees					
	1-9 (1)	10-49 (2)	50-249 (3)	250-499 (4)	500+ (5)	No answer/Don't know (6)
Latvia (1)	❍	❍	❍	❍	❍	❍
Globally (6)	❍	❍	❍	❍	❍	❍

Q16 What is the organization's annual turnover (last known)?

	Annual turnover							
		0.5-1.99 milj. EUR (2)	2-5 milj. EUR (3)	6-10 milj. EUR (4)	11 - 20 milj. EUR (5)	20-49 milj. EUR (6)	50 + milj. EUR (7)	No answer/Don't know (8)
Latvia (1)	❍	❍	❍	❍	❍	❍	❍	❍
Globally (2)	❍	❍	❍	❍	❍	❍	❍	❍

Page Break

End of Block: Demo Fiz/Jur

Start of Block: Block A

Q58 What data collection and/or analytical reviews are prepared in your organization?

☐ Financial statements required by law (1)

☐ Organizational budget and its analysis (2)

☐ Summary and analysis of return/cost/targeting of marketing activities (3)

☐ Product/service sales summaries and analyses (4)

☐ Product/service production summaries and analyses (5)

☐ Collections and analyses of customer behaviour (6)

☐ Collections and analyses of human resource management data (7)

☐ Risk management data compilations and analyses (8)

☐ Other (Write) (10) ____

Q39 Which of the statements best matches the use of internal and external data (public databases, social network information, etc.) of the organization? Used are:

☐ Internal data only (1)

☐ Mostly internal data, some external (2)

☐ Internal and external data approximately equal (3)

☐ Mostly external data (4)

☐ External data only (5)

☐ No answer/Don't know (6)

Q40 What data sources do you use in your organization?

☐ Internal data of all types (1)

☐ Credit rating/Credit bureau information (2)

☐ Data from public/state databases (3)

☐ Social media data (4)

☐ Third Party Marketing Data (5)

☐ Geolocation data (6)

☐ Telecommunications (7)

☐ Emails (8)

 Web behaviour (digital footprint) (9)

 Other (write) (10) ____

 ⊗No answer/Don't know (11)

Q31 Which of the following statements best describes the organization regarding data management and quality?

 Poor - Poor data quality and management, making any analysis difficult. No functions/commands with a strict data focus. (1)

 Insufficient - Data can be used but are functionally or procedurally isolated. Data governance issues are rarely discussed at the management level of an organization. (2)

 Satisfactory - Key data areas are identified and data is centralized in a repository/storage. (3)

 Good - Integrated, accurate, master data is available in a centralized data warehouse. The data is under the control of IT. Few unique data sources. (4)

 Excellent – data is seen as a strategic asset, there is a separate team that manages the data. New data sources are constantly being identified and delivered to the business. (5)

 No answer/Don't know (6)

Q17 Which of the following statements best describes your organization's analytics community?

 No analysts at all (6)

 Uncoordinated analytical activities (1 or more analysts acting separately) (1)

 Local analytical teams that have started sharing tools, data and knowledge (2)

 A central analytical group, with partial coordination of analytical activities across the organization (3)

 A central analytical group that closely coordinates and develops analytical activities throughout the organization (4)

 Other (5)

Q18 Who is most often the project initiator for data and analytical activities in the organization?

☐ Mostly the head of the organization (1)

☐ Predominantly someone from Top Management (Director level, including Head of Organization) (2)

☐ Mostly a Head of Department (3)

☐ There are no initiatives whose projects are initiated by senior management (4)

☐ No answer/ Don't know (5)

Page Break

Q19 To what extent are the following statements true for the organization? Rate on a scale of 1-5, where 1 - completely disagree and 5 - completely agree.

	1 - completely disagree (1)	2 (2)	3 (3)	4 (4)	5 - completely agree (5)
Creation of organizational strategy is based on data and predictive analytics (1)	❍	❍	❍	❍	❍
The organization has a long-term Analytics development strategy (2)	❍	❍	❍	❍	❍
Developing analytics is an organizational strategy for increasing competitiveness (3)	❍	❍	❍	❍	❍
The analytical process throughout the organization is orderly, clearly defined and transparent (4)	❍	❍	❍	❍	❍
Analytics is used in most of the organization's operational and decision-making processes (5)	❍	❍	❍	❍	❍

Page Break

Q20 To what extent do the following statements apply to the organization? Rate on a scale of 1-5, where 1 - completely disagree and 5 - completely agree.

	1 - completely disagree (1)	2 (2)	3 (3)	4 (4)	5 - completely agree (5)
All types of analytical tools/platforms/software (descriptive/predictive, structured/unstructured and historical/real-time data, visualization) are widely and uniformly used in the organization's daily operations and decision-making processes (1)	❍	❍	❍	❍	❍
The organization's data processing process is carried out efficiently (2)	❍	❍	❍	❍	❍

Page Break

Q42 Which of the following statements best describes technologies to support analytics in an organization?

☐ Undeveloped, spreadsheet-based (Excel) and basic reporting tools (1)

☐ Basically reporting tools with limited predictive analytics tools (2)

☐ Reporting and predictive analytics tools are widely available in the organization (3)

☐ Reporting and predictive analytics tools are widely available across the organization, plus tools to analyse unstructured data (4)

☐ Reporting and predictive analytics tools are widely available in the organization, plus tools to analyse unstructured data (no database structure) with prescriptive triggers/alerts (5)

☐ No answer/Don't know (6)

Q26 Which of the listed tools/solutions are used in your organization for data processing and analytics? (Check all that apply)

□ MS Excel (4)

□ SQL (6)

□ R (1)

□ Python (7)

□ SAS (3)

□ SPSS (2)

□ MS Power BI (24)

□ Tableau (8)

□ MATLAB (11)

□ KNIME (12)

□ Alteryx (40)

□ RapidMiner (13)

□ Microsoft SQL Server (14)

□ Qlik (20)

□ WPS (43)

□ SAP Business Objects (28)

□ Teradata (33)

□ H2O (45)

□ TensorFlow (46)

□ Torch (47)

□ Hive (37)

□ Café (44)

□ Other (write in) (41) ____

Q21 How would you characterize the analytical development in the organization from the point of view of applied analytical solutions/methods? Are simple, basic descriptive analytical methods (descriptive analytics) used, or are in-depth, event and behaviour predicting and action recommending analytical methods (predictions, prescriptions analytics) used? Rate on a scale of 1-5, where 1 - simple methods, 5 - advanced analytical methods.

□ 1 - simple analytical methods (basic analytics) (1)

□ 2 (2)

□ 3 (3)

□ 4 (4)

□ 5 - advanced analytical methods (advanced analytics) (5)

□ Don't know (6)

Q23 How many (%) of analytical activities known to you/under your responsibility (data collections, analyses, reviews, reports, monitoring, etc.) are repeated or renewed at the following frequency?

1 time a year : ________ (1)

1 time per month : ________ (2)

1 time a week : ________ (3)

1 time a day : ________ (4)

Every few hours : ________ (5)

1 time per hour : ________ (6)

Reflected in real time : ________ (7)

Total : ________

Q27 Does the organization have a separate function/team/people working on research and development to support/ensure the development of analytics and testing and implementation of innovative solutions?

□ Yes (1)

□ No (2)

□ Don't know (3)

Page Break

Q28 Is there a specific person responsible for the following activities in the organization?

	Yes (1)	No, but there is an intention to appoint (2)	No and not planned (3)	Don't know (4)
General responsibility for data in the organization (1)	❍	❍	❍	❍
Data privacy (2)	❍	❍	❍	❍
Data security (3)	❍	❍	❍	❍
Data integration and management (4)	❍	❍	❍	❍
Data management (5)	❍	❍	❍	❍
Analytics and Insights (6)	❍	❍	❍	❍

Page Break

Q29 What policies related to data management are already in place in the organization?

	Yes (1)	No (2)	In development (3)	Don't know (4)
Data privacy policy (1)	❍	❍	❍	❍
Data security policy (2)	❍	❍	❍	❍
Social media use policy in the organization (3)	❍	❍	❍	❍
Policies that limit the risk of cybercrime in the organization (4)	❍	❍	❍	❍
Data access policy (5)	❍	❍	❍	❍
Policies Governing Data Collection, Maintenance, Use, Distribution and Archiving (6)	❍	❍	❍	❍
Policies governing use of employee devices (7)	❍	❍	❍	❍
Data accounting policy (8)	❍	❍	❍	❍

Page Break

Q30 How would you assess how much attention is paid to data quality in the organization? Rate on a scale of 1-5, where 1 - does not pay attention at all, 5 - will pay attention very much.

□ 1 - not addressed at all (1)

□ 2 (2)

□ 3 (3)

□ 4 (4)

□ 5 - very attentive (5)

□ Don't know (6)

Q32 Which of the statements best describes the organization regarding the use of 'big data'?

□ No need for 'big data' (1)

□ Currently there are no plans for 'big data' (2)

□ There is interest in 'big data', but no investments have been made yet and there is no plan to implement it (3)

□ Research is being done (4)

□ Plans to implement/start big data-related projects (5)

□ Active/ongoing pilot projects (6)

□ Implementation of big data solutions is currently underway (7)

□ Everything is implemented and secured to use/analyse 'big data' (8)

□ No answer/Don't know (9)

Page Break

Q34 To what extent are the following statements true for the organization? Rate on a scale of 1-5, where 1 - completely disagree and 5 - completely agree.

	1 - completely disagree (1)	2 (2)	3 (3)	4 (4)	5 - completely agree (5)
The organization has sufficient analytical human resources to perform the requested analytical activities (1)	❍	❍	❍	❍	❍
Existing analytical resources include appropriate knowledge/experience to apply more sophisticated analytical methods (2)	❍	❍	❍	❍	❍
The organization supports the acquisition and development of the necessary knowledge (training, conferences, support for testing new analytical techniques and solutions) (3)	❍	❍	❍	❍	❍
All analytical functions of the organization work well together (4)	❍	❍	❍	❍	❍

Page Break

Q35 Who is primarily responsible for the development of data and analytics in an organization?

□ Head of organization (CEO) (1)

□ Chief Financial Officer (CFO) (2)

□ Chief Risk Officer (CRO) (16)

□ IT director (CIO/CTO) (3)

□ Chief Data/Analytics (CDO/CAO) or equivalent role (4)

□ Director of Marketing (CMO) (5)

□ Sales Director (30)

□ Production Director (31)

□ Other directors level representatives (6)

□ Organization Board (7)

□ Head of business unit or department (8)

□ Various appointed data managers (9)

□ DWH or BI teams (10)

□ Team of Data Architects (11)

□ Individual departments (12)

□ Other (write) (13) ____

□ There is no one specific person responsible (14)

□ Don't know (15)

Page Break

Q38 To what extent are the following statements true for the organization? Rate on a scale of 1-5, where 1 - completely disagree and 5 - completely agree.

	1 - completely disagree (1)	2 (2)	3 (3)	4 (4)	5 - completely agree (5)
Data/information in an organization is considered an asset/value of the organization (1)	❍	❍	❍	❍	❍
Analytical reasoning takes precedence over managerial experience when dealing with important business issues (2)	❍	❍	❍	❍	❍
The organization invests in analytical technologies, recruiting and training analytical talent (3)	❍	❍	❍	❍	❍
It is important for an organization to increase its use of analytics to make better decisions (4)	❍	❍	❍	❍	❍

Page Break

Q37 To what extent do you agree with the statement that IT and Business work together to define what data is needed and should be retained, and that retention and access requirements are regularly reviewed and renewed? Rate on a scale of 1-5, where 1 - completely disagree and 5 - completely agree.

☐ 1 - completely disagree (1)

☐ 2 (2)

☐ 3 (3)

☐ 4 (4)

☐ 5 - completely agree (5)

☐ Don't know (6)

Page Break

Q45 To what extent are the following statements true for the organization? Rate on a scale of 1-5, where 1 - completely disagree and 5 - completely agree.

	1 - completely disagree (1)	2 (2)	3 (3)	4 (4)	5 - completely agree (5)
Existing technologies and systems are appropriate for the needs of the organization (1)	❍	❍	❍	❍	❍
An organizational data management structure has been established (2)	❍	❍	❍	❍	❍

Page Break

Q56 How would you describe the balance between intuition/assumptions and the use of data-based analytics in an organization in solving the following questions? Rate on a scale of 1-5, where 1 is intuition and 5 is analytics.

	1 - intuition (1)	2 (2)	3 (3)	4 (4)	5 - analytics (5)
Cost reduction (1)	❍	❍	❍	❍	❍
Financial forecasting (2)	❍	❍	❍	❍	❍
Optimizing daily operational processes (3)	❍	❍	❍	❍	❍
In identifying the target market (4)	❍	❍	❍	❍	❍
Creating Pricing Modes (5)	❍	❍	❍	❍	❍
Setting the organization's strategic goals (6)	❍	❍	❍	❍	❍
Employee performance evaluation (7)	❍	❍	❍	❍	❍
Real-time decision making (8)	❍	❍	❍	❍	❍
Creation of risk assessment models (9)	❍	❍	❍	❍	❍
Defining a marketing campaign (10)	❍	❍	❍	❍	❍
Introducing/developing new products and services (11)	❍	❍	❍	❍	❍

End of Block: Block A

Start of Block: Block - Issues

Q46 What are the main problems/obstacles that hinder the application/implementation/development of more advanced analytical approaches and solutions in the company? (Tick at least 3 most important)

□ Data security (1)

□ Data privacy (2)

□ Data quality (3)

□ Data availability/access (4)

□ Availability of appropriate analytical tools (5)

□ Obtaining business requirements (6)

□ Insufficient support from the top management of the organization (7)

□ It is not clear whether the investment will pay off (8)

□ No known best practice (9)

□ No adequate technical knowledge (10)

□ Not sure how to use the results (11)

□ Difficulties with unstructured data availability (12)

□ Existing database systems/software/solutions are unable to quickly process/deliver large and/or unstructured data in a user-friendly manner (13)

□ Inability to explain the results of complex analytical solutions in a language understandable to business users (14)

□ Inability to manipulate and integrate different data (15)

□ Insufficient number of analytical people and/or insufficient knowledge/experience (16)

□ Difficulty showing/evaluating the impact on business results in a monetary way (ROI, business case) (17)

□ Difficulty attracting and retaining analytical talent (18)

□ Structure/organization of analytical functions of the organization (19)

□ Difficulty in finding optimal analytical tools (20)

□ Position of supervisory authorities regarding data and application of analytical methods (21)

□ Costs/investments related to development and implementation (infrastructure, tools, people) (22)

□ Lack of centralized/unified data warehouse (DWH, Data lake)/ fragmented data sources (23)

□ Difficulties in collecting and analysing 'big data' (24)

□ Difficulty implementing automatic analytical solutions/models in production (25)

□ Other (write in) (26) ____

□ ⊗No obstacles (27)

End of Block: Block - Issues

Start of Block: Block - Solutions/Recommendations

Q51 What steps should be taken in order for analytical initiatives to be successful and for the organization to invest in the full development of the analytical function? (Tick at least 3 most important)

□ Building a team with the right expertise (1)

□ Centralization of analytics and/or creation of an Centre of Excellence that drives the entire analytics function in the organization (2)

□ Decentralization of analytics (3)

□ Creating an analytics development strategy (4)

□ Linking analytical results with the implementation of decision-making processes (5)

□ An organizational culture/perception that data/information is an essential asset should be promoted (6)

□ Selection of the most appropriate technologies/software (7)

□ Effective access to internal data must be ensured (8)

□ Effective access to external data must be ensured (9)

□ Active support of top management must be achieved (10)

□ Active cooperation of analytical specialists with business representatives should be encouraged (11)

□ Propose small real-life projects that demonstrate potential added value to business results (12)

□ Must demonstrate tangible business benefits from analytical initiative, organizational performance optimization and financial benefits (13)

□ Must clearly demonstrate how analytics improves competitiveness (14)

□ Choosing the right data-driven initiatives (15)

□ Must provide knowledge and patience in data integration (16)

□ Greater use of analytics in marketing and customer interaction issues should be ensured (17)

□ Potential value creation opportunities and risks must be identified (18)

□ Internal capacity should be created to create a 'data-driven' organization (19)

□ Policies related to data security, privacy, quality should be implemented (20)

□ Human capacity in 'big data' analytics must be ensured (21)

□ Incentive programs should be implemented to encourage sharing of data to improve the overall result (22)

□ Policies need to be developed that balance the organization's desire to use data and add value to the organization and customers' desire for security and privacy (23)

□ Technological barriers should be resolved and research and development issues should be accelerated in the target areas (24)

□ Investments in information technology infrastructure must be ensured (25)

□ Other (write in) (26) ____

□ ⊗No answer/Don't know (27)

End of Block: Block - Solutions/Recommendations

Start of Block: Block 5

Q52 What are the biggest benefits to the organization from various analytics initiatives? (Tick at least 3 most important)

□ Increasing competitiveness (1)

□ Reduced costs (2)

□ New business opportunities (3)

□ Smarter/better decision making (4)

□ Increased income/turnover from existing customers/products (5)

□ New, additional customers (6)

□ Increased market share (7)

□ Improved daily processes (8)

□ Increased customer satisfaction (9)

□ Deeper understanding of the market and competitors (10)

□ Risk and fraud reduction (11)

□ Automated 'real-time' decision-making processes (12)

□ Customer segmentation (13)

□ Deeper and more accurate understanding of business (14)

□ Better planning and forecasting (15)

□ Better empowerment from key strategic initiatives (16)

□ Better relations with customers and cooperation partners (17)

□ Better risk assessment and ability to respond to changes in the economic environment (18)

□ Better financial performance of the organization (19)

□ Better ability to respond to market changes (20)

□ Creating new products or services that increase the revenue stream (21)

□ Other (write in) (22) ____

□ ⊗No answer/Don't know (23)

Page Break

Q53 How long does it take for an organization to see a return on investment (tools, people, platforms, data sources, etc.) in data mining/access/analytics?

□ <= 6 months (1)

□ 7-12 months (2)

□ 13-18 months (3)

□ 19 -24 months (4)

□ 24+ months (5)

□ No positive return (6)

□ Don't know (7)

Q54 How would you characterize the organization's investments in data acquisition/access provision/analytics?

□ Increases (1)

□ Stay the same (2)

□ Decreases (3)

□ Don't know (4)

Q55 In which areas related to data acquisition/access provision/analytics does the organization invest the most?

☐ People (1)

☐ Tools/Platforms (2)

☐ Training (3)

☐ Data sources (4)

☐ Data privacy (5)

☐ Data management (6)

☐ Other (write) (7) ____

☐ ⊗ Does not invest anywhere (8)

Q43 Thank you very much for your answers and your time!

If you would like to contact the author of the study and a representative of RAA Consulting, contact information is available here: RAA Consulting.

To complete the survey, mark all that apply and press the ">>" button.

☐ I would like to receive the results of the study (indicate the recipient's e-mail address) (1) ____

☐ I would like to receive a free 1.5-hour consultation (specify contact information: e-mail, phone number, etc.) (2) ____

☐ I want to participate in the next stage of the research (indicate contact information: e-mail, phone number, etc.) (3) ____

☐ ⊗None of the above (4)

End of Block: Block 5

Appendix M. Analytics Maturity Assessment – Domain, Factor, Statement

Domain	Factor	Question	Statement	Mean	STD	VAR
Organization	Strategy	Q19_1	Organization's strategy is based on data and predictive analytics	3.17	1.21	1.46
		Q19_2	Organization has long term strategy of analytics development	3.07	1.27	1.62
		Q19_3	Development of analytics is organization's strategy to increase competitive advantage	3.19	1.22	1.48
	Process	Q19_4	Analytical processes are structured, well defined and transparent overall organization	3.03	1.23	1.52
		Q19_5	Analytics is used in most of the company's activities and decision-making processes	3.17	1.18	1.4
People	Analysts	Q34_1	Company has enough analytical human resources to carry out the required analytical performance	2.92	1.28	1.65
		Q34_2	Existing analytical resources own adequate knowledge / experience to apply more sophisticated analytical methods	2.87	1.26	1.60
		Q34_3	Company supports the development of skills and experience	3.01	1.27	1.62
		Q34_4	All analytical functions cooperate well across the company	2.91	1.19	1.42
Culture	Culture	Q38_1	Data/information is strategic asset of organization	3.26	1.29	1.66
		Q38_2	Analytical reasoning prevails over management experience in the face of important business issues	2.87	1.16	1.34
		Q38_3	Company invests in analytical technology, attraction of analytical talents and training	2.78	1.24	1.55
		Q38_4	Company's priority is to strengthen the use of analytics to make better decisions	3.1	1.22	1.48
Analytics	Process	Q20_1	All kinds of analytical tools / platforms / software (descriptive / for predictions, structured / unstructured and historical / 'real-time' data visualization) is widely and uniformly used in the company's daily operations and decision-making	3.03	1.16	1.35

			processes			
		Q20_2	Data mining/processing process is effective	3.15	1.16	1.34
	Usage - Balance between Intuition and Analytics	Q56_1	Cost reduction	3.38	1.13	1.27
		Q56_2	Financial Forecasting	3.46	1.12	1.25
		Q56_3	Daily business processes optimization	3.26	1.09	1.18
		Q56_4	Target market identification	3.21	1.12	1.25
		Q56_5	Pricing models	3.27	1.07	1.15
		Q56_6	Marking the company's strategic objectives	3.31	1.1	1.22
		Q56_7	Employee Performance Assessment	3.22	1.15	1.32
		Q56_8	Real-time decision-making	3.14	1.14	1.29
		Q56_9	Risk assessment models	3.25	1.13	1.27
		Q56_10	Defining marketing campaigns	3.1	1.1	1.2
		Q56_11	Introducing / developing new products and services	3.17	1.11	1.24
Data	Governance	Q28	Appointed person for specific governance activities	3.70		
		Q29	Data related policies introduced at organization	3.83		
	Quality	Q30	Management attention to data quality	3.46	1.17	1.38
		Q31	Data quality across organization	3.30		
	Sources	Q37	IT works together with business to define and improve data storage and data dictionary	3.68	1.14	1.3
		Q39	Internal and external data usage	3.95		
Technology	Big data	Q32	'Big data' usage at organization	2.02		
	IT Infrastructure	Q42	Tools for analytics/ Analytical platform	2.41		
		Q45_1	Technologies and systems are appropriate for organization needs	3.34	1.14	1.29
		Q45_2	Established organizational data management system	3.03	1.23	1.51

Appendix N. Data set

Data available on request from the author (santa.lemsa@va.lv).

Data set: data_answers_ENG.xlsx

Appendix O. R code – data transformation, descriptive statistics

Data available on request from the author (santa.lemsa@va.lv).

Code: Descriptive_stats.R

Appendix P. R code – data transformation, correlation analysis and modelling

Data available on request from the author (santa.lemsa@va.lv).

Code: Analysis_version2_AVG_values.R

Appendix Q. Descriptive statistics – Total

Size	**N = 555**[1]
Large	153 (28%)
Medium	125 (23%)
Micro	157 (28%)
No answer/Don't know	28 (5.0%)
Small	92 (17%)

[1]2022 Survey data

Industry	**N = 555**[1]
A Agriculture, forestry and fishing	41 (7.4%)
B-E Production	58 (10%)
F Construction	51 (9.2%)
G Wholesale and retail trade, repair of motor vehicles and motorcycles	41 (7.4%)
H-J,L-N, P-R, S Services	286 (52%)
K Finance	21 (3.8%)
O Public administration and defence, compulsory social security	57 (10%)

[1]2022 Survey data

Region	**N = 555**[1]
Kurzeme	51 (9.2%)
Latgale	53 (9.5%)
Riga	306 (55%)
Riga - surroundings	49 (8.8%)
Vidzeme	58 (10%)
Zemgale	38 (6.8%)

[1]2022 Survey data

Q54_1	**N = 555**[1]
Accountant, Finance Specialist or similar role	55 (9.9%)
Board of the organization	3 (0.5%)
Board of the organization, Owner	40 (7.2%)
Chief Data/Analytics (CDO/CAO) or equivalent role	2 (0.4%)
Chief Executive Officer (CEO)	48 (8.6%)
Chief Financial Officer (CFO)	15 (2.7%)
Chief Information / Technical officer (CIO/CTO)	8 (1.4%)
Chief Marketing Officer (CMO)	4 (0.7%)
Head of a business unit or department	83 (15%)
Other	27 (4.9%)
Other Directors level representatives	28 (5.0%)
Sales director	22 (4.0%)
Self-employed or a representative of a farm	49 (8.8%)
Senior expert, leading specialist	171 (31%)

[1]2022 Survey data

Q2	**N = 555**[1]
<30	22 (4.0%)
>=50	196 (35%)
30-34	86 (15%)
35-39	85 (15%)
40-44	80 (14%)
45-49	86 (15%)

[1]2022 Survey data

Q3	**N = 555**[1]
Men	229 (41%)
Women	326 (59%)

[1]2022 Survey data

Q4	**N = 555**[1]
Bachelor`s Degree	177 (32%)
Basic education	12 (2.2%)
College education	47 (8.5%)
Master`s Degree	186 (34%)
Other	4 (0.7%)
PhD	16 (2.9%)
Professional education	48 (8.6%)
Secondary education	65 (12%)

[1]2022 Survey data

Q7 - Multiple Choice Question	**N = 621**[1]
BA School of business and finance	13 (2.1%)
LLU	48 (7.7%)
LU	157 (25%)
Other	225 (36%)
RSU	24 (3.9%)
RTU	115 (19%)
Stockholm School of Economics in Riga	9 (1.4%)
Turiba University	30 (4.8%)

[1]2022 Survey data

Q14	**N = 555**[1]
I don`t know	27 (4.9%)
No	382 (69%)
Yes	145 (26%)
Unknown	1

[1]2022 Survey data

Q15#1_1	**N = 555**[1]
1-9	156 (28%)
10-49	89 (16%)
250-499	49 (8.9%)
50-249	123 (22%)
500+	103 (19%)
No answer/Don't know	28 (5.1%)
Unknown	7

[1]2022 Survey data

Q15#1_2	**N = 555**[1]
1-9	13 (10%)
10-49	14 (11%)
250-499	7 (5.5%)
50-249	17 (13%)
500+	53 (41%)
No answer/Don't know	24 (19%)
Unknown	427

[1]2022 Survey data

Q16#1_1	**N = 555**[1]
<0.5 milj. EUR	123 (23%)
0.5-1.99 milj. EUR	62 (12%)
11 - 20 milj. EUR	11 (2.1%)
2-5 milj. EUR	46 (8.6%)
20-49 milj. EUR	20 (3.7%)
50 + milj. EUR	31 (5.8%)
6-10 milj. EUR	28 (5.2%)
No answer/Don't know	215 (40%)
Unknown	19

[1]2022 Survey data

Q58 - Multiple Choice Question	**N = 1,528**[1]
Aggregations and analyses of customer behaviour	141 (9.2%)
Collections and analyses of human resource management data	127 (8.3%)
Financial statements required by law	357 (23%)
Organizational budget and its analysis	265 (17%)
Other	57 (3.7%)
Product/service production summaries and analyses	337 (22%)
Risk management data compilations and analyses	128 (8.4%)
Summary and analysis of return/cost/targeting of marketing activities	114 (7.5%)
Unknown	2

[1]2022 Survey data

Q39	**N = 555**[1]
External data only	7 (1.3%)
Internal and external data approximately the same	164 (30%)
Internal data only	117 (21%)
Mostly external data	24 (4.3%)
Mostly internal data, some external	143 (26%)
No answer/Don't know	100 (18%)

[1]2022 Survey data

Q40 - Multiple Choice Question	**N = 1,232**[1]
Credit rating/credit bureau information	54 (4.4%)
Data from public/government databases	209 (17%)
Emails	214 (17%)
Geographic location data	56 (4.5%)
Internal data of all types	321 (26%)
No answer/Don't know	73 (5.9%)
Other	7 (0.6%)
Social media data	115 (9.3%)
Telecommunications	104 (8.4%)
Third Party Marketing Data	46 (3.7%)
Web behaviour (digital footprint)	33 (2.7%)

[1]2022 Survey data

Q31	**N = 555**[1]
Excellent - data is seen as a strategic asset, there is a separate team that manages the data. New data sources are constantly being identified and delivered to the business.	50 (9.0%)
Good - Integrated, accurate, master data is available in a centralized data warehouse. The data is under the control of IT. Few unique data sources.	144 (26%)
Insufficient - Data can be used but are functionally or procedurally isolated. Data governance issues are rarely discussed at the management level of an organization.	77 (14%)
No answer/Don't know	113 (20%)
Poor - Poor data quality and management, making any analysis difficult. No functions/commands with a strict data focus.	17 (3.1%)
Satisfactory - Key data areas are identified and data is centralized in a repository/storage.	154 (28%)

[1]2022 Survey data

Q17	**N = 555**[1]
A central analytical group that closely coordinates and develops analytical activities across the organization	72 (13%)
A central analytical group, with partial coordination of analytical activities across the organization	65 (12%)
Local analytics teams that have started sharing tools, data and knowledge	80 (14%)
No analysts at all	199 (36%)
Other	62 (11%)
Uncoordinated analytical activities (1 or more analysts acting separately)	77 (14%)

[1]2022 Survey data

Q18	N = 555[1]
Mostly a Head of Department	86 (15%)
Mostly someone from Senior Management (director level, including the head of the organization)	135 (24%)
Mostly the head of the organization	167 (30%)
No answer/ Don't know	135 (24%)
There are no initiatives whose projects are initiated by senior management	32 (5.8%)

[1]2022 Survey data

Q19_1	N = 555[1]
1	65 (12%)
2	79 (14%)
3	198 (36%)
4	122 (22%)
5	91 (16%)

[1]2022 Survey data

Summary Statistics for Q19_1

Min	Max	Mean	SD	Variance	Count
1	5	3.171171	1.208229	1.459817	555

Q19_2	**N = 555**[1]
1	86 (15%)
2	82 (15%)
3	186 (34%)
4	110 (20%)
5	91 (16%)

[1]2022 Survey data

Summary Statistics for Q19_2

Min	Max	Mean	SD	Variance	Count
1	5	3.068468	1.272734	1.619852	555

Q19_3	**N = 555**[1]
1	68 (12%)
2	69 (12%)
3	199 (36%)
4	125 (23%)
5	94 (17%)

[1]2022 Survey data

Summary Statistics for Q19_3

Min	Max	Mean	SD	Variance	Count
1	5	3.194595	1.217341	1.48192	555

Q19_4	**N = 555**[1]
1	78 (14%)
2	101 (18%)
3	181 (33%)
4	116 (21%)
5	79 (14%)

[1]2022 Survey data

Summary Statistics for Q19_4

Min	Max	Mean	SD	Variance	Count
1	5	3.030631	1.234638	1.524331	555

Q19_5	**N = 555**[1]
1	60 (11%)
2	82 (15%)
3	206 (37%)
4	120 (22%)
5	87 (16%)

[1]2022 Survey data

Summary Statistics for Q19_5

Min	Max	Mean	SD	Variance	Count
1	5	3.165766	1.182567	1.398465	555

Q20_1	**N = 555**[1]
1	69 (12%)
2	95 (17%)
3	208 (37%)
4	118 (21%)
5	65 (12%)

[1]2022 Survey data

Summary Statistics for Q20_1

Min	Max	Mean	SD	Variance	Count
1	5	3.027027	1.162434	1.351254	555

Q20_2	**N = 555**[1]
1	58 (10%)
2	85 (15%)
3	200 (36%)
4	137 (25%)
5	75 (14%)

[1]2022 Survey data

Summary Statistics for Q20_2

Min	Max	Mean	SD	Variance	Count
1	5	3.154955	1.156268	1.336956	555

Q42	**N = 555**[1]
Basic reporting tools with limited predictive analytics tools	101 (18%)
No answer/Don't know	152 (27%)
Reporting and predictive analytics tools are widely available across the organization	84 (15%)
Reporting and predictive analytics tools are widely available across the organization, plus tools to analyse unstructured data	56 (10%)
Reporting and predictive analytics tools are widely available across the organization, plus tools to analyse unstructured data (no database structure) with prescriptive triggers/alerts	33 (5.9%)
Undeveloped, spreadsheet-based (Excel) and basic reporting tools	129 (23%)

[1]2022 Survey data

Q26 - Multiple Choice Question	**N = 931**[1]
Alteryx	1 (0.1%)
Caffe	14 (1.5%)
H2O	6 (0.6%)
Hive	4 (0.4%)
KNIME	4 (0.4%)
MATLAB	9 (1.0%)
Microsoft SQL Server	97 (10%)
MS Excel	441 (47%)
MS Power BI	58 (6.2%)
Other	74 (7.9%)
Python	28 (3.0%)
Qlik	16 (1.7%)
R	10 (1.1%)
RapidMiner	3 (0.3%)
SAP Business Objects	36 (3.9%)
SAS	11 (1.2%)
SPSS	12 (1.3%)
SQL	56 (6.0%)
Tableau	11 (1.2%)
TensorFlow	4 (0.4%)
Teradata	8 (0.9%)
Torch	5 (0.5%)
WPS	23 (2.5%)

[1]2022 Survey data

Q21*Target*var	**N = 555**[1]
1	164 (30%)
2	68 (12%)
3	91 (16%)
4	73 (13%)
5	37 (6.7%)
No answer/Don't know	122 (22%)

[1]2022 Survey data

Q23_1	**N = 555**[1]
0%	138 (25%)
1-24%	156 (28%)
25-49%	261 (47%)

[1]2022 Survey data

Q23_2	**N = 555**[1]
0%	199 (36%)
1-24%	167 (30%)
100%	38 (6.8%)
25-49%	72 (13%)
50-74%	55 (9.9%)
75-99%	24 (4.3%)

[1]2022 Survey data

Q23_3	**N = 555**[1]
0%	301 (54%)
1-24%	194 (35%)
100%	10 (1.8%)
25-49%	30 (5.4%)
50-74%	17 (3.1%)
75-99%	3 (0.5%)

[1]2022 Survey data

Q23_4	**N = 555**[1]
0%	332 (60%)
1-24%	157 (28%)
100%	16 (2.9%)
25-49%	22 (4.0%)
50-74%	21 (3.8%)
75-99%	7 (1.3%)

[1]2022 Survey data

Q23_5	**N = 555**[1]
0%	412 (74%)
1-24%	125 (23%)
100%	5 (0.9%)
25-49%	7 (1.3%)
50-74%	2 (0.4%)
75-99%	4 (0.7%)

[1]2022 Survey data

Q23_6	**N = 555**[1]
0%	434 (78%)
1-24%	118 (21%)
25-49%	3 (0.5%)

[1]2022 Survey data

Q23_7	**N = 555**[1]
0%	383 (69%)
1-24%	111 (20%)
100%	26 (4.7%)
25-49%	22 (4.0%)
50-74%	8 (1.4%)
75-99%	5 (0.9%)

[1]2022 Survey data

Q27	**N = 555**[1]
I do not know	106 (19%)
No	262 (47%)
Yes	187 (34%)

[1]2022 Survey data

Q28_1	**N = 555**[1]
I do not know	87 (16%)
No, but there is an intention to appoint	71 (13%)
Not and not planned	118 (21%)
Yes	279 (50%)

[1]2022 Survey data

Q28_2	**N = 555**[1]
I do not know	69 (12%)
No, but there is an intention to appoint	61 (11%)
Not and not planned	107 (19%)
Yes	318 (57%)

[1]2022 Survey data

Q28_3	**N = 555**[1]
I do not know	70 (13%)
No, but there is an intention to appoint	50 (9.0%)
Not and not planned	94 (17%)
Yes	341 (61%)

[1]2022 Survey data

Q28_4	**N = 555**[1]
I do not know	106 (19%)
No, but there is an intention to appoint	71 (13%)
Not and not planned	137 (25%)
Yes	241 (43%)

[1]2022 Survey data

Q28_5	**N = 555**[1]
I do not know	94 (17%)
No, but there is an intention to appoint	62 (11%)
Not and not planned	120 (22%)
Yes	279 (50%)

[1]2022 Survey data

Q28_6	**N = 555**[1]
I do not know	122 (22%)
No, but there is an intention to appoint	66 (12%)
Not and not planned	140 (25%)
Yes	227 (41%)

[1]2022 Survey data

Q29_1	**N = 555**[1]
Don’t have	72 (13%)
Have	347 (63%)
I do not know	81 (15%)
In the development process	48 (8.8%)
Unknown	7

[1]2022 Survey data

Q29_2	**N = 555**[1]
Don’t have	70 (13%)
Have	351 (64%)
I do not know	79 (14%)
In the development process	48 (8.8%)
Unknown	7

[1]2022 Survey data

Q29_3	**N = 555**[1]
Don’t have	143 (26%)
Have	213 (39%)
I do not know	122 (22%)
In the development process	70 (13%)
Unknown	7

[1]2022 Survey data

Q29_4	**N = 555**[1]
Don’t have	138 (25%)
Have	216 (39%)
I do not know	141 (26%)
In the development process	54 (9.8%)
Unknown	6

[1]2022 Survey data

Q29_5	**N = 555**[1]
Don’t have	93 (17%)
Have	284 (52%)
I do not know	115 (21%)
In the development process	52 (9.6%)
Unknown	11

[1]2022 Survey data

Q29_6	**N = 555**[1]
Don’t have	90 (16%)
Have	296 (54%)
I do not know	106 (19%)
In the development process	54 (9.9%)
Unknown	9

[1]2022 Survey data

Q29_7	**N = 555**[1]
Don’t have	93 (17%)
Have	273 (50%)
I do not know	118 (22%)
In the development process	60 (11%)
Unknown	11

[1]2022 Survey data

Q29_8	**N = 555**[1]
Don’t have	85 (16%)
Have	251 (47%)
I do not know	136 (25%)
In the development process	66 (12%)
Unknown	17

[1]2022 Survey data

Q30	**N = 555**[1]
0	66 (12%)
1	39 (7.0%)
2	50 (9.0%)
3	157 (28%)
4	134 (24%)
5	109 (20%)

[1]2022 Survey data

Summary Statistics for Q30

Min	Max	Mean	SD	Variance	Count

Min	Max	Mean	SD	Variance	Count
1	5	3.458078	1.174691	1.379899	489

Q32	**N = 555**[1]
Active/ongoing pilot projects	20 (3.6%)
Currently, the implementation of 'big data' solutions is in the process	11 (2.0%)
Everything is implemented and secured to use/analyse 'big data'	14 (2.5%)
No answer/Don't know	223 (40%)
No need for 'big data'	103 (19%)
Plans to implement/start projects related to 'big data'	13 (2.3%)
Research is underway	66 (12%)
There are currently no plans for 'big data'	75 (14%)
There is interest in 'big data', but no investments have been made and there is no plan to implement it	30 (5.4%)

[1]2022 Survey data

Q34_1	**N = 555**[1]
1	105 (19%)
2	93 (17%)
3	171 (31%)
4	114 (21%)
5	72 (13%)

[1]2022 Survey data

Summary Statistics for Q34_1

Min	Max	Mean	SD	Variance	Count
1	5	2.918919	1.282591	1.645039	555

Q34_2	**N = 555**[1]
1	105 (19%)
2	100 (18%)
3	184 (33%)
4	96 (17%)
5	70 (13%)

[1]2022 Survey data

Summary Statistics for Q34_2

Min	Max	Mean	SD	Variance	Count
1	5	2.866667	1.264721	1.599519	555

Q34_3	**N = 555**[1]
1	91 (16%)
2	94 (17%)
3	165 (30%)
4	126 (23%)
5	79 (14%)

[1]2022 Survey data

Summary Statistics for Q34_3

Min	Max	Mean	SD	Variance	Count
1	5	3.014414	1.274496	1.624341	555

Q34_4	**N = 555**[1]
1	82 (15%)
2	112 (20%)
3	200 (36%)
4	97 (17%)
5	64 (12%)

[1]2022 Survey data

Summary Statistics for Q34_4

Min	Max	Mean	SD	Variance	Count
1	5	2.908108	1.192874	1.422949	555

Q35	**N = 555**[1]
Board of the organization	68 (12%)
Chief Data/Analytics officer (CDO/CAO) or equivalent role	22 (4.0%)
Chief Executive Officer (CEO)	126 (23%)
Chief Financial Officer (CFO)	19 (3.4%)
Chief Information / Technology officer (CIO/CTO)	35 (6.3%)
Chief Marketing Officer (CMO)	3 (0.5%)
Chief Risk Officer (CRO)	6 (1.1%)
Data Architect Team	5 (0.9%)
DWH or BI teams	5 (0.9%)
Head of a business unit or department	19 (3.4%)
I do not know	95 (17%)
Individual departments	24 (4.3%)
Other	12 (2.2%)
Other Directors level representatives	8 (1.4%)
Production director	6 (1.1%)
Sales director	7 (1.3%)
There is no one specific person responsible	50 (9.0%)
Various appointed data managers	45 (8.1%)

[1]2022 Survey data

Q38_1	**N = 555**[1]
1	67 (12%)
2	81 (15%)
3	175 (32%)
4	107 (19%)
5	125 (23%)

[1]2022 Survey data

Summary Statistics for Q38_1

Min	Max	Mean	SD	Variance	Count
1	5	3.255856	1.28843	1.660051	555

Q38_2	**N = 555**[1]
1	85 (15%)
2	102 (18%)
3	223 (40%)
4	90 (16%)
5	55 (9.9%)

[1]2022 Survey data

Summary Statistics for Q38_2

Min	Max	Mean	SD	Variance	Count
1	5	2.87027	1.157817	1.340541	555

Q38_3	**N = 555**[1]
1	114 (21%)
2	106 (19%)
3	180 (32%)
4	99 (18%)
5	56 (10%)

[1]2022 Survey data

Summary Statistics for Q38_3

Min	Max	Mean	SD	Variance	Count
1	5	2.778378	1.244294	1.548268	555

Q38_4	**N = 555**[1]
1	78 (14%)
2	74 (13%)
3	197 (35%)
4	128 (23%)
5	78 (14%)

[1]2022 Survey data

Summary Statistics for Q38_4

Min	Max	Mean	SD	Variance	Count
1	5	3.097297	1.217165	1.481491	555

Q37	**N = 555**[1]
0	84 (15%)
1	29 (5.2%)
2	33 (5.9%)
3	134 (24%)
4	141 (25%)
5	134 (24%)

[1]2022 Survey data

Summary Statistics for Q37

Min	Max	Mean	SD	Variance	Count
1	5	3.675159	1.140455	1.300637	471

Q45_1	**N = 555**[1]
1	45 (8.1%)
2	71 (13%)
3	179 (32%)
4	171 (31%)
5	89 (16%)

[1]2022 Survey data

Summary Statistics for Q45_1

Min	Max	Mean	SD	Variance	Count
1	5	3.338739	1.135509	1.289381	555

Q45_2	**N = 555**[1]
1	79 (14%)
2	98 (18%)
3	182 (33%)
4	121 (22%)
5	75 (14%)

[1]2022 Survey data

Summary Statistics for Q45_2

Min	Max	Mean	SD	Variance	Count
1	5	3.027027	1.227391	1.506488	555

Q56_1	**N = 555**[1]
1	43 (7.7%)
2	57 (10%)
3	198 (36%)
4	158 (28%)
5	99 (18%)

[1]2022 Survey data

Summary Statistics for Q56_1

Min	Max	Mean	SD	Variance	Count
1	5	3.383784	1.125078	1.265802	555

Q56_2	**N = 555**[1]
1	40 (7.2%)
2	50 (9.0%)
3	186 (34%)
4	173 (31%)
5	106 (19%)

[1]2022 Survey data

Summary Statistics for Q56_2

Min	Max	Mean	SD	Variance	Count
1	5	3.459459	1.115883	1.245195	555

Q56_3	**N = 555**[1]
1	42 (7.6%)
2	73 (13%)
3	213 (38%)
4	153 (28%)
5	74 (13%)

[1]2022 Survey data

Summary Statistics for Q56_3

Min	Max	Mean	SD	Variance	Count
1	5	3.259459	1.085379	1.178047	555

Q56_4	**N = 555**[1]
1	52 (9.4%)
2	67 (12%)
3	224 (40%)
4	135 (24%)
5	77 (14%)

[1]2022 Survey data

Summary Statistics for Q56_4

Min	Max	Mean	SD	Variance	Count
1	5	3.212613	1.118366	1.250743	555

Q56_5	**N = 555**[1]
1	42 (7.6%)
2	65 (12%)
3	222 (40%)
4	154 (28%)
5	72 (13%)

[1]2022 Survey data

Summary Statistics for Q56_5

Min	Max	Mean	SD	Variance	Count
1	5	3.268468	1.07061	1.146206	555

Q56_6	**N = 555**[1]
1	46 (8.3%)
2	61 (11%)
3	202 (36%)
4	167 (30%)
5	79 (14%)

[1]2022 Survey data

Summary Statistics for Q56_6

Min	Max	Mean	SD	Variance	Count
1	5	3.30991	1.103568	1.217862	555

Q56_7	**N = 555**[1]
1	57 (10%)
2	67 (12%)
3	207 (37%)
4	144 (26%)
5	80 (14%)

[1]2022 Survey data

Summary Statistics for Q56_7

Min	Max	Mean	SD	Variance	Count
1	5	3.221622	1.149274	1.320831	555

Q56_8	**N = 555**[1]
1	60 (11%)
2	78 (14%)
3	208 (37%)
4	142 (26%)
5	67 (12%)

[1]2022 Survey data

Summary Statistics for Q56_8

Min	Max	Mean	SD	Variance	Count
1	5	3.140541	1.13767	1.294292	555

Q56_9	**N = 555**[1]
1	56 (10%)
2	51 (9.2%)
3	227 (41%)
4	141 (25%)
5	80 (14%)

[1]2022 Survey data

Summary Statistics for Q56_9

Min	Max	Mean	SD	Variance	Count
1	5	3.248649	1.125425	1.266582	555

Q56_10	**N = 555**[1]
1	59 (11%)
2	70 (13%)
3	242 (44%)
4	124 (22%)
5	60 (11%)

[1]2022 Survey data

Summary Statistics for Q56_10

Min	Max	Mean	SD	Variance	Count
1	5	3.100901	1.095074	1.199187	555

Q56_11	**N = 555**[1]
1	53 (9.5%)
2	75 (14%)
3	221 (40%)
4	136 (25%)
5	70 (13%)

[1]2022 Survey data

Summary Statistics for Q56_11

Min	Max	Mean	SD	Variance	Count
1	5	3.171171	1.113374	1.239601	555

Q53	**N = 555**[1]
<6 months	53 (9.5%)
13 - 18 months	73 (13%)
19 - 24 months	60 (11%)
24+ months	29 (5.2%)
7 -12 months	116 (21%)
No positive return	12 (2.2%)
Unknown	212 (38%)

[1]2022 Survey data

Q54_2	**N = 555**[1]
Decreases	37 (6.7%)
I do not know	173 (31%)
Increases	146 (26%)
They remain the same	199 (36%)

[1]2022 Survey data

Q55 - Multiple Choice Question	**N = 746**[1]
Data management	75 (10%)
Data privacy	55 (7.4%)
Data sources	54 (7.2%)
Do not invest anywhere	109 (15%)
Other	15 (2.0%)
People	180 (24%)
Tools/Platforms	132 (18%)
Training	126 (17%)

[1]2022 Survey data

Q13 - Multiple Choice Question	N = 740[1]
ENTERTAINMENT AND RECREATION	26 (3.5%)
ACCOMMODATION AND FOOD SERVICE	21 (2.8%)
ADMINISTRATIVE AND SUPPORT SERVICE ACTIVITIES	16 (2.2%)
AGRICULTURE; FORESTRY AND FISHING	41 (5.5%)
ARTS	26 (3.5%)
CONSTRUCTION	58 (7.8%)
EDUCATION	71 (9.6%)
ELECTRICITY; GAS; STEAM AND AIR CONDITIONING SUPPLY	20 (2.7%)
FINANCIAL AND INSURANCE ACTIVITIES	30 (4.1%)
HUMAN HEALTH AND SOCIAL WORK	49 (6.6%)
INFORMATION AND COMMUNICATION	62 (8.4%)
MANUFACTURING	28 (3.8%)
MINING AND QUARRYING	13 (1.8%)
OTHER SERVICE ACTIVITIES	79 (11%)
PROFESSIONAL; SCIENTIFIC AND TECHNICAL ACTIVITIES	23 (3.1%)
PUBLIC ADMINISTRATION AND DEFENCE; COMPULSORY SOCIAL SECURITY	69 (9.3%)
REAL ESTATE ACTIVITIES	18 (2.4%)
TRANSPORTATION AND STORAGE	30 (4.1%)
WATER SUPPLY; SEWERAGE; WASTE MANAGEMENT AND	12

Q13 - Multiple Choice Question	**N = 740**[1]
REMEDIATION ACTIVITIES	(1.6%)
WHOLESALE AND RETAIL TRADE; REPAIR OF MOTOR VEHICLES AND MOTORCYCLES	48 (6.5%)

[1]2022 Survey data

Q46 - Multiple Choice Question	**N = 1,394**[1]
Availability of appropriate analytical tools	41 (2.9%)
Costs/investments related to development and implementation (infrastructure	111 (8.0%)
Data availability/access	51 (3.7%)
Data privacy	52 (3.7%)
Data quality	63 (4.5%)
Data security	62 (4.4%)
Difficulties in collecting and analyzing 'big data'	25 (1.8%)
Difficulties with the availability of unstructured data	36 (2.6%)
Difficulty attracting and retaining analytical talent	47 (3.4%)
Difficulty finding optimal analytical tools	41 (2.9%)
Difficulty implementing automatic analytical solutions/models in production	40 (2.9%)
Difficulty showing/assessing the impact on business results in monetary form (ROI	22 (1.6%)
Existing database systems/software/solutions are unable to quickly process/deliver large and/or unstructured data in a user-friendly manner	39 (2.8%)
Inability to explain the results of complex analytical solutions in a language understandable to business users	29 (2.1%)
Inability to manipulate and integrate different data	27 (1.9%)
Insufficient number of analytical people and/or insufficient knowledge/experience	93 (6.7%)
Insufficient support from the top management of the organization	44 (3.2%)
It is not clear whether the investment will pay off	105 (7.5%)

Q46 - Multiple Choice Question	**N = 1,394**[1]
Lack of centralized/unified data warehouse (DWH	27 (1.9%)
No adequate technical knowledge	104 (7.5%)
No known best practice	62 (4.4%)
Not sure how to use the results	58 (4.2%)
Obtaining business requirements	31 (2.2%)
Other	21 (1.5%)
Position of supervisory authorities regarding data and application of analytical methods	33 (2.4%)
Structure/organization of analytical functions of the organization	40 (2.9%)
There are no obstacles	90 (6.5%)

[1]2022 Survey data

Q51 - Multiple Choice Question	**N = 1,458**[1]
Policies related to data security, privacy, quality should be implemented	42 (2.9%)
Active cooperation of analytical specialists with business representatives should be encouraged	44 (3.0%)
Active support of top management should be achieved	78 (5.3%)
An organizational culture/perception that data/information is an essential asset should be fostered	39 (2.7%)
Building a team with the right expertise	120 (8.2%)
Centralizing analytics and/or creating an Analytics Knowledge Center that drives the entire analytics function in the organization	28 (1.9%)
Choosing the most appropriate technology/software	71 (4.9%)
Choosing the right data-driven initiatives	23 (1.6%)
Creating an analytics development strategy	50 (3.4%)
Decentralization of analytics	29 (2.0%)
Effective access to external data must be ensured	49 (3.4%)
Effective access to internal data must be ensured	66 (4.5%)
Greater use of analytics in marketing and customer interaction issues should be ensured	34 (2.3%)
Human capacity in big data analytics must be provided	39 (2.7%)
Implementation of linking analytical results with decision-making processes	51 (3.5%)
Incentive programs should be implemented to encourage data sharing to improve the overall result	38 (2.6%)
Internal capacity must be created to create a 'data-driven' organization	35 (2.4%)

Q51 - Multiple Choice Question	**N = 1,458**[1]
Investments in information technology infrastructure must be ensured	53 (3.6%)
It must be demonstrably demonstrated how analytics improves competitiveness	78 (5.3%)
Knowledge and patience in data integration must be provided	76 (5.2%)
Must demonstrate tangible business benefits from analytics initiative	47 (3.2%)
No answer/Don't know	124 (8.5%)
Other	10 (0.7%)
Policies need to be developed that balance the organization's desire to use data and add value to the organization with the customer's desire for security and privacy	24 (1.6%)
Potential value creation opportunities and risks must be identified	33 (2.3%)
Small real-life projects that demonstrate potential added value to business results should be proposed	53 (3.6%)
Technological barriers should be resolved and research and development issues in the target areas should be accelerated	40 (2.7%)

[1]2022 Survey data

Q52 - Multiple Choice Question	**N = 2,293**[1]
A deeper and more accurate understanding of the business	88 (3.8%)
A deeper understanding of the market and competitors	95 (4.1%)
Automated real-time decision-making processes	51 (2.2%)
Better ability to respond to changes in the market	119 (5.2%)
Better financial performance of the organization	96 (4.2%)
Better leverage from key strategic initiatives	57 (2.5%)
Better planning and forecasting	190 (8.3%)
Better relations with customers and cooperation partners	74 (3.2%)
Better risk assessment and ability to respond to changes in the economic environment	89 (3.9%)
Creating new products or services that increase your income stream	83 (3.6%)
Customer segmentation	67 (2.9%)
Improved daily processes	162 (7.1%)
Increased customer satisfaction	120 (5.2%)
Increased income/turnover from existing customers/products	75 (3.3%)
Increased market share	71 (3.1%)
Increasing competitiveness	155 (6.8%)
New additional customers	100 (4.4%)
New business opportunities	100 (4.4%)
Other	11 (0.5%)
Reduced costs	157 (6.8%)
Reducing risk and fraud	85 (3.7%)
Smarter/better decision making	148 (6.5%)

Q52 - Multiple Choice Question	**N = 2,293**[1]
[1]2022 Survey data	

Appendix R. Descriptive statistics – Q21, target variable

Data available on request from the author (santa.lemsa@va.lv).

Data file: Descriptive_statistics_By_TARGET.docx

Appendix S. Descriptive statistics – Size

Data available on request from the author (santa.lemsa@va.lv).

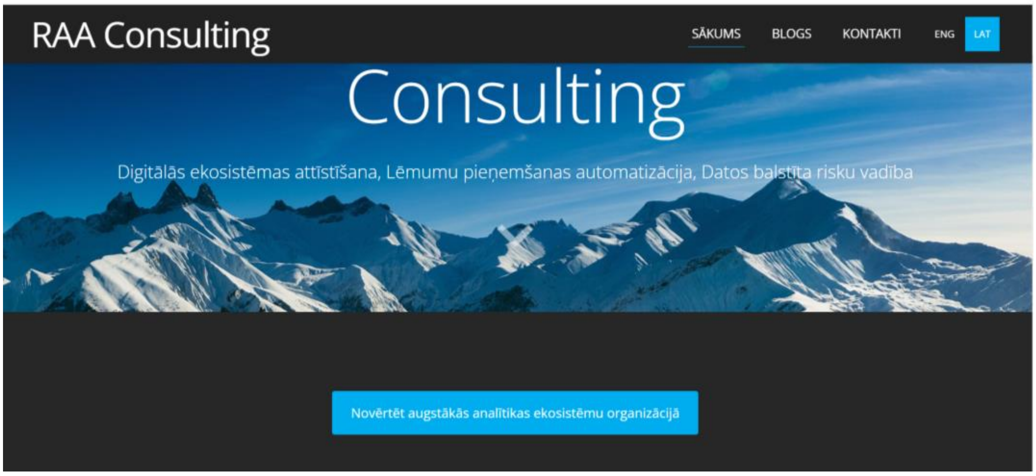
Data file: Descriptive_statistics_By_SIZE.docx

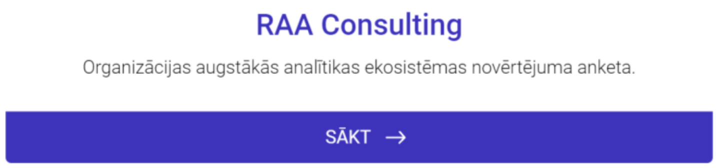
Appendix T. Descriptive statistics – Industry

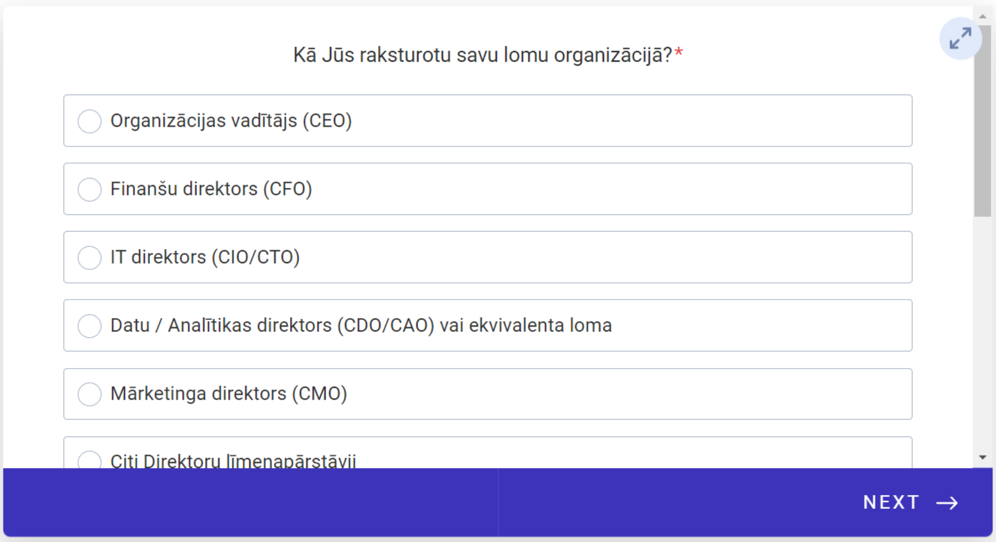
Data available on request from the author (santa.lemsa@va.lv).

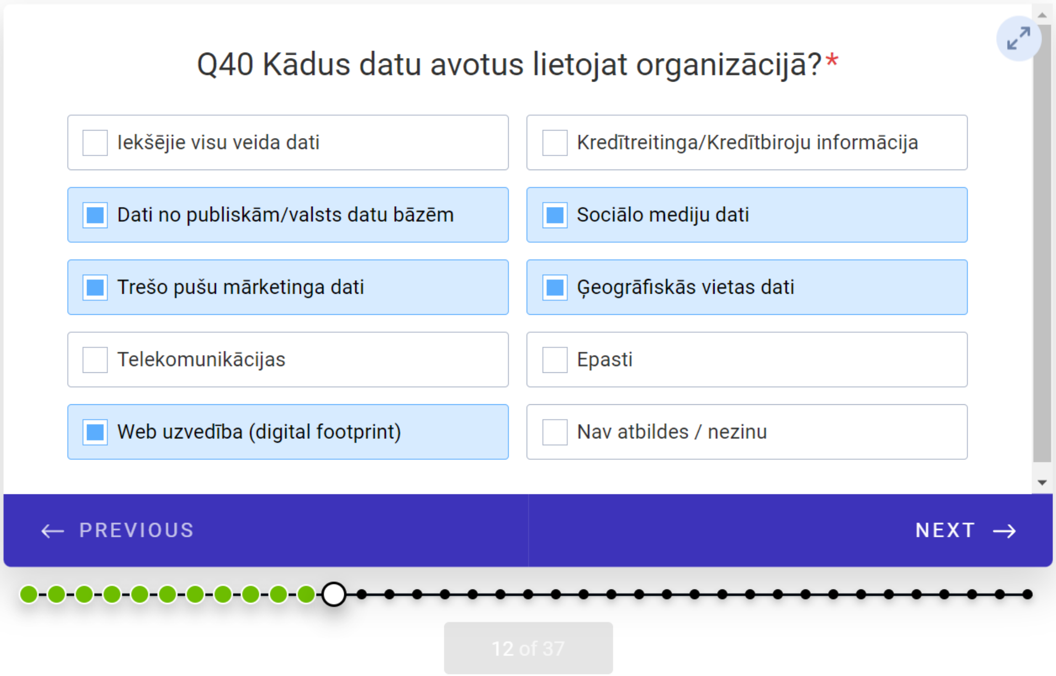
Data file: Descriptive_statistics_By_INDUSTRY.docx

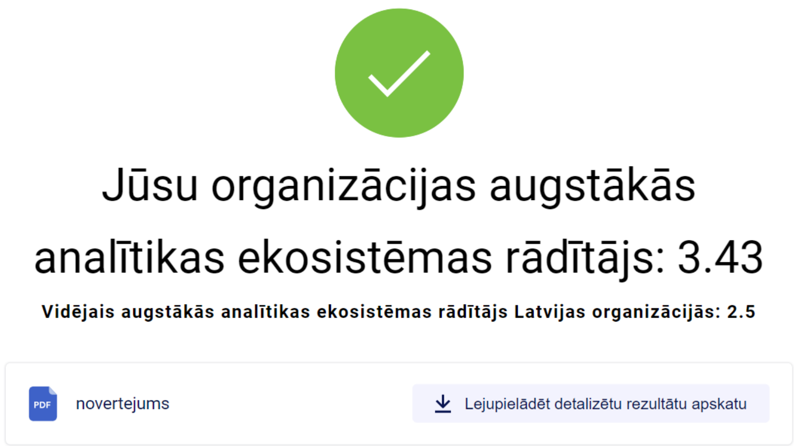
Appendix U. Advanced analytics maturity assessment and recommendation tool – Visualization








Q40 Kādus datu avotus lietojat organizācijā?*
Iekšējie visu veida dati
Kredītreitinga/Kredītbiroju informācija
Dati no publiskām/valsts datu bāzēm
Sociālo mediju dati
Trešo pušu mārketinga dati
Ģeogrāfiskās vietas dati
Telekomunikācijas
Epasti
Web uzvedība (digital footprint)
Nav atbildes / nezinu
PREVIOUS
NEXT
12 of 37


Jūsu organizācijas augstākās analītikas ekosistēmas rādītājs: 3.43
Vidējais augstākās analītikas ekosistēmas rādītājs Latvijas organizācijās: 2.5
PDF
novertejums
Lejupielādēt detalizētu rezultātu apskatu

novertejums.pdf 1 / 4 100%

REZULTĀTS

2023. gada 26. septembris

Jūsu organizācijas augstākās analītikas ekosistēmas rezultāts: 3.43

3. līmenis: speciālists (koordinēta operatīvā analīze) Analītiķi tiek plaši izmantoti operatīvi ar zināmu koordināciju starp analītikas komandām. Var būt izveidotas datu noliktavas, krātuves vai datu ezeri. Analītika ir integrēta daudzos darbības procesos un lēmumu pieņemšanā. Notiek koordinācija starp analītiskajām komandām, labākās prakses apmaiņa un noteikta centrālā pārraudzība. Dati tiek glabāti datu noliktavās, krātuvēs vai datu ezeros, lai nodrošinātu labāku piekļuvi un pārvaldību. Datu pārvaldības prakse ar dažām datu īpašumtiesībām.

novertejums.pdf 2 / 4 100%

Organizācija: 3.25

Rekomendācija:

Stratēģiskā saskaņošana: nodrošiniet, lai analītikas iniciatīvas būtu pilnībā saskaņotas ar organizācijas stratēģiskajiem mērķiem un uzdevumiem.Uz datiem balstīta vadība: veiciniet uz datiem balstītas vadības kultūru visā organizācijā, augstākā līmeņa vadītājiem aktīvi atbalstot analīzi.Analītikas pārvaldība: ieviesiet uzlabotas analītikas pārvaldības prakses, lai nodrošinātu ētisku un atbilstošu datu izmantošanu.Daudzfunkcionāla sadarbība: pastipriniet sadarbību starp analītikas komandām un biznesa vienībām, lai nodrošinātu analītikas ieskatu izmantošanu visās jomās.Investīcijas inovācijās: piešķiriet resursus inovatīviem analītikas projektiem, kas var veicināt konkurences priekšrocības.

Cilvēki: 4

Rekomendācija:

Inovācijas čempioni: identificējiet un sniedziet iespēju inovāciju čempioniem, kuri var paplašināt analītikas iespējas.Uzlaboto prasmju ekosistēma: attīstiet progresīvu prasmju ekosistēmu, tostarp AI ētiku, kvantu skaitļošanu un progresīvas tehnoloģijas.Globālais talants: piesaistiet pasaules labākos talantus datu zinātnē, mašīnmācībā un jaunās jomās no dažādām vidēm.Datu vadība: attīstiet datu vadību, kas virza inovācijas un veicina sadarbību starp funkcijām.Akadēmiskās partnerības: sadarbojieties ar universitātēm un pētniecības iestādēm, lai paliktu analītikas zināšanu priekšgalā.

2