

VILNIUS GEDIMINAS TECHNICAL UNIVERSITY

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**ECONOMIC ASSESSMENT
OF BUSINESS MODEL
TRANSFORMATION IN INDUSTRY 4.0**

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VILNIAUS GEDIMINO TECHNIKOS UNIVERSITETAS

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PRAMONĖ 4.0 SĄLYGOMIS
EKONOMINIS VERTINIMAS

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Abstract

Industry 4.0 solutions envision a significant impact on the potential of economic efficiency and growth in industries. Some authors suggest up to 50 per cent of overall efficiency increase and up to 200 per cent of output volume increase. The problem addressed in this dissertation lies in facing a high uncertainty balanced with the potential of high efficiency and growth due to the rapid and comprehensive effect of Industry 4.0 on industry and society. New technologies rapidly appear in the market, but lack the historical data to benchmark a possible return on investment. This research object is the economic assessment of growth, efficiency and risk involved when transforming a business model in response to Industry 4.0 in manufacturing.

The objective of the dissertation is to examine the interrelationship between Industry 4.0 enablers and business models, to design and empirically test the integrated economic assessment concept of the allocation of the financial, human and time resources when transforming the business model in Industry 4.0. The dissertation resolves the following key tasks: 1) using scientific literature analysis, to systemise the scientific approaches and results in the assessment of economic efficiency to be used to assess the alternatives of the allocation of financial, human and time resources when transforming business models due to Industry 4.0 technological and socio-economic implications; 2) to identify Industry 4.0 key factors that influence the transformation of a business model; 3) to analyse and determine the key indicators to assess the alternatives of the allocation of financial, human and time resources when transforming the business model in response to Industry 4.0; 4) to develop the original concept for the economic assessment; 5) to empirically approve the created method in large furniture manufacturing companies, introducing the limitations of the methodology and future research directions.

The dissertation results present an integrated economic assessment concept consisting of three parts: a 6-step economic assessment logframe, four composite indexes with 33 component indicators: indexes of growth, efficiency, financial risks and non-financial risks, and the growth-efficiency matrix with a risk component, which offers four segments. The integrated economic assessment concept facilitates the assessment of the allocation of resources when transforming business models through the implementation of Industry 4.0 solutions. The suggested integrated economic assessment concept allows investors and shareholders to make more grounded investment decisions, executive decision-makers to plan and reallocate resources when transforming business models with the implementation of Industry 4.0 solutions, and policymakers to plan more focused regional development and EU investment programmes.

Reziumė

Pramonė 4.0 turi reikšmingą poveikį įmonių ekonominio efektyvumo ir augimo potencialui. Kai kurie autoriai teigia, kad efektyvumas gali didėti net iki 50 procentų, o augimas net iki 200 procentų. Disertacijoje keliama problema yra paskaitinta didelio efektyvumo bei augimo potencialo dėl visapusiško *Pramonės 4.0* poveikio pramonėje ir visuomenėje. Naujos technologijos rinkoje atsiranda ir kinta labai greitai, dėl greitų pokyčių veiksmingumui ir ekonominiams rezultatams prognozuoti trūksta istorinių duomenų. Disertacijos tyrimo objektas yra ekonominis efektyvumo, augimo ir rizikos vertinimas, kai transformuojamas verslo modelis *Pramonės 4.0* sąlygomis gamybos srityje.

Disertacijos tikslas – išnagrinėti *Pramonė 4.0* įgalinančių technologijų ir verslo modelių tarpusavio sąsajas, parengti ir empiriškai išbandyti vertinimo koncepciją, vertinant įmonės išteklių paskirstymą, kai verslo modelis transformuojamas dėl *Pramonės 4.0* poveikio. Disertacijoje sprendžiami šie pagrindiniai uždaviniai: 1) atlikus mokslinės literatūros analizę, susisteminti metodus efektyviam ekonominio efektyvumo vertinimui, kuris bus naudojamas vertinant finansinių, žmogiškųjų ir laiko išteklių paskirstymo alternatyvas, transformuojant verslo modelius dėl *Pramonės 4.0* technologinių ir socialinių bei ekonominių padarinių, 2) nustatyti *Pramonės 4.0* pagrindinius veiksnius, turinčius įtakos verslo modelio transformacijai, 3) išanalizuoti ir nustatyti pagrindinius rodiklius, reikalingus vertinti finansinių, žmogiškųjų ir laiko išteklių paskirstymą, transformuojant verslo modelį dėl *Pramonės 4.0* poveikio, 4) parengti ekonominio vertinimo koncepciją, 5) empiriškai patvirtinti sukurta metodą didelėse gamybos įmonėse, įvardinti metodikos apribojimus ir tolesnių mokslinių tyrimų kryptis.

Disertacijoje sukurta integruota ekonominio vertinimo koncepcija, susidedanti iš trijų dalių: 1) 6 etapų ekonominio vertinimo loginės schemos, 2) keturi sudėtiniai indeksai su 33 rodikliais: augimo, efektyvumo, finansinės ir nefinansinės rizikos indeksai ir 3) augimo-efektyvumo matrica su rizikos komponentu, kuri leidžia įmones pozicionuoti keturiuose segmentuose. Integruota ekonominio vertinimo koncepcija palengvina išteklių paskirstymo vertinimą, įmonėje transformuojant verslo modelį dėl *Pramonės 4.0* sprendimų įgyvendinimo. Siūloma integruota ekonominio vertinimo koncepcija leidžia investuotojams ir akcininkams priimti labiau pagrįstus investicinius sprendimus, įmonių vadovams planuoti ir perskirstyti išteklius, pertvarkant verslo modelius dėl *Pramonės 4.0* sprendimų įgyvendinimo, o politikos formuotojams planuojant labiau koncentruotą regioninę plėtrą ir ES investicijų programas.

Notations

Abbreviations

AI – artificial intelligence
CBA – cost-benefit analysis
CE – cost efficiency
CPS – cyber-physical systems
DE – dynamic efficiency
EVA – economic value added
FARE – factor relationship analysis
FTE – full-time equivalent
IoT – internet of things
IRR – internal rate of return
NPV – net present value
OECD – Organisation for Economic Co-operation and Development
OEE – overall equipment efficiency
OFE – overall factory efficiency
P – profitability
PEE – production equipment efficiency
ROA – return on assets
ROI – return on investment

ROS – return on sale

TEEP – total efficient equipment performance

VA – value-added

VAIC – value-added intellectual coefficient

VOT – valuable operating time by the total available time (TT)

WEF – World Economic Forum

Definitions

Business model – the business model concept is a scheme for better understanding the business logic of a company by describing how value is offered, created, delivered and captured (Osterwalder & Pigneur, 2010).

Digital business model – a business model is digital if changes in digital technologies trigger fundamental changes in the way businesses are carried out and revenues are generated (Veit et al., 2014).

Digital economy – markets based on digital technologies that facilitate the trade of goods and services through e-commerce and based on data acquired by digital technologies (OECD, 2012).

Industry 4.0 (the fourth industrial revolution) – the concept that involves the technical integration of cyber-physical systems into manufacturing and logistics and the use of the Internet of Things and services in industrial processes, which implies social and human involvement and shifts from a centralised to a decentralised way of working. The impact on value creation, business models, downstream services and work organisation is significant (Kagermann et al., 2013).

Internet of Things – objects become capable of communicating with each other, the Internet and humans – either directly or via media devices (Weinberger et al., 2016).

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¹ The annexes are supplied in the enclosed compact disc.

Introduction

Formulation of the Problem

Industry 4.0-driven business models and transformations in the value chain bring rapid and considerable positive outcomes for companies and countries' economies. A complex of significant challenges (such as speed of changes, expectations for extremely high increases of growth and efficiency, the necessity for financial resources and the lack of historical data) distinguishes Industry 4.0-driven transformations from other usual changes in the market. This complex requires high inputs and promises high outputs, but the uncertainty is also very high.

Existing assessment methods do not allow the assessment of the effective allocation of resources when transforming business models due to Industry 4.0. The attention of scientists in economics and business can be observed only since 2016. Subsequently, publications in Clarivate Analytics Web of Science and Elsevier Scopus have increased by 50–80 per cent per year.

Summing up, the methodology to assess the allocation of companies' resources to challenge the trilemma of efficiency, growth and risk should enhance the implementation of Industry 4.0, with the transformation of the business models followed by manufacturing companies.

Aiming to address the issues outlined above, the research field was determined: how to assess the allocation of resources when transforming a business

model in Industry 4.0 to achieve both the increase of growth and efficiency in an environment of high uncertainty.

Relevance of the Thesis

Industry 4.0 provides opportunities to companies to transform their business model to expand successfully in the global markets. The Internet of Things, big data analytics and artificial intelligence implemented in manufacturing create the potential for extreme growth and efficiency. The shrinking of the boundary between human and computer activities and the availability of information allow new forms of business models.

Researches suggest a 30–50 per cent increase in efficiency and more than a 100 per cent increase in growth in the short term after the implementation of Industry 4.0 in manufacturing processes. The potential of growth and efficiency due to Industry 4.0 allows forecasting a dramatic contribution to the national economy.

The Object of Research

Economic assessment of the company when transforming business model as a result of Industry 4.0 in manufacturing.

The Aim of the Thesis

To create an integrated economic assessment concept to assess the allocation of the resources of the company when transforming the business model in response to Industry 4.0

The Tasks of the Thesis

1. To systemise the scientific findings to be used to assess the alternatives of the allocation of financial, human and time resources when transforming business models in response to Industry 4.0 technological and socio-economic implications.
2. Based on scientific literature analysis, to identify the key factors of Industry 4.0 that influence the transformation of a business model.

3. To analyse and determine the key indicators to assess the alternatives of allocating financial, human and time resources when transforming the business model due to Industry 4.0.
4. To develop the instruments that form the original integrated economic assessment concept.
5. To approve the created integrated economic assessment concept and instruments in large furniture manufacturing companies, to introduce the limitations of the methodology and future research directions.

Research Methodology

The following research methods are chosen to investigate the research object:

- Critical scientific literature analysis used to the assessment of the potential of Industry 4.0,
- Bibliometric analysis,
- Multicriteria decision-making methods such as FARE for determining categories and weights for the indexes,
- Disaggregation and grouping methods are used to process the data to determine a set and categories of the indicators,
- Statistical analysis for the calculation of the values of the indicators,
- Individual interviews to collect qualitative data for specifying groups of the component indicators,
- Focus groups to determine the weights of the categories in the hierarchical system of indicators,
- Qualitative content analysis to process collected data,
- Scientific interpretation with reference to a graphical analysis method used to process the research findings to the methodology's scalability.

Scientific Novelty of the Thesis

The dissertation provides the following new results to the economic sciences:

1. The developed integrated economic assessment concept, consisting of the economic assessment logframe, composite indexes and growth-efficiency matrix, allows assessing the alternatives to the allocation of resources in the large manufacturing companies when they transform business models in response to Industry 4.0 implementation.

2. The developed integrated economic assessment concept determined the dimensions in risk, efficiency and growth areas to be assessed when planning and implementing financial, time, and human resources.
3. The developed logframe determined the process and indexes determined the structure of the system of indicators to assess financial and nonfinancial risks, efficiency and growth when allocating resources.
4. The economic assessment logframe is composed of a 16-step process that facilitates the assessment process in the company. The process includes quantitative and qualitative methods, involves experts and employees.
5. The original combination of the four composite indexes with 33 component indicators serves as the assessment instrument.
6. The growth and efficiency matrix with risk components helps to assess the results of the indexes and facilitates the decisions regarding the allocation of the financial and human resources.

Practical Value of the Research Findings

1. The developed and empirically tested original integrated economic assessment concept consisting of the assessment logframe, four composite indexes and growth-efficiency matrix facilitates the making of more grounded decisions for the allocation of company and national resources.
2. First, the investors and shareholders can use the integrated economic assessment concept when deciding on the strategic Industry 4.0 implementation directions and their financial resources.
3. Second, the executive management in the companies can use the integrated economic assessment concept to assess and reorganise the allocation of resources to implement the decisions of the shareholders.
4. Third, policymakers can use it when they plan regional development through a higher value-added labour market and investment of EU and national funding in the digitalisation of companies and thus have more directed policymaking, implementing and controlling institutions.
5. Higher digitalisation, which brings more job places with higher average salaries, will contribute to the development of an innovative economy in the regions, thus contributing to the Lithuanian Agenda 2030 of the Sustainable Development Goals. More focused investment into the transformation of the Industry 4.0-driven business model will allow a more rapid expansion of the global value chain, thus contributing to the implementation of the recommendations provided in the recommendations for investment in 2021–2027 in the Assessment of the Lithuanian Economic Sector Funding after 2020.

The Defended Statements

1. The integrated approach of the assessment logframe and the composite indexes allows the company to assess the alternatives to the allocation of the resources when transforming business models in Industry 4.0.
2. The balance of three dimensions – efficiency, growth, and risk – facilitates a more precise assessment of financial, human and time resources allocation when transforming business models in Industry 4.0.
3. The dynamic approach included in the integrated economic assessment concept allows interpreting data during the period and gives a dynamic analysis of the economic assessment results.
4. The composition of the proposed weighted categories and indicators empowers a holistic approach to the assessment to facilitate the allocation of resources when implementing transforming business models in response to Industry 4.0.
5. The proposed composition of weighted categories and component indicators enables the integrated economic assessment concept to be adaptable to the specifics of the business.

Approval of the Research Findings

Four scientific articles on the subject and findings of the dissertation have been issued in total: 2 in foreign scientific journals, 1 of them in the Clarivate Analytics Web of Science database and Scopus database with impact factor and 1 in the international peer-reviewed journal; 1 in the international conference proceedings and 1 in the international scientific journal.

The author has made four presentations at three international scientific conferences: International Scientific Conference on Economics and Entrepreneurship (SCEE'2019) in Riga, Latvia, on 11/10/2019, International Scientific Conference Contemporary Issues in Business, Management and Economics Engineering in Vilnius, Lithuania on 09/05/2019 and International Scientific Conference “Active Society – Innovative Solutions”, in Vilnius, Lithuania on 11/10/2017.

The author also has made four presentations in doctoral seminars at Vilnius Gediminas Technical University, and one presentation in the international seminar abroad in University College London, UK.

Structure of the Dissertation

The dissertation is structured as follows: the introduction; three chapters with conclusions; general conclusions; references; the list of the author's publications; a summary in Lithuanian; and 5 annexes. The total scope of the dissertation is 137 pages, excluding annexes. 22 figures, 52 tables, 19 numbered formulas, and 196 references have been included in the dissertation.

Scientific Literature Analysis of the Assessment of Business Model Transformation in Industry 4.0

Chapter 1 reviews the scientific literature on the contemporary issues of the phenomenon of Industry 4.0 and the emerging and transforming of business models in Industry 4.0. The focus lies on economic efficiency and growth and analyses risks that should be reduced to explore the alternatives for allocating company resources when a business model is transformed in Industry 4.0. The scientific literature is analysed, and the chapter concludes by formulating the theoretical backgrounds of the organisation of the empirical research.

The findings of this chapter have been published in three scientific publications: Kovaitė & Stankevičienė, 2017, Kovaitė & Stankevičienė, 2019, Kovaitė et al., 2020.

1.1. Analysis of the Scientific Literature on the Transformation of the Business Model in Industry 4.0

This chapter reviews the scientific production of Industry 4.0, identifies the main concepts of Industry 4.0 and the technologies that distinguish the phenomenon among others, and impacts business and Internet-based communication significantly. Moreover, the implications for social and economic life are revolutionary. This chapter concludes by identifying the basis for further investigation into assessing the allocation of resources when transforming the business models in response to Industry 4.0 implications.

The scientific publications of Industry 4.0 in economics, management, business, and related sciences indexed in the Web of Science from 2010 to 2021 were analysed using bibliometric analysis (Ejsmont et al., 2020; Kipper et al., 2020). The visualisation was prepared using VOS Viewer (Eck van et al., 2010) software. The methodology is described in Chapter 2. Then a list of publications was extended to cover a broader range of researches. The systemised overview is presented in this chapter, and then the individual concepts are presented in more detail.

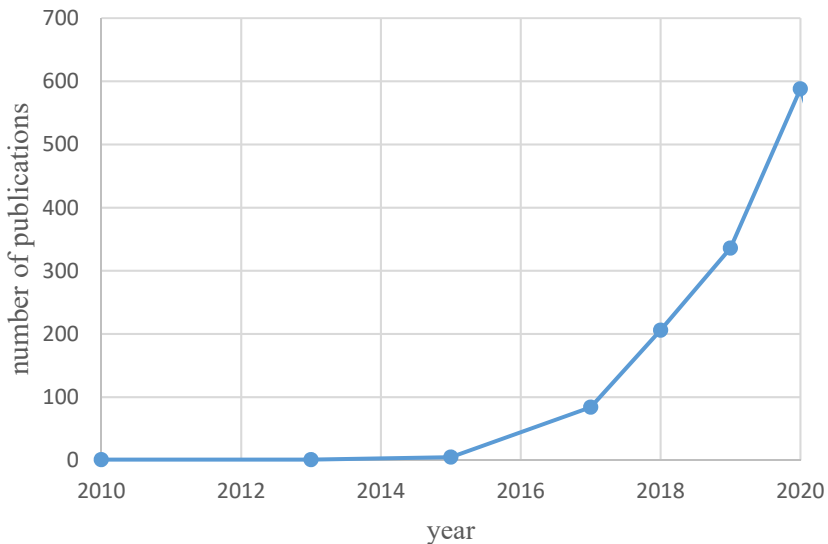


Fig. 1.1. Growth of the scientific production of Industry 4.0 between 2010 and 2020 (created by the author)

Figure 1.1 presents the increase in the scientific production of Industry 4.0 from 2010 to 2020 indexed in Clarivate Analytics with the following inclusion and exclusion criteria. Articles published in English on Web of Science (Clarivate Analytics) were selected. The keywords for the initial selection of the articles were “Industry 4.0”, with possible modifications of “4* industrial” and “four* industrial”. Then articles were selected from the related categories: economics, business; business finance; management; interdisciplinary social science. Thus, excluded categories were those related to mining, health, ecology, medicine and computer science were excluded. A more detailed process of methodology is explained in Chapter 2.

When analysing scientific publications’ growth, a total of 1456 publications was selected for further exploration. It became clear that the first signals of scientific attention were mentioned in 2015 (5 articles) and there was significant attention in 2017 (83 items). Since then, the increase has been very rapid: 206 articles in 2018, 336 articles in 2019, 588 articles in 2020. Figure 1.1 does not include 2021 because the research was conducted in the first quarter of the year. Still, it is worth mentioning that 235 published or early access articles in Clarivate Analytics on 10 March 2021 were presented.

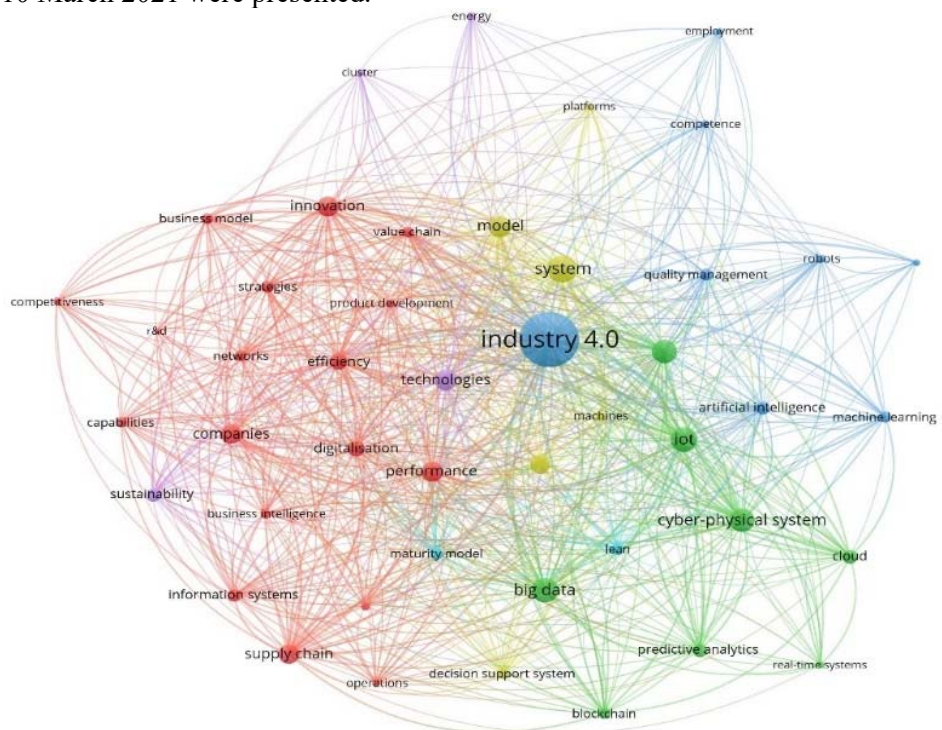


Fig. 1.2. The linkages of keywords (created by the author)

Figure 1.2 presents the linkages of the keywords used in the publications on Industry 4.0 between 2010 and 2021. The keyword “Industry 4.0” has occurred 1039 times and there is a very close relationship with the Internet of Things (IoT), big data, cyber-physical systems and intelligent factories. “Industry 4.0” appears in the middle of two significant clusters of keywords: keywords coming from computer science such as Internet of Things, big data, cyber-physical systems, machine learning; and the second cluster with keywords coming from business such as business intelligence, supply chain, value chain, innovation.

The keywords such as “efficiency” and “performance” lie in between those two clusters. They show the occurrence in the publications, but there are no supporting keywords to explore the economic impact of Industry 4.0 implementation in the companies that have been more focused on.

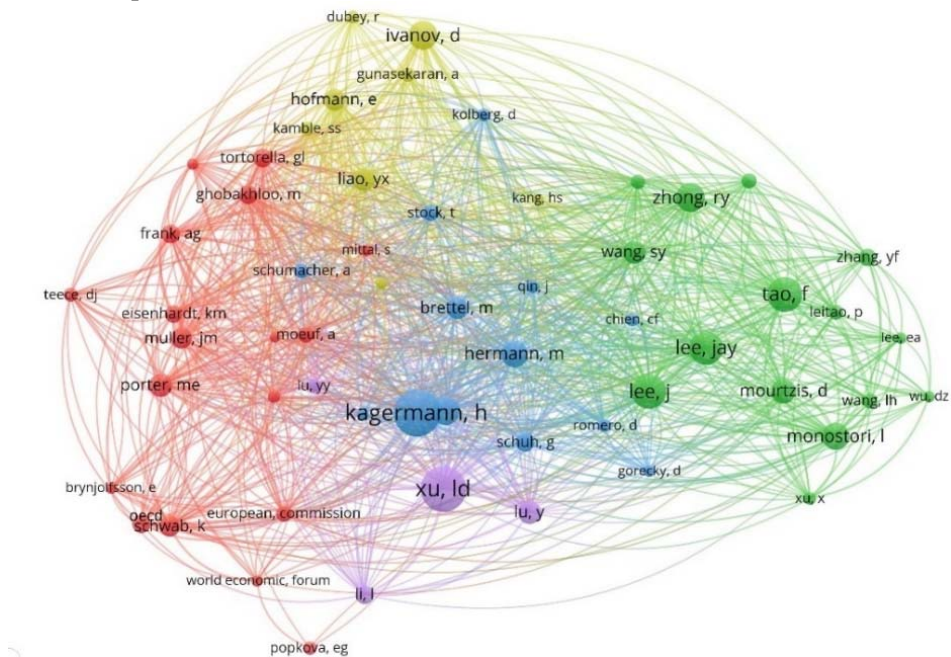


Fig. 1.3. The linkages of the most quoted authors (created by the author)

Figure 1.3 presents the linkages of the authors that are most quoted between 2010 and 2021. The research results suggest five main clusters of authors who are quoted most (Fig. 1.3). First of all, Kagermann is the most cited researcher, with 330 citations. Kagermann was the first to present Industry 4.0 on behalf of the German Trade Ministry in 2011, and, since then, he has been considered the basis for further explorations. He is in the middle of research working on the economic

and business effect of Industry 4.0 and unites Herman, Brettel and other researchers around the research topic. Ivanov and Hofman are the most cited in the cluster where engineering issues of Industry 4.0 are explored. Tao, Lee, and Zhong make the second cluster (Fig. 1.3), separated from other authors, and explore industrial and computing aspects of Industry 4.0. The institutions such as the European Commission, OECD, the World Economic Forum (WEF), and Deloitte form a separate cluster of the most cited institutions that define the institutionalisation of and policy towards Industry 4.0. Schwab Klaus as a visionary founder of the World Economic Forum, and Brynjolfsson Eric as a professor in MIT Digital Economy Institute, as individual authors, show the strongest linkage to the institutional cluster. The cluster formed by Porter, Teece, Müller, Eisenhart, and Schumacher form a set of explorations on business models and a close linkage to the institutional cluster. Kagermann and Schumacher's cluster provides research on the business side of Industry 4.0. Unfortunately, there is no clear cluster of the most cited researchers exploring the implications of Industry 4.0 at the micro or macro level, which indicates a scientific gap in the research field.

This chapter reviews the scientific production of Industry 4.0, identifies the main concepts of Industry 4.0 and the technologies that distinguish the phenomenon among others and make the impact on business and Internet-based communication so significant. Moreover, the implications for social and economic life are revolutionary. This chapter concludes with the indications of the empirical research on the assessment of business model transformation.

Industry 4.0 is a new and fast-developing phenomenon, rapidly changing business models of enterprises and the communication and behaviour of people. It focuses on the fusion between the physical and digital worlds, with a vertical and horizontal interconnection with cyber-physical systems (CPS) (Kagermann et al., 2013; Schwab et al., 2018). A variety of technology enablers, such as the Internet of Things (IoT), big data, cloud computing, augmented reality, robotics, artificial intelligence, intelligent products and services, and the decentralisation of communication between people and machines (Roblek et al., 2016; Rojko, 2017) are the key elements of Industry 4.0. The phenomenon of Industry 4.0 has led to rapid technological change in the way people and businesses operate in the workplace. Industry 4.0 clearly shows the interconnection between physical and virtual life. It illustrates the decentralisation of communication that is taking place between people, machines, and decision-making in the process of making the business accessible to the entire world.

There are significant “industrial, societal, and environmental impacts” that rapidly change the way we create value for customers, stakeholders, and industries. Furthermore, widespread industrial change is brought about by the digitalisation of technologies and processes, creating new challenges in measuring efficiency. The employment of digital technologies in the value chain dramatically

changes “opportunities for value creation in the economy”, as Porter and Heppelmann (2015) discuss. Moreover, they are driving improvements in efficiency and productivity. The term “Industry 4.0” was introduced by the German Ministry of Education and Research to promote the German high technology industry and its development strategy in 2011. The paper initiated by Germany Trade & Invest defines areas to research funding, indicating the expectations for the future development of Industry 4.0. The authors define “software systems and knowledge processing” and three specific research categories: 1) “software-intensive embedded systems with links to electronics, communication technology and microsystems technology; 2) the simulated reality for grid applications and infrastructure, software development for high-performance computing; 3) human-machine interaction with language and media technologies, bio-analogous information processing, service robotics and usability.” Kagermann (2013) concluded that Industry 4.0 would “involve the technical integration of CPS into manufacturing and logistics and the use of the Internet of Things and services in industrial processes. The implications for value creation, business models, downstream services, and work organisation” will be significant.

The concept of Industry 4.0 is further developed by Schwab (2017), who is considered a visionary in the field, and the World Economic Forum (Oztemel & Gursev, 2020; World Economic Forum (WEF), 2019; World Economic Forum [WEF] & Bain & Company, 2018). First, the concept was researched by computer manufacturing and engineering sciences. Only later, starting in 2014, the insights are widely accepted in the arena of policy, business and research (European Parliament, 2016). Scientists like provide a comparison of Industry 4.0 and similar definitions.

Schwab et al. (2018) assert that Industry 4.0 encompasses technologies, such as the Internet of Things (Nurse et al., 2017), big data (Niesen et al., 2016), cloud computing, robotics and artificial intelligence (Roblek et al., 2016) related to the decentralisation of communication between people and machines. Scholars like Stremousova and Buchinskaia (2019), following Schwab et al. (2018), stated, “we also offer a more comprehensive understanding of Industry 4.0 as an “an integrated model that is based on the convergence of nanotechnology, biomedicine, information technology, and cognitive science”. The digitisation of production is only one of the critical elements of the new model.

Baums et al. (2015) explain Industry 4.0 as a process of platformisation of value chains triggered by digital technologies. Digital transformation is not about making products “smarter” but changing the market structure to essentially defined digital platforms. These platforms are now virtual locations where services are offered based on accumulated data and redistributed added value. Weinberger et al. (2016) rely on three criteria: efficiency, quality, and flexibility to research Industry 4.0 implications on economics.

Table 1.1. Development of the concept of Industry 4.0 (created by the author)

Authors, year	Inter- net of Things / M2M	Artifi- cial in- telli- gence	3D / Ad- ditive printing	Big data and ana- lytics	Cloud com- pu- ting
Acioli et al., 2021		X			
Belhadi et al., 2021	X	X		X	X
Larrañeta et al., 2020			X		
Okorie et al., 2020	X	X		X	X
Leminen et al., 2020	X			X	X
Schwab et al., 2018	X	X	X	X	X
Landherr et al., 2016	X				
Atzori et al., 2017	X	X			
Dujin et al., 2014	X				
Liao et al., 2017	X	X		X	X
McKinsey&Company, 2016	X	X			
Zhang & Zhou, 2014	X	X		X	X
Rüßmann et al., 2015	X	X	X	X	
Bechtold et al., 2014	X	X	X	X	
Despeisse et al., 2017			X		
Kothman & Faber, 2016			X		
Costabile et al., 2017			X		
Niesen et al., 2016				X	
Hartmann et al., 2016				X	
Witkowski, 2017				X	
Lim et al., 2018				X	
Mathis & Köbler, 2016				X	
Wang et al., 2017					X
Hentschel et al., 2018					X
Xu & Hua, 2017				X	

The pillars described by scientists as distinctive features make the fourth industrial revolution so powerful, following on quickly after the third Industrial Revolution. Industry 4.0 is a term that describes the fourth wave of technological change that is taking place all over the world and which is having a disruptive impact on manufacturing and also the way we communicate and make decisions.

The First Industrial Revolution commenced in Great Britain during the middle decades of the eighteenth century, gathering pace with the introduction of water-powered production methods, followed by steam engines. The First Industrial Revolution refers to the period after the introduction of steam and water-powered production methods. Some publications indicate that the first industrial revolution started when the first mechanical loom was invented in 1784. The start of the Second Industrial Revolution is indicated by the introduction of electricity and assembly lines, which allowed mass production between the late nineteenth and early twentieth century. New technologies were applied to production in a factory system that spread rapidly throughout Western Europe and the USA.

Contrary to the first two revolutions, it took only a few decades – starting from the 70s – for the rapid adoption of electronics and IT to enable the automation of production in factories, and a few more decades later – in 2012 – the industry again introduces a concept that foresees revolutionary changes. In the late twentieth century, a third industrial revolution, brought about by the emergence of computing and computing sciences, led to the rapid – and widespread – decentralisation of communications and energy sharing. The age of the Internet and the World Wide Web had arrived. Integration of the Internet in daily life brought Internet-based services and e-commerce, social media, and made social and business processes quicker and easier to access.

Nowadays, different terms with a similar meaning are used by different countries. In emphasising the fusion between the physical and digital worlds with the vertical and horizontal interconnection using cyber-physical systems (CPS), Industry 4.0 differs markedly from the Third Industrial Revolution. CPS is presented as a critical technological drive. Using sensors and microprocessors, CPS allows us to autonomously exchange information, trigger actions, and control each other independently, for example, in real-time from anywhere.

Industry 4.0 brings numerous industrial and social life changes within only a few decades after the third industrial revolution. Industry 4.0 focuses on technological issues and cyber-physical interactions in the value chain and challenges all the areas: inequality; security; consumer and social behaviour; new ways of organising work and social life; an ageing society; and education.

The ongoing discussions among researchers on the necessary balance of theory-based research and application-oriented research show the different sectors' scientific interest. On the one hand, Sanders et al. (2016) write, “some researches in Industry 4.0 were purely theory-oriented, not readily adaptable to an application. Future research needs to be focussed on creating a conceptual framework and cyber-physical working system, integrating these parameters in a fully functional production environment”.

On the other hand, numerous publications primarily found in the research papers of worldwide consulting companies, such as Boston Consulting Group,

McKinsey & Company, show the bottom-up need for further research on Industry 4.0.

The extended attention found in the papers on strategy and funding priorities emphasises the importance of and lack of research on Industry 4.0 and its implications. Different sources provide information on the different technological changes that Industry 4.0 brings; most agree upon changes in the technological environment, business paradigms, and the changing supply chain.

Schwab et al., during their numerous interviews and speeches in World Economic Forum and similar occasions, envision changes and impacts on the individual at a global level, including: in the ways of leadership and governance systems involving multi-stakeholders; the economy (especially for growth, employment and the nature of work); business (consumer expectations, data-enhanced products, collaborative innovation and new operating models); global and national levels (governments, countries and cities, and international security); society (increasing inequality and community issues); and the individual (identity and ethics, human connection and managing public and private information (Schwab et al., 2018). They write about changing business paradigms as “the changes to the value chain require companies to embrace new business models”, safety and security, legal issues, intellectual property, standardisation and R&D (Cunningham & Link, 2021).

Scientists agree that new ways of using technologies, changes in behaviour, consumption, decision-making, communication, entertainment and other societal areas will emerge. “The changes are historic in terms of their size, speed, and scope” (Dujin et al., 2014). The latter argue that “the roles of designers, physical product suppliers, and the interfaces with the customer (contractor) will change” the way to communicate and that “the first step is the fragmentation of the value chain”. The Internet, 3D printing, participation in a vertical integration chain, and cloud technologies are expected to play a significant role in business. (Bag et al., 2021) The degree of Industry 4.0 implementation is essential and opens significant possibilities to emerging economies and developed countries.

Different countries have their strategies for implementing the phenomenon, and it has become a worldwide stream rather than planned in several industrial countries. Industrie 4.0 Germany, Made-in-China 2025 in China (Li, 2018), Industrial Internet initiative (IIC) in the USA are just a few examples of concepts and plans stimulated by the initiative of the Fourth Industrial Revolution all over the world. They all take the German background of Industry 4.0 introduced in 2011 and contribute to the concept with more specific issues. All the concepts in different countries rely on integrating cyber-physical systems into manufacturing and logistics processes first and using the Internet of Things, services and energy in industrial processes and have implications for value creation, business models, downstream services and work organisation. France refers to the implications for

the future of the industry phenomenon as the *Industrie du futur*. The implications for public social health and decentralised communication and participation in public life are observed along with other challenges raised in different countries. (Larrañeta et al., 2020) imply that the “citizen supply chain” empowered by 3D printing unlocks the potential of 3DP in future supply chains and is a game-changer in many industrial sectors. Remote work and production organisations using machine learning and the Internet of Things (Okorie et al., 2020) -based solutions suggest expanding possibilities to control processes from a distance.

During recent years, the role of Industry 4.0-driven technologies in the global value chain (Acioli et al., 2021; Belhadi et al., 2021), additive manufacturing (Larrañeta et al., 2020), the speed and accuracy of decisions remotely (Okorie et al., 2020) and other aspects have been actively explored. Belhadi et al. (2021) suggest enhancing big data analytics to benefit from the “real-time information on various supply chain activities to overcome the challenges”.

Based on the concept of Society 5.0 initiated in Japan in 2016, the first sights of further industrial development are observed and published in the first policy brief under the Directorate of Prosperity. The policy brief introduces a wave of researches (Culot et al., 2020) that, based on the technological advancements of Industry 4.0, will continue with highlights “to support the industry in its long-term service to humanity within planetary boundaries” (European Commission, 2021). Insights also contribute to the debates on the need to evaluate economic growth, integrating social fairness and prosperity indicators rather than solely economic indicators such as GDP growth.

The sub-section analyses the scientific publications on business models focusing on the explorations of the transformation of business models in response to Industry 4.0 technological and non-technological implications. It concludes with the extended business model that appears as a result of the Internet of Things and other Industry 4.0 implications. In research publications, the term *business model* is often used without more explanation and described as if readers understand it in advance. Arnold et al. (2017) and Remane, Hanelt, Tesch et al. (2017) analyse the taxonomies of business models. After more profound research of the texts, distinctions of the definitions can be found, Zott et al. (2011). A business model is defined as a statement or a description (Teece, 2018), a conceptual tool and architecture (Osterwalder & Pigneur, 2010), a structural template (Amit & Zott, 2001; Porter & Stern, 1998) or a pattern (Brousseau & Penard, 2009). Different authors analyse business models from different perspectives. Some defined a business model as a way to describe the business logic and presented a template to fill in to visualise the business logic, e.g. a business model canvas (Osterwalder et al., 2005)), a value chain template (Porter & Stern, 1998) and others.

Researchers of business models (Matthyssens, 2019; Osterwalder & Pigneur, 2010; Teece, 2018) describe them as a business logic that includes a set of mechanisms, their more or less independent relationships between partners, customers and suppliers, and explains the value creation and capturing of a company. A description of an enterprise's value to customers, how to communicate and “network of partners for creating, marketing, and delivering this value to generate profitable revenue streams” is defined as a business model (Osterwalder et al., 2005).

Table 1.2. The definition of business models (created by the author)

Author, year	Description
	The network of partners for creating, marketing, and delivering this value to generate profitable revenue streams
Amit & Zott, 2001 Snihur et al., 2020	A business model depicts the content, structure, and governance of transactions designed to create value through the exploitation of business opportunities
Teece, 2010	Describes the design or architecture of the value proposition, creation, delivery, and capture mechanisms [a firm] employs. The essence of a business model is in defining how the enterprise delivers value to customers, entices customers to pay for value, and converts those payments to profit

The section analyses the scientific publications and research that define the business model's interrelatedness to the research in Industry 4.0 and implications to the value proposition, creation, delivery, and capture.

Scientists (Amit & Zott, 2001,2012; Remane, Hanelt, Tesch, et al., 2017) introduce different types of business models influenced by digitalisation (Arnold et al., 2017; Jorg Weking et al., 2018). Many researchers offer to change business models from product-based to service-based models (Adrodegari & Saccani, 2017; Fleisch et al., 2014) data and cloud-based models(Gupta & George, 2016; J. Lee et al., 2015). Gassmann et al. (2013), in exploring A. Osterwalder's business model, Canvas, in his “Business Model Navigator”, identified 22 out of 55 business models influenced by digitalisation. As noticed during the literature review, most researchers use Osterwalder's business model canvas as a basis for their researchers. As noticed during the literature review, most researchers use Osterwalder's 2004 business ‘canvas’ model by and developed it further in 2010 and later as a basis for their research.

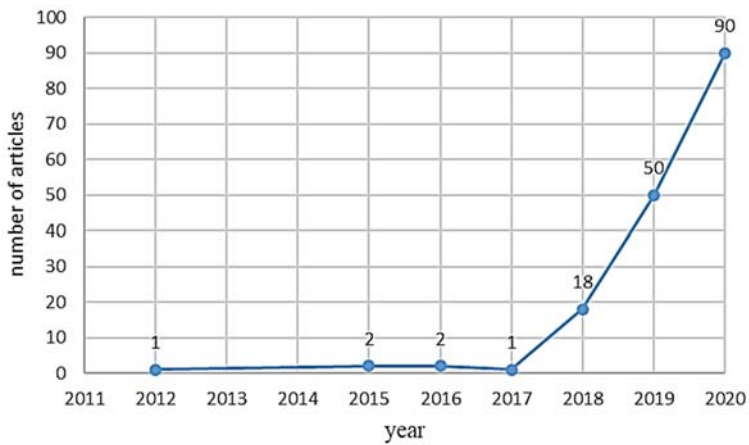


Fig. 1.4. The increase of publications on business models and Industry 4.0 between 2011 and 2020 (created by the author)

Figure 1.4 presents the increase in the scientific production on Industry 4.0 and business models from 2010 to 2020 indexed in Clarivate Analytics, with the following inclusion and exclusion criteria: only articles with the keywords “Industry 4.0” AND “business model” are included in the data set. The scientific production of 450 articles co-authored by 950 authors from 600 institutions was found and analysed below.

The first signals of scientific attention were mentioned in 2016 (10 articles). The increase is very rapid: 31 articles in 2017; 60 articles in 2018; 108 articles in 2019; 205 articles in 2020. Figure 1.4. does not include 2021 because it was conducted in the first quarter of the year. However, it is worth mentioning that there were 30 published or early access articles in Clarivate Analytics Web of Science in March 2021.

Scientists (Amit & Zott, 2001; Arnold et al., 2017; Osterwalder et al., 2005; Remane, Hanelt, Tesch et al., 2017; Zott et al., 2011) focus on the influence of the Internet of Things on business models and introduce different types of digitalised business models. The most significant influence on new business model development and thus value creation (Martínez-Román et al., 2019) is declared to have Internet-based technologies, such as the Internet of Things, cloud computing, big data, and robotics. Moreover, virtual and augmented reality and artificial intelligence are mentioned. Different parts of business models are also being researched, including the supply chain (Chopra and Sodhi, 2014; Revilla and Saenz, 2017), value creation and capture or revenue stream (Ibarra et al., 2018; Orellano et al., 2017).

Table 1.3. Findings on business models driven by the Internet (created by the author)

Technology	Authors	Findings on business models driven by the Internet or Industry 4.0
Internet-based/ digital business models	Teece & Linden, 2017	A term of a digital enterprise and the integration of the business processes is used.
	C. Lee & Lee, 2012	e-commerce as a term is used as a part of the business processes.
	Huemer et al., 2008	e3-value exploration in e-business is presented.
	Bagnoli et al., 2018, Guo et al., 2017	e-business is used as a term when digital solutions are implemented in the business processes.
	Brousseau & Penard, 2009	Three types of business models by Internet were identified: knowledge-based, assembling, matching. In a combination of types, nine business model types are identified.
	Remane, Hanelt, Nickerson, et al., 2017	Implementation of digital business models in traditional businesses and impact explored.
	Bock & Wiener, 2017	Digital solutions in the business model are explored: digital offering forms a physical product to digital service, digital pricing, digital platform, digital experience and data analytics.
Industry 4.0 business models	Remane et al., 2016	Sixteen business model types are based on (1) a creator selling the ownership of an asset that has significantly been transformed; (2) a distributor selling the ownership of an asset with limited transformation; (3) a landlord granting temporary use of the asset; or (4) a broker matching buyers and sellers of assets. The type of asset involved can be (1) financial, (2) physical, (3) intangible or (4) human.
	Fleisch et al., 2014, Fleisch et al., 2017, Wortmann et al., 2020	There are five layers of business models driven by the Internet of Things technologies: physical product, sensors; connectivity; analytics; and digital service. Higher levels represent more implementation of the Internet of Things.

The debate on digitalisation in manufacturing companies is often observed in research exploring the focus shift from product to service. Product to service concept is also facilitated by the Internet of Things and real-time interconnectivity, as argued by Frank et al. (2019), Kohtamäki et al. (2019) and Müller et al. (2020).

The scientific literature searches for a distinction between Internet-based and Industry 4.0-based business models. In many cases, both are called digital business models; therefore, it is essential to read the full text to understand what kind of business models are described.

Brousseau and Penard (2009) describe the digital business models describe as follows: matching based on transaction costs and network externalities; knowledge based on incentives and diffusion, access and quality; and assembling based on differentiation and economy of scale.

Many scientists relied on previous taxonomies of business models – five types of business models (cloud, data-based), three e-value (Huemer et al., 2008) – and explored modification based on Industry 4.0 enablers, such as the Internet of Things or big data. Nevertheless, since 2016, the first research results were introduced, such as those of Weinberger et al. (2016), which showed a different approach to tackling the Industry 4.0 business model taxonomy and presented a five-layer business model. The introduced Industry 4.0 business model taxonomies explore the distinction of business models based on the intensity of the Internet of Things or other enablers used in the business model, the autonomy of devices from a human intervention that communicate among each other, and the transformation from physical products to digital service. Scientists such as (Arnold et al., 2017; Streuer et al., 2016; Weking et al., 2020; Weking, Hein et al., 2018) explicitly explored the implication of Industry 4.0 enablers on business models.

This thesis focuses on business models as a way to create and capture value; business model ontologies can be structured in a four-step process – value proposition; value creation; value delivery; and value capture – in five layers as the matrix for implementation of Industry 4.0 solutions based on the Internet of Things. Industry 4.0 solutions (Müller & Daschle, 2018; SAP Digital Supply Chain, 2020) refer to the combination of Industry 4.0 technological drivers that allow interconnectivity, real-time data analytics between machines and nontechnological innovation that allow implementation of human-machine interaction successful.

Exploring the business models' key drivers on totally new business logic rather than offering modifications is observed. Value layers of the Internet of Things application (Figure 1.5) show the shift of the value created by applying the Internet of Things in the business model. The application of other Industry 4.0 technologies will be analysed according to the value creation process.

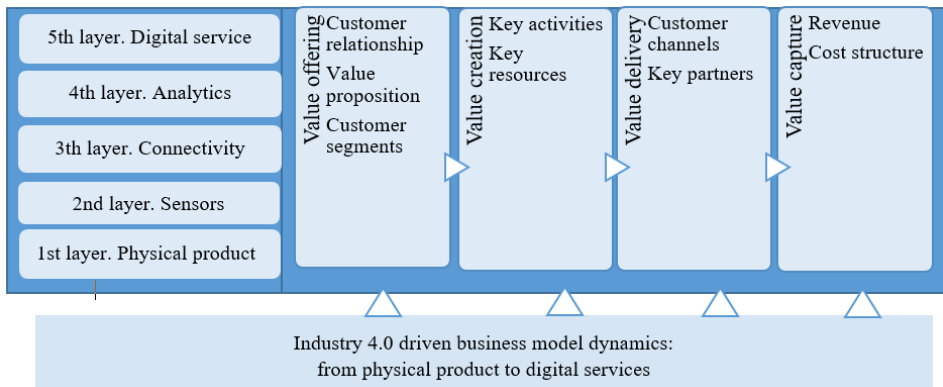


Fig. 1.5. The value dynamics following the five-layer business model of Industry 4.0 (created by the author according to Fleisch, 2010; Fleisch et al., 2014; Weinberger et al., 2016; Wortmann et al., 2020)

Many scientists explore business models in the digital context or Industry 4.0 context. Most of them rely on previous research results, e.g., e3value. However, it is seldom that taxonomies are based on the value chain dynamics. They do not explore step-by-step dynamics from physical products in the traditional business model of digital service based on data analytics. Weinberger et al. (2016), followed by Fleisch et al. (2017) and Wortmann et al. (2020), presented the five-layer business model in the Internet of Things based on Industry 4.0 implementation. The scientists researched their developed five-layer model. The model introduced a step-by-step transformation of a business model from traditional to digital service. Further researches of other independent scientists groups (Leminen et al., 2018, 2020; Weking et al., 2020; Weking, Hein, et al., 2018) explored not only the transformation process of the Internet of Things but also the implications of the Internet of Things on specific business model parts.

This research expanded the model and explores the implications of the Internet of Things across the value chain: value proposition, value creation, value delivery and value capture. The expanded version of the five layers of the model provides a clearer picture of what business model modifications and transformation across the value chain can be used in each of the five layers.

Table 1.4. The expanded matrix of a business model driven by Industry 4.0 (created by the author)

Layers	Value proposition	Value creation	Value delivery	Value capture
Digital service	Digital experience: personalisation, engagement, and community building (Bock & Wiener, 2017) Physical products with embedded digital technologies (Bock & Wiener, 2017)	Intelligent and connected networking of market players in a business ecosystem (Kraft et al., 2021) Saving electricity and pretending to be at home (Weinberger et al., 2016)	Platform business models in the two-sided and multisided market (Kraft et al., 2020)	Indirect revenue model (3) (Wortmann et al., 2020) Direct revenue model (6) (Wortmann et al., 2020) Demand-based pricing, supply based pricing, consumption-based pricing (Bock & Wiener, 2017)
Analytics	Product data, customer data, external data (Bock & Wiener, 2017)	Connected products (Kraft et al., 2021) Combining data from connected sources (Weinberger et al., 2016)		
Connectivity		Intelligent and connected operation and production (Kraft et al., 2021)		
Sensors		Motion detector to switch the light on and off (Weinberger et al., 2016)		
Physical product		Digital refinement of products (Kraft et al., 2021) Electricity bulb (Weinberger et al., 2016)		

In the further sections of this thesis, the research and approbation of the assessment based on the model presented in Table 1.4 are explained.

1.2. Analysis of the Scientific Literature on Risk Assessment in Industry 4.0

The section analyses the scientific publications on risk and its assessment, focusing on exploring the transformation of business models due to Industry 4.0. The section concludes with the companies' determined areas of risk assessment, defining risks that appear during the transformation of business models when implementing Industry 4.0.

The research shortage in risk assessment appears when the researcher starts narrowing explorations to a concrete research field. Risk is generally understood as the likelihood of a transition from an expected injury, loss or other negative consequences prevented by preventive action. Risk often relates to a degree of uncertainty that goes hand in hand with innovation and change. The definitions accepted by researchers for terminology in this field are closely aligned.

Reim et al. (2016) define risk as “a combination of the likelihood of loss and the impact of loss on events”.

$$R = L_n \times I_n, \text{ (according to Reim et al. (2016)),} \quad (1.1)$$

where R – risk; L – the likelihood of loss of n events; I – the impact of a loss of n events for the results of the enterprise; n – number of different events, risks, losses, or impacts.

Table 1.5. Overview of the types of risks related to Industry 4.0 (created by the author)

Researcher	Types of risks proposed
Reim et al., 2016	Physical risks include competence and infrastructure, investment risks, and IT risks, including data and information privacy, security and online integration.
Reim et al., 2016	– behavioural, – technical and – competence risks
Tupa et al., 2017	scarcity of human resources: new competence needed, changes and development are quick
Tupa et al., 2017	Information security, data loss, loss of integrity of information, errors of data processing, risk of cyber attacks.

Table 1.5 describes an overview of the types of risks related to Industry 4.0. The next step risks are systemised and grouped to assess (Haaker et al., 2017). The risk heat map allows us to map risks, comparing their impact and possibilities of appearing and prioritise them accordingly, using sensitivity analysis to assess

the sensitivity of variables, or scenario analysis to assess pessimistic and optimistic scenarios of the risk situation. Risk often correlates with some uncertainty, which always goes together with innovation and change. Most researchers agree on similar elements of the definition of *risk*.

With the fast transformation of the economy, the advantages and benefits of Industry 4.0 are widely discussed (Carayannis et al., 2021; Mensah & Gottwald, 2016; Zheng et al., 2015), while risks and uncertainties result from this transformation tide. Risks related to making decisions when choosing between alternatives in business models driven by Industry 4.0 have been rarely investigated.

Table 1.6. Risk of business model transformation driven by Industry 4.0 (created by the author)

Areas of risks	Authors	Findings
Technical risks	Reim et al., 2016	New capabilities and resources to be able to offer product-service solutions (PSS).
	Nurse et al., 2017	Internet of Things brings dynamics, and systems change fast. Technical improvements make real-time risk identification and assessment realistic
	Orellano et al., 2017	Data-based solutions as value creation and proposition.
	Yigitbasioglu, 2015	Cloud computing delivery model makes technology outsourcing possible and shows flexibility, speed of deployment, and access to quality software. It is shown as cost-effective with a pay-per-use revenue stream
	Hassan, 2017	IT resources have a significant influence on cloud computing adoption.
	Baecke & Bocca, 2017	Internet of Things enables companies to collect an increasing amount of sensor-generated data.
Data security risks	Tupa et al., 2017	The most common risk factors in the manufacturing area are related to information security, loss of integrity of information, errors of data processing, cyber-attacks
	Yigitbasioglu, 2015	The privacy and confidentiality of data, lack of understanding of the technology.
	Nurse et al., 2017	Cyber-attacks, the security of data and information
Acceptance by customers	Reim et al., 2016	Behavioural risks include less careful behaviour when using a product that a customer does not own (e.g., extensive usage of the product or service such as online reservation, anonymous comments and unmanageable feedback in the social media).

End of Table 1.6

Areas of risks	Authors	Findings
Acceptance by staff	Jacobsson et al., 2016	The risks classified as high were either related to the human factor and the competence or the software components of the system
	Kraft et al., 2020	Lack of willingness to change habits
	Cimini et al., 2021	Organisational culture to enhance on-job-training and skills change
Competence risks	Tupa et al., 2017	Scarcity of human resources: new competence needed.
	Yigitbasioglu, 2015	Regarding the perceived risks of cloud computing, there is evidence that concerns the lack of understanding inhibit its adoption
	Nurse et al., 2017	The processes where devices are interconnected, and the information is communicated without humans are integrated very fast. Fast changes require more system thinking skills, due to rapid changes and lack of knowledge, essential risks might be missed
	I. Lee & Lee, 2015	Managing big industrial data covers all necessary steps from acquiring data, processing the information and supporting decision-making.
	Chopra & S.Sodhi, 2014	Decentralisation of processes (e.g. building resilience by segmenting or regionalising supply chains, avoiding centralisation of resources), in the long run, overinvesting maybe more profitable than not investing enough.
	Kraft et al., 2020	Established rigid procedures, defence of existing structures
	Cimini et al., 2021	Configuration of structure
Financial risks	Zhou et al., 2017	As the investment nature is of a long cycle and high risk, the “organisational factors” in the implementation cannot be ignored.
	Hassan, 2017	IT investment has a major impact on cloud computing

Table 1.6 expands the understanding of the types of risks in the business models driven by Industry 4.0. The explanations are based on the literature review conducted by the authors of this article. There are a series of risks identified in different articles that can be clustered into five types: technical, competence, behavioural, data security and financial risks.

Table 1.7. Different models of risk assessment of business models driven by Industry 4.0 (created by the author)

Author, year	Main findings	Relation to the business model
Revilla & Saenz, 2017	Four-dimension model of the Internet of Things and its relationship with the frequency of disruption of the supply chain.	Key activities
Schlüter et al., 2017	Model using Monte Carlo and other risk assessment methods is developed, uses the Internet of Things	Key activities
Tupa et al., 2017	A model linking risk to key performance indicators using the Internet of Things	Key activities
Reim et al., 2016	Types of risks are discussed: delivery competence; technical and behavioural risks; and developing a risk management framework based on the Internet of Things for product-service system	Value proposition, delivery and capture
Haaker et al., 2017	Stress testing is built upon scenario planning to evaluate the robustness of the business model. Heat map “allows testing the robustness of business models to future uncertainties”.	Overall model

According to the findings, risk assessment models focus on the overall business model (Haaker et al., 2017). Some scientists investigate the application of specific risk assessment methods (Schlüter et al., 2017) or on specific parts of business models.

The findings show that the primary risk assessment process is followed, and the methods should be best adapted to the high uncertainty situation. Moreover, the findings show that the Internet of Things and other technological solutions collect, process and communicate risk events in real-time.

1.3. Analysis of the Scientific Literature on the Assessment of Efficiency and Growth when Transforming Business Model in Industry 4.0

The section analyses the scientific production on the concepts of efficiency ratios and methods of efficiency assessment. The investigations focus on the explorations of the transformation of business models in response to Industry 4.0. The section concludes with the determined areas of efficiency and growth assessment

that appear during the transformation of business models when implementing Industry 4.0.

The scientific literature analysis starts with the terminology, which is widely used as agreed by scholars. The Independent Evaluation Group – World Bank 2007, explains *efficiency* as “the extent to which the investment has converted or is expected to convert its resources/inputs (such as funds, expertise time) economically into results to achieve the maximum possible outputs, outcomes, and impacts with the minimum possible inputs”.

Table 1.8. Input–output–outcome when transforming the business model in Industry 4.0 (created by the author)

Part of business model	Input	Output	Outcomes
Value proposition	Expenditure in R&D.	Increase of customers and customer segments. New product segments. Increased sales.	Growth in revenues. Diversity of customer and product segments.
Value creation	Expenditure on raw material. Expenditure on energy. Units of material. Hours spent.	Units produced. Number of health issues in the production. Hours saved.	Growth in output volume. Decrease in spoilage and lockdowns. Decrease in health accidents.
Value delivery	Full-time equivalent (FTEs) in delivery. Expenditure on fuel and exploitation.	Number of products in the warehouse or on the way. Number of deliveries delivered in time; Number of deliveries to be re-sent. A number of health issues or accidents in the warehouse and delivery.	Growth of accuracy of deliveries. Decrease of health accidents.
Value capture	Expenditure on the collection of receivables.	Time to collect receivables.	More accurate forecast on cash flow. Higher profitability.

Efficiency talks about the amount of output produced with given inputs. It refers to outcomes gained with the produced outputs. The relationship between

input, output and outcomes and the assessment of each step is significant. In general, efficiency is calculated by the ratio between output and input. The challenge of measuring efficiency is identifying transparent objects by which to calculate input and output. Identifying inputs and output in standard monetary and non-monetary terms, the dimensions of time as economies are never stable at any point.

Usually, the term *efficiency* refers to optimising resources and describes a performance level in which one uses the least amount of input to achieve the highest output. Not only materials, but also personnel time, energy and any other inputs are calculated in the input ratio. There are two approaches to efficiency found in the scientific literature: static efficiency and dynamic efficiency. More about different types of efficiency is in the next section of the thesis.

Table 1.9. The types of efficiency (created by the author)

Term	Author, year	Description
Efficiency	Wilson et al., 2018	An ability to produce output without wasting materials, time or energy.
Efficiency	Hendren, 2014	A common approach is to separate distribution issues (equity) from the sum of income or welfare (efficiency). The author proposes a compensation principle that leads to aggregating surplus or efficiency as a normative criterion. If one environment delivered a more significant total surplus relative to the status quo, the winners could compensate the losers through hypothetical income redistribution.
Allocative efficiency	Mandl et al., 2008	This reflects a situation when resources are distributed to produce goods and services considering consumers' priorities. Allocative efficiency can be reached when a product's price equals the marginal value of the customer's expectation and the total marginal cost.
Production efficiency	Mandl et al., 2008	No additional output can be produced without increasing the number of inputs and production works at the lowest average total cost.
Technical/ technological efficiency	Mandl et al., 2008, Kim et al., 2018	Reflects a relation between input and output, taking pure production as a final result

As Mateu & March-Chorda (2016) explain, only a few researchers propose methods to assess the business model *ex-ante*, i.e. before its implementation. Proposed methods can help business decision-makers plan changes in the business model before it is implemented and is part of the management area. Most methods are more managerial and suggest intuitive narrative ways of assessment. Brettel et al. (2012) show a “positive relationship between indicators and performance measures” in the introduced empirical research conducted using interviews in 234 technology-intensive companies. Profitability and growth are used as performance measures.

A lot more researchers exploring the *ex-post* assessment of the business model focus on separate business model blocks using measures like value-added (VA) for input, net present value (NPV), or internal return of rate (IRR) for output, or ratios like return on sales (ROS) for value creation, productivity, overall equipment efficiency (OEE) or overall factory efficiency (OFE) for key activities) for assessing outputs. (Eling & Luhn, 2010),

To date, researchers have rarely explored the assessment of business model changes due to Industry 4.0. The dynamic efficiency approach is found when supporting the assessment of the impact of dynamic changes in the business model beforehand. A complex of measures should be used within this approach to achieve reliable results. The approach to the resources explains the main difference between static and dynamic efficiencies.

The static efficiency concept declares that the main objective is to diminish the waste of the given resources and can be:

- allocative efficiency: „going as far as possible in the satisfaction of wants within the resource and technological constraints“ (Stanley, 1986);
- productive efficiency: aims to „supervise workers’ measure time spent and avoid any kind of waste” (Triantis, 2014);
- technical efficiency: (Latruffe, 2010; Nellutla et al., 2018)s;

Dynamic efficiency explores economic growth (Abel et al., 1989), calculating dynamic efficiency as the marginal productivity of capital derived from the accounting profit rate. E.g. if the marginal productivity of capital is above economic growth, it is considered dynamically efficient. Economic efficiency refers to the holistic outcomes of the previous mentioned. Researchers have explored different types of efficiency over the years. Dynamic efficiency calls for exploring the linkage with the concept of entrepreneurship, which generates and transmits new information, uses creativity and coordination forces to create value and new ends and means, is competitive in its origin and is never-ending. The situation is considered dynamic efficient when a return on investment is higher than their measured capital cost.

An overview of dynamic efficiency is introduced in Table 1.9 above.

Table 1.10. Main characteristics of dynamic efficiency (created by the author)

Author, year	Characteristics of dynamic efficiency
Kathuria, 2015	Explains five elements that identify dynamic efficiency: generally materialises in future, recurring, leads to innovation, provides the ability and incentive to innovate, endogenous new knowledge and learning. It is about improving allocative and productive efficiency over time using <i>learning, investment and innovation</i> .
Luo, 2018	It can be used in public as well as corporate institutions.
Abel et al., 1989	Explored the relationship between dynamic efficiency and economic growth and calculated dynamic efficiency as the marginal productivity of capital derived from accounting profit rate
Silva & Stefanou, 2007, Silva et al., 2015	The calculation of capital includes internal and external adjustment costs. Internal adjustment costs are understood as output-reducing costs calculated. The resources are used as investment support rather than production costs (e.g. installing new maintenance software, increasing personnel qualifications); it is a trade-off between current and future efficiency and growth).
Fallah-Fini et al., 2014	Time interdependence over different periods can be attributed to one or a combination of five factors, including production <i>delays</i> , inventories, <i>technological change</i> and vintage-specific capital, <i>adjustment</i> costs and incremental improvement and <i>learning</i> models.

Dynamic efficiency refers to efficiency over time and involves introducing new technologies and non-technological innovations to reduce costs. Dynamic efficiency is also referred to as an optimal mix of static efficiency (Ellerman, 2014; Fallah-Fini et al., 2014; Luo et al., 2018) and innovation for ongoing problem-solving and improvement. (Kapelko, 2017) adds that current production decisions (for example, investment in the capital) have to impact: constrain or enhance future production possibilities. In many publications, dynamic efficiency involves creativity, entrepreneurship, innovation and the impact over a time period. Understanding dynamic efficiency calls for an exploration of the concept of entrepreneurship that generates and transmits new information, uses creativity and coordination of forces to create value and new ends and means, and is competitive by its origin and never-ending.

The challenges of assessing dynamic efficiency have been explored by (Abel et al., 1989; Geerolf, 2018; Kathuria, 2015; Silva et al., 2015; Silva & Stefanou, 2007)). Abel et al. (1989) declare that the net cash flow criterion is the most general way to think about dynamic efficiency and compare the safe rate with the capital growth rate in the stock market. The formula of dynamic efficiency following Abel et al. (1989) is presented in formula (1.2):

$$\text{Dynamic efficiency} = \frac{\text{marginal productivity of capital}}{\text{accounting profit rate}}. \quad (1.2)$$

The assessment of dynamic efficiency was investigated, and recent decisions influence future production possibilities. The measurements obtained a broader perspective, i.e. “such an approach can be essential for capital-intensive industries which lack short-run flexibility due to adjustment costs” (Kapelko, 2017). It stretches the production possibility frontier, providing access to more and better goods and services over time.

Dynamic efficiency can be calculated as a capital investment ratio and capital income (formula 1.3). It is declared that a situation is dynamic efficient if capital investment is lower than capital income.

$$\text{Dynamic efficiency} = \frac{\text{capital investment}}{\text{capital income}}. \quad (1.3)$$

Table 1.11. The main characteristics of dynamic efficiency (created by the author)

Term	Author, year	Characteristics
Dynamic efficiency	Abel et al., 1989	Exploration of the relationship between dynamic efficiency and economic growth and calculate dynamic efficiency as the marginal productivity of capital derived from accounting profit rate.
Dynamic efficiency	Geerolf, 2018	The situation is considered dynamic efficient when a return on investment is higher than their measured capital cost.
Adjustment costs	Silva & Stefanou, 2007. Silva et al., 2015	External adjustment costs arise from market forces in the market for investment goods. External adjustment costs usually added to the other or administrative costs, line and internal costs are calculated as production costs in the technical product specification.
Adjustment costs, innovation and learning	Fallah-Fini, et al., 2014. Kathuria, 2015.	Time interdependence over different periods can be attributed to one or a combination of five factors, including production delays, inventories, technological change and vintage-specific capital, adjustment costs and incremental improvement and learning models. Explain the five elements that identify dynamic efficiency: generally materialises in future leads to innovation, provides the ability and incentive to innovate endogenous new knowledge and learning. It is about improving allocative and productive efficiency over time using learning, investment and innovation

Scholars argue about what should be included in the calculation of capital. Most researchers exclude land from capital calculations and explain it as finance and labour. A dynamic calculation can include accumulations from previous periods and thus create a continuous process. Some researchers, e.g. Silva and Stefanou (2007), include internal and external adjustment costs and Fallah-Fini et al. (2014) suggest including delays, technology change and learning costs.

Table 1.12. Overview of efficiency and growth assessment ratios when transforming business model in Industry 4.0 (created by the author)

Efficiency ratio	Author, year	Main findings
Overall equipment efficiency (OEE)	Hwang et al., 2017; Muchiri & Pintelon, 2008	OEE identifies hidden capacity, reduces overtime expenditures, and allows deferral of significant capital investment. The basic assumption in OEE is that the three elements have the same weight.
Overall Performance Efficiency (OPE)	Low et al., 2014	OPE considers two measurement elements: the performance efficiency and performance comparison of the set-up operation before and after the improvements were conducted.
Overall Asset Efficiency (OAE)	Muchiri & Pintelon, 2008	OAE shows business-level efficiency and measures the efficiency of individual equipment, discrete-type processes, and continuous process..
Profitability (P), Return on Sales (ROS), Return on Assets (ROA)	Tajeddini, 2015, Davidow, 2018, Zaborek et al., 2016	Four ratios (profitability, return on investment, return on sales, and return on assets) measure efficiency in a dynamic environment. The entrepreneurial dimension correlates independently rather than co-varies.
Economic Value Added (EVA),	Murray et al., 2016	The methodology is based on a single case study approach with empirical analysis. It analyses how the introduction of IoT innovations influences the value of a company's intellectual capital.
Working capital	Brandenburg, 2016	Provides some idea of the company's underlying operational efficiency.
Time-to-market launch	Szarucki & Menet, 2018	Co-producing value would accelerate the new product development process (time-to-market launch) and make the new products address the customer needs adequately.

In publications by Luo et al. (2018) and Famulski (2017), dynamic efficiency is explored in the public sector and social welfare. However, Famulski (2017), referring to Abel et al. (1989), states that “the level and fluctuation of dynamic

efficiency is greater for the corporate sector than it is for the aggregate economy”. The reference indicates that dynamic efficiency can be calculated both at the aggregate and firm levels.

Assessing the efficiency requires special methodological preciseness as determining inputs and output in a time frame requires special attention. A significant body of research on measuring economic performance tends to focus on economic efficiency measurement at a given point. However, it ignores the results of decision-making over generations concerning economic efficiency. Wilson et al. (2018), after a literature review, state that the terms efficiency and effectiveness are used together in most of the business model publications. The ratios show the possibilities to assess efficiency and growth in the companies when transformed to Industry 4.0. The scientists investigate the application of the ratios to be used, and the findings are presented below in Table 1.12. More scientific attention is found on measuring the efficiency of individual blocks of business models, such as key activities using OEE, and revenue stream using ROS. Few publications were found to assess the efficiency of the overall business model changes and use NPV, IRR, and cost–benefit analysis as a methodology. The findings suggest assessing growth using the added value and similar ratios. As Tesch and Brillinger (2017) and Wilson et al. (2018) suggest, the assessment can be quantitative and qualitative, analytical and effectual.

Some efficiency indicators use financial resources for input and finance as output, such as profitability, return on investment, return on sales or return on assets. Some efficiency indicators use financial resources for input and non-financial results, such as production quantities as output, e.g., adjustment or delay time per investment for training. Some efficiency indicators use nonfinancial inputs such as time or raw material in quantity and financial results as outcomes, e.g. sales or profit per FTE. Some efficiency indicators use non-financial inputs, such as time or raw material quantities and non-financial results as outcomes, e.g. production or sales quantities per FTE. Some efficiency indicators are a complex of financial and non-financial inputs and outputs, e.g. overall performance efficiency (OPE), overall factory efficiency (OFE) or overall equipment efficiency (OEE). The indicators mentioned above use internal accountancy information, and some of them are publicised in the standard financial accountancy accessible in open sources.

1.4. The Usage of a Composite Index, Indicators and Ratios

This section will explore the usage of indexes, ratios and net measures in efficiency, growth and risk. The definitions of an indicator, index and system of indicators and composite indicator are explored in this section. Moreover, the advantages and disadvantages are analysed.

A composite index consists of several single-component indicators. Single-component indicators are usually grouped into categories and categories into dimensions. Those single indicators are called components or component indicators.

A composite index visualises the overall holistic view of the multidimensional concept with a single index. A composite index can be split into component indicators and visualised on the dashboard. The index aims to provide a more detailed picture of the phenomenon while avoiding weight assignment and losing information from combining multiple indicators.

Different indicators visualise different complexities of information about the phenomenon (Edmonds et al., 2020; Greco et al., 2019; OECD, 2008; Oslo manual, 2018). In the scientific literature, composite indicators and indexes can be found. However, composite index refers to a hierarchical system when categories (Reckien, 2018) are used when a composite indicator, as Oslo Manual (2018), introduces values into a single index that reflects the complex phenomenon. Composite indices are relatively flexible because changes in selection, scaling, weighting and aggregation can be effected readily, as Booysen (2002) says.

The authors discuss different aspects of the composite indicator. According to Greco et al. (2019), a composite indicator is “based on sub-indicators that have no common meaningful unit of measurement, and there is no obvious way of weighting these sub-indicators”.

The objectives of the composite indexes include:

- Indexes help see the phenomenon changes through time if evaluated at regular periods in the longer term,
- Indexes help to integrate several elements into one that could not be compared otherwise,
- Indexes help to visualise the trend of the evaluated phenomenon,
- Indexes help to communicate with audiences (e.g. society, politicians, investors) in a simpler and easier-to-understand way,
- Indexes can serve as a benchmark or performance indicator to monitor the progress of the organisation or policy.

Table 1.13. Typology of indicators (created by the author, according to (Greco et al., 2019; OECD, 2008; Oslo manual, 2018))

Source	Name	Description
OECD, 2008	Indicator	An indicator is a quantitative or a qualitative measure derived from a series of observed facts that can reveal relative positions (e.g. of a country) in a given area
Oslo Manual, 2018	Single indicator	An indicator is a variable that represents the performance of different units along some dimension. Its value is generated through a process that simplifies raw data about complex phenomena to compare similar units of analysis across time or location
EUROSTAT, 2020; OECD, 2008	Input	Input indicator measures the material resources used in a policy or project to achieve the result
EUROSTAT, 2020; OECD, 2008	Output	Output indicator measures the goods or services that come out as a result of the policy or project
OECD, 2008	Composite index	It is essential to generate the “meaningful” composite index, which is derived from the theoretical framework.
Oslo Manual, 2018	Composite index	The composite indicator introduces and compiles multiple indicators into a single index based on an underlying conceptual model that reflects the dimensions or structure of the measured phenomena.
Reckien, 2018	Composite index	A composite index combines and aggregates multiple single indicators or sub-indices to

The OECD Handbook edited by Nardo et al. (OECD, 2008) recommends generating the “meaningful” composite index, where meaningfulness is derived from the theoretical framework. Therefore, identifying the weights and aggregation of component indicators (Edmonds et al., (2020) should be consistent with the underlying theoretical framework. The simplicity with which to understand and compare the status and the possibility of summarising a complex phenomenon with different measures (Foa & Tanner, 2012; OECD, 2008; Sharpe, 2004; Szenkman & Pilat, 2018) help to assess the progress of a social phenomenon over time and facilitate communication with the general public, promoting transparency and accountability.

In addition, there is some criticism about composite indicators and some negative aspects. Several of these are mentioned often. First, determining the concept concisely and measurably is a challenge as a multidimensional and complex phe-

nomenon is usually described. Moreover, component indicators should have a direct link to the concept, and it is challenging to select them (Bellenger & Herlihy, 2009; Burgass et al., 2017; Foa & Tanner, 2012; Greco et al., 2019; Guillaumont, 2009; Nardo et al., 2005; OECD, 2008; Sharpe, 2004; Szenkman & Pilat, 2018). As explained, some dangers are seen when using composite indicators. First of all, one can lose some analytics and see the index as a straightforward tool. A composite indicator can monitor the progress of the multidimensional and complex phenomenon and benchmark the performance over time. A composite indicator consisting of single indicators provides a framework to divide a complexity into simpler parts and help evaluate and communicate the progress that otherwise would not be possible. In their publications, different authors use the terms composite indicator (Greco et al., 2019; OECD, 2008) or index (Oslo Manual, 2018; Skaržauskienė, 2015). However, they feature the composition of dimensions and categories measured by single indicators (OECD, 2008) to compare the social phenomenon in timeline and locations. Some authors use input and output indicators to create a composite index. Many authors (Bartniczak & Raszkowski, 2018; Rowley et al., 2012; Singh et al., 2009) who construct composite indexes in their researches tend to refer to the Handbook on Constructing Composite Indicators (OECD, 2008). The handbook describes a 10-step process on how to construct a composite index. Below, all the steps, with the main aim of each of them, and the results, are analysed.

1. According to OECD 2008, the theoretical framework development consists of three steps: defining the concept, determining subgroups, and identifying the selection criteria for the underlying indicators. This stage aims to provide the scientific background for identifying and selecting variables (input, outputs and process) or their groups to measure the multidimensional concept. A clear definition of the concept has to be described. Scientific literature analysis and expert analysis are used to increase a variety of indicators and increase the robustness of the system of indicators. The result of this stage is a list of selected criteria to measure the multidimensional concept.

2. Data selection. This stage aims to select data with the necessary characteristics and forms an analytical basis for further research. It includes the following actions: check the availability and quality of data and create a summary table on data characteristics, such as availability (across the country, time), source (open, internal), type (hard, soft or input, output, process). The success of further research lies in the reliability, availability and measurability of the data.

3. Imputation of missing data aims to estimate missing data and complete the data set for further research through case deletion, single or multiple imputations (Allison, 2000; Bertsimas et al., 2018; EUROSTAT, 2020; Huisman, 2014; Reckien, 2018; Song & Shepperd, 2007; van Buuren, 2018; Zeng et al., 2018). It also aims to minimise bias and proceeds if the usual data selection process would

be very time- and budget-consuming – if not impossible – to collect. The following actions should be taken: to identify missing data and decide on the importance of the final result; provide a measure of the reliability of imputed values; and use single or multiple imputations to supplement the data set. There are three general methods for dealing with missing data: (i) case deletion; (ii) single imputation; or (iii) multiple imputations.

Table 1.14. Process on how to construct a composite index (created by the author according to Edmonds et al., 2020; EUROSTAT, 2020; Foa & Tanner, 2012; Greco et al., 2019; OECD, 2008; Oslo manual, 2018)

Step	Author, year
Theoretical framework	Foa & Tanner, 2012
Data selection	Foa & Tanner, 2012
Processing of data	Foa & Tanner, 2012; Munda & Nardo, 2005
Imputation of missing data	Allison, 2000; Bertsimas et al., 2018; EUROSTAT, 2020; Huisman, 2014; Nguyen et al., 2016; Reckien, 2018; van Buuren, 2018; Zeng et al., 2018
Multivariate analysis	Cronbach, 1951; Munda, 2012
Normalisation	Abson et al., 2012; Reckien, 2018; Schmidtlein et al., 2008; Tran et al., 2009; Yoon, 2012
Weighting and aggregation	Becker, 2015; Munda, 2012; OECD, 2008
Uncertainty and sensitivity analysis	Cherchye et al., 2008; Dobbie & Dail, 2013; Saisana, 2004
Back to the data	Cherchye et al., 2008; Dobbie & Dail, 2013; Marozzi, 2012; OECD, 2008; Saisana, 2004
Links to other indicators	Cherchye et al., 2008; OECD, 2008; Saisana, 2004

4. The multivariate analysis aims to study and assess the data set's suitability and to guide to methodological choices. According to Munda (2012); Munda & Nardo (2005), the following actions are taken: to assess the underlying structure and its suitability using principal component analysis, factor analysis, Cronbach coefficient alpha (c -alpha), cluster analysis or other methods, to group variables according to statistical similarity and provide the interpretation of results and to compare the statistically determined structure to the theoretical structure determined in the first stage (Cronbach, 1951). The multivariate analysis gives insight into the structure of the data set of the composite index and the correlation.

5. Normalisation helps indicators with different scales compare and provide a linear transformation of indicators to keep the correlation structure of the origi-

nal data and rating (Reckien, 2018; Tran et al., 2009). There are various normalisation methods to choose from: simple ranking, max-min ranking, standardisation and distance to a reference. Moreover, a weighted and additive approach to normalisation has to be considered (Abson et al., 2012; Schmidtlein et al., 2008; Yoon, 2012). The method should be chosen after an analysis of the pros and cons of each method.

Table 1.15. Comparison of methods of normalisation (created by the author according to Abson et al., 2012; Reckien, 2018; Schmidtlein et al., 2008; Tran et al., 2009; Yoon, 2012).

Method	Concept and process	Pros
Ranking	A commonly used way of normalisation	Not affected by outliers and allows the performance of countries to be followed over time to show relative positions
Min-Max	Normalises indicators to an identical range [0, 1] by subtracting the minimum value and dividing by the range of the indicator values	Extreme values could distort the transformed indicator. Min-Max normalisation also widens the range of indicators within a small interval and increases the influence on the composite index
Weighted and non-weighted additive	Summation of the values of multiple indicators that are assumed to contribute strongly to the object, then the indicators are normalised to the comparable scale	Using maximum value transformation, indicators were rescaled to values between 0 and 1 and then summed with or without weighting. The final sum can be normalised in the range of 0 to 1 for direct comparison

6. The weighting and aggregation stage aims to discuss the correlation between the indicators and the importance of each indicator or group of indicators, and possible compensability among the composite index indicators (Becker, 2015; Munda, 2012; OECD, 2008). Weighting methods such as equal weighting or others should be applied in the underlying theoretical framework and essentially are a judgement of value. Some methods of value judgement are based on statistical methods (e.g. factor analysis (FA), data envelopment analysis (DEA)). Some of them are based on participatory methods, e.g., budget allocation processes (BAPs), analytic hierarchy processes (AHPs) or factor relationship analysis (FARE), and the impact or contribution of component indicators on a composite index relies on expert opinion.

Equal weighting is an alternative used when a statistical or empirical knowledge of causal relationships is lacking or lacks consensus on the alternative among experts. When variables are grouped into categories and then further ag-

gregated into the composite index, the application of equal weighting may influence an unequal weighting of the category when the more significant number of variables have a higher weight in the final composite index. Statistical calculations or expert judgement results define weights. Participatory methods are feasible when a well-defined basis for a measured phenomenon and integrated with stakeholders, investors, citizens and employees to determine weights. (Munda & Nardo, 2005). Participatory methods appear challenging to compare among countries or industries if a standard methodology is not used.

7. Uncertainty and sensitivity analysis aims to assess the robustness of the composite index and determine the mechanism to include or exclude the indicator, the impact of missing data and its imputation, the choice of weights and normalization and aggregation methods (Dobbie & Dail, 2013; Marozzi, 2012). According to the OECD Handbook (2008), “the sensitivity measures show how much the uncertainty in the composite indicator would be reduced if that particular input source of uncertainty were removed”.

The continuous process of uncertainty and sensitivity analysis improves the structure. It ensures the robustness of a composite index as the uncertainty analysis focuses on the input factors’ uncertainty, and the sensitivity analysis focuses on uncertain factors on outputs (Cherchye et al., 2008; Saisana, 2004). Each step of a composite index creation can bring challenges, so as many sources of uncertainty as possible, such as selecting indicators, data quality, the impact of missing data, selection of normalisation methods, and weighting, should be valued. The way to assess the uncertainties can be the following: inclusion or exclusion of single component indicators; modelling data to complete a set of data; single or multiple imputations of missing data; use of weighing (participatory or endogenous methods); and aggregation (multicriteria, linear methods) schemes.

8. The back to data stage brings attention to the importance of primary data. It aims to re-evaluate the quality, causality and relevance of component indicators or subcomponents to a composite index. It aims to contribute to the relevant analysis and decision-making. The outcomes of this stage reveal the dominant indicators and explain the relationship between component indicators.

9. Links to other indicators. Other previously created single or composite indicators might correlate with a newly developed composite index. In this stage, it is important to double-check whether there are any overlaps and there is no single indicator used both as a component and as a dimension.

10. Visualisation of the results aims to create tools to communicate the results with different audiences, present them clearly and explain the sources and consequences of a social phenomenon.

To summarise, the findings suggest creating a composite index when the phenomenon is multidimensional, requiring different aspects to be assessed. The se-

lection criteria of components to include in the index are changes in the component indicators have an easily interpretable, linear relationship with the measured concept.

1.5. Conclusions of Chapter 1 and Formulating Tasks for the Dissertation

Having completed the scientific literature analysis, the following conclusions are made:

1. The scientific literature review shows limited attempts to research the possible impact of Industry 4.0 on business model transformation. Given the importance and novelty of the phenomenon of Industry 4.0, this emphasises a lack of holistic efficiency, growth and risk assessment methodologies and tools aimed at assessing the categories mentioned above to effectively allocate financial and human resources in the company when transforming the business model in Industry 4.0.
2. Industry 4.0-driven business model transformation mainly refers to dynamic efficiency, which can be used at the micro and the macro levels. Industry 4.0 in the dynamic efficiency approach suggests the possibility of reducing costs over time and increasing added value drastically. Moreover, Industry 4.0-driven business model transformations requires a combination of technological innovation, e.g., Internet of Things and big data analytics-based equipment in the production lines and non-technological innovation.
3. Each layer of internet of things-based business model from the proposed in the scientific literature review (1) physical product; 2) use of sensors; 3) connectivity, 4) data analytics and 5) data-based digital service) the level can be applied independently in different parts of the business models – value proposition, value creation; value proposition; and value delivery. Different combinations can be formed five layers of Industry 4.0-driven business models based on Internet usage intensity.
4. There are many indicators to assess efficiency in production and work with suppliers, partners, customers or other business model parts. As Industry 4.0 raises financial and non-financial challenges, the input and output can be both financial and non-financial when calculating the efficiency. Four different combinations of financial and non-financial ratios can be used for inputs and outputs.

5. Assessment of financial and human resource allocation requires a complex holistic approach, and different combinations of indicators with different weights are used. Therefore, composite indexes with a set of component indicators with different weights assigned should be created. A composite index can be used both for assessment at the corporate level and at the policy-making level.
6. Risk in Industry 4.0 is determined as a shift from the planned or current situation and calculated by multiplying the probability of its occurrence and impact on the final results if it occurs. Scientific literature analysis shows the importance both of financial and non-financial risks. The financial risks are commonly used in the company and include risks of liquidity, solvency or profitability.
7. The non-financial risks assessment provide uncovered possibilities and are more related to the context of Industry 4.0 in which risks might occur. In the explored context after the analysis, the non-financial risks in the micro-level in five areas are suggested: 1) technical risks, 2) competence risks, 3) behaviour of customers, suppliers and partners risks, 4) behaviour of staff risks, 5) data security risks.
8. Industry 4.0 promises rapid increases in company growth and efficiency when transforming the business model. Financial and non-financial risks accelerate changes, even more so when such variables as high speed of changes and lack of historical data are added. Reducing the financial and non-financial risks is one more area for assessing resources allocation to business model transformations in Industry 4.0. The risk assessment facilitates the reduction of risks and the prevention of a very high probability of specific risk. It lowers the impact of risk on the final expected outcome.

Methodology and Development of the Integrated Economic Assessment Concept of Business Model Transformation in Industry 4.0

Chapter 2 presents the original integrated economic assessment concept of business model transformation in Industry 4.0, the economic assessment logframe, four composite indexes and growth-efficiency matrix as parts of the assessment concept. The chapter concludes by presenting the economic assessment logframe, four composite indexes as an assessment instrument, the growth-efficiency matrix with a risk component, and an integrated economic assessment concept that combines the above-mentioned for the empirical research. Furthermore, the research protocol and the methodology for creating a composite index are also described.

The findings of this chapter are presented in a scientific paper published in 2019: Kovaitė & Stankevičienė, 2019.

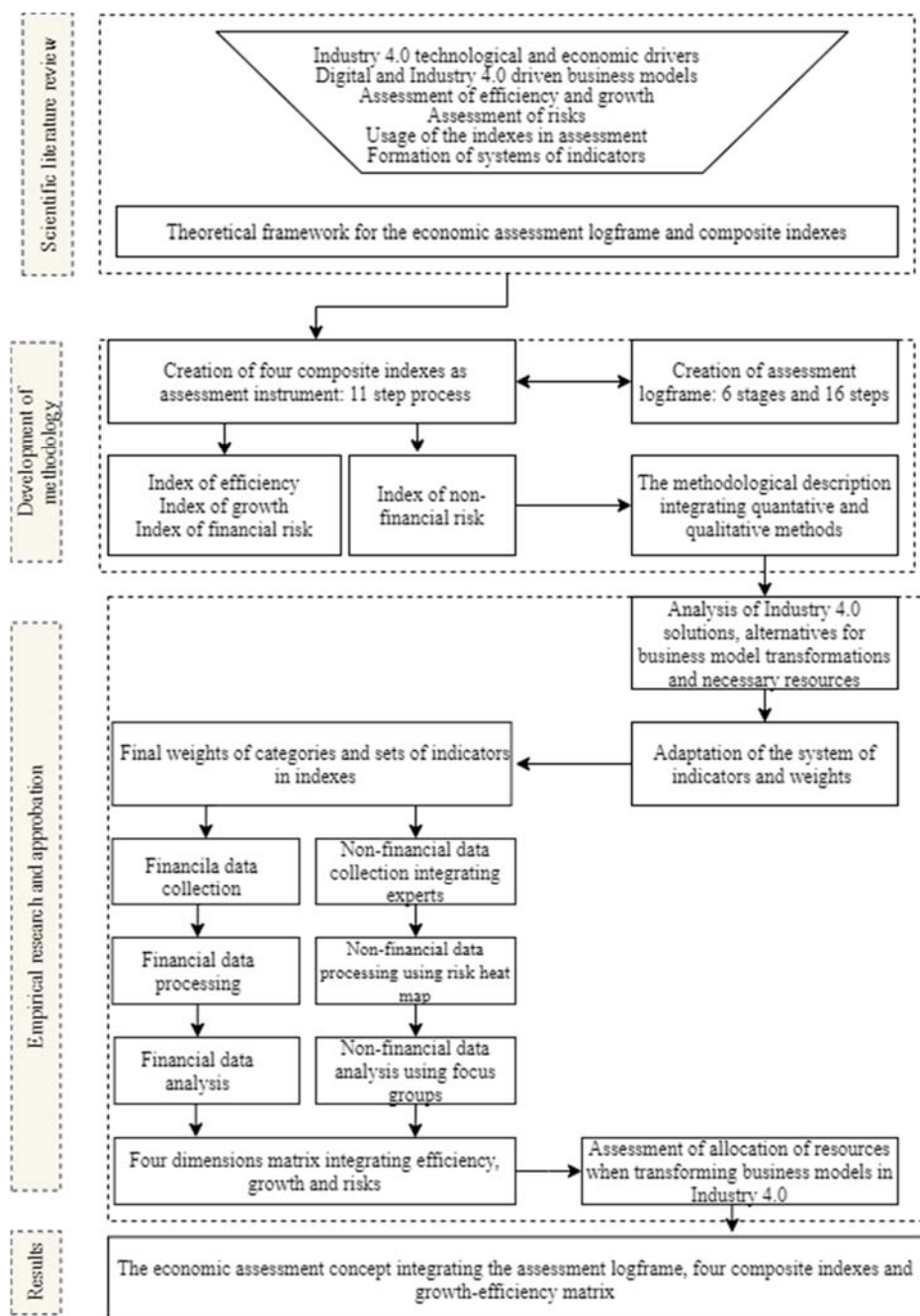


Fig. 2.1. The theoretical and empirical research design of the dissertation (created by the author)

2.1. The Research Design of the Economic Assessment Business Model Transformation in Industry 4.0

This section introduces the methodological background of the quantitative and qualitative research methods to create the original economic assessment concept of business model transformation in Industry 4.0. In addition, the chapter defines the process of creating the assessment logframe and the composite index as an assessment instrument.

The section introduces the methodology of the development process of the composite index as a system of indicators. Below, in Figure 2.2, a typical process of developing a system of indicators is presented to create the composite index.

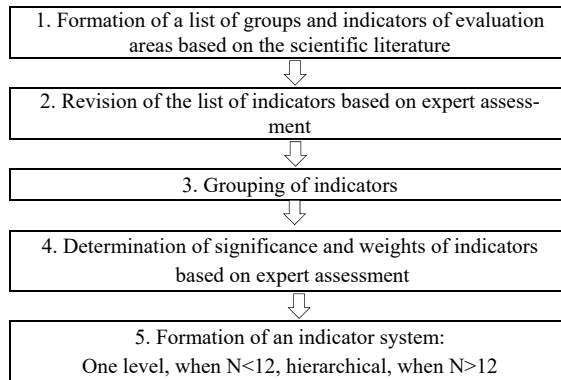


Fig. 2.2. The process of forming the system of indicators (according to Ginevičius, 2019; Ginevičius et al., 2017)

The expert judgement method is suggested in the second and fourth stages of forming the system of indicators. There are pros and cons (Banerjee et al., 2016; Gearhart et al., 2013; Podvezko, 2005; Szarucki & Menet, 2018), analysed in the scientific literature, involving experts in the research to determine the reliability of the estimation of experts. Spearman, Kendall's coefficient, Cronbach coefficient are used to evaluate the unanimity of experts' estimations.

Kendall's coefficient (Gearhart et al., 2013; Kendall, 1955; Podvezko, 2005) was calculated to evaluate the concordance of expert assessments. The coefficient values are from 0 to 1, where a value close to 0 shows that expert judgement varies a lot and a value close to 1 shows the unanimity of opinion. The Kendall coefficient is calculated using the following formula:

$$W = \frac{12S}{r^2n(n^2-1) - r \sum_{j=1}^r T_j}, \quad (2.1)$$

where r – a number of experts; n – a number of objects to evaluate.

$$S = \sum_{i=1}^m (e_i - \bar{e}), \quad (2.2)$$

where S – a sum-of-squares statistic over the row sums of ranks m_i ; e_i – a sum of ranks; $\bar{e}$ – average of sums of ranks.

$$T_j = \sum_{k=1}^{Hj} (t_k^3 - t_k), \quad (2.3)$$

where T – an indicator of tied ranks of j experts; H – a number of ranks of the same value of the j expert; t_k – a number of equally tied ranks in each (k) group of ties.

$$ChiSq = Wr(m-1). \quad (2.4)$$

In addition to the concordance coefficient, the competence coefficient is calculated according to the formula:

$$w_i = \frac{1}{\lambda} \sum_{j=1}^n x_j x_{ij}, \quad \forall i = 1, 2, \dots, m, \quad (2.5)$$

where $x_j = \frac{1}{m} \sum_{i=1}^m x_{ij}$, $j = 1, 2, \dots, n$ ir $\lambda = \sum_{j=1}^n \sum_{i=1}^m x_j x_{ij}$, x_{ij} – rank of j alternative of i expert; M – number of experts.

When the meanings of the experts' competence coefficients fall in the interval $\bar{w} - 1.96s \leq w_i \leq \bar{w} + 1.96s$, where $\bar{w}$ is the average of the competence coefficients, s – standard deviation. One can agree that there are no experts who do not have enough qualifications or are in the experts' group by accident.

After the coefficients of experts' opinion concordance and experts' qualification, the categories and component indicators' weights were identified. Different methods of weight identification are explored by scientists (Ginevičius & Podvezko, 2008; Podvezko, 2011) and used in different areas. Ranking direct weighting method and indirect weighting methods are mentioned among the most often used in research. Moreover, the factor relationship (FARE) method is also found in recent publications by Ginevičius (2011), Kraujalienė (2019), Stankevičienė & Vaiciukevičiūtė (2016) and others.

When using the direct weighting method, a sum of all experts' evaluations equals 1 or 100 per cent. The sum of the weights of all indicators w_i equals the average of all estimations c_i and is calculated following the formula (R. Ginevičius & Podvezko, 2008; Podvezko, 2009):

$$\bar{c}_i = \frac{\sum_{k=1}^r c_{ik}}{r} = \frac{s_i}{r}, \quad (2.6)$$

where $s_i = \sum_{k=1}^r c_{ik}$ is a sum of ranks of all r experts ($I = 1, 2, \dots, m$), m – number of indicators that are compared.

Normalisation is used after the weights of indicators are identified. When indicators are expressed in different systems, they need to be comparable if the multicriteria method is to be used. The method of normalisation depends on the objective of the multicriteria evaluation. When the alternatives are prioritised, normalisation of estimates of the indicators uses the following formula (Ginevičius & Ostapenko, 2015):

$$q_{ij}^* = \frac{q_{ij}}{\sum_{i=1}^n q_{ij}}, \quad (2.7)$$

where q_{ij}^* – the normalised value of i indicator of j alternative, q_{ij} – a value of i indicator of j alternative, n – number of indicators ($i = \overline{1, n}$).

The formula shows that the normalised value of the i -th indicator of the j -th alternative is obtained by dividing this value by the sum of the i -th indicator values for all alternatives. The method identifies the prioritised list of alternatives.

Recent research (Skvarciany et al., 2020) presented a group of methods that evaluate the status of a socio-economic system or an object. This group of methods aims to create a tool to assess the efficiency of a researched object. Then the normalisation uses the following formula (Ginevičius & Ostapenko, 2015):

$$q_{ij}^* = \frac{q_i}{q_i^{\max}} \quad (2.8)$$

where $q_i^{\max}$ – a maximum possible value of i -th indicator.

FARE (factor relationship), as the experts' judgment method, was used to determine the interdependence between the factors of risk and the business model factor and set weights for variables. As “the difference between the weights calculated by FARE and the criteria weights obtained by AHP technique is the smallest compared to other methods”, says Ginevičius (2011), the focus of the FARE method is a comparison performed to address the development of the decision-making system. The variables with the highest total values are considered the “most critical variable since the superior level of the essential variable is equal to one or over than one in comparison with other variables” (Kraujalienė, 2019). Therefore, the FARE method is selected as an expert evaluation method. The FARE method is based on the interrelationships between all criteria compared to each other with the object considered and helps estimate the multicriteria weights.

The findings from the research were used in the focus groups during the approbation of the economic assessment logframe and four composite indexes. The findings indicated six risk areas at the company level, and the factor relationship between the risk areas and the parts of the business model was investigated and defined.

Below, in Figure 2.3, the theoretical process of how to create a composite index is explained.

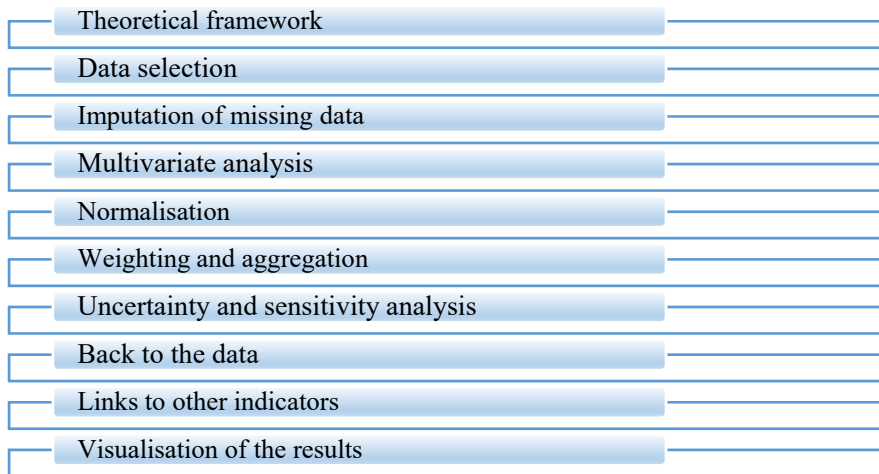


Fig. 2.3. The schemes of constructing the composite index
(created by the author according to OECD, 2008 and *Oslo Manual*, 2018)

The methodology of the individual experts' interview and content analysis introduces the interview and content analysis methodology as a qualitative research method used in the creation process and used in the assessment process. The interviews were conducted to answer how Industry 4.0 is experienced in the business model transformations and the companies value chain. A semi-structured interview (Castillo-Montoya, 2016; Hagens et al., 2009) was chosen to collect data for qualitative research. Twelve interviewees participated in the interviews.

A focus group (Kaiser, 2009; Morgan, 2012; Onwuegbuzie et al., 2009; Sim & Waterfield, 2019; Smithson, 2000) was used to test the results after the first round of the content analysis.

Qualitative content analysis (Bengtsson, 2016; Cavanagh, 1997; Elo et al., 2014; Hsieh & Shannon, 2005; Patton, 2002) was chosen to process the gathered data from the interviews. Content analysis (Mayring, 2000) is a valid method for drawing specific conclusions based on the analysed text. The content analysis

aims to diagnose 1) how an interviewee perceives the phenomenon by reflecting on their own experience, 2) the differences between the theoretical description of the analysed phenomenon and its expression in social reality. Applying the methodological concept of qualitative diagnostics (Cavanagh, 1997; Mayring, 2000; Potter & Levine-Donnerstein, 1999) in economic researches (Starr, 2014), the obtained results allow determining the peculiarities of the specific context in which the research subjects operate and to predict the change the activity brings in economic behaviour. The qualitative content analysis includes four steps (Burnard, 1991; Mayring, 2000): 1) multiple reading of the text, 2) separation of manifest categories based on keywords, 3) division of the content of the categories into subcategories, 4) the interpretation of the categories and subcategories and the substantiation of the evidence extracted from the text.

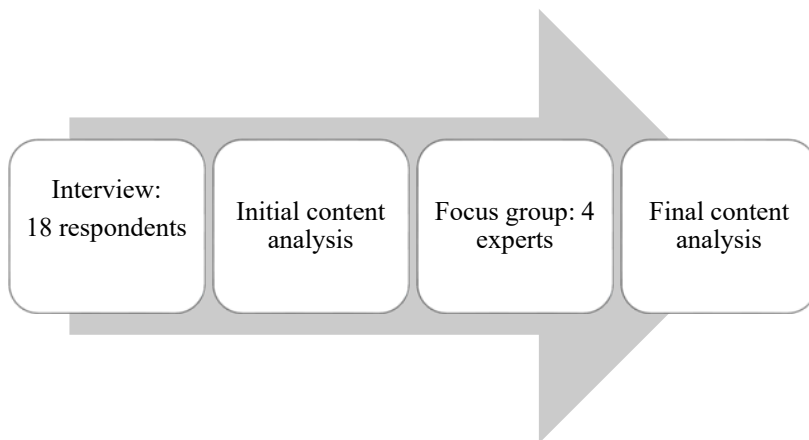


Fig. 2.4. The process of the qualitative research (created by the author)

Figure 2.4 introduces the process of qualitative research consisting of four steps. An improbable, objective, comfortable sample was organised to select interviewees. Different experts for the interviews and the focus group were selected to ensure that the focus group's findings may supplement the interviews' findings. The demography of the experts is introduced in Annex B.

Instrument. A questionnaire for a semi-structured interview was designed, consisting of 21 questions. The first group of questions focused on collecting demographic and experience data to ensure the interviewees met the requirements. The second part of the questionnaire consists of complex open-ended questions to collect data to answer how the companies experience the implementation of Industry 4.0 solutions. The third part of the questionnaire consists of questions to assess the experts' opinions. Each interview was 45–60 minutes long. To ensure

the validity of qualitative research, preliminary theoretical definitions and descriptions were avoided in the analysis process. A hypothetical scheme was not drawn, and the data of the content of the answers was not guided to meet the principle of openness in qualitative research. In qualitative content analysis, distinguishing and interpreting manifest information is assigned to analyse answers, create categories and subcategories, and interpret procedures. Meeting the principle of openness in qualitative research allows holistically analysing the text data set obtained by the interview method.

2.2. Design of the Integrated Economic Assessment Concept of the Business Model Transformation in Industry 4.0

This section presents the integrated economic assessment concept created to assess the allocation of financial, human and time resources when transforming the business model in Industry 4.0.

The integrated economic assessment concept of business model transformation in Industry 4.0 consists of six stages. The first stage aims to analyse. Industry 4.0 drivers applied to transform business models in manufacturing. The Industry 4.0-driven drivers appear in the market quickly and initiate business model transformations.

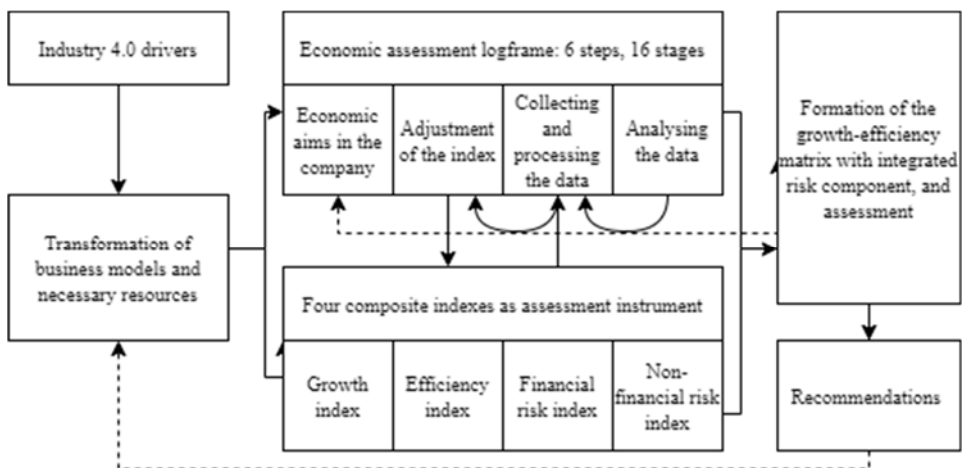


Fig. 2.5. The integrated economic assessment concept (created by the author)

The second stage, “Transformation of business models and necessary resources”, aims to identify possible alternatives for the business model that Industry 4.0 offers and determine financial, human and time resources necessary to keep the existing business model and resources to transform it. The alternatives require different allocation of resources that should be assessed before implementing the changes. The third stage, “Assessment logframe”, aims to guide the company through the 16-step assessment process, including quantitative and qualitative methods and a process of adjustment of the alternatives offered by Industry 4.0 to the specifics of the company, data collection, processing and analysis as well as followed by checking the data accuracy, availability and comparability. The fourth stage, “Four composite indexes”, aims to use the created four indexes to assess the potential of increasing efficiency, growth, financial risk and non-financial risk when transforming business models. A system of four composite indexes consists of 33 component indicators, which serve as the assessment instrument to be used in the assessment logframe. The fifth stage, “Formation of growth-efficiency matrix with risk component, and assessment”, concludes from the previous stages and aims to assess the alternatives of business model transformation and visualise them. The growth-efficiency matrix facilitates comparing alternatives of the possible increase of growth, efficiency, financial risk and non-financial risk assessed in the company or making a peer comparison among companies. The sixth stage, “Recommendations”, aims to formulate the recommendation for allocating resources necessary when transforming business models in Industry 4.0. The recommendations should be reflected with the second stage of the transformation of the business model to make sure the assessment of the alternatives of the allocation of resources is in line with the initial objective. The recommendations are to be formulated to the investors and shareholders, executive decision-makers and policymakers.

A detailed description of how the economic assessment logframe, four composite indexes and growth-efficiency matrix are created is described in Chapter 2. The application and approbation of the complete integrated economic assessment concept and each stage are presented in Chapter 3.

2.3. Creation of the Composite Indexes of Efficiency, Growth and Risks when Transforming Business Models in Industry 4.0

This section presents the methods applied in creating both the assessment process and the assessment instrument. Later, individual index-specific issues are described; also, in addition, the created assessment process and the whole structure

of the composite index are introduced. The composite index has been created based on the methodology presented in Chapter 2 of the dissertation. Four composite indexes: index for growth; the index for efficiency; index of financial risk; and index of non-financial risk of Industry 4.0 implementation are created, and below, a detailed description of the creation process is provided.

The assessment model has been developed following the author's scheme under the recommendations of the OECD (2008). The scheme is presented below in Figure 2.2. Each index followed the principles of this five-step process with minor modifications presented in the sections describing the creation of the indexes below.

The five-stage process protocol: a scientific literature analysis and expert judgement, which is described below. Calculating Kendall's concordance coefficient in each index is higher than 0.7, which shows the unanimity of experts' opinions.

Expert judgement has been used in the second and fourth stages of forming the efficiency composite index of the implementation of Industry 4.0. Expert judgement aims to revise a set of component indicators determining missing data and the possible impact, group the component indicators according to the business model canvas and value chain scheme, and give weight to both groups of indicators and single indicators in the group. The research objective and the theoretical model were explained to each of the experts individually.

A group of 18 experts for the development of the composite index was selected according to the following criteria:

- higher education in management, engineering or technology and
- at least three Industry 4.0-related projects and
- at least five years in decision-making in manufacturing companies or the association of related industries.

The names of experts for developing the composite index are undisclosed due to confidentiality and private data security regulation. The experts for the development process are named: E1, ... E18 and are presented in Annex B. Expert judgement was used in creating all four indexes. Kendall's coefficient (Kendall, 1955; Podvezko, 2005) was used to evaluate the compatibility of experts' valuations. The Kendall W coefficient values vary from 0 to 1. A value close to 1 indicates that the experts' valuations are unanimous. The Kendall W concordance coefficient being close to 0 indicates the considerable variation in expert judgement.

The assessment model follows the flow described below. The business model is understood to show that a value is proposed, created, delivered and captured. The impact of Industry 4.0 is understood as a change achieved after Industry 4.0 technological drivers are implemented in any part of the value chain in the company using financial and non-financial inputs.

IND_GROWTH	CAT_GROWTH	indicator	weight
	Added value per employee	GR1	0.7
	Shareholders fund per employee	GR2	0.3
IND_EFFICIENCY	CAT_VALUE PROPOSITION	VP	0.2
	Return on sales, %	VP1	
	Current liquidity ratio	VP2	
	Sales costs/revenue, %	VP3	
	CAT_VALUE CREATION	VC	0.4
	Unfinished production turnover	VC1	
	Labour productivity	VC2	
	Fixed assets turnover ratio	VC3	
	CAT_VALUE DELIVERY	VD	0.15
	Distribution ratio	VD1	
	Inventory turnover	VD2	
	Quick ratio	VD3	
	CAT_VALUE CAPTURE	VCp	0.25
	Cost efficiency ratio	VCP1	
	Return on assets	VCP2	
	Operating cash flow ratio	VCP3	
IND_FINARISK	CAT_SOLVENCY RISK		0.25
	Debt-to-equity	F1	
	Debt to asset	F2	
	CAT_BUSINESS RISK		0.5
	Profit before tax	F3	
IND_NONFINARISK	CAT_LIQUIDITY RISK	F4	0.25
	liquidity ratio		
	CAT_TECHNICAL RISK	T1 ... T3	0.15
	CAT_COMPETENCE RISK	C1 ... C4	0.25
	CAT_PARTNERS RISK	P1 ... P4	0.15
	CAT_STAFF RISK	S1 ... S4	0.35
	CAT_DATA RISK	D1 ... D3	0.1

Fig. 2.6. The structure of the composite indexes to assess efficiency, growth, financial and non-financial risks when transforming business model in Industry 4.0
(created by the author)

Literature analysis suggests five layers or types of a business model driven by Industry 4.0, according to the five-layer model introduced in Figure 1.5. Two layers in the physical world – physical product, sensor usage; one in the middle – connectivity usage; and two in the digital world – data analytics usage and digital service. Based on these changes due to Industry 4.0 driver implementation, alternative business models are suggested. Businesses face having to make a decision under a scarcity of information, a limitation of investment to implement solutions, and a lack of human resources to make solutions economical and profitable.

The assessment instrument consists of four composite indexes and is presented in Fig. 2.6 (where IND is the abbreviation to “index” and CAT is the abbreviation to “category”):

1. The efficiency composite index includes four weighted categories that reflect parts of the value chain, three indicators in each category, and 12 component indicators in total. The efficiency index assesses each part of the value chain’s potential value increase and the overall value increase.
2. The financial composite risk index consists of three weighted categories and four component indicators. The index aims to assess potential financial losses during the transformation of the business model in Industry 4.0.
3. The non-financial composite risk index consists of five weighted categories and 18 component indicators. The index aims to assess potential organisational, technical and security gaps during the implementation process.
4. The growth composite index includes two component indicators with weighted values. The index aims to assess the potential growth of added value in the company.

The efficiency composite index aims to assess the potential of efficiency increasing while modifying and transforming business models in Industry 4.0 solutions. Firstly, a scientific literature analysis was conducted. As a result, four categories reflecting the value chain were identified, and a set of 24 efficiency indicators in Industry 4.0 was selected and. Secondly, expert judgement was conducted. As a result, 20 indicators were included by experts based on the necessity to assess, and 32 indicators were excluded according to the potential data availability. Indicators were grouped into four categories according to the parts of the business model: value proposition, value creation, value delivery, and value capture. Moreover, the experts’ judgement weights for each category were given. The index was formed as a result of this six-stage process.

The first step. The scientific literature review on the business model’s efficiency assessment, focusing on empirical evidence derived from research into business models driven by Industry 4.0. The initial literature search includes publications in the Clarivate Analytics Web of Science database between 1999 and 2020. The keywords “business model” were combined using the Boolean operator AND or OR with the second keyword “Industry 4.0”. The initial search displayed

results for more than 37,000. The exclusion criteria using the keywords “dynamic efficiency”, “efficiency assessment”, OR “measurement”, “efficiency”, AND the search in the categories of research economics, management and business limited the scope to 2345 published articles. However, another search using the keyword “Industry 4.0” drastically reduced the number of articles. The abstracts of selected studies were read, and articles that presented only business models without focusing on efficiency were excluded. This stage left a total of 92 articles to read in their entirety.

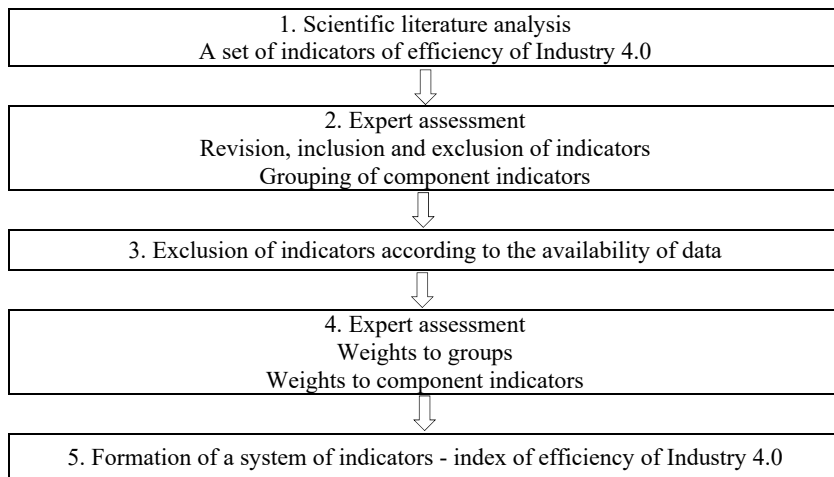


Fig. 2.7. A process of creation of a composite index of efficiency when transforming business model in Industry 4.0 (created by the author)

The articles covered the context where efficiency was discussed with the focus on business models and Industry 4.0. A list of indicators to assess the efficiency in the implementation of Industry 4.0 solutions all along the value chain was created after the scientific literature analysis and presented for the further stages of forming an index of efficiency.

The second step. The second stage of forming a system of indicators aims to revise and group the component indicators of efficiency using expert judgement. The experts were asked to revise and include or exclude indicators identified after a scientific literature analysis. Based on their practical experience, they were asked to exclude the efficiency assessment ratios that they did not consider essential and add to them if some were missing.

The first research questions to the experts were:

- Which indicators should be included in a set of component indicators?
- Which indicators assess different parts of a business model canvas?

Following the experts' experience, an extended list with 44 ratios was created. The change of indicators is presented in Annex A.

The third step aims to revise the impact of missing data and the availability of data. This stage includes testing the data availability necessary to calculate the values of indicators and the imputation of missing data, and assessing the impact of missing data. As exclusion criteria, the availability of data for peer comparison and differences of corporate calculation methodology were identified. Only data included in the financial accountancy that typically is presented by the global accountancy standard is used for the index. This criterion excluded several indicators, such as OEE, OFE, learning ratio, and downtime ratio. The fourth step aims to analyse the multicollinearity of indicators in each category. The indicators in the category were assessed and excluded if they did not relate to each other and if the same data were only used once. The fifth step aims to give weight to the formed categories of component indicators and prioritise component indicators.

The tasks to experts:

- apply a weight to the category of component indicators,
- prioritise the most critical ratios assessing the data available in the company in each part of the value chain.

Kendall's concordance coefficient was calculated, and it was close to 1 in all calculations, demonstrating that experts' opinions were unanimous and the result obtained is reliable. After inclusion and exclusion criteria were applied, the final set of component indicators was identified. All selected indicators were attributed to the different stages of the value chain. Four categories reflecting the business model parts were formed, and three component indicators were assigned to each category, 12 indicators in total. The progress of formation is presented in Annex A. After completing the step 6 process of forming a composite index of efficiency, the final set of component indicators grouped into four categories was used (Table 2.1). According to the expert assessment in step 5, the weights were given to each category. Names of the component indicators were assigned according to the business model part indicators represent.

Table 2.1. The structure of a composite index of efficiency when transforming business model in Industry 4.0 (created by the author)

No	The final set of component indicators	Formulas	Name	Weight
	CATEGORY_VALUE PROPOSITION			0.2
1	Return on sales	operating profit (loss) / revenue	VP1	
2	Current liquidity	current assets / current liabilities	VP2	
3	Sales cost-efficiency	sales costs / revenue	VP3	

End of Table 2.1

	CATEGORY_VALUE CREATION			0.4
4	Turnover of unfinished production	revenue / unfinished production	VC1	
5	Labour productivity	Revenue / FTE in hours worked	VC2	
6	Fixed assets turnover	revenue /average fixed assets	VC3	
	CATEGORY_VALUE DELIVERY			0.15
7	Distribution ratio	cost of distribution channel / revenue	VD1	
8	Inventory turnover	revenue /(beginning inventory + end inventory)/2	VD2	
9	Quick ratio	current assets/ current liabilities	VD3	
	CATEGORY_VALUE CAPTURE			0.25
10	Operating efficiency	(operating expenses + cost of goods sold) / net sales	VCp1	
11	Return on assets	return on assets	VCp2	
12	Operating cash flow	operating cash flow/ current liabilities	VCp3	

The non-financial risk composite index assesses the potential non-financial risks and their impact on transforming business models in Industry 4.0 solutions. The index consists of five weighted categories and 18 component indicators and forms a hierarchical system of indicators.

The process was organised in five stages, including scientific literature analysis, expert judgement, and weighting. The first stage. The review of the scientific literature was centred on the risk and its assessment of the business model, focusing on empirical evidence derived from research into business models driven by Industry 4.0. The literature search was conducted mainly on Clarivate Analytics between 2014 and 2020. The inclusion of the publications in the Clarivate Analytics database used the following integrated, complex keywords, e.g. “risk”, “digitisation”, “business model”. These were combined using the Boolean operator AND or OR with the second keyword, “Industry 4.0. Only full articles covering all three concepts – business models, Industry 4.0, and risk assessment – and only empirical research results in social sciences were included. Results covering health issues, disaster and environmental issues, computer science, and engineering were excluded. Only 15 articles were found that covered all aspects during the period from 2014 to 2020. The scope of the entire reading was extended with analytical publications from McKinsey Review, World Economic Forum and similar sources. After the literature content analysis, a list of five risk areas was selected.

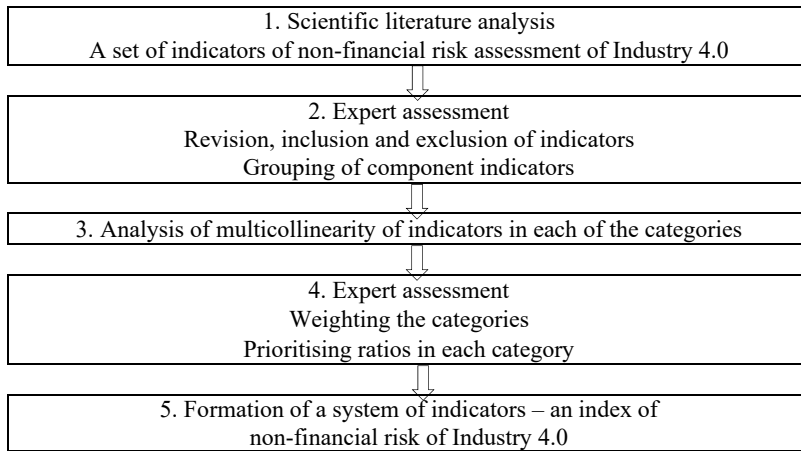


Fig. 2.8. A process of creation of a composite index of non-financial risk when transforming business model in Industry 4.0 (created by the author)

The findings from previous research indicated six risk areas at the company level, and the factor relationship between the risk areas and the parts of the business model was investigated and defined. Using FARE (factor relationship) as the experts' judgement method gave a solid ground to use the findings in the dissertation. The findings from the research were also used in the focus groups during the approbation of the assessment logframe and four composite indexes.

The second stage aims to revise the risk areas and group indicators for each risk area. The experts were involved, and a question to them was formulated:

- As a result of your expertise, which risk areas do you see as being significant? Please suggest including or excluding areas.
- What are the indicators for each risk area? Please rank the indicators provided in the list.

The areas of risks were revised, and it was suggested that the area “behavioural risks” be divided into two: acceptance by staff and acceptance by partners.

After the second stage, six risk areas and 27 indicators were suggested. The division of the area “behavioural risks” was also supported by numerous sources, such as Birkel et al. (2019), Vahidi et al. (2018) and ISO 31000 risk management (Purdy, 2010). The latter suggesting to use a twofold approach: inbound and outbound the company, to assess risk, split the process when describing the business model as a value chain and also distinguish internal and external communication (Felix et al., 2017; Yigitbasioglu, 2015) in any change process. Having two categories also deals with the challenge of missing data.

Table 2.2. The area of non-financial risks (created by the author)

Risk area	Description	Weight
Technical risks	Mismatch of software, infrastructure, and software necessary to offer product and service solutions, the Internet of Things, big data, data-based solutions, cloud computing, artificial intelligence in value creation and capture, and improvement of processes' real-time process monitoring and risk identification.	0.15
Competence risks	Organisational structure, responsibilities, procedures and qualifications of personnel, and a knowledge base and know-how of the company.	0.25
Acceptance by partners and customers risks	Changes in decision-making behaviour include being less cautious when using a product or service of impulse purchasing and return, uncontrolled feedback on social media, and habits of use of services.	0.15
Acceptance by staff risks	Habits of organising work and customer service processes, organisational culture, perception and social skills are human factors of software use.	0.35
Data security risks	Data loss, information integrity loss, data processing errors, risk of cyberattacks, privacy and confidentiality of data, possible misinterpretation of cyberattacks and fraud.	0.1

According to the experts' suggestions, the third stage aims to finalise a set of risk areas as categories for index and groups component indicators. Two dimensions were identified: financial and non-financial risks. The final areas of risks are the following: technical risks, acceptance by staff, acceptance by customers and partners, competence risks and data security risks and financial risks (Table 2.2 and Table 2.3). Financial risks were separated from the rest of the risks because financial risks require different data sources and data collection and processing methods.

The expert assessment was organised in the following way. The experts were asked to include indicators on assessing risks according to the possibility of data availability. The simple ranking was used to form 3–4 indicators in each category of risks. Five categories as non-financial risk areas and 18 indicators were finally identified and presented to the fourth stage for experts to weigh the categories.

The fourth stage aims to give weight to categories within the index. The experts' judgement using a simple ranking was used to give weights. Experts were asked to give weights to each of five categories from 0 to 1. The results provide the possibility to assess each category's significance in comparison to each other-

Kendall's concordance coefficient was calculated, and it was close to 1 in calculations, demonstrating that experts' opinions were unanimous, and the result obtained is reliable. The fifth stage aims to form an index out of results from the previous four stages. The final set of component indicators for non-financial risk assessment, grouped into five weighted categories consisting of 18 non-financial indicators, was identified at the fifth stage. This set is used as the non-financial risk index to form a composite index (Table 2.3). The financial risks were separated as described below.

Table 2.3. The structure of a composite index of non-financial risk when transforming business model in Industry 4.0 (created by the author)

Risk area	Description of the Indicators	Name	Weight
Technical risks			0.15
1	Mismatch of software	T1	
2	Difference in hardware	T2	
3	Difference in infrastructure	T3	
Competence risks			0.2
4	Organisational structure from hierarchical to decentralised	C1	
5	Employee qualifications: formal, professional	C2	
6	Procedures to more decentralised	C3	
7	Internal know-how and external availability	C4	
Acceptance by partners and customers risks			0.15
8	Customers' behaviour	P1	
9	Customers' segments	P2	
12	Partners' behaviour	P3	
11	Partners' segments	P4	
Acceptance by staff risks			0.25
12	Difference in skills	S1	
13	The difference in organisational habits	S2	
14	On-job learning situation	S3	
15	Organisational culture difference	S4	
Data security risks			0.1
16	Data loss	D1	
17	Data processing	D2	
18	Privacy	D3	

This financial risk index aims to assess the potential financial risks and their impact on modifying and transforming business models in response to Industry 4.0 solutions. Financial risks are separated from non-financial risks as the process is described in the previous section.

The index consists of three weighted categories and four component indicators. Assessment of the financial risks is based on the usage of the financial data from the standard financial accountancy and covers the following areas: solvency risk ($w = 0.25$) with debt-to-equity and debt-to-assets as component indicators; profit ($w = 0.5$) with profit before tax as a component indicator and liquidity risk ($w = 0.25$) with liquidity ratio as a component indicator.

Table 2.4. The areas of financial risks (created by the author)

Risk area	Description
Financial risks	Digital transformations require significant investment; lack of history of financial impact; long-term and short-term investment decisions, cash flow management are different from usual. Business, liquidity and solvency risks appear in this category.

The index consists of three weighted categories and four component indicators. Assessment of the financial risks is based on the usage of the financial data from the standard financial accountancy and covers the following areas: solvency risk ($w = 0.25$) with debt-to-equity and debt-to-assets as component indicators; profit ($w = 0.5$) with profit before tax as a component indicator and liquidity risk ($w = 0.25$) with liquidity ratio as a component indicator.

Table 2.5. The structure of a composite index of financial risk when transforming business model in Industry 4.0 (created by the author)

Indicator	Name	Weight
CAT_SOLVENCY RISK		0.25
Debt-to-equity	F1	
Debt to asset	F2	
CAT_BUSINESS RISK		0.5
Profit before tax	F3	
CAT_LIQUIDITY RISK		0.25
Liquidity ratio	F4	

The index of growth aims to assess potential growth when modifying and transforming business models due to Industry 4.0 solutions. The index consists of two component indicators – added value per person ($w = 0.7$) and shareholders' funds per person ($w = 0.3$) – forming a one-level indicator system.

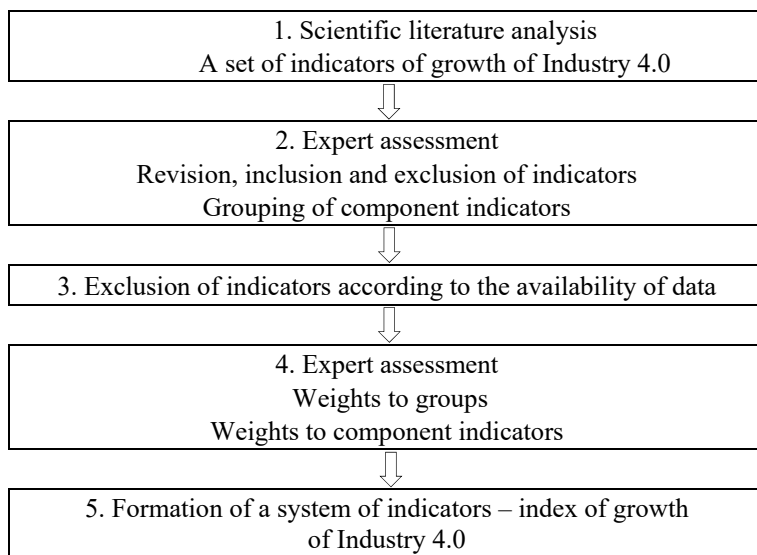


Fig. 2.9. Creation of a composite index of growth when transforming business model in Industry 4.0 (created by the author)

The first step. The scientific literature review on the indicators for the potential growth in Industry 4.0 focusing on empirical evidence derived from research on Clarivate Analytics between 2014 and 2020. The literature search included the databases, timing, category of research, type of document and keywords used by the authors. The search used the following integrated, complex keywords, e.g. “growth”, “assessment”, “business model”, using different combinations of the terms. These were combined using the Boolean operator AND or OR with the second keyword, “Industry 4.0”. Scientific articles are presented in a scientific peer-reviewed journal covering all three concepts: business models, Industry 4.0, and growth assessment. After the initial review of the scientific literature, analytical articles, and working papers published by the World Economic Forum and the McKinsey review, EUROSTAT and similar sources were included to expand the index’s scope of the possible inputs. After the literature analysis, a list of 11 indicators was selected.

The second step aims to revise potential growth assessments according to the potential data availability and impact of missing data. Experts included salaries, production in quantities, value-added per person and similar, and excluded indicators such as market value-added from the indicators’ set. Financial data availability was tested to ensure the results were congruent and comparable with other companies during the research period. The third step aims to analyse the multicollinearity of indicators to ensure that component indicators correlate. The data are

used not more than once in the index; neither index duplicates the result of another indicator. The fourth step aims to give weights to the component indicators and finalise a set of indicators to form the growth index. At the fifth step, the growth composite index is formed to assess growth when implementing a business model driven by Industry 4.0. Two component indicators are used as the growth index to form a composite index (Table 2.6).

Table 2.6. The structure of a composite index of growth when transforming business model in Industry 4.0 (created by the author)

Indicator	Name	Weight
CAT_GROWTH		
Added value per employee	GR1	0.7
Shareholders fund per employee	GR2	0.3

During the economic assessment logframe, the ratio increase compared with the previous year is calculated for the four-year research period, and the dynamics are taken into consideration. Each index, as described, consists of several categories, and each category consists of several component indicators. Each category after the expert assessment has different weights and brings different weighted inputs. The five steps principle process for the calculation of indexes are presented in the Figure 2.11. Formulas for calculating the indicators are used in the way they are commonly used in the financial analysis and are introduced in Table 2.7.

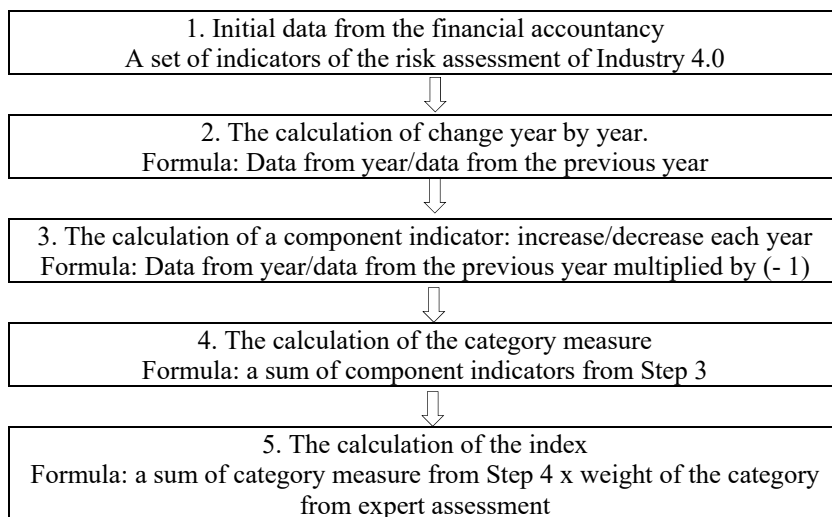


Fig. 2.10. The five-step process of the assessment process (created by the author)

Table 2.7. The formulas of calculation of indexes (created by the author)

$I_{GR} = \left(\frac{av_t}{av_{t-1}} - 1 \right) \times W_{av} + \left(\frac{sh_t}{sh_{t-1}} - 1 \right) \times W_{sh}$	I_{GR} – index of growth av – added value per FTE sh – shareholder fund per FTE t – a year $t - 1$ – previous year W – weight	(2.9)
$I_{RISKFINA} = \left(\frac{LIQ_t}{LIQ_{t-1}} - 1 \right) \times W_{LIQ} + \left(\frac{PFT_t}{PFT_{t-1}} - 1 \right) \times W_{PFT} + \left(\frac{SOL_t}{SOL_{t-1}} - 1 \right) \times W_{SOL}$	$I_{RISKFINA}$ – index of financial risk LIQ – liquidity risk PFT – profit-risk SOL – solvency risk t – a year $t - 1$ – previous year W – weight	(2.10)
$I_{EFF} = \left(\frac{VP_t}{VP_{t-1}} - 1 \right) \times W_{VP} + \left(\frac{VC_t}{VC_{t-1}} - 1 \right) \times W_{VC} + \left(\frac{VD_t}{VD_{t-1}} - 1 \right) \times W_{VD} + \left(\frac{VCp_t}{VCp_{t-1}} - 1 \right) \times W_{VCp}$	I_{EFF} – index of efficiency VP – category of a value proposition VC – category of value creation VD – category of value delivery VCp – category of value proposition capture t – a year $t - 1$ – previous year W – weight	(2.11)
$CAT_{VP} = \left(\frac{VP1_t}{VP1_{t-1}} - 1 \right) \times W_{VP1} + \left(\frac{VP2_t}{VP2_{t-1}} - 1 \right) \times W_{VP2} + \left(\frac{VP3_t}{VP3_{t-1}} - 1 \right) \times W_{VP3}$	CAT_{VP} – category of a value proposition $VP1$ – return on sale $VP2$ – current liquidity ratio $VP3$ – sales costs and revenue ratio t – a year $t - 1$ – previous year W – weight	(2.12)
$CAT_{VC} = \left(\frac{VC1_t}{VC1_{t-1}} - 1 \right) \times W_{VC1} + \left(\frac{VC2_t}{VC2_{t-1}} - 1 \right) \times W_{VC2} + \left(\frac{VC3_t}{VC3_{t-1}} - 1 \right) \times W_{VC3}$	CAT_{VC} – category of value creation $VC1$ – unfinished production turnover $VC2$ – labour productivity $VC3$ – fixed asset turnover t – a year $t - 1$ – previous year W – weight	(2.13)

End of Table 2.7

$CAT_{VD} = \left(\frac{VD1_t}{VD1_{t-1}} - 1 \right) \times W_{VD1} + \left(\frac{VD2_t}{VD2_{t-1}} - 1 \right) \times W_{VD2} + \left(\frac{VD3_t}{VD3_{t-1}} - 1 \right) \times W_{VD3}$	CAT_{VD} – category of value delivery $VD1$ – distribution ratio $VD2$ – inventory turnover $VD3$ – quick liquidity ratio t – a year $t - 1$ – previous year W – weight	(2.14)
$CAT_{VCP} = \left(\frac{VCp1_t}{VCp1_{t-1}} - 1 \right) \times W_{VCp1} + \left(\frac{VCp2_t}{VCp2_{t-1}} - 1 \right) \times W_{VCp2} + \left(\frac{VCp3_t}{VCp3_{t-1}} - 1 \right) \times W_{VCp3}$	CAT_{VCP} – category of value capture $VCp1$ – cost-efficiency ratio $VCp2$ – return on assets $VCp3$ – operating cash flow ratio t – a year $t - 1$ – previous year W – weight	(2.15)
$I_{NFRISK} = \frac{(RT_1 + RT_2 + RT_3)}{3x} W_T + \frac{(RC_1 + RC_2 + RC_3 + RC_4)}{4} W_C + \frac{(RS_1 + RS_2 + RS_3 + RS_4)}{4} W_S + \frac{(RP_1 + RP_2 + RP_3 + RP_4)}{4} W_P + \frac{(RD_1 + RD_2 + RD_3)}{3} W_D$	I_{NFRISK} – index of non-financial risk RT – Technical risks RC – Competence risks RS – Acceptance by staff risks RP – Acceptance by partners and suppliers risks RD – Data security risks W – weight	(2.16)

The calculation of the growth, efficiency and financial risks indexes is based on the increase of each indicator year by year, comparing one year with a previous year. The calculation of the index of non-financial risks is based on the judgement of a status situation. The formulas are presented above.

2.4. Creation of the Economic Assessment Logframe

In this section, the economic assessment logframe created to assess the efficiency, growth and risk of business model transformation in Industry 4.0 is presented below (Figure 2.11). The economic assessment logframe is composed of how the companies could organise the assessment themselves using the assessment logframe (Figure 2.11) and four composite indexes created as described in Chapter 2 (Figure 2.7).

The economic assessment logframe is based on the process of a spiral cycle that represents a learning cycle of continuous improvement and feedback aiming to answer the main question of how to allocate the company's resources when transforming the business model in Industry 4.0. The economic assessment logframe consists of six stages and 16 steps. The following six stages are suggested: 1) setting up the aim for the assessment to allocate the resources, 2) adaptation of the assessment indexes of efficiency, growth and risks and component indicators due to industry and company specifics, 3) collection and processing of economic and financial data, 4) analysis of data of indexes of the increase in the efficiency and growth and risk reduction, 5) assessment of the allocation of resources based on the conclusions, 6) revision on uncertainty and primary data using feedback on the comparison to the aims set up at the beginning of the process.

A group of experts for the approbation of the economic assessment logframe and four composite indexes as the assessment instrument was selected according to the criteria:

- higher education in management, economics, engineering or technology,
- at least five years in the middle- or top-management level in large furniture manufacturing company in Lithuania,
- participation in Industry 4.0 initiatives in a large furniture manufacturing company.

The names of experts for approbation are undisclosed due to reasons of confidentiality and private data security regulations. The experts for the approbation process are named: EA1, ... EAn. The accordance with the criteria of experts' qualification for individual interviews is presented in Annex B.

A group of experts for a focus group for the approbation of the integrated economic assessment logframe and four composite indexes as the assessment instrument was selected according to the following criteria:

- higher education in management, economics, engineering or technology,
- at least five years in the top management level in large furniture manufacturing companies in Lithuania,
- participation in at least three Industry 4.0 implementation projects in large furniture manufacturing companies in Lithuania,
- different responsibilities in the company.

The names of experts are undisclosed due to reasons of confidentiality and private data security regulations. The experts for the focus groups are named: FG1, FG2, FG3 and FG4. The experts' accordance with the criteria for the focus group is presented in Annex B.

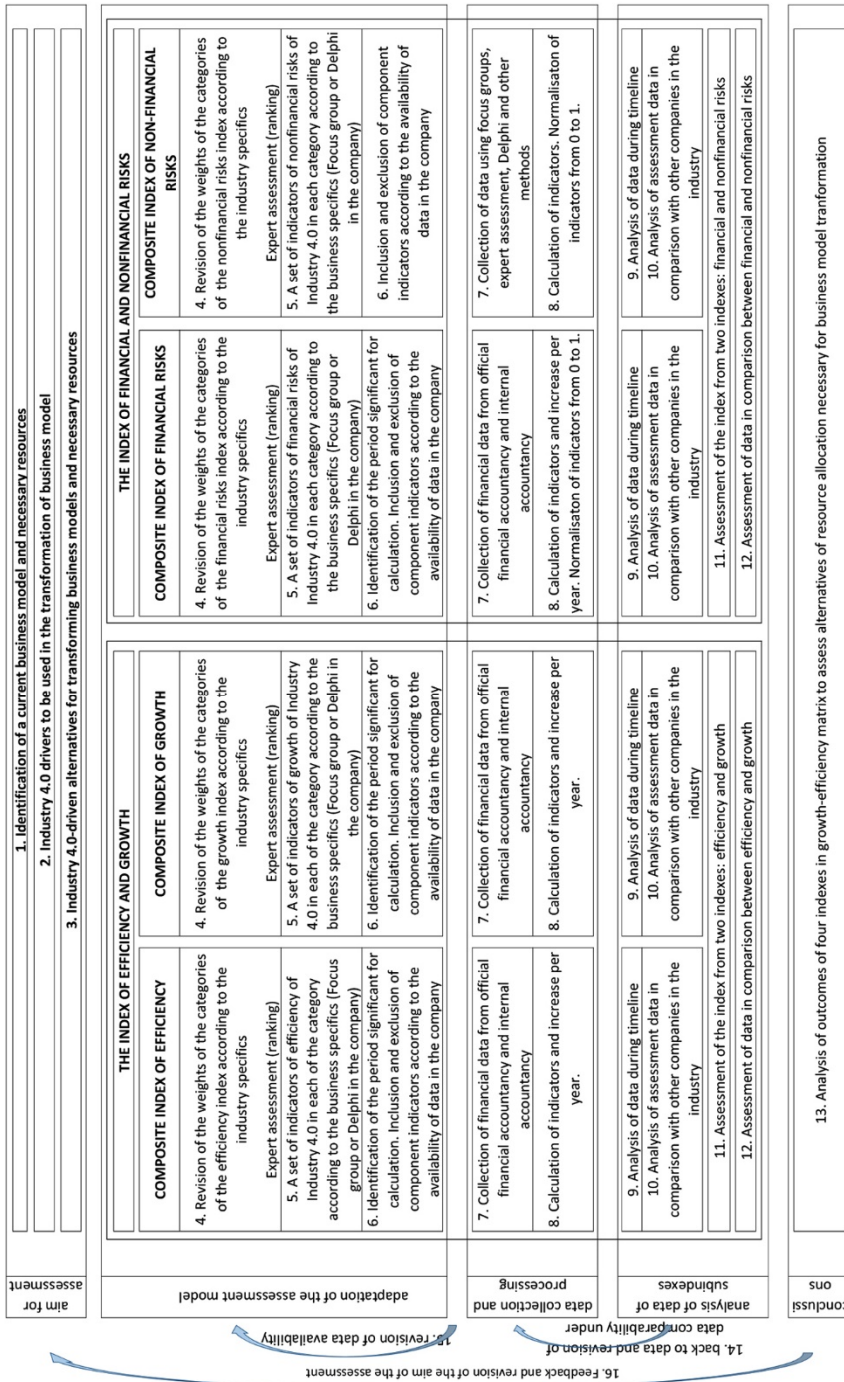


Fig. 2.11. The assessment logframe of efficiency, growth, financial and non-financial risks when transforming business model in Industry 4.0 (created by the author)

Each stage of the economic assessment logframe is explained below in more detail. The first, fifth, and sixth stages are standard to all indexes and are explained together. The second to fourth stages include four parallel processes for each index: efficiency, growth, financial risk and non-financial risk. The second to fourth stages are explained in parallel as they describe the processes of using the indexes. The processes of using the indexes of efficiency and growth consist of the same actions and, therefore, will be explained together. The processes of using indexes of financial and non-financial risks differ and will be explained separately.

The first stage, “Aim for assessment”, aims to formulate the main objective of the assessment when the company plans to transform its business model and implement Industry 4.0 solutions and consists of three steps. First, the identification of a current business model and used resources in the company. In the first step, the company identifies how much its business model matches the criteria of Industry 4.0 as related to the Internet of Things, artificial intelligence, big data, or other pillars and determines what kind of resources it needs. The second step is “Industry 4.0 technologies to be used to transform the business model”. The second step explores the technologies applied for the business model transformation and its possible implication. The third step is “Industry 4.0 business model alternatives and necessary resources”. In the third step, the company explains the value creation and capture process alternatives, possible growth, and reduction of risks. The usage of the efficiency index and the growth index consists of three stages (Figure 2.11.) and starts with the second stage, “Adaptation of the assessment model”. The second stage consists of three steps (4–6 in Figure 2.11): 1) revision of the weights of the categories in the index; 2) revision and adaptation of a set of indicators; and 3) identification of the period. The fourth step aims to revise the weights of the categories in the indexes according to the industry specifics. The industry assessment experts should be organised, and the weights of the existing categories can be corrected. The fifth step aims to revise and adjust a set of component indicators in the indexes according to the company's business specifics and data availability. The sixth step aims to identify the period, which is significant in calculating the indexes. The experts from the business and company assessment, using focus groups or similar methods, can be organised. Inclusion and exclusion of component indicators in the categories and weights of categories are applied, and the assessment period is identified after the second stage.

The third stage, “Data collection and processing”, consists of two steps (7 and 8 in Figure 2.11): 1) collection of financial data; 2) calculation of component indicators and the increase per year of component indicators. The seventh step aims to collect the financial data for the component indicators of efficiency and growth determined during the second stage described above. The financial data from the official financial and internal accountancy should be collected to saturate

with data all component indicators during all years identified as significant during the sixth step.

The eighth step aims to calculate the component indicators and categories and increase each component indicator and category per year during the significant period.

The weights determined in the fourth step should be applied. The calculation of the increase of each component indicator and the weighted category is finalised, and the data are ready for analysis after the third stage.

The fourth stage, "Analysis of data of the indexes", consists of four steps (9–12 in Figure 2.11): 1) analysis of data during timeline; 2) analysis of assessment data in comparison with the industry; 3) assessment of the efficiency and growth index; 4) assessment of data in the comparison between efficiency and growth. The ninth step aims to analyse the component indicators, weighted categories, and indexes of efficiency and growth during the significant period year by year. The tenth step aims to compare and analyse the weighted calculations of the component indicators, categories, and indexes of efficiency and growth with other companies in the industry. The eleventh step aims to add results from both indexes, calculate the composite index of efficiency and growth, and assess it. The twelfth step aims to analyse the comparison between the index of efficiency and the index of growth. The twofold analysis of weighted calculations is conducted after the fourth stage: first, the analysis of data of the company year by year shows the improvement of the company, and second, the analysis of data of the company compares the improvement of the company progress with others.

The assessment of risks includes applying two composite indexes: the financial and the non-financial risk index. The indexes of financial risk and non-financial risk are explained separately. The application of the index of financial risks consists of a similar process as described for the index of efficiency and growth. The difference is in the eighth step, "Calculation of indicators", of the third stage, "Data collection and processing". Besides its aim to calculate the categories and component indicators and increase each category and component indicator per year during the significant period the same way described above, this step aims to prepare data to compare financial and non-financial indicators. The weights determined in the fourth step should be applied. The weighted calculation of the increase of each category and component indicator is finalised, and then the data is ready for analysis after the third stage. Then the normalisation of all the indicators from 0 to 1 should be conducted to compare the financial and non-financial values possible.

The application of the index of the non-financial risks consists of the same stages as other indexes. It requires additional explanation because it is based on non-financial data, and the steps include different actions. The application of the index of the non-financial risks consists of three stages (Figure 2.11) and starts

with the second stage, “Adaptation of the assessment model”. The second stage consists of three steps (4–6 in Figure 2.11): 1) revision of the weights of the categories in the index; 2) revision and adaptation of a set of indicators; and 3) identification of the period. The fourth step aims to revise the weights of the categories in the index according to the industry specifics. The industry assessment experts should be organised using multicriteria methods, and the weights of the existing categories can be corrected accordingly. The categories are based on non-financial challenges, such as a change in infrastructure, data security, acceptance by staff and customers when implementing the transformation. The fifth step aims to revise and adapt a set of component indicators in the categories according to the business specifics and data availability in the company. Data are related to the changes in the organisation while assessing different alternatives for transformation. The sixth step aims to identify the year, which is significant to the implementation of transformation.

Assessing the non-financial risks of a situation in a concrete year is essential. The experts from the business and company assessment using focus groups, Delphi, multicriteria or similar methods can be organised. Conclusion and exclusion of component indicators in the categories and weights of categories are applied, and the assessment period is identified after the second stage.

The third stage, “Data collection and processing”, consists of two steps (7–8 in Figure 2.11): 1) collection of non-financial risk assessment data, 2) calculation of component indicators. The seventh step aims to collect the non-financial data for the component indicators that were determined during the second stage described above. Data for each component indicator probability and forecast impact should be collected to saturate all component indicators with data. The eighth step aims to calculate the non-financial risks based on the collected data and the categories of component indicators. The weights determined in the fourth step should be applied. Then the normalisation of all the indicators from 0 to 1 should be conducted to compare possible financial and non-financial values. The weighted risk heat map using the weighted values of the component indicators and categories is finalised, and normalised values are ready for analysis after the third stage.

The fourth stage, “Analysis of data of the index”, consists of three steps (9–11 in Figure 2.11): 1) analysis of data during timeline, 2) analysis of assessment data in comparison with the industry, 3) assessment of the non-financial risk index, 4) assessment of data in the comparison between financial and non-financial risks. The ninth step aims to analyse the weighted calculations of the component indicators and categories during the significant period year by year. The tenth step aims to compare and analyse the weighted calculations of the component indicators and categories of non-financial risks with other companies in the industry. The eleventh step aims to calculate the average results from both indexes, calculate the composite index of financial and non-financial risks, and assess. The

twelfth step aims to analyse the comparison between the financial risk index and the non-financial risk index. The twofold analysis of non-financial risk calculation is conducted after the fourth stage: first, the analysis of data of the company year by year shows the changes in the company, and second, the analysis of data of the company compares the improvement of the company's progress with others.

The fifth stage, "Assessment conclusions", aims to analyse the assessment outcomes and make assessments about four indexes. The growth-efficiency matrix with a risk component is used. After the fifth stage, the company is assigned to one of four segments in the growth-efficiency matrix with a risk component. Results help compare the company with other companies and the industry results and assess how to allocate the resources needed to transform the business model in Industry 4.0.

The sixth stage, "Feedback and revision of assessment", consists of three steps (14–16 in Figure 2.11): 1) revision of the appropriation of the collected data; 2) revision of the analysis of data; 3) revision of the conclusions. The fourteenth step follows up the data collecting and processing to revise and compare whether all necessary data are available and make some corrections in a set of component indicators if it appears to be necessary. The fifteenth step follows up the weighted calculated index analysis. It aims to revise whether the processed data are enough and relevant for the analysis and include some more data collecting and processing actions if it is essential. The overall data and conclusions are compared with the aim of the assessment set up in the first stage and ensured that the data are relevant to assess the efficiency and growth after the sixth stage.

2.5. Conclusions of Chapter 2

1. The research findings suggest the originally created integrated economic assessment concept with the economic assessment logframe and composite index with the unique composition of indicators to assess economic efficiency, growth, financial and non-financial risks in a business model transformation due to Industry 4.0 implications. The created integrated economic assessment concept not only allows to make assessments but also to adapt the composite indexes to the specifics of the industry.
2. The composed economic assessment logframe serves as a possibility to adjust the composite index to the company and the industry specifics and then use the composite indexes to assess alternatives of the business model transformation in Industry 4.0. The composite index is the assessment instrument to assess the growth, efficiency and risks occurring when transforming the business model in Industry 4.0 in

large manufacturing companies. Four indexes have equal weights: index of efficiency with four weighted categories that reflect value proposition, creation, delivery and capture, the index of growth with two weighted component indicators, the index of financial risks with three weighted categories and the index of non-financial risks with five weighted categories. When calculating component indicators, only the increase in comparison with a previous year is assessed. Component indicators in each category should be collected from standard financial accountancy, such as profit, sales, stock or investment, to compare with other companies in the industry if possible. The component indicators that were explored in the empirical research stage determine the base of each category.

3. A balanced usage of quantitative and qualitative methods is significantly important for the economic assessment in the context of Industry 4.0. Quantitative research methods are to be used to collect and process financial data for three indexes: efficiency, growth and financial risk. The mix of financial and non-financial estimates requires a specific research design consisting of quantitative and qualitative research methods. Qualitative research methods such as interviews and focus groups are to be used to collect and process qualitative data and ensure stakeholders' involvement. Taking into consideration the non-financial qualitative information by including professional expertise that is not incorporated into the accountancy and financial calculations in the assessment process complements the initial results of the assessment and the enriched results of the process to ensure a more thoughtful assessment and the quality of the research results.
4. The homogeneity, comparability, and reliability of the company's indicators and the industry are the key factors for the successful assessment of alternatives. First, possible relevant inputs and outputs are defined for each component indicator to assess efficiency in categories. Second, there is the collection of data for the selected indicators for efficiency growth and financial risk.
5. The quality of the assessment using the created index very much depends on primary data for component indicators. Data from internal accountancy should be used to compare the company's results with itself during a period. It is essential to ensure that the same methodology inside the company is used during all years of analysis. The application of a complex of suitable research methods should be considered to ensure a holistic approach to the assessment that allows assessing the efficiency of future decisions in investment.

3

The Empirical Approbation of the Integrated Economic Assessment Concept

Chapter 3 suggests and explains in detail the practical application of the created integrated economic assessment concept. The economic assessment logframe, the composition of the composite indexes and the growth-efficiency matrix are based on the synergy of theoretical and empirical research results. Theoretical and empirical research executed in previous chapters confirms the practical applicability of the integrated economic assessment concept to assess the allocation of company resources when transforming business models in Industry 4.0.

The findings of this chapter have been published in the scientific paper in 2020: Kovaitė et al., 2020.

3.1. Application of the Created Economic Assessment Logframe and Four Composite Indexes

The application and approbation were performed between 2020 and 2021. The following objectives of the application process are to test the created integrated

economic assessment concept, the economic assessment logframe, composite indexes and growth-efficiency matrix in the case of large manufacturing companies in Lithuania, to design the integrated economic assessment concept to assess the efficiency, growth and risk of the companies and to draw the conclusions and future research directions.

According to the research, other criteria to choose a set of companies for the approbation of the created composite indexes are based on the research, which follows the main criteria to include the companies that are most affected by Industry 4.0 solutions. The following concrete criteria were met:

- 1) analytical forecasts show a significant impact of Industry 4.0 on the efficiency and growth of the industry sector,
- 2) industry that implements Industry 4.0 solutions to modify business models actively in the sector level,
- 3) large companies according to the regulations of the Law of Small and Medium Enterprises,
- 4) availability of financial and managerial data for the period from the start of implementation of Industry 4.0 to the research end,
- 5) availability of historical data in the company for the period from Industry 4.0 to the research end.

The application and approbation of the integrated economic assessment concept, including the integrated economic assessment logframe, four composite indexes, and the growth-efficiency matrix, were organised in furniture manufacturing, which works under the European Classification of Economic Activities (NACE) 310900 (other furniture manufacturing) Lithuania. According to the research on Industry 4.0 application and its practical impact in the industry, several industries are most affected, and the furniture manufacturing industry is among them. Only large companies were chosen for the approbation process. According to the European legislation, large companies meet the requirements: 1) having more than 250 employees (FTE per year), 2) the company assets are either over EUR 43 million, or the annual turnover is over EUR 50 million.

The research was organised into three steps:

1) According to NACE and the scientific literature analysis, manufacturing companies from the C section were selected for the first analysis.

2) Large furniture manufacturing companies in Lithuania are working under NACE 310900, which covers other furniture manufacturing. The analysed companies' annual turnover is appr 80 per cent of the whole sector and can be considered representative. The financial data of nine large companies were analysed in this stage.

3) After applying the selection criteria – Implementing Industry 4.0 solutions in the company – six large companies out of nine from the second stage were selected for detailed research.

The names of companies are undisclosed due to reasons of confidentiality and are named alphabetically. The main characteristics of the companies are introduced in Annex D. The second stage companies were named: A, B, C, D, E, F, G, H, and J. Companies named A, B, C, D, E and F were selected for the third research stage. The period of research was 2014–2019. The researched companies started implementing Industry 4.0 in 2015, and the implementation with a possible impact period lasts 2–3 years. The main period of the presented results is 2015–2018 because the 2015 financial data from a year before (2014) is necessary, and a situation for 2019 is analysed in a dedicated section.

The companies researched in detail in the third stage of the research (A, B, C, D, E and F) are presented in blue in Table 3.1. They represent large furniture manufacturing companies from NACE 310900 that implemented Industry 4.0 solutions, and there are data available. The data from these companies are analysed and presented in more detail than companies G, H, and J. Companies G, H and J are included in the second stage; they are large furniture manufacturing companies with a lack of data on business model transformation in Industry 4.0. The results of G, H and J are presented in yellow in Table 3.1 and serve as a benchmark for the researched companies in the third stage with the rest of the sector. IND represents the overall situation in the furniture manufacturing industry. It serves as a benchmark for companies to compare with the average situation in the industry and is presented in green.

The results of the calculation of four indexes are described below. As described in Chapter 2 (Figure 2.6), the overall index consists of four indexes: growth, efficiency, financial risk and non-financial risk, each index consists of several categories, and each category consists of several component indicators. The categories are assessed to have different weights and bring different weighted inputs into the index.

The growth index presents the change of the values of the component indicators in the index of growth. The calculation is based on financial data from financial accounting documents, and the formula is presented in Chapter 2 formula (2.9). The efficiency index presents the change in the weighted categories' scores and calculates the increase in efficiency along the value chain. The calculation is based on financial data from financial accounting documents, and the formula is presented in formula (2.11). The index of financial risk is presented as the change in the value of the weighted categories. The calculation is based on financial data from financial accounting documents, and the formula is presented in Section 2, formula (2.10). The results show the increase or decrease compared to the previous year (when the calculations are shown year by year in a timeline) or as a weighted sum of each year's increase of component indicators and categories (when the calculations are shown as an index).

Table 3.1. Results of the index of growth and efficiency

2015-2018	IND	A	B	C	D	G	H	J	E	F
INDEX_GR	0.1171	0.3753	0.5969	0.6313	-0.1853	0.5905	0.3930	0.1500	0.7149	-0.0404
INDEX_EFF	-0.0558	0.3006	0.5312	-0.0595	0.0365	-0.0422	0.0793	-0.1845	0.3701	-0.0207
INDEX_EFF+GR	0.0614	0.6759	1.1281	0.5718	-0.1489	0.5483	0.4723	-0.0344	1.0851	-0.0611
ranking		3	1	4	9	5	6	7	2	8

Table 3.2. Results of the index of risk

2015-2018	IND	A	B	C	D	G	H	J	E	F
RISKFINA	-0.0551	0.5323	0.2443	0.3580	0.1027	0	0.0111	1	0.5691	0.1822
RISKNONF	1	0.1799	0.4346	0.3106	0.5147	1	0.7578	0.9128	0	0.6674
INDEX_RISK	0.4725	0.3561	0.3395	0.3343	0.3087	0.5	0.3844	0.9564	0.2846	0.4248
ranking		5	6	7	8	2	4	1	9	3

Table 3.3. Growth index and subindexes, accumulated for the period of 2015–2018 (created by the author)

2015-2018	IND	A	B	C	D	G	H	J	E	F
GR_Added vlaue	0.2452	0.6494v	0.5644	0.7457	-0.4716	0.5866	0.3228	0.2352	0.7825	0.0167
GR_Shareholders	-0.1817	-0.2644	0.6726	0.3644	0.4826	0.5996	0.5568	-0.0486	0.5573	-0.1734
INDEX_GR	0.1171	0.3753	0.5969	0.6313	-0.1853	0.5905	0.3930	0.1500	0.7149	-0.0404
ranking		6	3	2	9	4	5	7	1	8

Table 3.1 introduces the index of the efficiency and growth of business model transformation in the implementation of Industry 4.0 for the period 2015–2018 of the furniture manufacturing sector, including only large-sized companies (IND) and each researched company (A, B, C, D, E and F) and in other sector companies (G, H and J).

The index of efficiency and growth (INDEX_EFF_GR) is calculated by summing the results of the two indexes (IND_GR, which refers to growth, and IND_EFF, which refers to composite index of efficiency). A higher ratio indicates a higher increase in the value due to the accumulated results of growth and efficiency indicators during 2015–2018. The results show a weighted sum of each year's increase of component indicators and categories (when the calculations are shown as an index).

Results from Table 3.1 suggest that the sector index of growth and efficiency is 0.06 per cent over the four years. Four researched companies are above the industry sector level. Two companies present an increase in results that are higher than 100 per cent: company B is ranked 1 and shows 113 per cent, E is ranked second with 109 per cent. Only two companies show results lower than the industry sector level: D with –15 per cent and F with 6 per cent. The rest of the companies' results are close to 50 per cent. This shows a positive development and is shown in ascending order: C – 57 per cent, A – 68 per cent. The companies with no evidence of Industry 4.0 implementation show lower than average results; one company shows a negative change over the period.

The results presented in Table 3.1 line, INDEX_GR, show the overall growth of the sector and each company. Results suggest that sector growth, including added value per employee and stakeholder fund per employee, is 11.71 per cent over the four years. Most of the companies are significantly above the overall sector growth ratio. The highest growth ratios are shown (in a descending way): company E with 71.49 per cent, C – 63.13 per cent, B – 59.69 per cent and A – 37.53 per cent. Two companies have a negative growth ratio. A higher ratio indicates a higher growth situation.

The results presented in Table 3.1, line INDEX_EFF, show the efficiency of implementing Industry 4.0 solutions in the sector and each company, including all four stages of the value chain: value proposition, creation, delivery and capture. Results suggest that the sector efficiency through the whole value chain is 0.63 per cent over the four years. Most of the companies are above zero. The highest efficiency ratios are shown (in a descending way): company B with 53.12 per cent. E – 37.01 per cent. A – 30.06 per cent and D – 3.65 per cent. Two companies have a negative efficiency ratio. They are very close to the overall sector results: company C is –5.95 per cent and –2.07 per cent for D. A higher ratio indicates higher efficiency.

Table 3.2 introduces the index of the non-financial and financial risks of Industry 4.0 implementation from 2015 through 2018 in the furniture manufacturing sector, including only large-sized companies (IND) and each researched company (A, B, C, D, E and F) and in other sector companies (G, H and J).

The index of risk (INDEX) is calculated by the average sum of the two indexes' results: financial (INDEX_RISKFINA) and non-financial risks (SUB_RISKNONF). Risk indicators vary from 0 to 1. A higher ratio indicates a higher risk if Industry 4.0 is to be implemented.

Results from Table 3.2 suggest that the sector index of financial and non-financial risks is 0.47 per cent over the four years and is a medium risk level. Three researched companies show lower or almost equal risk levels than the industry sector level: E is ranked 9 and shows the lowest risk with 0.22, A is ranked 8 and shows low risk with 0.32, C is ranked 6 and medium risk 0.48. The remaining three researched companies show results above the sector level and still maintain a medium higher risk level: company B is ranked 5 and shows medium risk with 0.6, D is ranked 4 with 0.71, and F is ranked 3 with 0.74. Even if the risk level varies, none of the researched companies exceeds the medium risk level. Two companies with no evidence of Industry 4.0 implementation show high risk; one company shows a medium risk.

Analysing the three researched companies that show low to medium risk (A, C, E), the index results show that the index of the financial risks is higher (A – 0.47, C – 0.64 and E – 0.43). The low-risk level is because of a low non-financial risk level. Other companies (B, D, F) with the index of risks being a higher medium are affected by the very high financial risk index. An index of non-financial risk balances the situation.

Table 3.1 and Table 3.2 show the indexes. The results presented in Figure 3.1 serve to visualise the results from Table 3.1 and Table 3.2 and summarise all four indexes.

Axis X in Figure 3.1 shows the index of growth and efficiency, and axis Y shows the index of risk; the size of the bubbles shows the level of risk. Notifications next to the bubble indicate the name of the company and the level of risk.

When analysing each index's impact on the overall index, it is observed that the index of financial risk makes the most significant negative impact. The index of financial risk is negative in the sector results. For all companies except company E, and even the worst result in company E, the financial risk index is close to 0. The observation indicates that positive results of growth and efficiency are followed by increasing financial risk, and it suggests necessary actions in risk management plans.

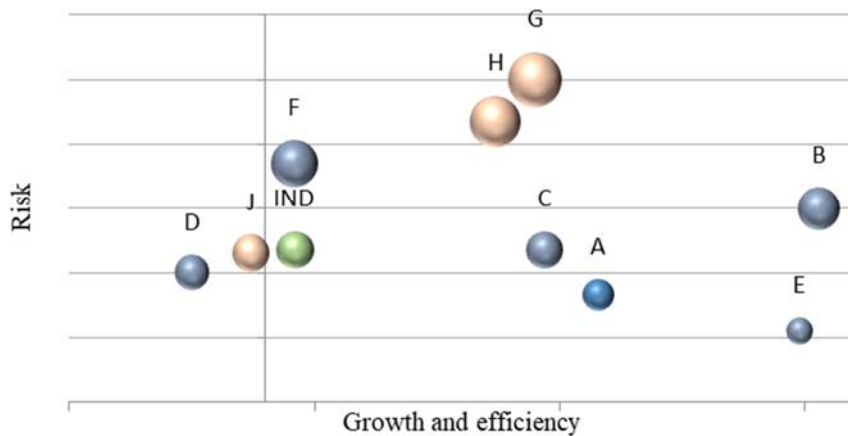


Fig. 3.1. The indexes of efficiency, growth and risks from 2015 to 2018 (created by the author)

The growth composite index is one level and consists of two component indicators: added value and shareholders. The component indicator of added value assesses the increase of added value per employee during the period, for the main researched companies (A, B, C, D, E, and F), the other companies (G, H and J) and in the sector (IND).

The component indicator of shareholders assesses the increase of shareholder funds per employee during the period in the sector, the main researched companies (A, B, C, D, E, and F), and other companies in the sector (I, G, H and J). The index of the whole period's growth is calculated as a weighted sum of a component indicator of added value ($w = 0.7$) and a component of shareholder funds ($w = 0.3$).

Table 3.3 introduces the overall ratio of index growth between 2015 and 2018 of the furniture manufacturing sector, including only large-sized companies (IND) and each researched company (A,...F).

The results presented in Table 3.3, line INDEX_GROWTH, show the overall outcomes accumulated by the two sectors and each company's indicators. Results suggest that sector growth, including added value per employee and stakeholder funds per employee, is 11.71 per cent over the four years. Four companies are significantly above the overall sector growth ratio. The highest growth ratios are shown (in a descending way): company E with 71.49 per cent, C – 63.13 per cent, B – 59.69 per cent, and A – 37.53 per cent. Two companies have a negative growth

ratio (F shows -4.04 per cent and D -18.53 per cent. A higher ratio indicates a higher growth and indicates a more favourable situation in the company.

Analysing each component indicator's impact on the index, a weight of each of them is an essential factor.

The results in Table 3.4 show the calculation of the overall growth index for each year that is explored. The results show an increase or decrease in comparison with the previous year.

The line INDEX_GR shows the sum of each year's results and equals the INDEX_GR line from Table 3.1. The results show that the negative results in the growth index result from a continuous decrease in the results. Company D (ranked the last, ninth) and company F (ranked eighth) are the only companies showing negative results. Company D shows the most significant negative result of -18.53 per cent, which is an accumulation of decreases each year from 2016, 2017 and 2018. An increase of 21.55 per cent in 2015 is corrected during the following years. Company E (ranked first) shows the best results of a 71.49 per cent increase during the period. It is influenced by an increase in the growth index three years in a row: 2015 – 35.63 per cent; 2016 – 41.87 per cent; and 2017 – 7.26 per cent. The last year, 2018, shows a decrease of 13.27 per cent, but it does not affect the overall results and keeps company E in the first position. Company C (ranked second) shows an increase in the growth index of 63.13 per cent during the period. An increase of 18.72 per cent in 2015 and a decrease by 16.33 per cent do not make a change, but a significant increase in growth by 53.89 per cent in 2017 growth, and 6.84 per cent after 2017, bring company C to the second position among other companies. Company B (ranked third) shows a significant increase in growth by 59.69 per cent. A continuous increase influences the results in growth: 2015 – 39.80 per cent; 2016 – 7.76 per cent; 2018 – 20.45 per cent. Only 2017 shows a decrease – of 8.33 per cent – which eliminates an increase of 20. Company A (ranked fourth) shows an increase in the growth index by 37.53 per cent during the period. The results are influenced by a significant increase of 44 per cent in 2017, with minor increases or decreases in the rest of the period: 2015, a decrease of 0.86 per cent, 2016 – a decrease of 7.11 per cent and 2018 – an increase of 1.5 per cent. In conclusion, the companies that show increases during the period show a continuous increase in the growth index, with less than one year of decrease in different years.

Figure 3.2 visualises the main results of a growth index of the sector (IND) and all companies in a timeline. The lines in different colours show the change in the index results during the period. Figure 3.2 shows the significant changes in each company. The trendline (in punctuation) is shown as a linear trendline of the sector index of growth.

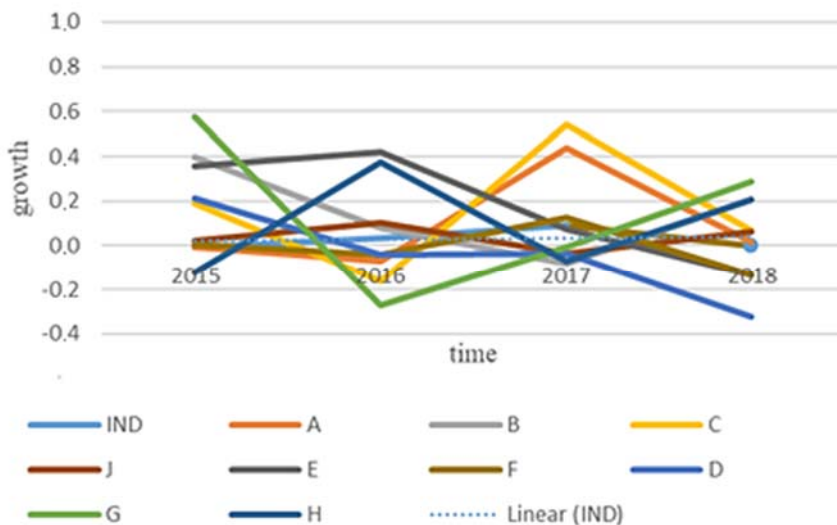


Fig. 3.2. Main results of growth index during 2015–2018 (created by the author)

The results in Table 3.5 show the calculation of the component indicator of the added value each year that is explored. The added value component indicator is one of the two indicators included in the growth index, and its weight in the index is 0.7. The results show an increase or decrease in comparison with the previous year.

The line GR_Added value shows the sum of the results of each year and equals the GR_Added value line from Table 3.1. The average in the sector (IND) shows a 24.52 per cent increase in the added value per employee from 2015 through 2018. Four researched companies (A, B, C and E) show results significantly above the average of the sector. One company (F) shows an increase of added value only by 1.67 per cent, and one company (D) shows a decrease in the added value.

Company E (ranked the first) shows the increase of the added value per employee by 78.25 per cent during the period. It is influenced by a significant increase of added value per employee during 2015 (44.15 per cent) and 2016 (45.93 per cent) and a significantly slower increase in 2017 (20.89 per cent). Three years in a row showed an increase in the added value, and this continuity is an essential factor. Even if 2018 shows a decrease in value-added value compared to the previous year, the overall increase is significantly above average and above most other researched companies in the sector. Company C (ranked second) shows an increase of the added value by 74.57 per cent during the period. It is influenced by an extreme increase in 2017 (75.51 per cent).

Table 3.4. Growth indexes year by year, period 2015–2018 (created by the author)

year	IND	A	B	C	D	G	H	J	E	F
2015	–0.0047	–0.0086	0.3980	0.1872	0.2155	0.5775	–0.1212	0.0234	0.3563	0.0049
2016	0.0341	–0.0711	0.0776	–0.1633	–0.0407	–0.2706	0.3757	0.1006	0.4187	–0.0396
2017	0.0892	0.4400	–0.0833	0.5389	–0.0352	–0.0050	–0.0682	–0.0345	0.0726	0.1247
2018	–0.0015	0.0150	0.2045	0.0684	–0.3250	0.2887	0.2067	0.0605	–0.1327	–0.1304
INDEX_GR	0.1171	0.3753	0.5969	0.6313	–0.1853	0.5905	0.3930	0.1500	0.7149	–0.0404
ranking		6	3	2	9	4	5	7	1	8

Table 3.5. Indicator of the added value per employee, year by year for the period of 2015–2018 (created by the author)

year	IND	A	B	C	D	G	H	J	E	F
2015	0.0259	0.0803	0.0991	0.1950	0.1690	0.6484	–0.2712	0.0493	0.4415	–0.0032
2016	0.0760	–0.1209	0.2683	–0.2489	–0.0938	–0.4180	0.4535	0.1398	0.4593	–0.0198
2017	0.1307	0.6348	–0.1155	0.7551	–0.0274	–0.0064	–0.1329	–0.0289	0.2089	0.1656
2018	0.0126	0.0552	0.3126	0.0445	–0.5193	0.3627	0.2733	0.0749	–0.3273	–0.1259
GR_Added value	0.2452	0.6494	0.5644	0.7457	–0.4716	0.5866	0.3228	0.2352	0.7825	0.0167
ranking		3	5	2	9	4	6	7	1	8

The remaining years show a fluctuation with the increase and decrease of the value-added: 19.5 per cent increase in 2015; 24.89 per cent decrease in 2016. The increase of 4.45 per cent after an extreme increase in 2017 also adds to an indicator's overall result. Company A (ranked the third) shows a significant increase of added value by 64.94 per cent during the period. It is influenced by an extreme increase in 2017 (63.48 per cent). The remaining years show a fluctuation with the increase and decrease of the value-added: 8.03 per cent increase in 2015, 12.09 per cent decrease in 2016. The increase of 5.52 per cent after an extreme increase in 2017 also adds to an indicator's overall result. Company B also shows a result (56.44 per cent) significantly above the sector's average. Company B shows an increase of 9.91 per cent in 2015 and 26.83 per cent in 2016. Like other companies, company B also has one year of decrease (11.55 per cent) in 2017, followed by a significant increase of 31.26 per cent in 2018, which brings company B double above the sector level. Company D is the only one to show negative results (−47.16 per cent) during the period. It is influenced by a continuous decrease each year and a significant decrease in 2018 (−51.93 per cent).

The results in Table 3.6 show the calculation of the component indicators of the shareholders' funds per employee each year. This component indicator is one of the two indicators in the growth index, and its weight in the index is 0.3. The results show an increase or decrease in comparison with the previous year.

The line GR_Shareholders shows the sum of the results of each year and equals the GR_Shareholders line from Table 3.1. The average in the sector (IND) shows an 18.17 per cent decrease in the shareholders' value per employee from 2015 through 2018. Four researched companies (B, C, D, and E) show results significantly positive and above the average of the sector, and two companies (F and A) show a decrease of the shareholders' value per employee (by 17.34 per cent and 26.44 per cent respectively).

Company B (ranked the first) shows the increase of the shareholders' value per employee by 67.26 per cent during the period. It is influenced by a significant increase in shareholders' value per employee during 2015 (109.56 per cent). The results show negative results in all the rest of the explored years: 36.73 per cent decrease in 2016; 0.82 per cent decrease in 2017; and a 4.76 per cent decrease in 2018. Company E shows an increase of 55.73 per cent during the period. A constant increase influences it in shareholders' funds per employee, showing 15.75 per cent in 2015, 32.4 per cent in 2016 and 32.12 per cent in 2018. Only 2017 shows a decrease in shareholders' funds per employee by 24.55 per cent. Company D shows an increase of 48.26 per cent of shareholder value per employee during the period. It is influenced by a significant increase of shareholder funds per employee in 2015 (32.42). The remaining period shows increases in 2016 (8.33 per cent) and 2018 (12.85 per cent) and a minor decrease in 2017 (5.34 per cent). Company C shows an increase of 36.44 per cent of shareholder value per employee during the period.

Table 3.6. Indicator of the shareholders' funds per employee, year by year for the period of 2015–2018 (created by the author)

year	IND	A	B	C	D	G	H	J	E	F
2015		-0.0760	-0.2160	1.0956	0.1690	0.3242	0.4120	0.2286	-0.0372	0.1575
2016		-0.0636	0.0450	-0.3673	0.0366	0.0833	0.0731	0.1942	0.0092	0.3240
2017		-0.0075	-0.0145	-0.0082	0.0345	-0.0534	-0.0016	0.0828	-0.0476	-0.2455
2018		-0.0345	-0.0789	-0.0476	0.1242	0.1285	0.1161	0.0512	0.0270	0.3212
GR_Shareholders		-0.1817	-0.2644	0.6726	0.3644	0.4826	0.5996	0.5568	-0.0486	0.5573
ranking		9	1	6	5	2	4	7	3	8

Table 3.7. Efficiency ocmposite index and subindexes, accumulated for the period of 2015–2018 (created by the author)

IND_EFF	IND	A	B	C	D	G	H	J	E	F
EFF_Value Proposition	-0.1979	0.0272	0.8908	0.4579	-0.1183	0.2066	0.4010	-0.9238	-0.0701	-0.0682
EFF_Value Creation	0.0313	0.8231	0.7482	-0.2266	0.1480	-0.1210	0.0813	-0.0408	1.0472	0.0113
EFF_Value Delivery	-0.0531	-0.1283	0.1741	-0.0954	0.1367	0.0374	0.1479	-0.1240	-0.0669	-0.2515
EFF_Value Capture	-0.0830	-0.0594	0.1107	-0.1846	-0.0782	-0.1630	-0.2222	0.1409	-0.0987	0.1044
INDEX_EFF	-0.0558	0.3006	0.5312	-0.0595	0.0365	-0.0422	0.0793	-0.1845	0.3701	-0.0207
ranking		3	1	8	5	7	4	9	2	6

It is influenced by a continuous positive result of shareholder funds per employee during each year of the explored period and shows 16.9 per cent in 2015, 3.66 per cent in 2016, 3.45 per cent in 2017 and 12.42 per cent in 2018. The results do not show an extreme increase as a company might expect from Industry 4.0 implementation.

The efficiency composite index is hierarchical and consists of four categories with weighted values. Each category consists of three component indicators. The categories are related to the business model's parts and reflect value proposition, creation, delivery, and capture. The detailed structure of the index of efficiency is introduced in Table 2.1. Each component indicator assesses the increase of a respective area during the period in the sector, the main researched companies (A, B, C, D, E and F) and other companies in the sector (G, H and J). The index of efficiency of the whole period is calculated as a weighted sum of categories reflecting value proposition ($w = 0.2$), value creation ($w = 0.4$), value delivery ($w = 0.15$) and value capture ($w = 0.25$).

Table 3.7 introduces the overall ratios of efficiency index and each category for the period of 2015–2018 of the furniture manufacturing sector, including only large-sized companies (IND) and each researched company (A...F).

The results presented in Table 3.7, line INDEX_EFF, show the overall accumulated outcomes of each company's four categories of the sector. Results suggest that the sector efficiency decreased by 5.58 per cent over the four years. All six companies are almost equal or above the overall sector efficiency ratio. Four companies show an increase of efficiency (in a descending way): B – 53.12 per cent; E – 37.01 per cent; A – 30.06 per cent; D – 3.65 per cent. Two companies show a minor decrease: F – 2.07 per cent decrease and C – 5.95 per cent. A higher ratio indicates a higher efficiency and indicates a more favourable situation in the company.

Analysing the impact of each component indicator on the index, the weight of each of them is an essential factor. Value creation plays the most crucial role in the sector and in each company where a positive increase is observed. In the sector (IND), value creation shows the only positive ratio (3.13 per cent) when other business models show negative efficiency results. Company B (ranked first) show an 87.82 per cent increase in value creation, and this is the only company that shows results in all four parts of the business model. Other companies with significant positive overall efficiency results show positive results in one or two parts of a business model. For example, A (ranked 3) shows 82.31 per cent in value creation, and 2.72 per cent in value proposition, E (ranked 2) shows 104.72 per cent in value creation. However, all the remaining parts of the business model show negative results.

The same results overview logic can be applied for the value proposition, value delivery, and value capture dimensions.

Table 3.8. Efficiency composite index, year by year for the period of 2015–2018 (created by the author)

year	IND	A	B	C	D	G	H	J	E	F
2015	–0.0142	0.3504	0.3934	–0.0498	0.1175	0.2334	0.0829	–0.0501	0.1705	–0.0211
2016	–0.0108	–0.1034	–0.1604	0.0213	–0.0518	–0.1551	0.0445	0.1187	0.4103	0.0831
2017	0.0191	0.1237	0.1677	–0.0266	–0.0063	–0.0590	0.0391	–0.1211	0.1263	–0.0540
2018	–0.0499	–0.0701	0.1305	–0.0044	–0.0229	–0.0615	–0.0872	–0.1319	–0.3370	–0.0287
INDEX EFF	–0.0558	0.3006	0.5312	–0.0595	0.0365	–0.0422	0.0793	–0.1845	0.3701	–0.0207
ranking		3	1	8	5	7	4	9	2	6

Table 3.9. Indicator of the efficiency of the value proposition, year by year for the period of 2015–2018 (created by the author)

year	IND	A	B	C	D	G	H	J	E	F
2015	0.0884	–0.1485	1.3610	0.1629	0.4629	0.4912	0.2392	–0.3249	–0.2783	–0.0643
2016	–0.1187	–0.0286	–0.4557	0.0550	–0.2477	–0.5555	0.1172	0.4336	0.1164	–0.0005
2017	–0.0332	0.2276	0.1088	0.0376	–0.0347	–0.0791	–0.0127	–0.1946	0.4606	0.0154
2018	–0.1344	–0.0232	–0.1234	0.2023	–0.2988	0.3500	0.0573	–0.8378	–0.3688	–0.0188
EFF VP	–0.1979	0.0272	0.8908	0.4579	–0.1183	0.2066	0.4010	–0.9238	–0.0701	–0.0682
ranking		5	1	2	8	4	3	9	7	6

efficiency results if a low increase or decrease appears in other parts of the business model.

The results in Table 3.8 show the calculation of the overall efficiency index each year that is explored. The results show an increase or decrease in comparison with the previous year.

The line SUB_EFF shows the sum of the results of each year and equals the SUB_EFF line from Table 3.8. The overall results of the sector (IND) show a decrease in efficiency of 5.58 per cent. Only in 2017 does the sector show a minor positive increase in efficiency by 1.91 per cent. The companies that show a high increase during the period also show an extremely high or high overall efficiency increase for two or three years. And the opposite – having two or three years of decrease, even a low decrease – brings overall negative results. Companies D, F, and C show a meagre increase of the low decrease of efficiency during the period (an increase of 3.65 per cent, a decrease of 2.07 per cent and 5.5 per cent, respectively), and negative results are observed at least 3 years in a row. B (ranked first) shows a very high increase in efficiency in 2015 (39.34 per cent), followed by a decrease in 2016 by 16.04 per cent, and then each year, the medium increase of the results of efficiency is observed 16.77 in 2017 and 13.05 per cent in 2018. Company E (ranked second) shows a very high increase of 41.03 per cent in 2016, a medium increase of 17.05 per cent a year before 2015 and 12.63 per cent a year after in 2017. Company A (ranked third) shows a very high increase of 35.04 per cent in 2015 and 12.37 per cent in 2017, followed by a negative correction of 10.34 per cent in 2016 and 7.01 per cent in 2018.

All companies except company B ranked first, showed a decrease in efficiency in 2018 compared to 2017.

The results presented in Figure 3.3 show the changes in the efficiency index in the sector and each company during the explored period. Figure 3.3 visualises the main results of the efficiency index of the sector (IND) and all companies in a timeline. The lines in different colours show the change in the results of the efficiency index during the period. The trendline (in punctuation) is shown as a linear trendline of the sector index of efficiency.

The results in Table 3.9 show the calculation of the category of the value proposition in each year that is explored. The value proposition category is one of the four categories that constitute the efficiency index, and its weight in the index is 0.2. The category is calculated as the accumulated values of three component indicators: return on sales, current liquidity ratio, and sales cost-efficiency ratio. The results show an increase or decrease in comparison with the previous year.

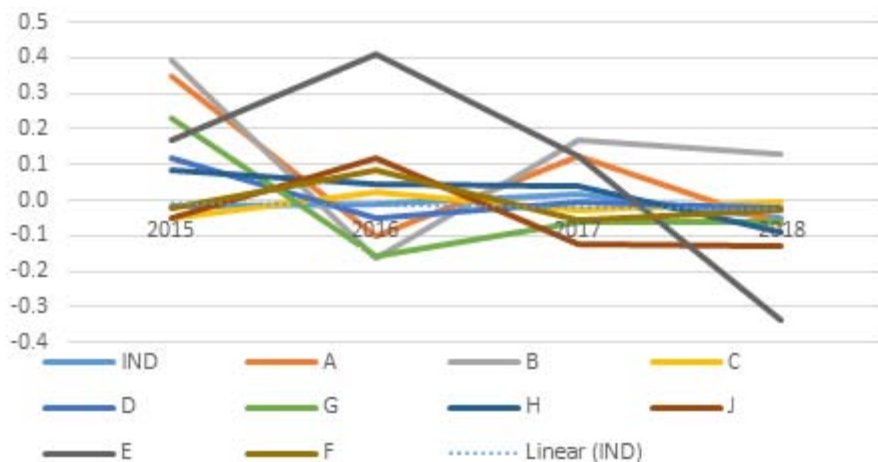


Fig. 3.3. The changes in the efficiency index during 2015–2018
(created by the author)

The line EFF_VP shows the sum of the results of each year and equals the EFF_VP line from Table 3.9. The overall results of the sector (IND) shows a decrease in efficiency on the value proposition of 19.79 per cent. Only in 2015, the sector shows a positive increase in efficiency by 8.84 per cent, but the overall result is corrected in the following years. Two companies show an extremely high overall result of 89.08 per cent in company B (ranked first) and 45.79 per cent in company C (ranked second). A high increase results from an extremely high increase in 2015 of 13.10 per cent in B and a continuous increase each year in company C. Other companies show a minor increase or decrease; they still show better results than the sector average. There is at least one year of very high to high increase in those companies, but the other years show a decrease, which influences the correction of the results. Company E showed 46.06 per cent in 2017. Company D showed a 46.29 per cent increase in 2015, and company A showed 22.76 per cent as their most significant increase during the period.

The results in Table 3.10 show the calculation of the value creation category each year that is explored. The value creation category is the most significant of the four categories that constitute the efficiency index, and its weight in the index is 0.4. The category is calculated as the accumulated values of three component indicators: turnover of unfinished production, labour productivity and fixed assets turnover ratio. The results show an increase or decrease in comparison with the previous year.

The line EFF_VC shows the sum of the results of each year and equals the EFF_VC line from Table 3.10. The overall results of the sector (IND) show an

increase in efficiency with the value creation of 3.13 per cent. During the period, a fluctuation is observed. The sector shows a minor decrease of 3.93 per cent in 2015 and 1.19 per cent in 2018. An increase of 4.94 per cent was observed in 2016 and 3.31 per cent in 2017. Five companies are close to or above the increase in the sector. Company E (ranked first) shows a 104.72 per cent increase in efficiency in value creation over the period. Three years in a row show high increases: an increase of 86.59 per cent in 2015; 74.68 per cent in 2016; and 5.04 per cent in 2017. A drastic decrease in 2018 after such a significant increase during the previous three years still brings the overall increase to more than 100 per cent over four years. Company A (ranked second) shows an overall increase of 82.31 per cent with three years of increase: 96.89 per cent in 2015, 17.05 per cent in 2017, and 2.68 per cent in 2018. The decrease of 34.31 per cent in 2016 shows a correction of an extremely high increase a year before. Company B (ranked third) shows a 74.82 per cent increase in value creation efficiency over the period. Very high increases of 46.39 per cent in 2018 and 31.97 per cent in 2017 are observed after a medium decrease of 11.56 in 2016 and 8.02 per cent in 2015. Company D (ranked fourth) shows 14.80 per cent, resulting in a continuous increase in efficiency during three years: 8.03 per cent in 2015, 8.28 per cent in 2016, and 5.05 per cent in 2018. The remaining companies (F) show results close to the results of the sector or decrease (C).

The results in Table 3.11 show the calculation of the category of value delivery for each year that is explored. The category of value delivery is one of the four categories that constitute the efficiency index, and its weight in the index is 0.15. The category is calculated as the accumulated values of three component indicators: distribution ratio, inventory turnover, and quick ratio. The results show an increase or decrease in comparison with the previous year.

The line EFF_VD shows the sum of the results of each year and equals the EFF_VD line from Table 3.11. The overall results of the sector (IND) show a decrease in efficiency with the delivery of 5.31 per cent. During the period, an increase was observed between 2016 (by 4.56 per cent) and 2017 (by 2.27 per cent). A higher decrease in 2018 influences the overall result. Two companies are higher than the average of the sector and above zero. Company B (ranked first) shows an increase of 17.41 per cent, which is influenced by an extremely high increase in delivery efficiency in 2015, followed by decreases each year. Company D shows an increase of 13.67 per cent, which is influenced by continuous increases during 2015 by 6.06 per cent, in 2016 by 10.5 per cent and in 2017 by 8.74 per cent.

Table 3.10. Indicator of the efficiency of the value creation, year by year for the period of 2015–2018 (created by the author)

year	IND	A	B	C	D	G	H	J	E	F
2015		-0.0393	0.9689	0.0802	-0.1383	0.0703	0.1802	0.1247	-0.0028	0.8659
2016		0.0494	-0.3431	-0.1156	-0.0180	0.0828	0.0093	-0.0165	0.0038	0.7468
2017		0.0331	0.1705	0.3197	-0.0056	-0.0556	-0.0942	0.0722	-0.0973	0.0504
2018		-0.0119	0.0268	0.4639	-0.0647	0.0505	-0.2164	-0.0991	0.0554	-0.6159
EFF_VC		0.0313	0.8231	0.7482	-0.2266	0.1480	-0.1210	0.0813	-0.0408	1.0472
ranking		2	3	9	4	8	5	7	1	6

Table 3.11. Indicator of the efficiency of value delivery, year by year for the period of 2015–2018 (created by the author)

year	IND	A	B	C	D	G	H	J	E	F
2015		-0.0320	-0.1870	0.9050	-0.0551	0.0606	0.3385	-0.0232	0.0478	-0.3703
2016		0.0456	0.3201	-0.3954	0.1066	0.1050	-0.0190	0.2789	-0.0313	0.1044
2017		0.0227	-0.0782	-0.1375	-0.1427	0.0874	-0.0241	0.0623	-0.0879	0.0978
2018		-0.0894	-0.1832	-0.1980	-0.0041	-0.1163	-0.2580	-0.1701	-0.0525	0.1011
EFF_VD		-0.0531	-0.1283	0.1741	-0.0954	0.1367	0.0374	0.1479	-0.1240	-0.0669
ranking		8	1	6	3	4	2	7	5	9

The results in Table 3.12 show the calculation of the category of the value capture each year that is explored. The value capture category is one of the four categories that constitute the efficiency index, and its weight in the index is 0.25. The category is calculated as the accumulated values of three component indicators: operating efficiency ratio, return on assets and operating cash flow ratio. The results show an increase or decrease in comparison with the previous year. The line EFF_VCP shows the sum of the results of each year and equals the EFF_VCP line from Table 3.12. The overall results of the sector (IND) show a decrease in efficiency with a value capture of 8.30 per cent. During the period, a slight decrease is observed in 2015 (4.55 per cent), in 2016 (5.45 per cent) and 2018 (1.95 per cent). The sector increase in efficiency in 2017 by 3.64 is noticed. Five companies are close to or above the average of the sector. All of them show positive results in at least two years during the period. Only one company shows results below the average level. However, only two companies show an increase in the efficiency of value capture. Company B shows the highest increase of 11.07 per cent during the period.

Although 2015 shows a decrease of 18.67 per cent, the following years indicate a rapid increase of 14.52 per cent in 2016 and 15.49 per cent in 2017 and 2018, keeping the same level. Company F shows an increase of 10.44 per cent during the period. A continuous increase is observed: 2.93 per cent in 2015, 12.50 per cent in 2016, and 3.49 per cent in 2017. The decrease of 8.48 per cent in 2018 indicates the termination of the increase cycle but still enables the overall results to be kept at a high level. Companies A, D and E are on the same sector level or above. Company A shows an increase of 8.24 per cent in 2015 and with a 3.4 per cent correction in 2016, and the increase of 8.7 per cent in 2017 still brings a positive result by the end of three years. The overall result for four years is influenced by the decrease of 19.48 per cent in 2018. Company D shows a 7.82 decrease during the period, which is slightly better than the sector result. A negative result of the period is influenced by 2015 (decrease of 4.93 per cent) and 2016 (decrease of 20.45 per cent). Two following years show positive results. The increase in 2017 (3.91 per cent) and a high increase in 2018 (13.65 per cent) show a positive trend. Company E shows a positive result only in 2016 by 29.07 per cent. A very high decrease corrects this very high increase, followed by almost the same level in 2017 (decrease of 0.27 per cent), in 2015 by 25.86 per cent, and a medium decrease of 12.81 per cent in 2018.

The financial risk index is hierarchical and consists of three categories with weighted values: category of solvency with two component indicators; category of business with one indicator; and category of liquidity with one indicator. A detailed structure of the financial risk index is introduced in Figure 2.10.

Table 3.12. Indicator of the efficiency of value capture, year by year for the period of 2015–2018 (created by the author)

year	IND	A	B	C	D	G	H	J	E	F
2015	-0.0455	0.0824	-0.1867	-0.0750	-0.0493	0.0491	-0.0454	0.0352	-0.2586	0.0293
2016	-0.0545	-0.0340	0.1452	0.0061	-0.2045	-0.1797	-0.0565	0.1408	0.2907	0.1250
2017	0.0364	0.0870	0.1549	-0.0421	0.0391	-0.0074	0.0138	-0.1205	-0.0027	0.0349
2018	-0.0195	-0.1948	-0.0027	-0.0736	0.1365	-0.0251	-0.1341	0.0854	-0.1281	-0.0848
EFF_VCp	-0.0830	-0.0594	0.1107	-0.1846	-0.0782	-0.1630	-0.2222	0.1409	-0.0987	0.1044
ranking		4	2	8	5	7	9	1	6	3

Table 3.13. Financial risk composite index and subindexes, accumulated for the period of 2015–2018 (created by the author)

CATEGORIES	IND	A	B	C	D	G	H	J	E	F
FINA_SOLVENCY	-0.2985	-0.8136	1.1484	-0.2790	-0.0864	0.3866	0.2581	-0.7381	0.0105	-0.4093
FINA_PROFIT	-0.0337	0.5632	1.3077	0.7256	-0.4461	0.4208	0.6815	-0.8877	-0.1570	0.4321
FINA_LIQUIDITY	0.1457	-0.1429	0.3667	0.0046	3.6306	2.0169	1.5597	-0.0191	0.2607	1.7374
INDEX_RISKFINA	-0.0551	0.0424	0.4584	0.2942	0.6630	0.8113	0.7952	-0.6331	-0.0107	0.5481
ranking		7	5	6	3	1	2	9	8	4

Each component indicator assesses the increase of a respective area during the period in the sector, the main researched companies (A, B, C, D, E and F), and other companies in the sector (G, H and J). The index of financial risk of the whole period is calculated as a weighted sum of categories and reflects solvency ($w = 0.25$), business ($w = 0.5$) and liquidity ($w = 0.25$).

Table 3.13 introduces the overall ratio of financial risks index for the period of 2015–2018 of the furniture manufacturing sector, including only large-sized companies (IND) and each researched company (A...F). A higher ratio shows a lower risk and a more favourable situation for the company.

The results presented in Table 3.13, line I_RISKFINA, show the overall financial risk ratio when implementing Industry 4.0 solutions in each sector, including solvency, liquidity, and business risk. Results suggest that the sector financial risk is –5.51 per cent over the four years, indicating a high financial risk in the sector. Most of the companies show results above the sector level and lower financial risks than the sector. The highest ratios in the financial risk index among the main research group of companies (in a descending way): company D with 66.3 per cent, F – 54.81 per cent, B – 45.84 per cent, C – 29.42 per cent, A – 4.24 per cent. Only E shows a 1.07 per cent decrease of financial indicators, which is a better result in comparison with the sector.

The results in Table 3.14 show the calculation of the financial risk index each year that is explored. The results show an increase or decrease in comparison with the previous year. An increase in results shows a more favourable situation in the sector or company.

The line I_RISKFINA shows the sum of the results of each year and equals the I_RISKFINA line from Table 3.14. The overall results of the sector (IND) show a decrease in financial results of 5.51 per cent. The sector showed a 10.28 per cent increase in 2015 in the financial indicators, followed by a decrease of 5.32 per cent and then a 0.64 per cent increase in 2017, followed by a decrease of 11.11 per cent in 2018. One company (company C) shows the increase of financial ratio in three years of the four years. Companies A, B, and E show two years of increase in the financial ratio. Companies D and F show an increase in the financial ratio for only one year. The number of years does not correlate with the overall result for the whole period of 2015–2018.

The results in Table 3.15 show the calculation of the category of the solvency risk each year that is explored. The solvency risk category is one of three categories that constitute the financial risk index, and its weight in the index is 0.25. The category is calculated as the accumulated values of two component indicators: debt to assets and debt to equity and expresses the increase or decrease in the ratio of debt. The results show an increase or decrease in comparison with the previous year. A higher value indicates a higher debt and means a less favourable situation.

Table 3.14. Financial risk composite index year by year in 2015–2018 (created by the author)

year	IND	A	B	C	D	G	H	J	E	F
2015	0.1028	-0.1867	0.9499	0.1006	1.1425	0.9795	0.4592	-0.1970	-0.2183	-0.0113
2016	-0.0532	0.2068	-0.4027	0.1985	-0.1842	-0.3028	0.2075	0.4458	0.2421	-0.0880
2017	0.0064	0.1459	0.1300	-0.0519	-0.0757	-0.0482	0.1641	-0.1008	0.2679	-0.1049
2018	-0.1111	-0.1237	-0.2188	0.0471	-0.2196	0.1828	-0.0356	-0.7812	-0.3024	0.7522
INDEX_RISKFINA	-0.0551	0.0424	0.4584	0.2942	0.6630	0.8113	0.7952	-0.6331	-0.0107	0.5481
ranking		7	5	6	3	1	2	9	8	4

Table 3.15. Category of solvency risk, year by year for the period of 2015–2018 (created by the author)

year	IND	A	B	C	D	G	H	J	E	F
2015	0.0287	-0.2282	0.5190	0.1412	0.1503	0.2664	0.1577	0.0081	0.1879	0.0147
2016	-0.1363	0.1325	-0.7463	-0.0911	-0.5798	-0.3791	0.0900	-0.0284	-0.0138	0.0342
2017	-0.1073	-0.2738	0.1168	-0.1527	-0.0333	0.1770	0.0556	-0.2423	0.3137	-0.0978
2018	-0.0835	-0.4442	-1.0380	-0.1765	0.3765	0.3224	-0.0452	-0.4755	-0.4773	-0.3603
FINA_SOLV	-0.2985	-0.8136	-1.1484	-0.2790	-0.0864	0.3866	0.2581	-0.7381	0.0105	-0.4093
ranking		8	9	5	4	1	2	7	3	6

The line FINA_SOLV shows the sum of the results of each year and equals the FINA_SOLV line from Table 3.15. The overall results of the sector (IND) show an increase in debt ratio by 29.85 per cent. The ratio increased by 16.5 per cent in 2016, which indicates an increased debt in the sector.

Later during the period, a decrease in debt is observed, although the increase decreased by 2.9 per cent in 2017 and 2.38 per cent in 2018, which shows a trend of a more favourable situation. The companies show a variety of increases in debt in comparison to the level in the sector. Three companies (B, A and F) are above the sector level, and three companies (companies C, D, and E) are below the level of the sector.

Five companies show increasing debt, and only company E shows a minor decrease in debt by 1.05 per cent. Company B (ranked first) shows a 114.84 per cent increase in debts over the period. Each year the debts are in high waves and are not stable. In 2015, there was a decrease of the debt ratio by 51.9 per cent; in 2016, the increase in the debt ratio was 74.63 per cent; in 2017, the decrease is by 11.68 per cent, and in 2018 a high increase of 103.8 per cent is noted. Company A (ranked second) shows an overall increase of debt of 81.36 per cent. The results show a continuous increase in debt – 22.82 per cent in 2015; 27.38 increase in 2017; and 44.42 per cent in 2018 – except in 2016 when a decrease of 13.25 per cent is noted. The remainder of the companies show fewer increases in debt, and company E shows an even decrease in debt to 1.05 per cent over the period. The results are influenced by a decrease in debt in 2015 of 18.79 per cent, followed by a minor increase of 1.38 per cent, then a decrease of debt ratio by 31.37 per cent in 2017 is followed by an increase 47.73 per cent in 2018.

The results in Table 3.16 show the calculation of the category of business risk each year that is explored. The category of business risk is one of three categories that constitute the financial risk index, and its weight in the index is 0.5. The category is calculated as the value of component profit indicators and expresses the increase or decrease of profit compared with the previous year. A higher value indicates a higher increase in profit and means a more favourable situation for business.

The line FINA_PROFT shows the sum of the results of each year and equals the FINA_PROFT line from Table 3.16. The overall results of the sector (IND) show a minor decrease in profit by 3.37 per cent during 2015–2018. A fluctuation is observed during this period. The ratio increased by 7.59 per cent in 2015, followed by 6.32 per cent in 2016. Later during the period, an increase in profit was observed of 9.03 per cent in 2017, followed by 13.68 per cent in 2018. The companies show a variety of increases in profit in comparison to the level in the sector. Four companies (B, A, C and F) are above the sector level, and two companies (company D and E) are below it.

Table 3.16. Category of profit risk, year by year for the period of 2015–2018 (created by the author)

year	IND	A	B	C	D	G	H	J	E	F
2015	0.0759	-0.0390	1.5153	0.1851	0.4098	0.8785	0.3753	-0.4017	-0.5133	0.1311
2016	-0.0632	-0.0924	-0.5323	0.3397	-0.1980	-0.6160	0.0089	0.9094	0.5178	0.0944
2017	0.0903	0.5691	0.3683	0.0889	-0.1698	-0.1330	0.1175	-0.0520	0.3130	0.2362
2018	-0.1368	0.1255	-0.0437	0.1120	-0.4881	0.2913	0.1797	-1.3434	-0.4746	-0.0297
FINA_PROFT	-0.0337	0.5632	1.3077	0.7256	-0.4461	0.4208	0.6815	-0.8877	-0.1570	0.4321
ranking		4	1	2	8	6	3	9	7	5

Table 3.17. Category of liquidity risk, year by year for the period of 2015–2018 (created by the author)

year	IND	A	B	C	D	G	H	J	E	F
2015	0.2308	-0.4404	0.2500	-0.1092	3.6000	1.8947	0.9286	0.0071	-0.0345	-0.3220
2016	0.0500	0.8796	0.2000	0.2055	0.2391	0.4000	0.7222	-0.0070	-0.0536	-0.5750
2017	-0.0476	-0.2808	-0.3333	-0.2328	0.0702	-0.1039	0.3656	-0.0567	0.1321	-0.7941
2018	-0.0875	-0.3014	0.2500	0.1410	-0.2787	-0.1739	-0.4567	0.0376	0.2167	3.4286
FINA_LIQ	0.1457	-0.1429	0.3667	0.0046	3.6306	2.0169	1.5597	-0.0191	0.2607	1.7374
ranking		9	5	7	1	2	4	8	6	3

Four companies (B, C, A, and F) show an increasing profit as the overall result, and two companies, D and E, show a decrease in profit. Company B (ranked first) shows a very high increase of 130.33 per cent of profit during 2015–2018. Company B shows an extremely high increase in profit of 151.53 per cent in 2015, followed by 53.23 per cent in 2016, then in 2017, the increase of profit is 36.83 per cent, followed by 4.37 per cent.

Company C (ranked second) shows an overall extremely high increase in profit of 72.56 per cent. The continuous positive results of the increase in profit are observed during each year of the explored period: an increase of 18.51 per cent in 2015; an increase of 33.97 per cent in 2016; an increase of 8.89 in 2017; and 11.20 in 2018. Company A shows a very high increase of 56.32 per cent during the period. Two years show a decrease in profit: a decrease of 3.9 per cent in 2015; and 9.24 per cent in 2016. However, in 2017, there was a sudden high increase of 56.91 per cent, followed by an even higher increase of 12.55 per cent. Company F also shows a very high increase in profit of 43.21 per cent during the period. Almost all years show a continuous increase in profit: an increase of 13.11 per cent in 2015, an increase of 9.44 per cent in 2016 and a high increase of 23.62 per cent in 2017; in 2018, there is an exceptional but very minor decrease of 2.97 per cent. Company E shows a decrease of 15.7 per cent during the period. Company E shows a volatile situation, and a high decrease follows a high increase: a decrease of 51.33 per cent in 2015 is followed by 51.78 per cent in 2016, then a high increase of 31.3 per cent in 2017 is followed by a high decrease of 47.46 per cent in 2018. Company D shows a high decrease of 44.61 per cent during the period. Company D showed a high increase (40.98 per cent) in 2015, but then three years of decrease in profits were observed: a decrease of 19.8 per cent in 2016; a decrease of 16.98 per cent in 2017; and a very high decrease of 48.81 per cent in 2018.

The results in Table 3.17 show the calculation of the category of liquidity risk for each year that is explored. The category of liquidity risk is one of three categories that constitute the financial risk index, and its weight in the index is 0.25. The category is calculated as the value of component indicators of the liquidity ratio and expresses the increase or decrease of the liquidity ratio compared with the previous year. A higher value indicates a higher increase in debt and means a more favourable situation.

The line FINA_LIQ shows the sum of the results of each year and equals the FINA_LIQ line from Table 3.17. The overall results of the sector (IND) show an increase in liquidity ratio of 14.57 per cent during 2015–2018. The first two years of the period show increasing results: an increase of 23.08 per cent in 2015 and 5 per cent in 2016. The remaining years show decreases: a decrease of 4.76 per cent in 2017; and 8.75 per cent in 2018. The companies show a variety of increases in liquidity ratio in comparison to the level in the sector. Four companies (B, A, C

and F) are above the sector level, and two companies (company D and E) are below it.

Four companies (D, F, E, and B) show an increase in the liquidity ratio above the average level of the sector, and two companies (C and A) show an increase below it or even a decrease in the liquidity ratio (company A). Company D (ranked first) shows a very high increase by 363.06 per cent of liquidity ratio during 2015–2018. The most significant influence comes from 2015, with a 360 per cent increase in liquidity ratio, an increase of 23.91 per cent in 2016, and 7.02 per cent in 2017, followed by a decrease of 27.87 per cent in 2018 added to the overall result. Company F shows a very high increase of 173.74 per cent of liquidity ratio during 2015–2018. The most significant influence comes from 2018 with a 342.86 per cent increase in the liquidity ratio when previous years showed a constant decrease: a decrease of 32.2 per cent in 2015; a decrease of 57.5 per cent in 2016; and a decrease of 79.41 per cent in 2017. The difference to the next company is even more significant. Company B shows an increase of 36.67 per cent during the period. The increase was 25 per cent in 2015, 20 per cent in 2016, followed by a decrease of 33.33 per cent in 2017 and again an increase of 25 per cent in 2018. Company E shows an increase of 26.07 per cent. The first years show minor decreases in the liquidity ratio: a decrease of 3.45 per cent in 2015 and 5.36 per cent in 2016. In 2017 an increase of 13.21 per cent was shown, and 2018 showed an even higher increase of 21.67 of the liquidity ratio. Company C shows a meagre increase of 0.46 per cent during the period. A fluctuation is observed year by year: a decrease of 10.92 per cent in 2015 followed by a decrease of 20.55 per cent in 2016, a decrease of 23.28 per cent, followed by a decrease of 14.1 per cent in 2018.

Table 3.18 shows the financial risk results after the normalisation from 0 to 1 to compare the financial risk results among companies. A higher number indicates higher financial risk and a less favourable situation for the company.

The non-financial risk index is hierarchical and consists of five categories with weighted values: category of technical risks with three component indicators; category of competence risks with four component indicators; a category of risk related to the acceptance by partners and customers with four component indicators; a category of risks related to the acceptance by staff with four component indicators; and data security risks with three component indicators. A detailed structure of non-financial risks composite index is introduced in Figure 2.10. Each component indicator assesses the increase of a respective area during the period in the sector, the main researched companies (A, B, C, D, E, and F), and other companies in the sector (G, H and J).

Table 3.18. The normalisation of the financial risks index (created by the author)

2015–2018	IND	A	B	C	D	G	H	J	E	F
INDEX_RISKFINA	–0.06	0.53	0.24	0.36	0.1	0	0.01	1	0.57	0.18
ranking		3	5	4	7	9	8	1	2	6

Table 3.19. The normalisation of the non-financial risks composite index (created by the author)

2015–2018	IND	A	B	C	D	G	H	J	E	F
INDEX_RISK-NONF	1	0.18	0.43	0.31	0.51	1	0.76	0.91	0	0.67
ranking		8	6	7	5	1	3	2	9	4

The non-financial risks composite index for the whole period is calculated as a weighted sum of categories and reflects technical risk ($w = 0.15$), competence risk ($w = 0.25$), risk related to acceptance by partners and customers ($w = 0.15$), risk related to staff ($w = 0.35$) and data security risks ($w = 0.1$).

Table 3.19 introduces the overall ratio of the non-financial risks composite index for the period of 2015–2018 of the furniture manufacturing sector, including only large-sized companies (IND) and each researched company (A...F). A higher ratio shows a higher risk and a less favourable situation in the company.

Table 3.19 shows the results of the non-financial risks composite index after the normalisation from 0 to 1 to compare the results of the non-financial risk among companies. A higher number indicates higher non-financial risk and a less favourable situation in the company.

Figure 3.4 shows the results of the non-financial risks after collecting data from the experts. After experts assessed the probability and impact of each risk indicator from 0 to 3, the average in each of the categories was calculated. A sum of weighted categories is presented in the risk heat map. The minimum value for each axis is 0, and the maximum is 3. A combination of both scores assigns a company to one of three risk levels: high, medium or low. Indicators in the green area show a negligible non-financial risk. Indicators in the yellow-orange zone show a medium level of non-financial risk. Indicators in the red zone show a high level of non-financial risk. According to both characteristics, two companies, E and A, show themselves in the medium level of non-financial risk. Company E is in the medium-low zone with low scores in both probability (1.30) and impact (1.48). Company A is in the medium-high zone with a low probability of 1.35 but a higher impact of 2.13. Company C is in the medium-high zone with a low probability (1.55) and higher impact (2.30). Company D is in the high-medium zone with a low probability (1.85) and higher impact (2.50). Company B is in the high-medium zone with a low probability (1.95) and higher impact (2.20). Company F is in the high-high zone with a low probability (2.30) and higher impact (2.40). Company J is in the high-high zone with a low probability (2.60) and higher impact (2.60). Company G is in the high-high zone with a low probability (2.70) and higher impact (2.70). Company H is in the high-high zone with a low probability (2.50) and higher impact (2.20).

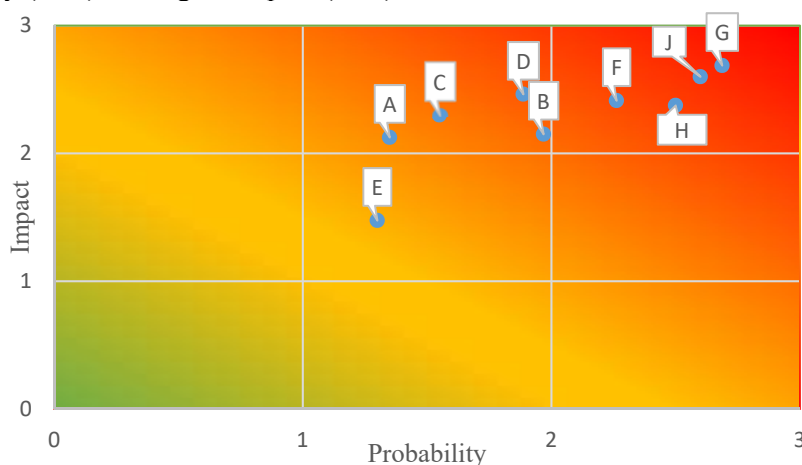


Fig. 3.4. The heat map of non-financial risks (created by the author)

The remain three companies from the leading researched group are in a higher risk level: B with a high probability (1.97) and a high impact (2.15); D with a high probability (1.89) and a very high impact (2.46). Company F is in a high-risk zone with a high probability (2.26) and a very high impact (2.41). Even being in a higher risk zone, those companies have a slightly lower risk level than the other companies in the industry.

Table 3.20. The levels of non-financial risks (created by the author)

Risk area	w	A	B	C	D	G	H	J	E	F
Technical risks	0.15	4	3	1	4	9	4	9	2	4
Competence risks	0.25	3	7	4	4.5	6.5	5	6.5	1	6.25
Acceptance by partners and customers risks	0.15	2.5	2.75	6	3.75	9	6.5	9	2.5	4
Acceptance by staff risks	0.35	3.75	5.75	5	8.25	9	9	7.75	3.5	9
Data security risks	0.1	2	3	4	2	9	9	9	1.33	3.33
Total risk level		3.24	4.93	4.2	5.38	8.38	6.88	7.94	2.28	6.25
ranking		8	6	7	5	1	3	2	9	4

Table 3.20 shows the level of non-financial risks for each company in each category. The values in each category are calculated in two steps: first, by multiplying the probability by impact based on expert assessment and, second, then by dividing by some indicators which are different in different categories. The total risk level is calculated by multiplying a value by weight. The minimum possible value is 0, and the maximum is 9.

The level of non-financial risk in companies varies from 2.28 to 8.38. The non-financial risks of the main group of researched companies vary from 2.28 to 6.25, and it indicates being lower than other companies in the sector. Company E (ranked ninth) shows the lowest non-financial risk at 2.28. The most significant risk in company E comes from the risk of acceptance by staff, with 3.5. Other risk areas are (in descending order): acceptance by partners and customers risks with 2.5; the technical risk with 2; data security risk with 1.33; and competence risk with 1. Company A (ranked eighth) shows a low non-financial risk of 3.24. The most significant risk in company A comes from the risks of the technical risk with

4. Other risk areas are (in descending order): acceptance by staff risk with 3.75; competence risk with 3; acceptance by partners and customers risk with 2.5; and data security risk with 2. Company C (ranked seventh) shows a low-medium non-financial risk with 4.2. The most significant risk in company C comes from the risks of acceptance by partners and customer risk with 6. Other risk areas are (in descending order): acceptance by staff risk with 5, competence risk and data security risk with 4 each, and technical risk with 1. Company B (ranked sixth) shows a medium non-financial risk with 4.93. The most significant risk in company B comes from the risks of the competence risk with 7.

Other risk areas are (in descending order): acceptance by staff risk with 5.75; technical and data security risk with 3 each; and acceptance by partners and customer risk with 2.75. Company D (ranked fifth) shows a medium non-financial risk with 5.38. The most significant risk in company D comes from the risk of acceptance by staff risk at a very high level of 8.25. Other risk areas are (in descending order): competence risk with 4.5; technical risk with 4; acceptance by partners and customers risk with 3.75; and data security risk with 2. Company F (ranked fourth) shows a medium-high non-financial risk with 6.25. The most significant risk in company F comes from the risk of acceptance by staff with the highest possible level of 9. Other risk areas are (in descending order): competence risk with 6.25; technical risk and acceptance by partners and customers risk with 4; and data security risk with 3.33.

Table 3.21. The levels of non-financial risks of the main research group (created by the author)

Com- pany	Technical risks	Compe- tence risks	Acceptance by partners and customers risks	Acceptance by staff risks	Data secu- rity risks
A	4	3	2.5	3.75	2
B	3	7	2.75	5.75	3
C	1	4	6	5	4
D	4	4.5	3.75	8.25	2
E	2	1	2.5	3.5	1.33
F	4	6.25	4	9	3.33
Total risk level	3.00	4.29	3.58	5.88	2.61
rank- ing	4	2	3	1	5

Table 3.21 shows the distribution of the non-financial risks in each category. Each category's values are calculated in two steps: first, by multiplying the probability by impact based on expert assessment and, second, then by dividing by the number of companies to have an average in each category. The minimum possible value is 0, and the maximum is 9.

The empirical results show the acceptance by staff risk as the most significant and is at a medium-high level with 5.88. Other risks are medium to a low level (descending): competence risks with 4.29; acceptance by partners and customer risk with 3.58; technical risk with 3; and data security risks with 2.61. No category is at a very low-risk level.

3.2. Analysis of Findings from Qualitative Research

The categories and subcategories of the qualitative content analysis were formed after the scientific literature review. During the content analysis, indicators and quotes from interviews were chosen to collect proof for the categories.

A content analysis conducted from interviews and focus groups shows various experiences in the companies where Industry 4.0-based solutions and business model transformations were implemented.

Table 3.22. Findings from the category “Perception of the phenomenon of Industry 4.0” (created by the author)

Subcategories	Indicators/ comments
Digitalisation of processes	We have implemented sensors in the equipment. We expect the efficiency to be very high, at least 30 per cent per year in the production line. Electronic solutions work well in the company, but real-time data require more modern infrastructure in the company.
The digitalisation of the business model	We get an order from the client that is conducted by artificial intelligence. There is no human interaction in the process between the client order and inbound warehouses in the first steps of the production. Customer relationship and segmentation management of channels and production process are digitalised and make them quicker. Real-time data collected, processed, and analysed is a key factor that transforms a business model. Data shared with clients, suppliers, and partners make a significant difference in the business model.

End of Table 3.22

Subcategories	Indicators/ comments
Sensors	We have sensors in all our vehicles in logistics, and they are autonomously moving from a production line to the warehouses. Sensors help to collect data to know the spoilage in the manufacturing process. Processed data collected with the help of sensors allow operators and managers to have real-time information on outputs, spoilage and downtime.
Data collection and analytics	Data are collected, processed, analysed and visualised in real-time using IoT and big data technologies. Data are difficult to read and understood by all levels of decision-making. Data collection and processing is a more straightforward process than decision-making.

The category “Perception of the Industry 4.0 phenomenon” emphasises the scope of the Industry 4.0 phenomenon. Interviewees focus on a different understanding of what Industry 4.0 is; some identify it with implementing sensors into the equipment. Some of them work with data collection and visualisation, only a few talk about transforming business models, including data usage in value creation and capture. Some interviewees mention the disruption of the business model from selling a physical product to providing services. Data usage to transform parts of the business model into service in the researched companies is discussed. Electronic solutions and high-speed Internet are mandatory factors to introduce and adopt the digitalisation of the business model.

Table 3.23. Findings from the category “Efficiency in Industry 4.0”
(created by the author)

Subcategories	Indicators/ comments
Storage of material and finished production	Real-time data from the warehouse help keep less unused and unnecessary material in the warehouse or better use of space.
Time for operation	Clients can get the answer immediately without our intervention in most cases. Only 10–20 per cent of case clients need a more specific solution. Production timing is more accountable than before.

End of Table 3.23

Subcategories	Indicators/ comments
Lower downtime	We have information about downtime in real-time and, depending on the situation, can assess the resources needed and solve them online. After an analysis of the reasons for downtime, we can prevent it more effectively.
Indicators	Locally collected information is used to assess efficiency. We do not calculate the complete formula in OEE and OFE because we cannot collect quality data. The competence indicator is calculated by comparing the level of competence with downtime. Data are collected in real-time through IoT technology.
Increase of speed to get data for decision-making	Efficiency increase is expected by 20–30 per cent during the first 2–3 months if the organisation is ready. Efficiency increase is influenced by an increase in sales or reduction of employers.

Results in the category “Efficiency” emphasise areas for increasing efficiency and indicators to assess efficiency. Interviewees pick out several most significant factors for increasing efficiency: 1) time to perform an operation, 2) time and frequency of downtime, 3) raw material used per unit, 4) spoilage in units, 5) time to remanufacture in case of spoilage, 6) use of financial resources more efficiently. All interviewees experience an increase in speed in all operations and the overall process. Reasons for downtime, level of competence, correlation of time with downtime and other data are analysed as significant factors to be more efficient. Moreover, interviewees mentioned several more factors for increasing efficiency other than the value creation part of the business model, such as sales costs, efficiency in the value proposition, distribution channel efficiency in value delivery and client or product segment efficiency in value capture. More real-time data analysis allows allocating space in the warehouse and financial resources to keep the necessary reserve of materials for production. Interviewees mentioned that these data are collected internally and can be processed to be used for efficiency assessment. However, all interviewees experienced peer comparison challenges and benchmarked themselves with other actors in the industry. Interviewees mention how to collect and process data to assess efficiency – e.g. sensors in the critical places of the manufacturing process – and those ways differ from company to company. The collection of data in different parts of the business model is very different. Usual indicators such as OEE are used with certain modifications, e.g. OEE is used only with two components (performance and output). The quality indicator is not included in the formula. Interviewees mentioned that collecting

and processing data in real-time help to analyse the reasons for downtime, assess and allocate necessary resources to have downtime less frequently and for a shorter period.

Table 3.24. Findings from the category “Growth related to Industry 4.0” (created by the author)

Subcategories	Indicators/ comments
Added value	Added value per employee is one of the most important targets in our company. We expect the increase of the added value of approx. 30 per cent over five years.
Number of employees	The number of employees is not changing so fast, but the number of employees with low qualifications has decreased. The number of employees working in the production line with higher qualifications is increasing.
Increase in salaries	Salaries in the company increased by almost double. We aim to increase the salaries to all levels of employees.

Results in the category “Growth related to Industry 4.0” emphasise the areas that allow companies to grow economically, such as added value per employee or shareholders’ equity per employee and to provide better financial conditions to employees, such as increased salaries. All interviewees focused on the indicators per employee and mentioned the financial growth of the company and the long-term social aspect of financial growth. Analysing the increase in the added value and related issues are discussed, such as the necessity for higher qualifications of employees and a continuous on-job learning system to meet the requirements of a new workplace.

Table 3.25. Findings from the category “Risks related to Industry 4.0” (created by the author)

Subcategories	Indicators/ comments
Organisational structure	Information flow is quicker and more accessible to everyone.
New competences	We do not know how to describe quality in the way programmers could make a software to collect data. Employees have to start thinking and behaving differently, and this requires much effort to change. Employees are used to walking around and socialising while working; digital solutions make them change their habits.

End of Table 3.25

Subcategories	Indicators/ comments
	We do not have enough patience to wait long enough for the results and lack of the skills to discuss and reflect on achievements and mistakes.
Financial risks	We have enough cash or the possibility to get credit to implement Industry 4.0 technologies; what we lack is the readiness for the processes, structure, competencies, and qualifications to make a return on investment in time. We invested in the equipment, but the return on investment is too low at the moment.
A balance between financial and non-financial risks	When implementing Industry 4.0 technological solutions, the key issue is non-technological changes. We have enough investment possibilities but do not have enough cash for non-technological organisational changes.
Data analysis	Data are difficult to read and understand at all levels of decision-making. Information is accessible at all levels of the organisation. However, the skills to read, understand and use data for overall results are shallow in lower hierarchy levels. People who know how to analyse data barely understand business needs. Therefore, even high-level management cannot easily use data to make decisions.
Habits in the workplace	We get client orders conducted by artificial intelligence (AI) after processing the forecast of sales, changes in the buyers' behaviour, purchasing power, future prices of products. No one can double-check the orders due to the scope and amount of data if there is a mistake. If there is a mistake in the forecast, we cannot control it and only find out about it/and only know about it after about 3 or 4 weeks.
The integrity of partners in the value chain	Our suppliers do not invest in digitalised solutions so much, so we cannot be as efficient as we could be. We get client orders that AI conducts, and we have to adapt our IT systems to it. Otherwise, we do not get orders from this client. Our production line and warehouse are fully digital. We can send the manufactured products to the client whereby the only human intervention drives delivery. However, our client does not have a digitalised inbound logistics process, and more human work is needed.
The integrity of all processes in the company	The production lines were digitalised and collect and processed real-time data. Other parts in the value chain, such as bookkeeping or warehouse of raw materials, are still not automatised.

Results in the category “Risks and challenges” emphasise that all the companies and interviewees spend significant time explaining how employees’ behavioural change is essential to successfully implementing Industry 4.0 solutions. Software and products that service providers offer change quickly, and interviewees mentioned that they do not have the skills to reflect on such quick changes with no historical data behind them. This makes it essential to have the skills to forecast during the uncertainty period. Management is more open to other opinions and discussions; the accountability process and organisational structure must be changed. Decentralisation of the processes brings a new organisational culture, including new discussion and socialising habits, on-job learning, continuous feedback, improvement and open-door traditions. It means a significant change in the traditional business to which manufacturing usually belongs to. All non-financial risks are understood as the basis for the implementation of Industry 4.0-related transformations.

Interviewees mention that financial risks are just a small part of the overall assessment of the implementation of Industry 4.0. Financial risks such as liquidity, solvency, or profit are the usual issues in the company, and it is known how to address them. The financial risk increase is mentioned when the balance between long-term and short-term investment is debated, as an investment in equipment changes is usually solved through long-term loans. The process is transparent, and the interest rate is low. Challenges are mentioned when interviewees mention the spending required to meet the non-financial risks related to non-technological organisational changes in the company. Those changes are to be financed by the operating net cash and compete with other operational expenses.

3.3. Approbation of the Proposed Integrated Economic Assessment Concept of Business Model Transformation in Industry 4.0

This section analyses the application of the integrated economic assessment concept with the assessment logframe, composite indexes and growth-efficiency matrix and its practical approbation in large furniture manufacturing companies. The section concludes with a growth-efficiency matrix with risk component when allocating resources to transform business models Industry 4.0.

The growth-efficiency matrix with a risk component (Figure 3.5) shows four possible segments after assessing growth and efficiency after the business model transformation in Industry 4.0. Companies are positioned in the matrix according to the increase of efficiency, growth, and risk level.

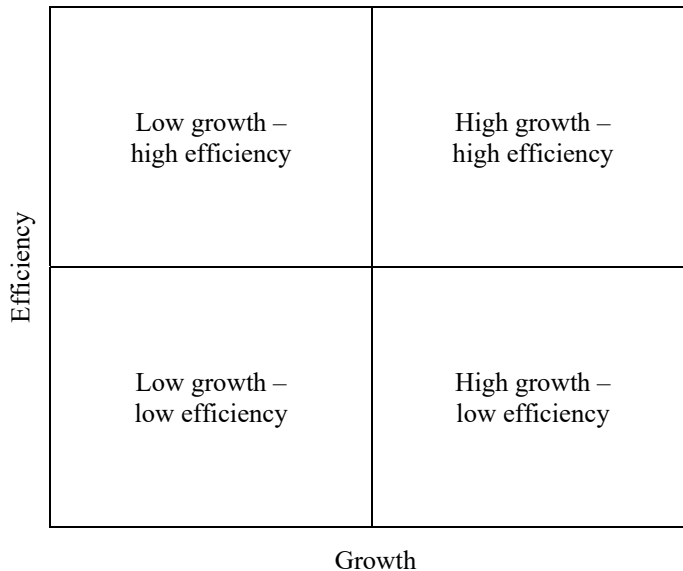


Fig. 3.5. The growth-efficiency matrix (created by the author)

There are four possible assessments suggested:

- 1) There is a segment of low growth (LG) and low efficiency (LE) in the bottom-left quadrant. The companies that are low in the increase in growth and low in the increase in efficiency position themselves in this LG–LE segment.
- 2) There is a segment of low growth (LG) and high efficiency (HE) in the top-left quadrant. The companies with a low increase in growth and a high increase in efficiency position themselves in the LG–HE segment.
- 3) There is a segment of high growth (HG) and low efficiency (LE) in the bottom-right quadrant. The companies with a high increase in growth and a low increase in efficiency position themselves in the HG–LE segment.
- 4) There is a segment of high growth (HG) and high efficiency (HE) in the top-right quadrant. The companies with a high increase in growth and a high increase in efficiency position themselves in the HG–HE segment.

When transforming business models in Industry 4.0, the companies should assess their position according to the growth and efficiency, based on the financial data, and assess their risk level. The size of the bubble shows the level of risk – both financial and non-financial. Bigger bubbles indicate a higher level of risk. The risk is understood as a catalyst for growth and efficiency. To forecast the resulting trend, they should use the overall values of the indexes and the values of the categories and component indicators.

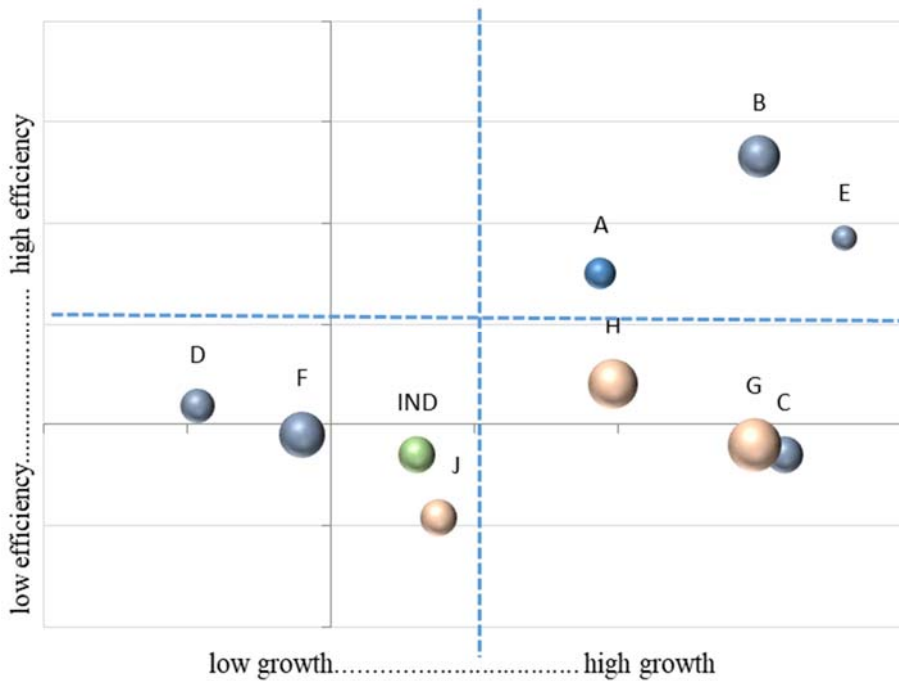


Fig. 3.6. Main findings of the assessment of growth and efficiency
(created by the author)

Risks are segmented into high to medium and medium to low. The risk index consists of financial and non-financial risk, and the results should consider both indexes and categories that make up the risk index.

Companies in the LG–LE segment show both a low index of the increase in growth and a low index of the efficiency in results. Low growth indicates a low increase in added value; this confronts the initial idea and indicates that the goals of Industry 4.0 implementation cannot be reached. Low efficiency shows a low increase in all or some parts of the business model problems and indicates an imbalance in the different parts of the business model and the value chain. The parts of the business model with the lowest and highest increase in efficiency should be identified, and the ways to increase the lowest parts should be implemented.

Table 3.26. The explanation of the levels of the financial and non-financial risks (created by the author)

Risk index	Description
Financial risk	
High–medium	High financial risk indicates an urgent need for balancing debts and liabilities in comparison with assets and equity as the increase of debt is getting higher; also solving liquidity issues such as low increase of net cash flow can be a reason for a sudden stop or too slow implementation of changes and paying attention to the low increase of profit.
Medium–low	Medium to low financial risk indicates that the financial ratio shows a constant increase in liquidity and profit and a decreased debt. This indicates that financial support to implement Industry 4.0 is enough. Even if some issues appear, the solution can be found without significantly interrupting the implementation of Industry 4.0 and transforming the business model.
Non-financial risk	
High–medium	High non-financial risk indicates the need to revise the preparedness of the company to implement the Industry 4.0 solution into the business model to achieve the expected results. The most significant changes are met in the organisation structure and culture, staff competencies and skills, relationships with customers and partners, and data privacy issues. The biggest gaps should be narrowed, and the company prepared for changes.
Medium–low	Medium to low non-financial risk indicates that the organisational structure, culture, staff competencies, and skills are ready to implement Industry 4.0 solutions. The company has an organisational culture where learning and continuous improvement are part of daily routine, enough personnel with the necessary qualifications, data analytics is a part of decision-making, procedures are clear and well-thought-out. There are minor necessary changes. Still, the possible gaps are observed and assessed during the business model transformation, and changes need to be implemented.

Companies in this LG–HE segment show a low index of the increase in growth and high-efficiency results. Low growth indicates a low increase in added value and shareholder funds. This confronts the initial idea and indicates that the goals of Industry 4.0 implementation are not to be reached. High efficiency shows a high increase in all or some parts of the business model and indicates a good balance in the different parts of the business model and the value chain.

Table 3.27. The implication of risks for low-growth and low-efficiency segment (created by the author)

Risk level	Description
High–medium	High to medium financial risk in the LG–LE segment indicates insufficient financial resources to implement Industry 4.0 solutions and necessary company changes. Too low an increase of cash flow or other current assets influences too slow an implementation speed, and the results of Industry 4.0 impact do not meet the expected level. High to medium non-financial risks in the LG–LE segment indicate that the company structure, personnel, processes, and equipment are not prepared for the changes that Industry 4.0 brings. High non-financial risks show insufficient human resources and institutional support to get the best out of the Industry 4.0 business model. The expected results are not to be achieved even if solutions from a technological point of view are purchased and the company has enough financial support. High non-financial risks in this segment also show that the business model will not be transformed and will not bring value as expected.
Medium–low	Medium to low financial risk in a segment of LG–LE indicates that financial support is enough to implement Industry 4.0 solutions and necessary company changes. They are not used to getting the best out of Industry 4.0 and business model innovation. Too low an increase of cash flow or other current assets influences too slow an implementation speed, and the results of Industry 4.0 impact do not meet the expected level. Medium to low non-financial risk in a segment of LG–LE indicates that the company structure, personnel, processes and equipment are not prepared for the changes that Industry 4.0 brings. The expected results can be achieved even if technological solutions promise medium results.

Table 3.28. The implication of risks for the low growth and high efficiency segment (created by the author)

Risk level	Description
High–medium	High to medium financial risk in the LG–HE segment indicates that high efficiency is achieved by increasing liabilities and decreasing liquidity. Under the influence of low growth, the financial risks become even higher even if the increase in efficiency helps to save. High to medium financial risks in an LG–HE segment do not grow enough to have a significant value of efficiency. Business model transformation or disruption could be a solution that requires lower financial risk at first.

End of Table 3.28

Risk level	Description
	High to medium non-financial risks in a segment of LG–HE indicate that the organisational processes, structure and culture are not prepared to implement Industry 4.0 to increase growth to capture value out of efficiency. Business model transformation is an essential step after financial and non-financial risks are controlled.
Medium–low	Medium to low financial risk in a segment of LG–HE indicates that the achieved efficiency after implementing Industry 4.0 solutions increases, and financial risks are controlled. The balance of the necessary increase in liquidity and acceptable liabilities is achieved. This indicates a possible start to plan the transformation of the business model, aiming to increase growth. Medium to low non-financial risks in a segment of LG–HE indicates that the company structure, personnel, processes and equipment are prepared for the changes that Industry 4.0 brings. Medium to low non-financial risks indicate that the implementation of the Industry 4.0 business model can bring expected results. Using the created institutional background can facilitate the increase in the efficiency that might move the company from the low left segment to the HG–HE.

Companies in this HG–LE segment show a high index of the increase in growth and a low index of the increase in efficiency. The empirical results show an accumulated increase of 57 per cent during the four years' research period. High growth indicates a high increase in added value and shareholder funds. Results of high growth meet the initial goal of Industry 4.0. In the analytical literature, Industry 4.0 forecasts at least a 30 per cent increase of added value. During the first year after implementation of Industry 4.0, the empirical research results show 35 to 55 per cent of growth, which showed a sustainable accumulated growth of more than 60 per cent during the following years. High growth in this segment indicates the increase of both component indicators: added value and shareholder funds. Low efficiency in the HG–LE segment shows a low increase in efficiency in all or some parts of the business model. This indicates different increases in different parts of the business model, and the efficiencies do not grow along with the whole business model. Low efficiency in this segment indicates a very low or negative increase in at least one category of the index, which shows that even after investment in modern equipment and solutions, the efficiency increase is not enough. Low efficiency in the HG–LE segment shows the imbalance within the business model and between growth indicators and efficiency.

Table 3.29. The implication of risks for high growth and low efficiency segment (created by the author)

Risk level	Description
High–medium	High to medium financial risk in an HG–LE segment indicates that there is a possibility that growth expands so quickly that issues with the cash flow become a burden for meeting the agreements and improving the efficiency after the growth. High to medium non-financial risks show that problems can appear because of insufficient qualification and readiness of the organisational processes, structure and culture. High to medium risks in a complex with high growth and low efficiency indicate that customer and partner behavioural changes are not foreseen enough. The change of customers is one of the reasons for this segment to face decreasing growth. Keeping a low efficiency, there is a high potential to get back to the LG–LE segment with a high debt and liability situation.
Medium–low	Medium to low financial risk in an HG–LE segment indicates that financial cash flow is positively increasing and debt ratios are stable or even decreasing. A company in the HG–LE segment should consider implementing an Industry 4.0 solution to stimulate the increase in efficiency and maintain the growth increase. Medium to low non-financial risk in an HG–LE segment indicates that the company structure, personnel, processes, and equipment are prepared for the changes that Industry 4.0 brings. Medium to low non-financial risks indicate that the Industry 4.0 business model's implementation can bring expected results. Using the created institutional background can facilitate the increase in the efficiency that might move the company from the segment of HG–LE to HG–HE.

Companies in this HG–HE segment show a high increase in growth and a high increase in efficiency results. The empirical results show the accumulated increase of 57 to 112 per cent during the four years. High growth indicates a high increase in added value and shareholder funds. Results of high growth meet the initial goal of Industry 4.0. in analytical literature. Industry 4.0 forecasts at least a 30 per cent increase in added value and at least a 30 per cent increase in efficiency. Increased results from both areas are expected. During the first year after implementation of Industry 4.0, the empirical research results show 35 per cent of growth, which showed a sustainable accumulated growth of more than 60 per cent during the following years. High growth in this segment indicates the increase of both component indicators – added value and shareholder funds. High efficiency in the HG–HE segment shows a high increase in efficiency in all or a very high efficiency in one or two parts of the business model and a lower or even minor decrease in efficiency in other parts. The empirical research results suggest 75 to

110 per cent of the accumulated increase in efficiency in at least one part of the business model. The possibility in this segment is a focus on a more balanced increase in efficiency through all parts of the business model rather than on investing in one or two parts. An increase of efficiencies spreads along with the whole business model over one or two following years.

Table 3.30. The implication of risks for a high-growth and high-efficiency segment (created by the author)

Risk level	Description
High–medium	High to medium financial risk in the HG–HE segment indicates a too quick increase of debt and decreased or unstable liquidity. This can bring challenges to meet the requirements of the agreements from the customers or investors. On the other hand, if controlled carefully, this can lead to a more extensive transformation or disruption of business models and increase even higher growth and efficiency. High to medium non-financial risks show that the business model transformation might fail because of a lack of readiness for organisational processes, structure and culture, and infrastructure or data privacy. Failures in this segment because of non-financial risks can be long-lasting and affect a decrease in growth or efficiency. High to medium financial and non-financial risks in an HG–HE segment look for stability and a stable increase rather than fluctuations. This is an indicator of keeping a business model that is already employed.
Medium–low	Medium to low financial risk in the HG–HE segment indicates that financial cash flow is positively increasing and debt ratios are stable or even decreasing. A company in the HG–HE segment has successfully implemented the Industry 4.0 solution, which showed a high increase in results. They can consider implementing more modifications to the business model. Medium to low financial risk in the HG–HE segment indicates a possible unused potential of Industry 4.0. Business model disruption should be planned carefully and without intervening in the existing successful practice. Medium to low non-financial risks in an HG–HE segment indicates that the company structure, personnel, processes and equipment have the experience to act effectively and can duplicate the experience in another area. Also, medium to low non-financial risks can indicate stability in the organisation, hindering those motivated by implementing fast changes. There is a potential to lose those people with the know-how. The process would quickly decrease the non-financial risk and bring the level of risk from high to medium. Therefore, the medium to low non-financial risks, especially in a complex with medium to low financial risks, is an indicator to plan additional Industry 4.0 business model transformations.

Industry 4.0, according to the scientific and analytical literature, suggests bringing efficiency or growth. Usually, growth and efficiency are seen as dilemmas, and companies have to assess which direction to develop: to grow or be more efficient. Risk-reducing is a usual task for business entities. Although implementing Industry 4.0 requires a new approach, a balance between financial and non-financial risks catalyses finding a way between growth and efficiency.

Industry 4.0 allows both: growth and efficiency at the same time. Therefore, risk assessment becomes a significant factor in finding a way between growth and efficiency.

3.4. Conclusions of Chapter 3

Chapter 3 closes with the following conclusions:

1. The categories in the efficiency index in the manufacturing industry among large companies show different weights to the index: the category of the value proposition ($w = 0.2$); the category of value creation ($w = 0.4$); the category of value delivery ($w = 0.15$); and the category of value capture ($w = 0.25$). The efficiency index in all the companies from the main research group is higher than the average industry efficiency result.
2. The index of growth in the furniture manufacturing industry among large companies shows different weights. They are calculated per employee: added value per employee ($w = 0.7$); and shareholders' funds per employee ($w = 0.3$). The growth index in four companies from the main research group is significantly higher than the average industry efficiency result, and two companies show lower results. Those two companies have implemented only the technological part of Industry 4.0 solutions. They have not allocated resources to the non-technological transformation of the organisational competencies, staff skills, and procedures.
3. The categories in the index of financial risks in the furniture manufacturing industry among large companies show different weights to the index: the category of solvency ($w = 0.25$); the category of profit ($w = 0.5$); and the category of liquidity ($w = 0.25$). The index of financial risks in all the companies from the main research group is lower than the average industry financial risks result.
4. The categories in the index of the non-financial risks in the furniture manufacturing industry among large companies show different

weights to the index: the category of technical risk ($w = 0.15$); the category of competence risk ($w = 0.25$); category of acceptance of partners and customers risks ($w = 0.15$); the category of acceptance of staff risks ($w = 0.35$); and the category of data security risks ($w = 0.1$). The non-financial risks index in all the companies from the main research group is lower than the average industry non-financial risks index.

5. The growth-efficiency matrix with a risk component is used to present the alternatives when transforming the business model in Industry 4.0. The X-axis shows the growth scaling results from low (LG) to high (HG) growth. The Y-axis shows efficiency scaling results from low (LE) to high (HE) efficiency. The Z-axis shows a combined score from the financial and non-financial risks and is visualised as a bubble. It is suggested that the companies be assigned to one of four quadrants according to the combination of efficiency and growth: LG–LE, LG–HE, HG–LE and HG–HE, with the Z dimension, visualised as a bubble. The tri-dimensional system of four quadrants helps companies to compare their position with other companies in the industry.
6. After the companies' assignment into one of the four segments, the results show that three companies, out of six from the main research group, are in the HG–HE segment, two companies are in the LG–LE segment, and one company is in the HG–LE segment. Compared with other companies not included in the main research group, two are in the HG–LE segment and one in the LG–LE segment. The overall industry finds itself in the LG–LE segment. The results show that companies that implement Industry 4.0 solutions in their business models tend to show a higher increase in efficiency and growth than the average industry results. Most of them have better results than those of their closest competitors.
7. The presented research results show that the created integrated economic assessment concept with assessment logframe, composite indexes, and growth-efficiency matrix is suitable for assessing the allocation of financial, human and time resources when transforming the business model in Industry 4.0. Also, the integrated economic assessment concept can be adapted and scalable to other industries or the size of the company.

3.5. Limitations and Future Research Directions

The limitations of the presented research occur in several directions. First, the start and finish of the implementation of Industry 4.0 solutions is not precisely determined and depends on how the company itself defines the scope. The second direction is the availability and comparability of data at the industry and micro levels, as there is a lack of studies conceptualising the economic effect. The comparability of data between the companies can be done only using standard accounting data and not internal data. However, the companies have access to internal data, e.g. spoilage, adjustment time, data from sales or different customers and segments. Having access to this data, the companies can conduct more detailed research and make more detailed assessments. Thirdly, the assessment process requires expert involvement, which allows to adapt assessment indexes according to the industry and business specifics. This involvement brings some uncertainties as it requires professionalism from the expert side. If a company has lower expertise in the area, the assessment results can also be achieved using the presented version of the composition of the indexes.

Future research lies in three directions:

1. Economic assessment of business model transformation in Industry 4.0 in different industries and countries should be further assessed. The further assessment can be conducted based on data from the companies' standard financial accountancy obtained in the global databases and can compare industries globally.
2. Research could investigate the progress of the company after the first years of business model transformation. Internal data collection possibilities allow separating the business model parts and data from different production lines or segments, such as the point of sale, or data such as adjustment time, spoilage, learning costs and expenditure on R&D are necessary. The adaptation of the created index should be organised following the developed economic assessment logframe.
3. Four composite indexes could develop the integrated one index, including both micro and macro-level data.

General Conclusions

1. The systematic scientific literature analysis shows that Industry 4.0 is a complex phenomenon that has recently received scientific attention in 2014 and is moving horizontally through different disciplines: computer science and economics. Different interpretations of the terminology of Industry 4.0 can be observed, and the main concepts lie in a fusion of the computer–human interaction through real-time data exchange between machines without the necessity of direct human intervention.
2. Usage of a complex of key enablers of Industry 4.0, such as the Internet of Things, big data analytics, and artificial intelligence, forms the basis for the business model transformation in the manufacturing industries.
3. The balance of four key indexes – growth, efficiency, financial risk and non-financial risk – form the basis for the assessment of the allocation of financial, human and time resources when transforming the business model in Industry 4.0. The increases in growth and efficiency are assessed, and financial and non-financial risks are considered.
4. The original integrated economic assessment concept, which includes the economic assessment logframe, four composite indexes to assess the efficiency and growth of financial and non-financial risks, should be used to make an economic assessment when transforming business models un-

der high uncertainty. The assessment concludes with the growth-efficiency matrix with a risk component to assess alternatives or company peer comparison.

5. The assessment logframe suggests a complex of quantitative and qualitative research methods, including participatory qualitative methods such as focus groups. A complex of methods provides more factual information to make assessments for a long-term impact and complements the findings of the quantitative method. This way, people responsible for the transformations are involved in assessing the alternative allocation of resources process. The involvement of responsible people increases engagement and commitment to performance efficiency and success.
6. After applying the assessment logframe and calculations of indexes in the large furniture manufacturing industry, a limited time of approximately three years when implementing Industry 4.0 solutions is observed. During the first of the three years after the start of the implementation of Industry 4.0, the accumulated increase in efficiency of up to 53 per cent is observed, and the accumulated increase in growth of up to 71 per cent is observed. The overall increase in efficiency and growth of up to 112 per cent over three years is observed. Later, the increase in both dimensions is corrected and shows a significant decrease in efficiency or growth.
7. Industry 4.0-driven business model transformation is considered a long-term enhancer of the economy. The integrated economic assessment concept allows segmenting the companies in the matrix according to the potential to increase efficiency and growth followed by the risks. The empirical research shows that when non-financial risks are lower, efficiency and growth are higher or more stable. The major findings of the research demonstrate the benefits of deploying the assessment methodology in the researched industry and the possibilities of scaling it to other industries.
8. The scientific novelty and significance lie in creating the following: the original integrated economic assessment concept; the original 16-step assessment logframe, four composite indexes – growth, efficiency, financial risks and non-financial risks; and the growth-efficiency matrix with a risk component. The integrated economic assessment concept and facilitating instruments are relevant to large manufacturing companies and scalable to other industries.
9. The application of the integrated economic assessment concept guides investors and shareholders to assess the allocation of investment; decision-makers to assess the alternative allocation of financial, human and time resources and decide on the alternative of Industry 4.0-driven business model transformation; and policymakers can use the created methodology

when planning and assessing investment enhancement programmes based on EU or national funding and regional planning when assessing Industry 4.0-driven innovations.

10. The study showed that the companies that have implemented Industry 4.0 solutions, according to all the indicators measured by the composite index, are positive and better than the industry average. The efficiency index is better than the industry average for all companies from the main research group.
11. The estimate of the growth index in four companies is up to 300 per cent higher than the industry average. As shown by the qualitative study results, companies from the main research group with lower growth index estimates are the result of a protracted process and are associated with increased risk.
12. The integrated concept of economic evaluation, due to its flexibility, can be adapted to individual business specifics and other industries, evaluating alternatives for the allocation of financial, human and time resources in manufacturing industries by transforming the business model Industry 4.0.

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List of Scientific Publications by the Author on the Topic of the Dissertation

Papers in the Reviewed Scientific Journals

Kovaitė, K., Šūmakaris, P., Stankevičienė, J. (2020). Digital Communication Channels in Industry 4.0 Implementation: the Role of Internal Communication. *Management: Journal of Contemporary Management Issues*. 25(1), 171–191. <https://doi.org/10.30924/mjcmi.25.1.10>. ISSN 1331-0194.

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Papers in Other Editions

Kovaitė K., Stankevičienė, J. (2019). Risks of Digitalisation of Business Models. *Proceedings in International Scientific Conference Contemporary Issues in Business. Management and Economics Engineering*. Vilnius. VGTU. <https://doi.org/10.3846/cibmee.2019.039>

Summary in Lithuanian

Įvadas

Problemos formulavimas

Pramonės 4.0 inicijuoti verslo modeliai ir pokyčiai vertės grandinėje duoda labai greitų ir reikšmingų teigiamų rezultatų įmonėms ir šalių ekonomikai. Keitimasis duomenimis realiuoju laiku tampa decentralizuotas. Dėl stebimų pokyčių greičio, lūkesčių dėl itin spartaus augimo ir efektyvumo didėjimo, investicijų į technologines ir netechnologines inovacijas būtinybės, istorinių duomenų trūkumas skiria *Pramonės 4.0* pokyčius nuo įprastų rinkos naujovių.

Esami vertinimo metodai neleidžia įvertinti, ar veiksmingai paskirstomi finansiniai, žmogiškieji ir laiko ištekliai transformuojant verslo modelius dėl *Pramonės 4.0* įgyvendinimo. Mokslininkų ekonomikos kryptyje susidomėjimas nagrinėjama tema stebimas tik nuo 2016 m., *Clarivate Analytics Web of Science* ir *Elsevier Scopus* mokslinių straipsnių skaičius kasmet auga 50–80 proc. Tačiau trūksta mokslinių tyrimų ekonominio vertinimo srityje, kaip paskirstyti išteklius transformuojant įmones dėl *Pramonės 4.0* sprendimų.

Apibendrinant galima teigti, kad *Pramonės 4.0* sprendimų įgyvendinimas Lietuvoje, nors ir turintis didelį potencialą, yra lėtas. Įmonių išteklių paskirstymo vertinimo koncepcija, ieškant balanso tarp efektyvumo, augimo ir rizikos, turėtų padėti įgyvendinti *Pramonės 4.0* sprendimus, transformuojant gamybos įmonių verslo modelius.

Siekiant išspręsti pirmiau aprašytus klausimus, buvo nustatyta mokslinių tyrimų sritis: kaip įvertinti išteklių paskirstymą, transformuojant verslo modelį *Pramonės 4.0* sąlygomis, kaip pasiekiamas augimo ir efektyvumo didėjimas esant dideliame neapibrėžtumui.

Kiti klausimai siejasi su *Pramonės 4.0* skatinamų verslo modelių pertvarkymu ir jų alternatyvomis, efektyvumo, augimo ir rizikos vertinimo rodikliais ir rizikos sritimis, su kuriomis susiduria įmonės, ir vertinimo metodais, taikomais tiek bendrovės, tiek pramonės šakos lygmeniu.

Darbo aktualumas

Tyrimai rodo, kad ekonominis efektyvumas, įdiegus *Pramonės 4.0* sprendimus, turi potencialą per trumpą laiką padidėti 30–50 proc. Spartūs pokyčiai skatina surasti balansą tarp efektyvumo ir augimo didėjimo bei rizikų galimybes.

Vertinant išteklių perskirstymą *Pramonės 4.0* sąlygomis, turi būti sprendžiamas didesnio neapibrėžtumo dėl pokyčių spartos ir masto bei istorinių duomenų trūkumo uždavinys. Iš tyrimų (World Economic Forum, 2019) matyti, kad pasaulyje dėl *Pramonės 4.0* gamybos apimtys didėja iki 200 proc.

Pramonė 4.0 suteikia įmonėms galimybių transformuoti savo verslo modelį, kad galėtų sėkmingai plėstis pasaulinėse rinkose. Gamyba Lietuvoje sudaro 22–24 proc. bendrojo vidaus produkto ir daugiau kaip 60 proc. produkcijos eksportuojama. Prie šio indėlio prisideda *Pramonės 4.0* skatinamas ekonomikos augimas ir efektyvumas. Apdirbamajai pramonei tenka svarbus vaidmuo, o *Pramonės 4.0* nulemtas augimo ir efektyvumo potencialas leidžia prognozuoti didelį indėlį į nacionalinę ekonomiką.

Tyrimo objektas

Įmonės ekonominis vertinimas, transformuojant verslo modelį *Pramonės 4.0* sąlygomis.

Darbo tikslas

Sukurti integruotą ekonominio vertinimo koncepciją, skirtą įmonės išteklių paskirstymui įvertinti, transformuojant verslo modelį *Pramonės 4.0* sąlygomis.

Darbo uždaviniai

Darbo tikslui pasiekti buvo sprendžiami šie uždaviniai:

1. Susisteminti mokslinių tyrimų rezultatus, orientuojantis į ekonominį finansinių, žmogiškųjų ir laiko išteklių paskirstymo alternatyvų, pertvarkant verslo modelius dėl *Pramonės 4.0* technologinio, socialinio ir ekonominio poveikio, vertinimą.
2. Remiantis mokslinės literatūros analize, nustatyti pagrindinius *Pramonės 4.0* veiksmus, darančius įtaką verslo modeliams.
3. Analizuoti ir nustatyti pagrindinius rodiklius, skirtus finansinių, žmogiškųjų ir laiko išteklių paskirstymo alternatyvoms įvertinti, pertvarkant verslo modelį *Pramonės 4.0* sąlygomis.
4. Parengti vertinimo instrumentus, kurios sudaro integruotą ekonomikos vertinimo koncepciją.
5. Empiriškai patikrinti sukurtą vertinimo koncepciją didelėse baldų gamybos įmonėse, pateikti apribojimus ir tolimesnių tyrimų kryptis.

Tyrimų metodika

Nagrinėjant darbo objektą taikyti šie metodai:

- kritinė mokslinė literatūros analizė ir pagrindinių dinaminio efektyvumo veiksnių pritaikymas *Pramonės 4.0* potencialui įvertinti,
- mokslinės literatūros tyrimo bibliometrinė analizė,
- daugiakriteriai sprendimų priėmimo metodai, pvz., FARE indeksų kategorijoms ir svoriams nustatyti,
- duomenims apdoroti naudojami išskaidymo ir grupavimo metodai, siekiant nustatyti rodiklių ir indeksų kategorijas,
- statistinė analizė rodiklių ir kategorijų padidėjimui apskaičiuoti,
- pusiau struktūruotų interviu metu renkami kokybiniai duomenys, siekiant nustatyti indeksų komponentų rodiklius ir kategorijas,
- atrinktosios grupės diskusijos metu nustatomi indeksų kategorijų svoriai,
- kokybinė turinio analizė, skirta iš interviu surinktiems kokybiniams duomenims apdoroti,
- mokslinė interpretacija, remiantis grafinės analizės ir loginiu abstrakcijos metodu, buvo naudojama tyrimo rezultatams apdoroti.

Darbo mokslinis naujumas

Disertacijos mokslinis naujumas ekonomikos mokslams:

1. Sukurta ekonominio vertinimo koncepcija, kurią sudaro vertinimo loginė schema ir sudėtiniai indeksai, leidžia įvertinti finansinių ir žmogiškųjų išteklių paskirstymo alternatyvas didelėse gamybos įmonėse, kai jos transformuoja verslo modelius dėl *Pramonės 4.0* įgyvendinimo.
2. Integuota ekonominio vertinimo koncepcija nustatė rizikos, efektyvumo ir augimo dimensijas, kurios turi būti vertinamas, kai planuojamas ir įgyvendinamas finansinių, laiko ir žmogiškųjų išteklių paskirstymas.
3. Sukurta ekonominio vertinimo loginė schema nustato procesą, o indeksai nustatė rodiklių sistemos struktūrą, kuriais vadovaujantis turėtų būti daromas ekonominis vertinimas, paskirstant išteklius.
4. Vertinimo loginę schemą sudaro 16 pakopų procesas, kuris palengvina vertinimo procesą. Procese naudojami kiekybiniai ir kokybiniai metodai ir įtraukiami ekspertai bei įmonės darbuotojai, siekiant sprendimų tvarumo.
5. Sukurti keturi sudėtiniai indeksai su 33 rodikliais kaip vertinimo instrumentas.
6. Augimo–efektyvumo matrica su rizikos komponentais padeda palyginti sudėtinių indeksų rezultatus ir palengvina akcininkams, investuotojams, įmonių vadovams ir politikos formuotojams priimti sprendimus dėl išteklių paskirstymo, transformuojant verslo modelius *Pramonės 4.0* sąlygomis.

Darbo rezultatų praktinė reikšmė

1. Sukurta ir empiriškai išbandyta integruota ekonominio vertinimo koncepcija, kurią sudaro vertinimo loginė schema, keturi sudėtiniai indeksai, augimo–efektyvumo matrica, padeda priimti labiau pagrįstus sprendimus dėl įmonės ir nacionalinių išteklių paskirstymo.
2. Investuotojai ir akcininkai, sprenddami dėl strateginių *Pramonės 4.0* įgyvendinimo krypčių ir dėl savo finansinių išteklių paskirstymo, gali naudoti integruotą ekonominio vertinimo koncepciją.
3. Įmonių vykdančieji vadovai gali naudoti integruotą ekonominio vertinimo koncepciją, kad įvertintų, peržiūrėtų ir perskirstytų finansinius, žmogiškuosius ir laiko išteklius akcinių sprendimams įgyvendinti ir palygintų savo rezultatus su konkurentų rezultatais ir bendra situacija pramonės šakoje.
4. Politikos formuotojai gali naudoti integruotą vertinimo koncepciją, planuodami regioninę plėtrą ir ES bei nacionalinį finansavimą įmonių skaitmeninimui.
5. *Pramonės 4.0* inicijuojamas skaitmeninimas kuria daugiau didesnio darbo užmokesčio darbo vietų ir nuotolinio darbo galimybes regionuose, tai prisidės prie pajamų nelygybės mažinimo ir inovacijų plėtros regionuose, o kartu ir prie Lietuvos darnaus vystymosi tikslų darbotvarkės iki 2030 m. įgyvendinimo. Tikslingesnės investicijos į skaitmeninimą regionuose paskatins glaudesnę mokslo, pramonės ir visuomenės bendradarbiavimą ir prisidės prie Lietuvos pažangos strategijos iki 2030 m. įgyvendinimo. Didesnės kryptingesnės investicijos į *Pramonės 4.0* sprendimus leis sparčiau didinti efektyvumą ir augimą, lengviau dalyvauti pasaulinėje vertės grandinėje ir taip prisidėti įgyvendinant Rekomendacijas dėl investicijų 2021–2027 m. Lietuvos ūkio sektoriaus finansavimo vertinimo po 2020 m.: mokslas, technologijos ir inovacijos

Ginamieji teiginiai

1. Integruota ekonominio vertinimo koncepcija, kurią sudaro 16 pakopų vertinimo loginė schema, keturi sudėtiniai indeksai kaip vertinimo instrumentas ir augimo–efektyvumo matrica, leidžia įmonei įvertinti išteklių paskirstymo alternatyvas, transformuojant verslo modelius *Pramonės 4.0* sąlygomis.
2. Trijų dimensijų – efektyvumo, augimo ir rizikos – balansas padeda tiksliau įvertinti finansinių, žmogiškųjų ir laiko išteklių paskirstymą, transformuojant verslo modelius *Pramonės 4.0* sąlygomis.
3. Dinaminis požiūris integruotoje ekonominio vertinimo koncepcijoje leidžia interpretuoti laikotarpio duomenis ir pateikti tikslesnę ekonominio vertinimo rezultatų analizę.
4. Siūlomas sudėtinių indeksų derinys, kurį sudaro kategorijos ir rodikliai, leidžia taikyti holistinį vertinimo metodą, kuris palengvina priimamų sprendimų dėl išteklių paskirstymo, transformuojant verslo modelius *Pramonės 4.0* sąlygomis procesą.
5. Siūlomas kategorijų ir rodiklių derinys sudėtinuose indeksuose leidžia vertinimo koncepciją pritaikyti prie verslo specifikos.

Darbo rezultatų apibavimas

Disertacijos tema parengti ir atspausdinti keturi straipsniai: du – tarptautiniuose užsienyje leidžiamuose moksliniuose žurnaluose, iš kurių vienas yra įtrauktas į Clarivate Analytics Web of Science duomenų bazę ir Scopus duomenų bazėje turi cituojamumo rodiklį, vienas – tarptautinės konferencijos medžiagoje ir vienas – tarptautiniame moksliniame žurnale.

Disertacijos rezultatai buvo pristatyti keturis kartus trijose tarptautinėse konferencijose: „Economics and Entrepreneurship (SCEE‘2019) Rygoje, Latvijoje, „Contemporary Issues in Business, Management and Economics Engineering” 2019 metais Vilniuje, Lietuvoje, ir “Active Society – Innovative Solutions” 2017 metais Vilniuje, Lietuvoje.

Disertacijos rezultatai taip pat pristatyti keturiuose doktorantų seminaruose Vilniaus Gedimino technikos universiteto Verslo vadybos fakultete ir viename tarptautiniame seminare užsienyje Londono universiteto koledže, Jungtinėje Karalystėje.

Disertacijos struktūra

Disertaciją sudaro šios dalys: įvadas, trys skyriai su išvadomis, bendrosios išvados, literatūros sąrašas, autorės publikacijų sąrašas, santrauka lietuvių kalba ir 5 priedai. Disertaciją sudaro 137 puslapiai, neįskaičiuojant priedų, 22 paveikslai, 52 lentelės, 19 sunumeruotų formulių ir 196 moksliniai šaltiniai.

1. Mokslinės literatūros analizės verslo modelio transformacijos vertinimo *Pramonės 4.0 sąlygomis* apžvalga

Pirmajame disertacijos skyriuje pateikta mokslinės literatūros apžvalga. Skiriamas dėmesys įmonių efektyvumui ir augimui, taip pat analizuojama rizika, kurią reikėtų sumažinti, nagrinėjamas įmonių finansinių ir žmogiškųjų išteklių paskirstymas, transformuojant verslo modelį *Pramonės 4.0 sąlygomis*.

Atlikus mokslinės literatūros analizę, daromos šios išvados:

1. Mokslinės literatūros apžvalga rodo ribotus bandymus ištirti galimą *Pramonės 4.0* poveikį verslo modelio pertvarkymui. Atsižvelgiant į *Pramonės 4.0* reiškinio svarbą ir naujumą pabrėžiama, kad trūksta integruotų efektyvumo, augimo ir rizikos vertinimo metodikų ir priemonių, kuriomis siekiama įvertinti pirmiau minėtas kategorijas, kad būtų galima veiksmingai paskirstyti įmonės finansinius ir žmogiškuosius išteklius pertvarkant verslo modelį *Pramonės 4.0 sąlygomis*.
2. Verslo modelio *Pramonės 4.0 sąlygomis* pertvarkymas daugiausia susijęs su dinaminio efektyvumu, kurį galima naudoti ir mikro-, ir mezo-, ir makrolygiais. *Pramonės 4.0* inicijuotiems verslo modeliams pertvarkyti reikalingas technologinių inovacijų (pvz., daiktų internetas ir didžiųjų duomenų analizės įranga gamybos linijose) ir netechnologinių inovacijų (pvz., procesų ir organizacinių naujovių diegimas) derinys.
3. Kiekvienas iš penkių lygių (fizinis produktas; jutiklių naudojimas; junglumo; duomenų analizės ir duomenimis pagrįsta skaitmeninė paslauga) gali būti taikomas įvairiose verslo modelių dalyse: *vertės pasiūlymas*, *vertės kūrimas*, *vertės*

pasiūlymas ir *vertės pristatymas* individualiai, gali būti sudaromi skirtingi deriniai, kuriuose *Pramonės 4.0* sprendimai atsiskleidžia skirtingai.

4. Rodikliai naudojami vertinti ekonominę efektyvumą gamyboje ir darbe su tiekėjais, klientais ar partneriais. Skaičiuojant efektyvumą, *Pramonės 4.0* finansiniai ir nefinansiniai iššūkiai verčia naudoti skirtingas finansines ir nefinansines įvesties ir išvesties vertes ir jų kombinacijas. Yra reikalingos keturios finansinių ir nefinansinių rodiklių kombinacijos.
5. Finansinių ir žmogiškųjų išteklių paskirstymo vertinimui reikalingas kompleksinis integruotas požiūris ir yra naudojamas skirtingų svorių indeksų ir rodiklių derinys. Tam skirti sudėtiniai indeksai su skirtingus svorius turinčiais rodikliais. Sudėtinis indeksas gali būti naudojamas tiek įmonių lygmeniu, tiek pramonės, tiek ir politikos formavimo lygmeniu.
6. Rizika *Pramonėje 4.0* nustatoma kaip nukrypimas nuo planuojamos padėties ir apskaičiuojama dauginant jos atsiradimo tikimybę ir poveikį galutiniams rezultatams, jei ji įvyksta. Įmonės finansinė rizika yra plačiai naudojama vertinimui ir įtraukia likvidumo, mokumo ar pelningumo riziką.
7. Nefinansinės rizikos vertinimas suteikia papildomos informacijos vertinimo metu ir yra labiau susijusi su aplinkybėmis, kuriomis gali kilti rizika. Siūlomos penkios sritys, kuriose vertinama nefinansinė rizika mikromokygiu *Pramonė 4.0* sąlygomis: 1) techninė rizika; 2) kompetencijos rizika; 3) rizika, susijusi su klientų, tiekėjų ir partnerių segmentais ir elgsena; 4) rizika, susijusi su darbuotojų elgsena; 5) kibernetinio saugumo rizika.
8. *Pramonė 4.0* įgalina sparčiai didinti augimą ir efektyvumą pertvarkant verslo modelį. Pridėjus tokius kintamuosius kaip greiti pokyčiai ir istorinių duomenų trūkumas, finansinė ir nefinansinė rizika dar labiau kelia iššūkius. Finansinės ir nefinansinės rizikos mažinimas – dar viena sritis, skirta išteklių paskirstymui įvertinti transformuojant verslo modelius *Pramonės 4.0* sąlygomis. Tai sumažina rizikos poveikį galutiniam numatomam rezultatui.

2. Verslo modelio transformacijos *Pramonės 4.0* sąlygomis integruotos ekonominio vertinimo koncepcijos metodologija ir kūrimas

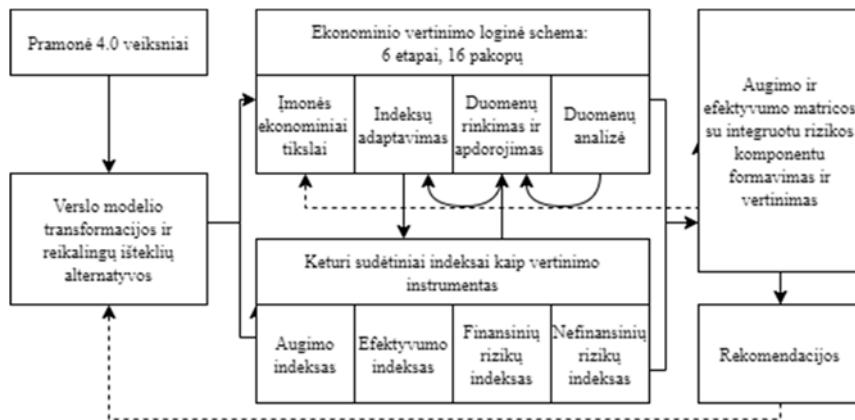
Šiame skyriuje aprašomas metodologinis pagrindimas ir tyrimo eiga, tyrimo etika ir rezultatai, pristatoma integruota ekonominio vertinimo koncepcija, kurią sudaro vertinimo loginė schema, keturi sudėtiniai rodikliai kaip vertinimo instrumentas ir augimo–efektyvumo matrica su rizikos komponentu, skirta vertinimo rezultatams vizualizuoti.

Disertacijos tyrimo eigą sudaro šie keturi etapai:

1. Integruotos ekonominio vertinimo koncepcijos sukūrimo metodologinis pagrindimas ir tyrimo eiga.
2. Empirinis tyrimas ir aprobavimas.
3. Rezultatų pristatymas ir išvadų formulavimas.

Verslo modelio transformacijos *Pramonės 4.0* sąlygomis ekonominio vertinimo koncepcija sudaryta siekiant įvertinti finansinių, žmogiškųjų ir laiko išteklių paskirstymą transformuojant verslo modelį *Pramonės 4.0* sąlygomis ir pristatoma S2.1 paveiksle.

Verslo modelio transformacijos *Pramonės 4.0* sąlygomis ekonominio vertinimo koncepciją sudaro 6 etapai. Pirmuoju etapu analizuojami *Pramonės 4.0* technologinius veiksniai, taikomus verslo modeliams transformuoti. Antruoju etapu „Verslo modelių ir būtinų išteklių pertvarkymas“ nustatomos galimos verslo modelio, kurį siūlo *Pramonė 4.0*, alternatyvos ir finansiniai, žmogiškieji ir laiko ištekliai.



S2.1 pav. Integruota ekonominio vertinimo koncepcija (sudaryta autorės)

Trečiuoju etapu „Vertinimo loginė schema“ pristatomas 16 pakopų vertinimo procesas, naudojant kiekybinius ir kokybinius metodus ir *Pramonės 4.0* siūlomų alternatyvų adaptavimą įmonės specifikai, duomenų rinkimą, apdorojimą ir analizę, tikrinant duomenų tikslumą, prieinamumą ir palyginamumą. Ketvirtuoju etapu „Keturi sudėtiniai indeksai“ naudojami sukuri indeksai efektyvumo, augimo, finansinės rizikos ir nefinansinės rizikos didėjimo potencialui įvertinti, transformuojant verslo modelius. Keturių sudėtinių indeksų sistema naudojama kaip vertinimo instrumentas, ir ją sudaro 33 rodikliai. Penktasis etapas „Augimo–efektyvumo matricos formavimas su rizikos komponentu ir vertinimas“ užbaigia ankstesnius etapus ir vertinamos verslo modelio transformacijos alternatyvos ir jos vizualizuojamos. Matrica padeda palyginti įmonės įvertintas galimo augimo, efektyvumo, finansinės rizikos ir nefinansinės rizikos alternatyvas arba palyginti įmones tarpusavyje. Šeštuoju etapu „Rekomendacijos“ siekiama suformuluoti rekomendacijas perskirstyti išteklius, reikalingus verslo modeliams transformuoti *Pramonės 4.0* sąlygomis. Rekomendacijos turėtų būti palygintos su antrajame etape numatytais planais, siekiant užtikrinti išteklių paskirstymo alternatyvų atitiktį pradiniam tikslui. Rekomendacijos suformuluotos investuotojams ir akcininkams, vadovams – sprendimus įmonėje priimančioms ir įgyvendinantiems asmenims ir politikos formuotojams.

Vertinimo instrumentą sudaro keturi sudėtiniai indeksai:

1. Efektyvumo sudėtinį indeksą sudaro keturios kategorijos su svoriais, atspindinčios vertės grandinės dalis, po tris rodiklius kiekvienoje kategorijoje, ir iš viso 12 rodiklių.

Vertės pasiūlymo kategorijoje yra šie rodikliai: pardavimų graža, likvidumo rodiklis ir pardavimo sąnaudų ir apyvartos rodiklis. Vertės kūrimo kategorijoje yra šie rodikliai: nebaigtos produkcijos apyvartumas, darbo našumas ir ilgalaikio turto apyvartumas. Vertės pristatymo kategorijoje yra šie rodikliai: paskirstymo rodiklis, atsargų apyvartumas ir greitis likvidumo rodiklis. Vertės gavimo kategorijoje yra šie rodikliai: kaštų panaudojimo efektyvumo rodiklis, turto graža ir pinigų srauto rodiklis. Efektyvumo indeksu siekiama įvertinti kiekvieną galimo vertės grandinės efektyvumo padidėjimo dalį ir bendrą efektyvumo padidėjimą.

2. Finansinės rizikos sudėtinį indeksą sudaro 3 kategorijos su svoriais ir 4 rodikliai. Mokumo rizikos kategorijoje yra šie rodikliai: skolos ir nuosavybės santykis ir skolos ir turto santykis. Kiti rodikliai yra: pelnas prieš mokesčius ir likvidumo rodiklis. Indeksu siekiama įvertinti galimus finansinius nuostolius.

3. Nefinansinės rizikos sudėtinį indeksą sudaro 5 kategorijos su svoriais ir 18 rodiklių. Indeksu siekiama įvertinti galimas organizacines, technines ir saugumo spragas verslo modelio transformacijos įgyvendinimo proceso metu.

4. Augimo sudėtinį indeksą sudaro du rodikliai su svoriais. Indeksą su daro šie rodikliai: pridėtinė vertė darbuotojui ir akcininkų fondai darbuotojui. Indeksu siekiama įvertinti galimą įmonės augimo finansinių rodiklių didėjimą.

Toliau pateikiama sudaryta 16 pakopų ekonominio vertinimo loginė schema, skirta verslo modelio transformavimo pramonės sektoriuje efektyvumui, augimui ir rizikai įvertinti. Įmonėms suteikiama galimybė pačioms lanksčiai adaptuoti ir organizuoti vertinimą, naudojantis vertinimo logine schema (S2.2 pav.) ir sudarytais keturiais sudėtiniais indeksais kaip vertinimo instrumentu.

Ekonominio vertinimo loginė schema yra paremta spiralinio ciklo procesu, kuris atspindi nuolatinio tobulėjimo ciklą ir grįžtamąjį ryšį, siekiant atsakyti į pagrindinį klausimą, kaip paskirstyti įmonės išteklius, transformuojant verslo modelį *Pramonės 4.0* sąlygomis. Loginę schemą sudaro šeši proceso žingsniai: 1) vertinimo tikslo, perskirstant išteklius, nustatymas, 2) efektyvumo, augimo ir rizikos vertinimo rodiklių bei svorių adaptavimas dėl pramonės ir įmonės specifikos, 3) ekonominių ir finansinių duomenų rinkimas ir apdorojimas, 4) efektyvumo didinimo, augimo ir rizikos mažinimo indeksų duomenų analizė, 5) išteklių paskirstymo vertinimas remiantis duomenų analizės išvadomis, 6) neapibrėžtumo ir pirminių duomenų patikslinimas, naudojantis grįžtama informacija, lyginant su pirmame žingsnyje nustatytais tikslais.

Kuriant vertinimo koncepciją, gautos šios išvados:

1. Integruotą vertinimo koncepciją sudaro vertinimo loginė schema ir sudėtinis indeksas, skirti ekonominiam efektyvumui, augimui, finansinei ir nefinansinei rizikai įvertinti, transformuojant verslo modelį *Pramonės 4.0* sąlygomis.
2. Sudaryta vertinimo loginė schema leidžia pritaikyti sudėtinį indeksą prie įmonės ir sektoriaus specifikos, o po to naudoti sudėtinius indeksus verslo modelio transformacijos alternatyvoms *Pramonės 4.0* sąlygomis įvertinti.
3. Keturi sudėtiniai indeksai turi vienodą svorį: efektyvumo indeksas su keturiomis kategorijomis su svoriais, atspindinčiomis vertės pasiūlymą, kūrimą, pristatymą ir gavimą, augimo indeksą su dviem rodikliais su svoriais, finansinės rizikos indeksą su trimis kategorijomis su svoriais ir nefinansinės rizikos indeksą su penkiomis kategorijomis su svoriais.

Vertinimo tikslas	1. Esamo verslo modelio identifikavimas ir reikalingi ištekliai																																			
	2. Pramonė 4.0 veiksniai verslo modelio transformacijai																																			
	3. Verslo modelio transformacijos Pramonė 4.0 sąlygomis alternatyvos ir reikalingi ištekliai																																			
Vertinimo metodas	<table><tr><th colspan="2">AUGIMO IR EFEKTYVUMO VERTINIMAS</th><th>FINANSINIŲ IR NEFINANSINIŲ RIZIKŲ VERTINIMAS</th></tr><tr><th>EFEKTYVUMO INDEKSAS</th><th>AUGIMO INDEKSAS</th><th>FINANSINĖS RIZIKOS INDEKSAS</th></tr><tr><td>4. Efektyvumo indekso kategorijų svorių peržiūra pagal industrijos specifiką Ekspertų vertinimas</td><td>4. Augimo indekso kategorijų svorių peržiūra pagal industrijos specifiką Ekspertų vertinimas</td><td>4. Finansinės rizikos indekso kategorijų svorių peržiūra pagal industrijos specifiką Ekspertų vertinimas</td></tr><tr><td>5. Efektyvumo rodiklių rinkinys kiekvienai kategorijai pagal industrijos specifiką</td><td>5. Augimo rodiklių rinkinys kiekvienoje kategorijoje pagal industrijos specifiką</td><td>5. Finansinės rizikos rodiklių rinkinio kiekvienoje kategorijoje pagal industrijos specifiką patvirtinimas</td></tr><tr><td>6. Vertinimui reikšmingo laikotarpio nustatymas. 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Nefinansinės rizikos rodiklių nuo 0 iki 1 normalizavimas.</td></tr><tr><td>9. Finansinių duomenų efektyvumo rodikliams skaičiuoti analizė tyrimo laikotarpiu</td><td>9. Finansinių duomenų augimo rodikliams skaičiuoti analizė tyrimo laikotarpiu</td><td>9. Finansinių duomenų finansinės rizikai skaičiuoti analizė tyrimo laikotarpiu</td></tr><tr><td>10. Efektyvumo rodiklių analizė, palyginimas su kitomis industrijos įmonėmis ir su industrijos rezultatais.</td><td>10. Augimo rodiklių analizė, palyginimas su kitomis industrijos įmonėmis ir su industrijos rezultatais.</td><td>10. Finansinės rizikos rodiklių analizė, palyginimas su kitomis industrijos įmonėmis ir su industrijos rezultatais.</td></tr><tr><td>11. Efektyvumo ir augimo indeksų rezultatų vertinimas.</td><td>11. Efektyvumo ir augimo indeksų rezultatų vertinimas.</td><td>11. Finansinės ir nefinansinės rizikos indeksų rezultatų vertinimas</td></tr><tr><td>12. Duomenų vertinimas, lyginant veiksmingumą ir augimą</td><td>12. Duomenų vertinimas, lyginant veiksmingumą ir augimą</td><td>12. Duomenų vertinimas, lyginant finansinę ir nefinansinę riziką</td></tr></table>			AUGIMO IR EFEKTYVUMO VERTINIMAS		FINANSINIŲ IR NEFINANSINIŲ RIZIKŲ VERTINIMAS	EFEKTYVUMO INDEKSAS	AUGIMO INDEKSAS	FINANSINĖS RIZIKOS INDEKSAS	4. Efektyvumo indekso kategorijų svorių peržiūra pagal industrijos specifiką Ekspertų vertinimas	4. Augimo indekso kategorijų svorių peržiūra pagal industrijos specifiką Ekspertų vertinimas	4. Finansinės rizikos indekso kategorijų svorių peržiūra pagal industrijos specifiką Ekspertų vertinimas	5. Efektyvumo rodiklių rinkinys kiekvienai kategorijai pagal industrijos specifiką	5. Augimo rodiklių rinkinys kiekvienoje kategorijoje pagal industrijos specifiką	5. Finansinės rizikos rodiklių rinkinio kiekvienoje kategorijoje pagal industrijos specifiką patvirtinimas	6. Vertinimui reikšmingo laikotarpio nustatymas. Efektyvumo rodiklių įtraukimas ir atsisakymas, atsižvelgiant į įmonėje turimus duomenis	6. 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Finansinių duomenų augimo rodikliams skaičiuoti analizė tyrimo laikotarpiu	9. Finansinių duomenų finansinės rizikai skaičiuoti analizė tyrimo laikotarpiu	10. Efektyvumo rodiklių analizė, palyginimas su kitomis industrijos įmonėmis ir su industrijos rezultatais.	10. Augimo rodiklių analizė, palyginimas su kitomis industrijos įmonėmis ir su industrijos rezultatais.	10. Finansinės rizikos rodiklių analizė, palyginimas su kitomis industrijos įmonėmis ir su industrijos rezultatais.	11. Efektyvumo ir augimo indeksų rezultatų vertinimas.	11. Efektyvumo ir augimo indeksų rezultatų vertinimas.	11. Finansinės ir nefinansinės rizikos indeksų rezultatų vertinimas	12. Duomenų vertinimas, lyginant veiksmingumą ir augimą	12. Duomenų vertinimas, lyginant veiksmingumą ir augimą	12. Duomenų vertinimas, lyginant finansinę ir nefinansinę riziką
	AUGIMO IR EFEKTYVUMO VERTINIMAS		FINANSINIŲ IR NEFINANSINIŲ RIZIKŲ VERTINIMAS																																	
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Rezultatai	13. Keturių indeksų rezultatų analizė, naudojant augimo-efektyvumo matricą su rizikos komponentu, siekiant įvertinti išteklį paskirstymo alternatyvas transformuojant verslo modelius Pramonė 4.0 sąlygomis																																			

S2.2 pav. Efektyvumo, augimo, finansinės ir nefinansinės rizikos vertinimo, transformuojant verslo modelį
Pramonės 4.0 sąlygomis, loginė schema (sudaryta autorės)

4. Vertinimo metu naudojami įvairūs kiekybiniai ir kokybiniai metodai. Kiekybiniai mokslinių tyrimų metodai renka ir apdoroja finansinius duomenis trimis indeksais: efektyvumo, augimo ir finansinės rizikos. Norint palyginti finansinius ir nefinansinius rodiklius, naudojamas minimalios normos normalizavimo metodas ir reitingavimas. Kokybiniai mokslinių tyrimų, organizuojant interviu ir atrinktųjų grupių diskusijas, metu papildomi pradiniai vertinimo rezultatai ir užtikrinamas nuodugnesnis vertinimas.
5. Įmonės ir pramonės rodiklių homogeniškumas, palyginamumas ir patikimumas yra svarbūs veiksniai, lemiantys sėkmingą alternatyvų vertinimą. Pirma, siekiant įvertinti kategorijų tinkamumą, kiekvienam rodikliui nustatomi galimi svarbūs įvediniai ir išvediniai. Antra, renkant duomenis pagal pasirinktus efektyvumo, augimo ir finansinės rizikos rodiklius bei lyginant bendrovės ekonominis rezultatus su artimiausių konkurentų rezultatais, turėtų būti naudojami faktiniai finansinės apskaitos duomenys.
6. Vertinimo kokybė naudojant sukurtus indeksus labai priklauso nuo pagrindinių rodiklių duomenų pilnumo. Vidinės apskaitos duomenys turėtų būti naudojami bendrovės rezultatams palyginti per tam tikrą laikotarpį. Labai svarbu užtikrinti, kad visais analizės metais būtų taikoma ta pati duomenų rinkimo ir apdorojimo metodika įmonės viduje. Reikėtų apvarstyti galimybę taikyti tinkamą mokslinių tyrimų metodų kompleksą, kad būtų užtikrintas integruotas holistinis vertinimo metodas, leidžiantis įvertinti investicijų sprendimų veiksmingumą.

3. Integruotos ekonominio vertinimo koncepcijos aprobavimas

Aprobavimo metu buvo testuojama sukurta integruota vertinimo koncepcija, kurią sudaro vertinimo loginė schema, sudėtiniai indeksai kaip vertinimo instrumentas ir augimo–efektyvumo matrica galutiniams rezultatams vizualizuoti didelėse gamybos įmonėse, patvirtinti integruotos ekonominio vertinimo koncepciją įmonių efektyvumui, augimui ir rizikai įvertinti, transformuojant verslo modelius *Pramonės 4.0* sąlygomis bei, remiantis rezultatais, išvadoms ir būsimoms mokslinių tyrimų kryptims suformuluoti.

Sudaryta integruota ekonominio vertinimo koncepcija testuota ir aprobuota 2020–2021 metais. Įmonių grupė koncepcijai testuoti buvo parinkta, remiantis šiais kriterijais:

- 1) analitinės prognozės rodo didelį *Pramonės 4.0* poveikį šios pramonės šakos efektyvumo ir augimo potencialui;
- 2) pramonės šaka, kurioje aktyviai įgyvendinami *Pramonės 4.0* sprendimai;
- 3) didelės įmonės, vadovaujantis Smulkaus ir vidutinio verslo plėtros įstatymo reglamentavimu;
- 4) finansinių ir valdymo duomenų prieinamumas laikotarpiu nuo *Pramonės 4.0* sprendimų įgyvendinimo pradžios iki tyrimo pabaigos;
- 5) turimi istoriniai laikotarpio nuo *Pramonės 4.0* sprendimų įgyvendinimo pradžios iki tyrimo pabaigos duomenys.

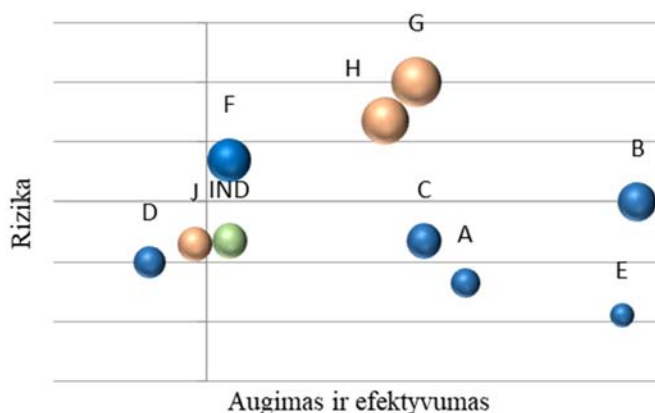
Mokslinėje ir analitinėje literatūroje yra paminėtos kelios pramonės šakos kaip labiausiai paveiktos *Pramonės 4.0*, ir baldų gamybos pramonė yra tarp jų.

Empiriniai tyrimai buvo suskirstyti į tris etapus:

1) Atrinktos gamybos įmonės, vykdančios EVRK C sekcijoje nurodytą veiklą.
 2) Toliau nagrinėtos didelės baldų gamybos įmonės Lietuvoje, dirbančios pagal EVRK 310900 (kitų baldų gamyba). Šiame etape buvo analizuojami 9 didelių bendrovių finansiniai duomenys. Analizuojamų įmonių bendra metinė apyvarta sudaro 80 proc. viso sektoriaus ir gali būti laikoma reprezentatyvia grupe.

3) Išsamiems tyrimams buvo atrinktos šešios didelės įmonės dėl duomenų pilnumo visu tyrimo laikotarpiu.

S3.1 paveiksle pavaizduoti įmonių bei pramonės šakos rezultatai, pateikiant augimo ir efektyvumo padidėjimo rezultatus ir finansinės bei nefinansinės rizikų reikšmes.



S3.1 pav. Efektyvumo, augimo ir rizikų santykis (sudaryta autorės)

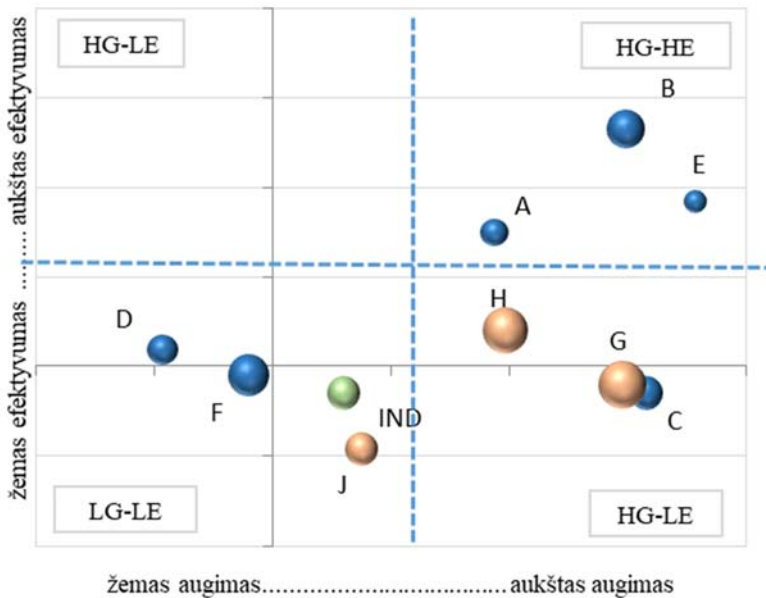
X ašyje matoma bendra augimo ir efektyvumo indekso reikšmė, Y ašyje – finansinės ir nefinansinės rizikos vidurkio reikšmė. Analizuojant S3.1 paveiksle pavaizduotus duomenis, matoma, kad net keturių įmonių iš pagrindinės tiriamosios grupės (A, B, C ir E) bendros augimo ir efektyvumo didėjimo reikšmės yra reikšmingai didesnės negu pramonės šakos rezultatų didėjimo vidurkis (IND).

Sudarytoje augimo–efektyvumo matricoje su rizikos komponentu (S3.2 pav.) pristatyti keturi galimi segmentai, kuriuose įmonės gali būti pozicionuojamos pagal augimo, efektyvumo ir rizikų padidėjimo rezultatus po verslo modelio transformacijos *Pramonės 4.0* sąlygomis.

Siūlomi keturi galimi vertinimai:

- 1) Žemiausiame kairiajame kvadrante yra žemo augimo (LG) ir žemo efektyvumo (LE) segmentas. Šiame LG–LE segmente yra įmonės, kurių augimas nedidelis, o efektyvumo didėjimas – žemas.
- 2) Viršutiniame kairiajame kvadrante yra žemo augimo (LG) ir aukšto efektyvumo (HE) segmentas. Bendrovės, kurių augimas nedidelis ir kurių efektyvumas labai padidėjo, patenka į LG-HE segmentą.

- 3) Apatiniame dešiniajame kvadrante yra aukšto augimo (HG) ir žemo efektyvumo (LE) segmentas. Įmonės, kurių augimas reikšmingai padidėjo, o efektyvumas padidėjo nedaug, yra HG-LE segmente.
- 4) Viršutiniame dešiniajame kvadrante yra aukšto augimo (HG) ir aukšto efektyvumo (HE) segmentas. Įmonės, kurioms būdingas didelis augimas ir didelis efektyvumas, yra HG-HE segmente.



S3.2 pav. Pagrindinės augimo–efektyvumo matricioje pateiktos vertinimo išvados, įvertinus rizikas (sudaryta autorės)

Transformuodamos verslo modelius dėl *Pramonės 4.0*, įmonės vertina augimo ir efektyvumo pokytį ir rizikos lygį, naudodamos pristatytą matricią. Burbulo dydis rodo rizikos lygį – tiek finansinės, tiek nefinansinės. Didesni burbulai rodo didesnę riziką, taip pat šalia esantys skaičiai nurodo rizikos dydį skalėje nuo 0 iki 1, kai vertės arčiau 1 rodo didesnę riziką. Tolesnėje analizėje rizika skirstoma į aukštą–vidutinę ir vidutinę–žemą. Riziką sudaro ir finansinė, ir nefinansinė rizika (žr. S3.1 lentelę), o vertinant vietą segmente turėtų būti atsižvelgiama ir į augimo bei efektyvumo, ir į rizikos indeksus.

Apibendrinant rezultatus (žr. S3.2 pav.), žemo augimo ir žemo efektyvumo indeksu (LG-LE) segmento įmonių ir augimo, ir efektyvumo padidėjimas labai nedidelis arba netgi mažėja, t. y. rodo neigiamą rodiklį. Žemas augimo indeksas indikuoja nedidelį pridėtinės vertės padidėjimą; tai prieštarauja pradinei *Pramonės 4.0* įgyvendinimo tikslų idėjai. Žemas efektyvumo didėjimas liudija, kad įvairiose verslo modelio dalyse ir vertės grandinėje yra disbalansas. Tokioje situacijoje turėtų būti nustatytos verslo modelio dalys, kurių

efektyvumas mažiausias ir didžiausias, ir įgyvendinti veiksmai, leidžiantys padidinti dalių, kurių rezultatai yra mažiausi, efektyvumą.

S3.1 lentelė. Finansinės ir nefinansinės rizikos lygio paaiškinimas (sudaryta autorės)

Rizikos lygis	Aprašymas
Finansinė rizika	
Aukšta–vidutinė	Aukšta ir vidutinė finansinė rizika rodo, kad reikia skubiai subalansuoti skolas ir įsipareigojimus, palyginti su turtu ir (arba) nuosavu kapitalu, nes skolos didėjimas gali trukdyti tolesniam augimo didėjimui. Reikia atkreipti dėmesį į galimas likvidumo problemas, pvz., pernelyg mažas grynųjų pinigų srauto padidėjimas gali priversti staigiai stabdyti arba per lėtai įgyvendinti pokyčius. Nedidelis pelno padidėjimas gali sukelti akcininkų nepasitenkinimą ir stabdyti pokyčius.
Vidutinė–žema	Vidutinė ir žema finansinė rizika žymi, kad finansinis santykis rodo nuolatinį pastovų likvidumo ir pelno didėjimą ir mažėjančią skolą. Pakanka finansinės paramos <i>Pramonės 4.0</i> įgyvendinti. Net jei iškyla tam tikrų problemų, sprendimas gali būti rastas, nenutraukiant <i>Pramonės 4.0</i> įgyvendinimo.
Nefinansinė rizika	
Aukšta–vidutinė	Aukšta ir vidutinė nefinansinė rizika rodo, kad verta peržiūrėti įmonės pasirenimą transformuoti verslo modelį įgyvendinant <i>Pramonės 4.0</i> sprendimus, jeigu norima pasiekti laukiamus rezultatus. Svarbiausi įmonės vidiniai pokyčiai yra susiję su organizacijos struktūra ir kultūra, darbuotojų kompetencija ir įgūdžiais, santykiais su klientais ir partneriais, duomenų saugos klausimais. Didžiausios nustatytos spragos turėtų būti mažinamos, kad įmonė būtų pasiruošusi pokyčiams.
Vidutinė–žema	Vidutinė ir žema nefinansinė rizika rodo, kad organizacinė struktūra, procedūros ir kultūra, darbuotojų kompetencija ir įgūdžiai, techniniai sprendimai yra pasirenkę transformuoti verslo modelį, įgyvendinant <i>Pramonės 4.0</i> sprendimus. Įmonė turi organizacinę kultūrą, kurioje mokymasis ir nuolatinis tobulinimas yra kasdienybės dalis, pakanka darbuotojų, turinčių reikiamą kvalifikaciją, reguliari duomenų analizė yra sprendimų priėmimo dalis, procedūros yra aiškos, gerai apgalvotos ir visiems suprantamos. Yra nedidelių būtinų pakeitimų ir, siekiant laukiamų rezultatų, reikia įgyvendinti neesminius pokyčius.

Žemo augimo ir aukšto efektyvumo indekso (LG-HE) segmento įmonių augimo rezultatai yra nedideli, efektyvumo rezultatai yra reikšmingai didėjantys. Žemas augimas rodo nedidelį pridėtinės vertės ir akcininkų fondų vienam darbuotojui padidėjimą. Tai nesutampa su pradiniu *Pramonės 4.0* įgyvendinimo tikslu. Aukštas efektyvumas rodo didelį visų arba kelių verslo modelio dalių padidėjimą ir efektyvumo pusiausvyrą įvairiose verslo modelio dalyse ir vertės grandinėje.

Aukšto augimo ir žemo efektyvumo indekso (HG-LE) segmente įmonių augimo didėjimas yra reikšmingas, o efektyvumas – žemas. Empiriniai rezultatai rodo, kad per ketverių metų tiriamąjį laikotarpį padidėjo 57 proc. Didelis augimo didėjimas žymi, kad pridėtinė vertė ir akcininkų lėšos vienam darbuotojui reikšmingai didėja. Didelio augimo rezultatai atitinka pirminį *Pramonės 4.0* tikslą. Analitinėje literatūroje prognozuojama, kad pridėtinė vertė, diegiant *Pramonę 4.0* sprendimus, padidės bent 30 proc. Per pirmuosius metus po *Pramonės 4.0* įgyvendinimo empirinių tyrimų rezultatai rodo 35–55 proc.

augimą, o per tolesnius trejus metus sukauptas augimo didėjimas buvo didesnis nei 60 proc. Su reikšmingu augimo didėjimu šiame segmente siejamas abiejų rodiklių – pridėtinės vertės ir akcininkų lėšų – padidėjimas. Mažas efektyvumo didėjimas šiame segmente rodo labai mažą padidėjimą arba sumažėjimą bent vienoje kategorijoje, o tai patvirtina, kad, net ir investavus į šiuolaikinę įrangą ir sprendimus, efektyvumo padidėjimas nėra pakankamas. Mažas HG-LE segmento efektyvumo indeksas rodo verslo modelio ir augimo bei efektyvumo disbalansą.

Aukšto augimo ir aukšto efektyvumo indekso (HG-HE) segmente įmonių rezultatai rodo didelį augimo ir didelį efektyvumo padidėjimą. Empiriniai rezultatai rodo, kad verslo modelio transformacijos per ketverius metus sukauptas padidėjimas siekia 57–112 proc. Didelis augimas rodo, kad reikšmingai padidėjo pridėtinė vertė ir akcininkų lėšos vienam darbuotojui. Analitinėje literatūroje yra prognozuojama, kad, įgyvendinus pokyčius, pridėtinė vertė padidės bent 30 proc., o efektyvumas – bent 30 proc. Tačiau keliama aukštesni lūkesčiai ir tikimasi, kad bendri rezultatai bus reikšmingesni. Per pirmuosius metus po *Pramonės 4.0* įgyvendinimo pradžios empirinių tyrimų rezultatai rodo augimo padidėjimą iki 35 proc., o tai žymi, kad vėlesniais metais sukauptas augimas buvo didesnis nei 60 proc. Didelis šiame segmente esančių įmonių augimo didėjimas rodo abiejų komponentų rodiklių – pridėtinės vertės ir akcininkų lėšų – padidėjimą. Iš empirinių tyrimų rezultatų matyti 75–110 proc. sukauptas efektyvumo padidėjimas bent vienoje verslo modelio dalyje. Šiame segmente daugiausia dėmesio skiriama labiau subalansuotam efektyvumo didinimui visose verslo modelio dalyse, o ne investicijoms į vieną ar dvi verslo modelio dalis.

Aprobavimo metu suformuluotos tokios išvados:

1. Efektyvumo sudėtinio indekso kategorijos indekse turi skirtingą svorį: vertės pasiūlymo kategorija ($w = 0,2$), vertės kūrimo kategorija ($w = 0,4$), vertės pristatymo kategorija ($w = 0,15$) ir vertės surinkimo kategorija ($w = 0,25$). Visų pagrindinės tyrimų grupės įmonių efektyvumo indeksas yra didesnis nei vidutinis pramonės šakos efektyvumo indeksas.
2. Augimo sudėtinio indekso kategorijos turi skirtingą svorį. Rodikliai skaičiuojami vienam darbuotojui: pridėtinė vertė vienam darbuotojui ($w = 0,7$) ir akcininkų lėšos vienam darbuotojui ($w = 0,3$). Keturių pagrindinės mokslinių tyrimų grupės įmonių augimo sudėtinio indekso rezultatas yra žymiai didesnis nei vidutinis pramonės šakos augimo padidėjimo rezultatas, o dviejų bendrovių rezultatai yra mažesni. Dvi pastarosios įmonės įgyvendino tik technologinę *Pramonės 4.0* sprendimų dalį ir neskyrė išteklių netechnologinių inovacijų (organizacinių kompetencijų, personalo įgūdžių ir procedūrų) pertvarkymui.
3. Finansinės rizikos sudėtinio indekso kategorijos turi skirtingą svorį: mokumo kategorija ($w = 0,25$), pelno kategorija ($w = 0,5$) ir likvidumo kategorija ($w = 0,25$). Visų pagrindinės mokslinių tyrimų grupės įmonių finansinės rizikos sudėtinis indeksas yra mažesnis nei vidutinis pramonės šakos finansinės rizikos indeksas, ir rodo mažesnę finansinę riziką negu vidutiniškai pramonės šakoje.
4. Nefinansinės rizikos sudėtinio indekso kategorijos turi skirtingą svorį: techninės rizikos kategorija ($w = 0,15$), kompetencijos rizikos kategorija ($w = 0,25$), rizikos, susijusios su partnerių ir klientų elgsena, kategorija ($w = 0,15$), rizikos, su-

sijusios su darbuotojų elgsena kategorija ($w = 0,35$) ir kibernetinio duomenų saugumo rizikos kategorija ($w = 0,1$). Nefinansinės rizikos indeksas visose pagrindinės mokslinių tyrimų grupės įmonėse yra mažesnis už vidutinį pramonės nefinansinės rizikos indeksą.

5. Augimo–efektyvumo matrica su rizikos komponentu naudojama alternatyvoms įvertinti, kai verslo modelis transformuojamas *Pramonės 4.0* sąlygomis. Įmonėms siūlomos alternatyvos, randant padėtį keturiuose segmentuose pagal efektyvumo ir augimo derinį: LG-LE, LG-HE, HG-LE ir HG-HE su Z dimensija burbulo vizualizacijoje. Keturių segmentų sistema padeda įmonėms palyginti savo pozicijas su kitomis šio sektoriaus įmonėmis arba palyginti savo vertinamas kečias verslo modelio transformacijos alternatyvas.
6. Pritaikius vertinimo loginę schemą ir sudėtinius indeksus įmonės pozicionuojamos viename iš keturių segmentų. Rezultatai rodo, kad trys įmonės iš šešių pagrindinės mokslinių tyrimų grupės, priskiriamos HG-HE segmentui, dvi įmonės – LG-LE segmentui, o viena įmonė priklauso HG-LE segmentui. Lyginant su kitomis, į pagrindinę mokslinių tyrimų grupę neįtrauktomis pramonės šakos įmonėmis, dvi jų priskiriamos HG-LE segmentui ir viena – LG-LE segmentui. Vidutiniai pramonės šakos rezultatai priskiriami LG-LE segmentui. Rezultatai rodo, kad įmonių, kurios savo verslo modelius transformuoja, diegdamos *Pramonės 4.0* sprendimus, efektyvumo ir augimo padidėjimas didesnis nei vidutiniai pramonės rezultatai. Dauguma šių įmonių augimo ir efektyvumo rodiklių yra geresni negu artimiausių konkurentų rezultatai.
7. Pateikti tyrimų rezultatai rodo, kad sudaryta integruota ekonominio vertinimo koncepcija su vertinimo loginė schema, keturiais sudėtiniais indeksais ir augimo–efektyvumo matrica yra tinkama, vertinant finansinių, žmogiškųjų ir laiko išteklių paskirstymo alternatyvas gamybos pramonės įmonėse transformuojant verslo modelį *Pramonės 4.0* sąlygomis.

Bendrosios išvados

1. Sisteminė mokslinės literatūros analizė rodo, kad *Pramonė 4.0* yra kompleksiškas reiškinys, tik nuo 2014 metų sulaukęs mokslininkų dėmesio ir vykstantis horizontaliai per įvairias disciplinas: nuo kompiuterių mokslo iki ekonomikos. Skelbiama įvairių *Pramonės 4.0* sąvokos aiškinimų, o pagrindinė sąvokos apibrėžtis yra kompiuterinės ir žmogaus sąveikos sintezė realiuoju laiku, keičiantis duomenimis tarp įrenginių, nereikalaujant tiesioginio žmogaus įsikišimo.
2. Pagrindinių *Pramonės 4.0* technologinių veiksmių, tokių kaip daiktų internetas, didžiųjų duomenų analizė ir dirbtinis intelektas, naudojimas sudaro pagrindą verslo modelio transformacijai pramonėje.
3. Sukurta originali integruota ekonominio vertinimo koncepcija, kurią sudaro vertinimo loginė schema, keturi sudėtiniai indeksai ir augimo–efektyvumo matrica turėtų būti naudojama, kai vertinamas finansinių, laiko ir žmogiškųjų išteklių paskirstymas, transformuojant verslo modelius *Pramonės 4.0* sąlygomis.

4. Keturių sudėtinių indeksų balansas: augimas, efektyvumas, finansinė rizika ir nefinansinė rizika sudaro pagrindą ekonominiam vertinimui. Vertinamas augimo ir efektyvumo įmonėje didėjimas, atsižvelgiant į finansinę ir nefinansinę riziką.
5. Vertinimo loginė schema yra sukurtas kiekybinius ir kokybinius tyrimų metodų derinį įtraukiantis procesas, kurio pritaikymas suteikia daugiau faktinės informacijos vertinimui ir papildoma kiekybinio metodo rezultatus. Tokiu būdu už transformacijas atsakingi asmenys dalyvauja, vertinant alternatyvų išteklių paskirstymą ir tai didina įsitraukimą ir įsipareigojimą siekti veiksmingumo ir sėkmės.
6. Teigiamas diegiamų *Pramonės 4.0* sprendimų poveikis įmonių efektyvumui ir augimui stebimas trejų metų laikotarpiu. Per pirmuosius trejus metus nuo *Pramonės 4.0* įgyvendinimo pradžios pastebimas bendras efektyvumo padidėjimas iki 53 proc. ir augimo padidėjimas iki 71 proc. Per trejus metus bendras efektyvumo ir augimo padidėjimas siekė iki 112 proc. Vėliau abiejų rodiklių padidėjimas koreguojamas ir rodo efektyvumo arba augimo didėjimo sumažėjimą.
7. Verslo modelio transformacija *Pramonės 4.0* sąlygomis suprantama kaip ilgalaikio ekonomikos augimo pagrindas. Integruota ekonominio vertinimo koncepcija leidžia suskirstyti įmones į segmentus.
8. Mokslinis naujumas ir svarba pasireiškia sukūrus integruotą ekonominio vertinimo koncepciją, kurią sudaro vertinimo 6 etapų loginė schema, keturi sudėtiniai indeksai kaip vertinimo instrumentas: augimas, efektyvumas, finansinė ir nefinansinė rizika; ir augimo–efektyvumo matrica su rizikos komponentu.
9. Integruotos ekonominio vertinimo koncepcijos taikymas padeda investuotojams ir akcininkams įvertinti investicijų paskirstymą; sprendimus priimančiams vadovams padeda sprendimų priėmimo dėl išteklių planavimo ir perskirstymo, transformuojant verslo modelį *Pramonės 4.0* sąlygomis, procese ir įgyvendinant akcininkų sprendimus; politikos formuotojams, planuojant ir vertinant inovacijų ir investicijų skatinimo programas regionų plėtrai, planuojant ir kontroliuojant Europos Sąjungos arba nacionalinio finansavimo veiksmingumą.
10. Atliktas tyrimas parodė, kad įmonėse, kurios diegė *Pramonės 4.0* sprendimus pagal visus sudėtinio indekso vertinamus rodiklius, rezultatai yra teigiami ir geresni negu pramonės vidurkis. Efektyvumo indeksas yra geresnis negu pramonės šakos vidurkis visose nurodytose įmonėse.
11. Augimo indekso įvertis keturiuose įmonėse yra net 1,5–3 kartus aukštesnis negu pramonės šakos vidurkis. Įmonės, kurių augimo indekso įverčiai yra žemesni, kaip parodė kokybinio tyrimo rezultatai, yra užsitęsusio proceso išdava ir susijusi su padidėjusia rizika.
12. Integruota ekonominio vertinimo koncepcija dėl savo lankstumo gali būti pritaikoma individualiai verslo specifikai ir kitoms pramonės šakoms, vertinant finansinių, žmogiškųjų ir laiko išteklių paskirstymo alternatyvas gamybos pramonės įmonėse transformuojant verslo modelį *Pramonės 4.0* sąlygomis.

Annexes¹

- Annex A.** The changes of a set of indicators during the process of formation of the index of efficiency
- Annex B.** The experts' qualifications accordance with the criteria
- Annex C.** Measurements of curvature and deflection of the test beams
- Annex D.** Declaration of Academic Integrity
- Annex E.** Copies of scientific publications by the author on the topic of the dissertation

¹The annexes are supplied in the enclosed compact disc.

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ECONOMIC ASSESSMENT
OF BUSINESS MODEL
TRANSFORMATION IN INDUSTRY 4.0

Doctoral Dissertation

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Economics (S 004)

VERSLO MODELIO TRANSFORMACIJOS
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