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THE IMPACT OF DIGITALIZATION ON THE PERFORMANCE OF PETROCHEMICAL COMPANIES

Master thesis by

2-year student of program

«Master in Management»

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ЗАЯВЛЕНИЕ О САМОСТОЯТЕЛЬНОМ ХАРАКТЕРЕ ВЫПУСКНОЙ КВАЛИФИКАЦИОННОЙ РАБОТЫ

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ABSTRACT

Master student’s name	Filimonova Elina Sergeevna
Master Thesis title	The impact of digitalization on the performance of petrochemical companies
Educational Program	Master in Management Program
Main field of study	Management
Year	2024
Academic Advisor’s Name	Andrey V. Zyatchin, Candidate of Science, Saint-Petersburg University, 2010, Associate Professor, Department of Operations Management, Academic director of EMBA and MBA Program
Research goal	Identify how the factors characterizing digitalization can affect labor productivity in a petrochemical industry
Research objectives	1. Conduct an extensive review of academic literature to identify the critical factors that enable or hinder petrochemical companies in adopting digital technologies. 2. Determine the key factors that can boost labor productivity when utilizing digital solutions in the petrochemical industry. 3. Develop a conceptual framework that illustrates the factors impacting labor productivity due to digitalization in the petrochemical sector. 4. Collect primary data and empirically validate the proposed research model. 5. Provide evidence-based recommendations to petrochemical companies to ensure the effective implementation of digital solutions.
Research result	1) A structural equation model depicting the digitalization process in chemical and petrochemical companies was developed, comprising eight latent variables. This model encapsulates the key factors influencing digitalization, including the organization's attitude towards digitalization and change; employees' competence; competition; market conditions; innovative push; corporate technology infrastructure; and the alignment between business strategy and information systems (IS). The eighth element in the model is digitalization itself, which serves as a mediating variable between the digitalization factors and labor productivity. 2) Three factors were identified as having the most significant impact on digitalization in the chemical and petrochemical

	industry: the alignment between business strategy and information systems (IS); the maturity of corporate technology infrastructure; and the organization's attitude towards enhancing employees' competence. 3) Practical recommendations were formulated for chemical and petrochemical companies to facilitate successful digitalization. These recommendations encompass four key directions: • Aligning the organization's business strategy with its information technology (IT) strategy; • Enhancing the interconnectivity and integration of corporate systems; • Transitioning towards simpler and more generalized technologies; • Developing and implementing a comprehensive program to enhance employees' competencies and skills.
Key words	Digitalization, petrochemical industry, labor productivity

АННОТАЦИЯ

Автор	Филимонова Элина Сергеевна
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Цель исследования	Определить как факторы, которые характеризуют цифровизацию, могут повлиять на производительность труда в нефтехимической отрасли
Задачи исследования	1. Изучить исследования в области цифровизации нефтехимических компаний и выявить факторы, которые препятствуют или стимулируют организации к внедрению цифровых решений; 2. Определить факторы, которые могут повысить производительность труда в контексте использования цифровых решений; 3. Разработать исследовательскую модель факторов, влияющих на производительность труда в результате цифровизации в нефтехимической отрасли; 4. Собрать первичные данные и протестировать созданную модель; 5. Разработать рекомендации для нефтехимических компаний по успешному внедрению цифровых решений.
Результаты исследования	1) Разработана структурная модель процесса цифровизации в химических и нефтехимических компаниях, состоящая из восьми переменных. Модель включает в себя основные факторы, влияющие на цифровизацию: отношение компании к цифровизации и изменениям; компетентность сотрудников; конкуренция; состояние рынка; инновационный толчок; корпоративные технологии; согласованность бизнес-процессов и информационных

	систем (ИС). Восьмым элементом модели является сама цифровизация как переменная, которая является медиатором между факторами цифровизации и производительностью труда. 2) Определены три фактора, которые оказывают наибольшее влияние на цифровизацию в химической и нефтехимической промышленности: согласованность бизнес-процессов и информационных систем (ИС); корпоративные технологии; отношение компании к компетенциям сотрудников. 3) Разработаны практические рекомендации для химических и нефтехимических компаний. Сформулированные рекомендации включают в себя 4 направления: • Согласование бизнес-стратегии и ИТ-стратегии компании; • Повышение взаимосвязанности корпоративных систем; • Переход на простые и обобщенные технологии; • Разработка и внедрение комплексной программы повышения квалификации сотрудников.
Ключевые слова	Цифровизация, нефтехимическая отрасль, производительность труда

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INTRODUCTION

Currently, scholarly investigations are exploring frameworks of digitalization that incorporate people as integral elements [Verina and Titko, 2019; Vial, 2019]. Authors argue that successful digitalization requires "motivated employee involvement". Moreover, Metlyakhin A.I et al. (2020) states that one of the main factors of labor productivity growth is scientific and technological progress in general, as well as the introduction of digital technologies and computerization of labor. Consequently, nowadays an important area of research is how labor productivity as one of the factors of company's performance is affected by digitalization.

Nevertheless, the prevailing number of studies predominantly adopts a qualitative approach, lacking quantitative examinations that delineate the correlation between digitalization and labor productivity. A conceptual model of the channels through which digitalization affects labor productivity was proposed by Varlamova and Larionova in 2020. Two schools of thought exist regarding the impact of digitalization on labor productivity. Borovskaya et al. (2020) propose that digitalization can enhance labor productivity by streamlining workflows, improving production processes, and optimizing resource allocation. Conversely, other researchers like Skinner (2014), Van Ark (2016), and Anderton et al. (2023) emphasize a two-way relationship between digitalization and labor productivity. Given the conflicting perspectives and the absence of standardized assessment methods, there is a pressing need to investigate the key factors of digitalization and their effects on labor productivity growth. Developing a quantitative framework can assist organizations in making informed decisions and prioritizing the utilization of digital technologies to boost labor productivity.

Research subject: Digitalization process in petrochemical industry.

Research object: Russian petrochemical industry.

Research goal: Identify how the factors explaining digitalization can affect labor productivity in the petrochemical industry.

Research objectives:

1) Conduct an extensive review of academic literature to identify the critical factors that enable or hinder petrochemical companies in adopting digital technologies.
2) Determine the key factors that can boost labor productivity when utilizing digital solutions in the petrochemical industry.

3) Develop a conceptual framework that illustrates the factors impacting labor productivity due to digitalization in the petrochemical sector.
4) Collect primary data and empirically validate the proposed research model.
5) Provide evidence-based recommendations to petrochemical companies to ensure the effective implementation of digital solutions.

Research questions:

1) What factors influence the introduction of digital technologies and labor productivity in the company?
2) How labor productivity can be affected through introducing digital solutions in the petrochemical company?

This study aims to bridge the gap in existing literature by creating a quantitative framework that clarifies the correlation between digitalization factors and labor productivity factors specifically in the petrochemical industry. It also aims to present empirical evidence and a measurement framework that encompasses both digitalization and labor productivity factors, thereby enhancing the practicality of the results in managerial decision-making.

In a managerial context, this research strives to provide practical insights for managers to comprehend how digitalization impacts labor productivity within their companies. By analyzing the influence of digitalization factors on labor productivity, the study seeks to offer empirical evidence to assist managerial decision-making in effectively utilizing digital technologies to improve productivity. Ultimately, this research equips managers with valuable knowledge about the advantages and consequences of digitalization on labor productivity, empowering them to make informed choices to optimize performance within their organizations.

The first chapter of this study examines the definitions of digitalization and labor productivity, as well as the factors influencing them, and analyzes the current state of digitalization and labor productivity in the Russian manufacturing industry with data from Rosstat. Additionally, a literature review is included to explore the impact of digitalization on labor productivity.

Chapter 2 focuses on refining the research model, formulating hypotheses, selecting methodological approaches for evaluating factors, and outlining the strategic methodology for sample selection and data collection.

In Chapter 3, statistical analysis is conducted using data collected directly from representatives of chemical and petrochemical manufacturing firms. Hypothesis testing and evaluation of the research model's significance are carried out, leading to the development of practical recommendations for chemical and petrochemical companies based on the study's findings.

CHAPTER 1. DIGITALIZATION AND LABOR PRODUCTIVITY

Digitalization is a multilateral and complex term that can be interpreted in various ways in the context of everyday business operations. Consequently, it is crucial to establish a precise definition of digitalization and its related concepts, as well as labor productivity. Furthermore, gaining a profound understanding of the factors that influence both digitalization and labor productivity is essential. In addition, it is crucial to identify how and through what channels digitalization affects labor productivity. To accomplish this, the subsequent chapter will undertake a comprehensive review and analysis of existing research in this field.

1. Definition and concept of digitalization

Currently, the term "digitalization" is widely discussed and emphasized in both academic and business settings. However, this term is often used in conjunction with other terms, such as “digital transformation” and “digital innovation”. Although these terms may appear similar, it is essential to differentiate between them.

Osmundsen et al. (2018) proposes a conceptual model for the relationship between digitalization and relevant concepts (Figure 1).

Source: Osmundsen et al., 2018

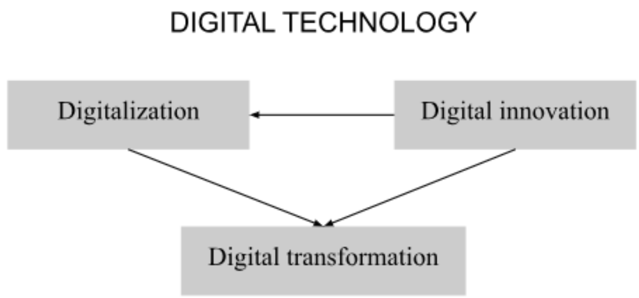

Figure 1. *Conceptual model of digitalization and related concepts.*

According to the scholarly works of Osmundsen et al. (2018) and Verhoef et al. (2021), the term "digitalization" encompasses the utilization of digital technologies to transform socio-technical systems, rather than merely converting analog information into a digital format. Alongside this term, Bloomberg (2018) and Verhoef et al. (2021) highlight the concept of "digitization", which is a more straightforward term referring to the conversion of analog information into binary code (zeroes and ones), enabling computers to store and process such data.

Osmundsen et al. (2018) conceptualizes "digital innovation" as a multifaceted process that involves the creative integration of digital technologies to produce novel solutions, often combining digital and physical elements. This process aims to catalyze socio-technical transformations and generate additional value for end-users.

Regarding the broader concept of "digital transformation", there is currently no universally accepted definition. Various definitions have been proposed by scholars, with a summary of these provided in Table 1.

Table 1. Definitions of the term “digital transformation”.

Source	Definition
Bloomberg (2018)	Digital transformation is a customer-centric strategic initiative that drives business change across the organization. It necessitates the adoption of digital technologies coupled with comprehensive organizational restructuring to align with evolving customer needs and expectations.
Liere-Netheler et al. (2018)	Digital transformation entails leveraging new digital technologies like social media, mobile, analytics, and embedded devices to drive substantial business enhancements such as improving customer experience, optimizing operations, and innovating new business models.
Vial (2019)	Digital transformation is a structured approach aimed at improving an organization by implementing substantial changes to its attributes using a combination of information technology, computing, communication, and connectivity.
Albukhitan (2020)	Digital transformation signifies the fusion of digital technologies and novel business models across all sectors, leading to profound shifts in industry operations and the delivery of value to customers.
Nechaev (2021)	Digital transformation involves the strategic integration of digital and information technologies into enterprises, which has the potential to significantly alter how they operate. This includes activities such as collaborating with partners, conducting research, generating demand, processing data, improving operations, and connecting with global value chains.
Verhoef et al. (2021)	Digital transformation impacts the entirety of a company and its business practices, transcending mere digitalization which focuses on basic organizational processes and tasks. It restructures processes to alter the business logic or value creation mechanisms of a firm.

Source: author’s compilation

To summarize, researchers generally define “digital transformation” as a significant change in an organization's operations, accompanied by the implementation of advanced technologies, with the goal of enhancing business practices.

Given that digital transformation is a relatively broad concept, it is reasonable to examine its constituent parts. Verina and Titko (2019) offer considering digital transformation as a conceptual model including its drivers and outcomes (Figure 2).

Source: Verina and Titko, 2019

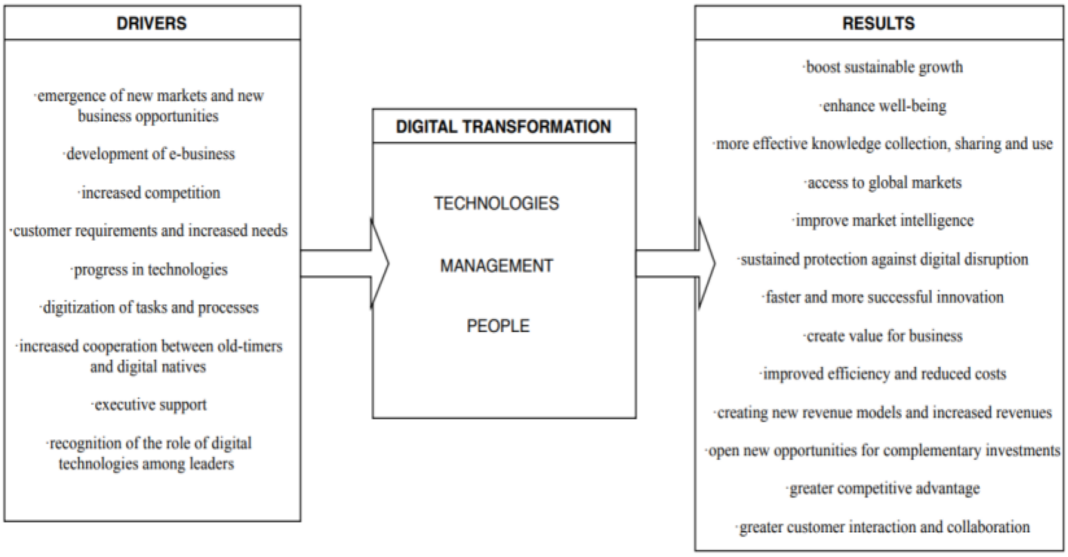

Figure 2. *Conceptual model of digital transformation.*

The concept of digital transformation can be broken down into three key components, as illustrated in the diagram. The central element represents the core of the digital transformation process itself. The elements on either side depict the various inputs and outputs associated with this process. More precisely, these peripheral components encompass the driving factors behind digital transformation initiatives, as well as the anticipated outcomes of successfully implementing such a strategy.

When examining the three primary constituents of a digital transformation framework, the following key aspects emerge.

The category "Management," covers the fundamental aspects of a company's operation, including its business model, operating model and processes, strategic plan, organizational structure, cultural aspects, communication mechanisms, as well as the products and services that it offers.

The "People" category includes all stakeholders, both from the inner and outer perimeter. From the point of view of the internal environment of the company, its human capital can be allocated here, that is, employees, managers, specialists, directors, owners. As for the external environment, it includes not only the company's contractors, including suppliers and partners, but also the customers themselves, as well as competitors and other interested parties. In addition, the category of "People" includes such important aspects as "Talent" and "Competencies".

The most significant and extensive category "Technologies" encompasses all major technologies currently in use or which could be used to digitally transform processes. Numerous researchers and experts have identified several fundamental technologies that underlie digital transformation (Table 2).

Table 2. *Analysis of digital transformation technologies.*

	Artificial Intelligence (AI)	Cloud Services	Internet of Things (IoT)	Robotics	Big Data	3D modeling / Digital twins	Cyber-security	Virtual reality (VR) / Augmented reality (AR)
Deberdieva et al., 2019	+	+	+	+	+	+		
Karapaev & Nureyev, 2019	+		+	+	+			+
Verina & Titko, 2019	+	+	+		+		+	
Kobzev et al., 2020				+	+	+		
Nechaev, 2021		+	+	+	+		+	+
Izmaylov, 2022	+			+	+			
Mechikova & Klimachev, 2023	+	+	+	+	+	+	+	+
Anderton et al., 2023	+	+	+		+			
Todorova, 2023	+	+	+		+	+		+
Total	*7*	*6*	*7*	*6*	*9*	*4*	*3*	*4*

Source: author’s compilation

Table 3. *Analysis of technologies specific to digital transformation in the petrochemical industry.*

	Corporate Information system (CIS)	ERP systems	Advanced Process Control (APC)	Drones, unmanned aerial vehicles (UAVs)	Data Science	Industrial Internet of Things (IIoT)	RFID-technologies	Additive Manufacturing
Albukhitan, 2020			+			+		+
Shinkevich et al., 2020		+	+				+	
Dolonina & Shinkevich, 2021	+	+	+	+	+	+		
Total	*1*	*2*	*3*	*1*	*1*	*2*	*1*	*1*

Source: author’s compilation

The literature review reveals that the main technologies driving digital transformation are Big Data, AI, IoT, Cloud Computing, and Robotics (Table 2). In comparison, Advanced Process Control (APC) emerges as the technology most frequently mentioned in the petrochemical industry literature as being specific to that sector (Table 3).

In turn, Verhoef et al. (2021) proposes a flow model for digital transformation (Figure 3).

Source: Verhoef et al., 2021

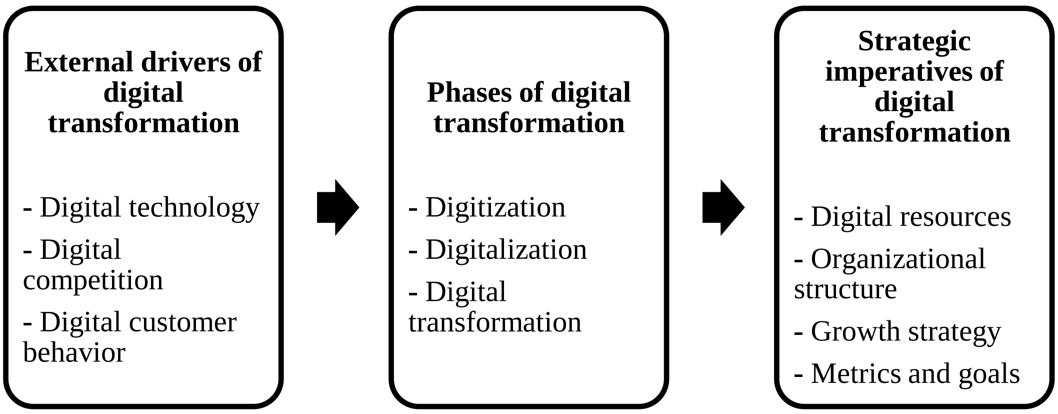

Figure 3. *Flow model of digital transformation.*

The authors' model identifies three major external factors driving the need for digital transformation within the industry. Firstly, the proliferation of relevant technologies clearly indicates that businesses must digitally transform their operations to maintain competitiveness. Furthermore, the introduction of these new digital technologies has the potential to impact a firm's cost structure through the replacement of more expensive human resources with robots or virtual assistants during service delivery, as well as through the optimization of logistics processes and reduction of supply chain costs through the application of artificial intelligence (AI) and blockchain technologies.

Secondly, the rapid evolution of competition within the industry due to these technologies places increased pressure on firms to adopt digital strategies to maintain their market share and ensure long-term success.

Third, consumer behavior is changing in response to the digital revolution. Digital channels play a crucial role in customer experience, influencing both online and physical sales. It is undeniable that if businesses fail to adjust to these changes, they will become less attractive to consumers and are likely to lose out to businesses that do take advantage of these technologies.

In this model, the authors also mention the previously discussed phases of digital transformation. A novel element in this model is the strategic imperatives of digital transformation. The first component pertains to digital resources, which signify a company's ownership and control over assets and capabilities. Assets encompass the company's resource endowments in physical and intellectual forms, while capabilities typically reside in human, information, or organizational capital, serving to integrate assets and facilitate their effective deployment. In addition to the requisite digital resources for achieving digital transformation, a critical consideration is the organizational adjustments necessary to accommodate digital change, particularly in terms of fostering a flexible organizational structure conducive to digital adaptation. Another strategic imperative highlighted by the author is the digital growth strategy. Various digital growth strategies are available to digital enterprises, with a predominant approach involving the utilization of digital platforms. Lastly, the Metrics and Goals imperative is emphasized. To fully leverage the benefits of digital transformation, digital firms must gauge performance enhancements against key performance indicators (KPIs) to support learning and refine the business model.

Vial (2019) provides the most comprehensive model, in the form of digital transformation component blocks (Figure 4).

Source: Vial, 2019

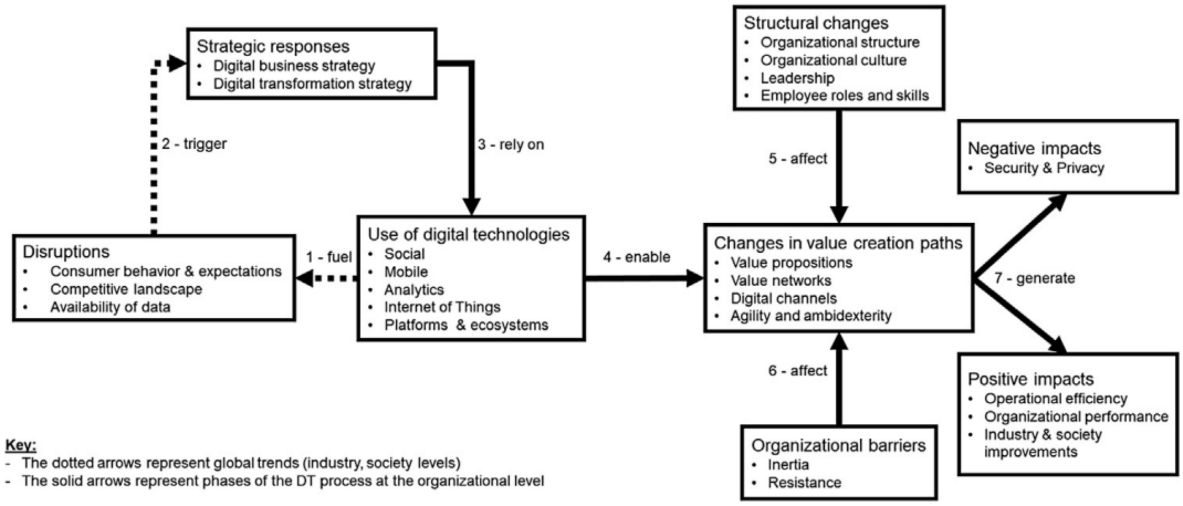

Figure 4. *Blocks of digital transformation process.*

This framework is based on the relationships that emerged between components describing digital transformation (DT) as a process in which digital technologies play a central role in both the creation and reinforcement of disruptions occurring at the societal and industrial levels. These disruptions prompt strategic reactions from organizations, which are a primary focus of DT research.

In synthesizing the three proposed perspectives on digital transformation, it is evident that the strategic selection, effective implementation, and proficient utilization of advanced digital technologies are pivotal. Organizations are urged to not only adopt these technologies but also navigate structural adjustments and surmount impediments that impede their transformative endeavors. These modifications yield favorable outcomes for organizations, and in certain instances, for individuals and society at large. Nonetheless, there exists the potential for adverse consequences. Notably, the frameworks proposed by Verina and Titko (2019), Vial (2019), and Verhoef et al. (2021) underscore the indispensable role of human resources within digital transformation initiatives, prompting further exploration into the precise impact of digital transformation on labor productivity within organizational settings.

2. Definition and concept of labor productivity

It is evident that digitalization has a significant impact on the performance of a company and its overall effectiveness. One of the key indicators of efficiency at present is a company's productivity.

The evolving landscape of digitalization is reshaping the expectations for employment quality. Personal competencies of employees are gaining significance, as they directly influence labor productivity. Shifts in supply and demand dynamics within the labor market are leading to a rise in non-traditional forms of employment. Digitalization enables remote work, freeing employees from geographical constraints. In the contemporary context, employees are expected to possess not only professional expertise but also proficiency in IT technologies and communication skills. These additional competencies empower individuals to engage in new modes of work, such as remote employment, enhancing their adaptability and effectiveness in the evolving digital work environment.

According to Syverson (2011), productivity can be succinctly defined as the output derived from a specific set of inputs. Typically, productivity is quantified as a ratio of output to input.

Nowadays there exist diverse methodologies for assessing productivity levels. In a broad sense, productivity can be characterized as the efficient utilization of resources to accomplish defined objectives. Several key aspects should be emphasized concerning this characterization:

- Efficient resource utilization;
- Clear and comprehensive definition and comprehension of objectives;
- Availability of resources that are dedicated to fulfilling the specified objectives.

Presently, labor productivity remains a pivotal indicator of a nation's economic effectiveness. It signifies the revenue generated by economic entities at both micro and macro levels, playing a crucial role in determining the overall well-being of a population. Various interpretations of the term "labor productivity" are outlined in Table 4.

Table 4. *Definitions of the term "labor productivity".*

Source	Definition
Syverson (2011)	Labor productivity is a metric that represents production

	efficiency by comparing output to a designated input. It signifies the quantity of goods or services generated per unit of input, which may encompass labor hours, workforce size, or a blend of different input factors.
Goel et al. (2017), Kharitonova & Rozanova (2020)	Labor productivity can be understood as a metric that gauges an employee's work efficiency over a defined timeframe. It provides a quantitative assessment of how effectively an individual worker utilizes their time and effort to contribute to the organization's output during a given period.
Shcherbakov (2022)	Labor productivity is a measure of the efficiency with which labor is employed in the production process. It can be determined by taking the total value of goods or services produced and dividing it by the total number of labor hours expended in generating that output. This ratio provides insight into how effectively and efficiently a company or industry utilizes its human resources to generate economic value.

Source: author's compilation

Analyzing the various interpretations of the concept of labor productivity presented above, we can conclude that the productivity of an individual or organization undoubtedly reflects the efficiency level of a person, group of people, enterprise, or industry in general.

With the increasing role of digitalization, the requirements for job quality are evolving. Personal competencies of employees are highly valued as they directly impact labor productivity. Furthermore, there have been shifts in labor market demand and supply, leading to a greater prevalence of non-traditional forms of employment. Digitalization no longer ties employees to specific locations but offers opportunities for remote work. Today, employees are expected to possess not only professional competence but also knowledge of IT technologies and communication skills. These additional skills enable individuals, under equal conditions, to transition to new modes of work, including remote employment.

There are various methodologies for calculating labor productivity metrics. Nechaev (2021) outlines two common approaches: measuring the value of output per unit of time or per employee and calculating a labor productivity index relative to the previous year's data. At the micro level, labor productivity evaluations directly impact the calculation of a company's product cost per unit of time (man-hours). However, assessing labor productivity in enterprises is complex due to the lack of unified statistical databases.

According to Shcherbakov (2022), in organizations that have multiple branches, the productivity of employees in certain roles may not align with market needs. This discrepancy is often a result of insufficient market demand for the products, services, or tasks carried out at these locations, causing the results of their work to be viewed as non-profitable. In such cases, the productivity of labor at these sites is reflective of a potential production capacity that is unique to each location and its workforce, taking into account the available resources and organizational environment.

On the other hand, Goel et al. (2017) characterizes labor productivity as the ratio of output to input labor, but this description is constrained as it presupposes that inputs such as labor, materials, technology, and capital operate independently to affect output. This perspective implies a simplistic cause-and-effect model of productivity, disregarding the interconnected relationships among these inputs where changes in one element can impact others.

In practical scenarios, disparities in labor productivity levels among companies can arise even when they employ identical production technologies, especially if one firm utilizes capital more intensively due to varying factor prices. To address this discrepancy, researchers such as Syverson (2011) and Anderton et al. (2023) employ a productivity measure unaffected by the intensity of observable factor inputs, known as total factor productivity (TFP) or multifactor productivity.

In summary, contemporary challenges in measuring labor productivity encompass issues with output and input metrics, along with variations in productivity levels across companies. Methodological complexities in labor productivity calculations, including the impact of digitalization on job quality and evolving workforce expectations, persist. Labor productivity remains crucial for economic efficiency and societal well-being, highlighting its importance for national rankings and investment attractiveness.

3. Digitalization and labor productivity in Russian petrochemical industry

Petrochemistry is the field of chemistry that is focused on petroleum and its derivatives[1]. In the context of the petrochemical industry, it is evident that this sector plays a vital role within the oil and gas industry and other advanced technology and processing sectors, serving as a foundation for further technological advancements. The demand for petrochemical products continues to rise and is projected to increase significantly by 2030. As the market landscape evolves alongside technological progress, there is a notable shift

[1] Petrochemistry definition. Dictionary.com – Access: https://www.dictionary.com/browse/petrochemistry (date: 10.02.2024)

towards customization. Petrochemical firms are required to adapt to this trend and embrace the changes brought about by the Industrial Revolution, which includes digital transformation and the integration of comprehensive automation across all operational facets. The petrochemical industry is facing a significant shift that requires companies to adopt disruptive technologies to stay competitive in the face of intense market rivalry. Developing innovative solutions that challenge conventional business practices has become essential for petrochemical firms to retain their competitive edge in this rapidly evolving landscape.

When considering the utilization of digital technologies by Russian enterprises in general, it is noteworthy that there has been a decline in the adoption of personal computers, servers, internet usage, and the presence of company websites over the past five years. By the conclusion of 2022, approximately 80% of personal computers and 41% of servers in the Russian Federation were connected to the internet. Additionally, approximately 76% of internet traffic and approximately 46% of organizations in the country would be utilizing the website[2].

Source: author's compilation

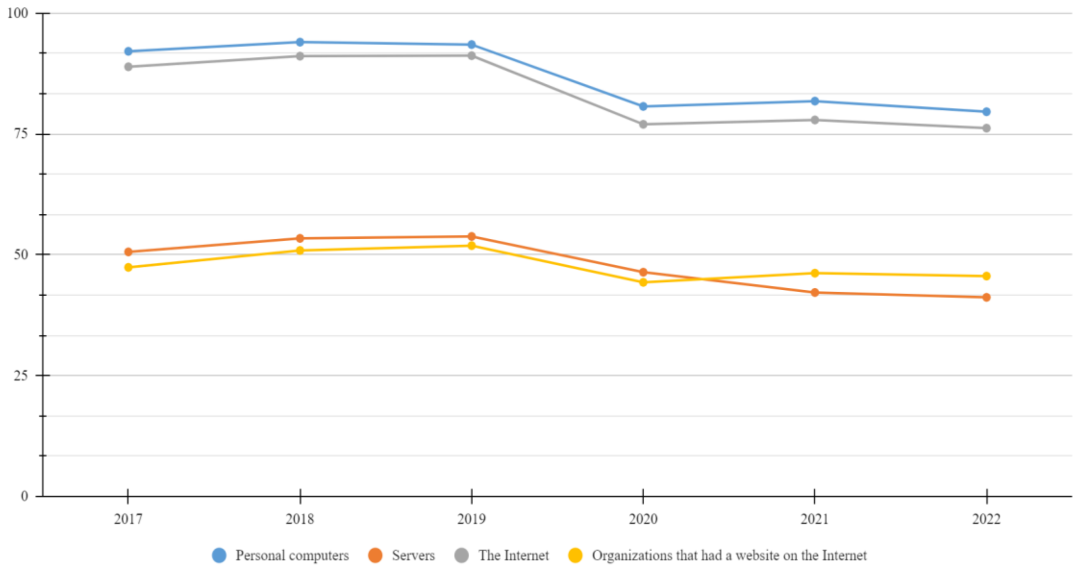

Figure 5. *The dynamics of the proportion of organizations utilizing information and communication technology (ICT) in the Russian Federation.*

[2] Rosstat. Federal State Statistics Service - the Russian federal executive body responsible for gathering official statistical information in the Russian Federation. Access: https://rosstat.gov.ru/ (date: 20.02.2024)

In the past three years, Russian companies have been utilizing modern digital technologies like electronic data exchange, geoinformation systems, digital platforms, data processing technologies, artificial intelligence, cloud services, and the internet of things, as reported by The Federal State Statistics Service[3]. Therefore, based on these statistics, it is difficult to draw a general conclusion about the overall trend in the use of these advanced digital technologies among Russian organizations, as the dynamic usage of various technologies varies (Figure 6).

Source: author's compilation

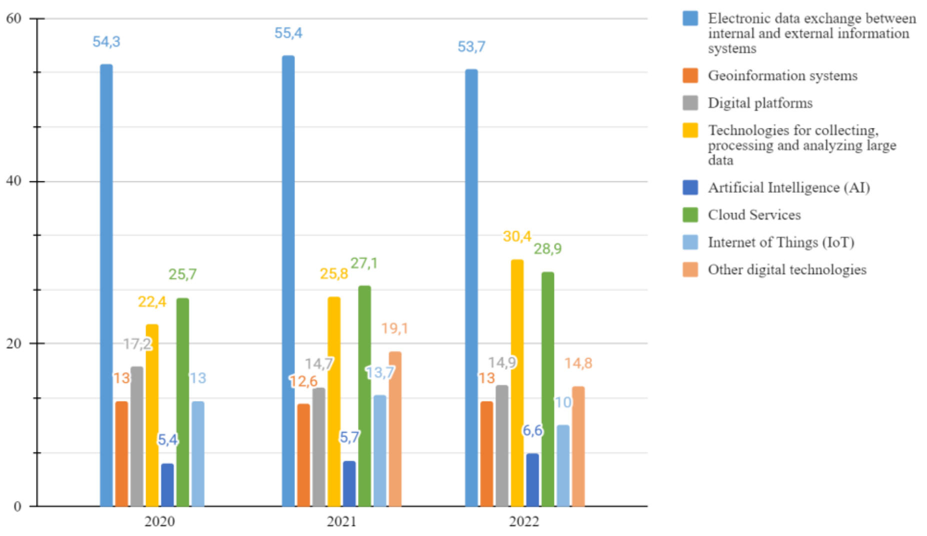

Figure 6. *The dynamics of the proportion of organizations utilizing digital tools in the Russian Federation.*

Returning to the current state of digitalization in the Russian petrochemical sector, it is difficult to draw any general conclusions about trends in the adoption of modern digital technologies. Rosstat has released data on the use of local area networks (LAN), the Internet, and their own websites by companies in the chemical industry in Russia. In this regard, the trend in adoption of these technologies follows a downward path similar to that observed across all Russian organizations. As of the end of 2022, 70% of companies in the chemical sector in Russia used Lens, 88% used the internet, and 60% had their own websites[4].

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[3] Ibid.
[4] Ibid.

According to the Russian Rating Agency for Enterprise Efficiency (RAEX), today, the largest companies operating in the chemical and petroleum chemical industry are EuroChem, SIBUR, UralChem, PhosAgro and Uralkali[5]. The full list of the 10 top-ranked companies in the chemical and petroleum industry, as per the RAEX 600 rating for 2022, is presented in Appendix Table 1.

The dynamics of labor productivity can be observed based on the labor productivity index that is calculated as a ratio of the physical volume of gross value added in an industry to total labor costs in that industry. Gross value added and total labor costs are determined based on the results of activities of institutional units, grouped by their primary type of activity[6]. Regarding the current labor productivity index in Russia, the statistics for the past five years are presented in Figure 7.

Source: author’s compilation

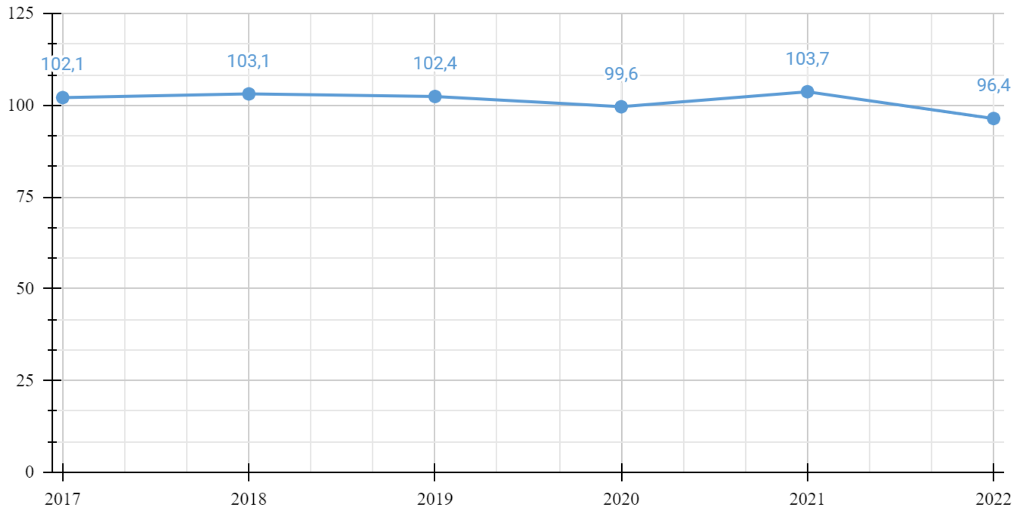

Figure 7. *Labor productivity index in the economy of the Russian Federation in 2017-2022, in % compared to the previous year.*

As shown in the graph, labor productivity in the Russian economy overall decreased by 3.6% in 2022 compared to the previous year[7]. Accurately assessing the level of labor

[5] RAEX. The Russian Rating Agency for Enterprise Efficiency - The 10 largest companies in the chemical and petrochemical industry from the RAEX-600 2022 rating. Access: https://raex-rr.com/largest/including_industry/chemical_industry/2022/ (date: 16.11.2023)
[6] Rosstat. Federal State Statistics Service - the Russian federal executive body responsible for gathering official statistical information in the Russian Federation. Access: https://rosstat.gov.ru/ (date: 20.02.2024)
[7] Ibid.

productivity in the Russian petrochemical industry is challenging due to the limited availability of published data from Rosstat regarding productivity levels of companies within this sector.

Based on the assessment of the current status of digitalization and labor productivity in the Russian petrochemical sector, it is evident that the rate of digitalization has been gradually slowing down in recent years. Additionally, in 2022, there was a notable decline in the level of labor productivity across the Russian economy.

The labor productivity within an economy, industry, or company is influenced by various factors, making it difficult to attribute the growth solely to one factor like digitalization. Rosstat's data on the labor productivity index provides a holistic view of the collective impact of factors such as innovations, investments, and research and development on productivity growth at a macro level.

4. Theories about factors affecting digitalization and labor productivity

To thoroughly analyze the factors influencing digitalization and labor productivity, it is crucial to establish a clear understanding of what constitutes a factor. A factor can be defined as an element, circumstance, condition, or influence that contributes to a specific outcome.

While the concept of digitalization is relatively recent, various theories have emerged in this domain, broadly categorized into those focusing on the drivers of digitalization and those emphasizing critical success factors.

- The Diffusion of Innovations (DOI) model, originally developed by Everett M. Rogers in 1962 and expanded in 1996, was created to explain how innovations are adopted through various factors such as individual characteristics, organizational attributes, and external influences. It has since been applied to understand how organizations integrate information technology (IT) and digital solutions.
- The Technology, Organization, and Environment (TOE) framework, introduced by Tornatzky and Fleischer in 1990, proposes that the adoption of technological innovations is influenced by three main factors: the technological context (existing and new technologies), organizational context (firm characteristics and resources), and environmental context (industry dynamics, competitors, and regulatory factors).

These theories and models provide valuable insights into the factors that drive digitalization within organizations, enabling researchers and practitioners to identify and analyze the key elements that contribute to the successful adoption and implementation of digital technologies.

The Technology-Organization-Environment (TOE) framework is a valuable tool for understanding how companies integrate new technologies into their strategies and operations[8]. This framework enables the analysis of factors influencing innovation adoption and implementation, thereby aiding managers in identifying areas for enhancement. Instead of viewing organizational, technological, and external contexts as separate entities impacting decision-making, the technological environment acts as a link between organizational and external factors in shaping company decisions. Decision-making is swayed by how organizational and external factors influence technological considerations.

Both the Diffusion of Innovations (DOI) and Technology-Organization-Environment (TOE) frameworks highlight the importance of internal and external influences in driving businesses to adopt digital technology. While the DOI theory focuses on individual attitudes towards innovation, the TOE model prioritizes external and technological factors.

Scholarly research shows that combining these theories helps to understand the drivers behind digital technology adoption and the resulting business transformation. Factors driving this transformation include changes in customer behavior and expectations, advancements in technology, industry trends, shifts in competition, and regulatory changes. These factors align more closely with the TOE model [Osmundsen et al., 2018].

Most researchers define the factors driving digitalization by investigating barriers that impede organizations from embracing digital technologies. These barriers are divided into internal organizational factors like resistance to change, lack of digital skills, and inadequate financial resources, as well as external factors such as regulatory constraints, absence of industry standards, and inadequate digital infrastructure [Deberdieva et al., 2019; Dolganova & Deeva, 2019; Mityaeva & Zavodilo, 2019; Karapaev & Nureyev, 2019; Altukhova, 2020; Albukhitan, 2020; Dolonina & Shinkevich, 2021; Izmaylov, 2022].

[8] Gillani, F., Chatha, K. A., Jajja, M. S. S., & Farooq, S. (2020). Implementation of digital manufacturing technologies: Antecedents and consequences. International Journal of Production Economics, 229, 107748. https://doi.org/10.1016/j.ijpe.2020.107748

Thus, analyzing the work of the above-mentioned researchers, it can be noted that the most frequently mentioned "fear factors" or barriers that hinder organizations on the path to digital transformation are the following. First of all, lack of skills among employees or a lack of qualified personnel. Secondly, outdated infrastructure, lack of consistency and fragmentation within the organization. Thirdly, the high cost of digital transformation, coupled with the specific ethical decline of digital products and services and insufficient budget, poses significant challenges for organizations.

In addition to the factors discussed earlier, there could be additional challenges such as reluctance to change, setting unrealistic expectations, or lacking awareness of the digital transformation process and information security issues. Several researchers [Liere-Netheler et al., 2018; Osmundsen et al., 2018; Albukhitan, 2020; Dolonina, & Shinkevich, 2021] have focused on the motivators, advantages, and key success factors of digitalization in their research. Key drivers of digitalization include cost savings, support from management, employee involvement, and government participation. The primary benefits of digitalization encompass enhanced and streamlined business operations, sustainable expansion, improved working conditions, and heightened security measures.

In their examination of the petrochemical industry, Hassani et al. (2017) delineate the critical prerequisites for digital transformation in these enterprises:

- Ensuring the sustainable use and production of petroleum;
- Competing effectively with other industries;
- Automating tasks that are expensive, hazardous, or prone to errors;
- Addressing challenges linked to low oil prices;
- Securing access to future oil and gas reserves.

Lenkova et al. (2017) emphasize the current drivers of digitalization within Russian petrochemical firms. The researchers classify these drivers into 7 primary categories, as detailed in Table 5.

Table 5. *Drivers of digitalization in Russian petrochemical companies*

Group of factors	Description
Political and legal	The absence of clear legislative guidelines in areas such as taxation, patents and licenses, depreciation, and antitrust poses a challenge in establishing a regulatory framework that could effectively support, regulate, and incentivize innovative endeavors within oil and gas chemical companies.

Financial and economic	Insufficient financial support for pioneering projects, a prioritization of short-term strategies over long-term objectives, a lack of robust material, technical, and scientific research foundation, restricted reserves, an emphasis on immediate profits, and insufficient investment support from the parent company within the framework of corporatization are hindrances to advancement.
Organizational and management	Outdated, rigid organizational management structures, authoritarian (bureaucratic) leadership styles, departmental silos, excessive centralization, and limited industry-wide and regional collaboration contribute to operational constraints.
Social and psychological	Deep-seated stereotypes, uncertainty, resistance to change, and behavioral unpredictability further hinder advancements.
Scientific and educational	Insufficient education and training for managers at all levels in innovative management, along with a lack of a unified system for personnel development, greatly hinders the success of innovative projects.
Technical and technological	Outdated equipment and technology, lack of modern infrastructure, and minimal resources all create barriers to implementing new and innovative solutions.
Research	Scarce funding and inadequate state support pose obstacles to fundamental and applied research and development in the field of oil and gas chemistry. Furthermore, the limited engagement of academic researchers from universities in scientific inquiry raises concerns regarding research involvement.

Source: Lenkova et al., 2017

When examining factors that impact a company's efficiency, labor productivity serves as a key indicator. Goel et al. (2017) offers a comprehensive taxonomy and detailed analysis of the elements influencing labor productivity. The researchers classify these factors based on their origin and their effect on individual employees, the organization as a whole, and the industry (Table 6).

Table 6. *Labor productivity factors*

Category	Factors
Internal to employee	• Employee's physical and mental well-being; • Employee motivation and enthusiasm; • Employee education; • Employee attitudes, beliefs, values, and skills.
Internal to organization but external to employee	• Working conditions; • Compensation;

	• Work environment; • Organizational structure and culture; • Training, learning, and development opportunities; • Human resource policies; • Technology adoption compared to industry standards; • Emphasis on clear business objectives; • Focus on enhancing productivity.
Internal to industry but external to organization	• Number of competitors in the industry; • Regulatory bodies within the industry.
Internal to nation but external to industry	• Macroeconomic conditions of the country; • Government regulations and policy changes.
International factors	• Movement of skilled labor across countries; • Adoption of global best practices and technological advancements; • Global macroeconomic conditions.

Source: Goel et al., 2017

In addition to the aforementioned factors, Simachev et al. (2020) also highlight such factor as the duration of a company's activity. The author points out that the young workforce of a company is an important factor in the dynamic of labor productivity, along with the size of the firm, which can be explained by its more advanced technological and organizational capabilities. Furthermore, according to the author, growth in labor productivity is driven by the availability of investment, and this trend is observed in both leading companies in terms of labor productivity and those with lagging performance.

Shcherbakov (2022) has broadened the analysis of labor productivity factors to include elements related to distribution, such as the effectiveness of marketing strategies, market conditions, and a company's market position. While this approach may seem unconventional, it suggests that improved labor productivity can lead to increased sales and overall commercial success.

Upon examining the factors pertaining to digital transformation and labor productivity, the following deductions can be drawn. When assessing the factors influencing digital transformation within most organizations, the focus is often on the impediments hindering the integration of advanced digital technologies by contemporary entities. These obstacles bear resemblance to those encountered by firms across various industries. Regarding factors associated with labor productivity, multiple research endeavors have posited a correlation between the adoption of digital technologies and heightened labor productivity. These investigations propose that the introduction of novel digital tools, such as investments in digital initiatives, may foster favorable advancements in labor productivity. Nonetheless, these conclusions are subject to debate, with limited empirical support available to substantiate them.

5. Connection between digitalization and labor productivity

The relationship between increased labor productivity and the integration of advanced digital technologies is a topic of significant interest and importance. Goel et al. (2017) explores the correlation between enhanced labor productivity, the adoption of advanced digital technologies in organizations, the allocation of research and development funds, and the subsequent rise in these expenditures.

Moreover, Varlamova and Larionova (2020) emphasize that incorporating digital technologies, such as information and communication technologies (ICT), has the potential to boost labor productivity by expediting business processes, cutting transaction costs, and optimizing resource utilization. These technologies enable businesses to achieve higher productivity levels through automation, data analysis, and improved operational efficiency. Additionally, the authors present a conceptual model illustrating the pathways through which digital transformation impacts labor productivity (refer to Figure 8).

Source: Varlamova & Larionova, 2020

Figure 8. *Conceptual model of the channels through which digital transformation affects labor productivity.*

The proposed model delineates the following concept: digital transformation entails the extensive integration of Information and Communication Technologies (ICT) within organizational frameworks. This integration subsequently fosters the informatization of labor processes, often culminating in their automation and robotization, thereby amplifying the intricacy of production procedures. In parallel, digital transformation has catalyzed a rapid expansion of high-tech sectors, prompting a metamorphosis in their manufacturing methodologies. Consequently, within the realm of digital transformation's impact on labor productivity, we have identified two primary avenues: the dissemination and utilization of foundational digital transformation assets such as personal computers and internet accessibility and the proliferation of high-tech industries as principal entities in digital production.

Borovskaya et al. (2020) highlight how digitalization can impact labor productivity in terms of efficiency outcomes. Their research indicates that digitalization has the capacity to enhance labor productivity through the optimization of workflows, improvement of production processes, and better allocation of resources. The efficiency gains derived from digital transformation can enhance output per labor hour, thereby fostering comprehensive productivity enhancements in sectors like petrochemicals. The researchers suggest that the progress made in digital transformation and labor productivity are closely linked, presenting opportunities to enhance labor productivity growth. These opportunities include:

- Improving the quality of data collection and processing related to economic digital transformation at the federal level;
- Increasing efforts to teach digital skills through additional education programs, especially in vocational training;
- Encouraging a culture that values digital knowledge and incorporates it as a key factor in production, expanding the use of digital skills in various social and professional settings;
- Streamlining data processing, improving information exchange speed, reducing the duration of business processes, and enhancing efficiency in interactions within technological processes as ways to identify potential efficiency gains;
- Developing models for territorial-industrial development in federal districts to improve territorial and industrial connectivity within the framework of digital transformation.

Conversely, a subset of scholars [Skinner, 2014; Van Ark, 2016; Anderton et al., 2023] focus on the reciprocal relationship between digital transformation and labor productivity. Despite the availability of advanced digital tools, significant challenges hinder substantial growth in labor productivity. Issues such as measurement inaccuracies in the service sector, delays in technology implementation, and complexities within organizational settings can impede the full potential of digital technologies to enhance productivity. This phenomenon, known as the "Productivity Paradox," has been a central theme in economic analysis. Scholars have proposed various explanatory frameworks encompassing measurement inaccuracies, delays in technology adoption, slowdowns in technological progress, and barriers to effectively disseminating innovations across industries.

6. Conclusion on Chapter 1

The digitalization of industries creates significant opportunities for businesses and presents them with global challenges. Opportunities offered by efficient production and novel business models are promising, but the risks are equally significant. Big data analytics, automation, and the digital customer interface challenge established value chains, necessitating that businesses increase their digital maturity, establish information and communication infrastructures, and coordinate their actions based on regulatory frameworks, as standards define the digital future.

Digitalization in the manufacturing sector affects individuals, as well as business entities, enterprises, and corporate networks. While the adoption and adaptation of new technologies is possible, the main challenge lies in the ability of individuals to adopt, implement, train, and optimize processes utilizing these technologies.

Analyzing literature sources regarding digitalization and related concepts, it can be noted that human factors receive limited attention. However, several researchers have pointed out that successful digitalization requires motivated employee involvement and that the human component is more significant than the technological aspect.

When discussing the definition of labor productivity, this chapter examined various approaches to defining the concept, as well as practical methods for assessing labor productivity. However, one of the primary factors contributing to labor productivity growth is the overall advancement of science and technology, including the adoption of digital technologies and the computerization of work.

In considering the relationship between digitalization and labor productivity, there are currently two approaches in literature. On one hand, digitalization enhances labor productivity. On the other hand, the concept of the "Productivity Paradox" is mentioned, suggesting the opposite effect.

CHAPTER 2. DEVELOPMENT OF RESEARCH MODEL

This chapter concentrates on finalizing the research model by conducting a thorough review of related literature to pinpoint potential factors impacting digitalization and labor productivity. After selecting key factors from the literature, hypotheses are developed to shape the research model. Moreover, this chapter delves into the methodologies chosen to evaluate these factors, along with the strategic approach employed for selecting samples and collecting data.

1. Development of research framework and research propositions

1.1. Factors overview

To develop a comprehensive research model, it is crucial to gain a thorough understanding of the factors influencing a company's digital transformation. This section will delve into an extensive analysis of these factors, commencing with a review of traditional theories and an examination of factors outlined in the Diffusion of Innovations (DOI) model discussed in Chapter 1.

The DOI model categorizes factors into three groups, with the initial group focusing on individual characteristics. In this category, the model underscores the importance of attitudes towards change, particularly highlighting the mindset of top management, key decision-makers, and organizational leaders in accepting innovation. The readiness of these individuals to incorporate new methods and their openness to innovation are crucial for the organization to adopt new technologies and digital transformation efforts. A positive outlook on change from both employees and management not only increases the likelihood of effectively implementing new technologies but also impacts the success of the digital transformation journey. Verina and Titko's (2019) research on digital transformation further highlights the importance of cultural values and attitude towards change in propelling and supporting digital transformation endeavors.

The success of a company's digital transformation is heavily impacted by internal organizational factors derived from the DOI and TOE frameworks. These factors play a vital role in shaping the organizational environment and facilitating the adoption of new technologies. Moreover, the following factors have also been recognized as advantageous for digital transformation in the TOE model and in the research by Chau and Tam (1997).

1) Formalization refers to the extent to which a company's operations are governed by established rules and procedures. Companies with higher levels of formalization find it easier to adopt new technologies, highlighting the importance of clear regulations and operational protocols in successful digitalization. Such companies require less time, resources, and effort to implement digital initiatives.

2) Centralization refers to how power and decision-making authority are distributed within the organizational structure.

3) The size of the company, determined by the size of its workforce. Organizational slack, which indicates the availability of unallocated resources, plays a key role in the DOI model. Having higher levels of slack can aid in the adoption of innovation.

4) Interconnectedness indicates the level of connectivity among components of the corporate social system through interpersonal networks.

5) Organizational complexity refers to the intricacy of corporate infrastructure and the depth of knowledge and skills possessed by organizational members. While complexity can present challenges to adoption, it can also motivate companies to seek technological solutions to enhance efficiency and overcome barriers.

These internal organizational characteristics, derived from the DOI and TOE frameworks, collectively shape the organizational environment and significantly impact the success of digital transformation initiatives[9].

Alongside internal factors, the DOI model incorporates external organizational characteristics, including system openness, which refers to how accessible a company's technological infrastructure and business network are to outside connections. System openness is seen as a beneficial factor in enabling digital transformation initiatives.

The TOE framework, discussed in Chapter 1, is a recognized model that categorizes the factors influencing digital transformation into technological, organizational, and external components.

Technological factors play a crucial role in propelling digital transformation. The introduction of new technologies is a key facilitator, making it easier to adopt innovations successfully. Companies operating in environments where competitors are embracing new

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[9] Chau, P. Y., & Tam, K. Y. (1997). Factors affecting the adoption of open Systems: an exploratory study. Management Information Systems Quarterly, 21(1), 1. https://doi.org/10.2307/249740

technologies, consumers are tech-savvy, and the market is favorable are more likely to embrace digital changes. The incorporation of technology into the market compels all industry participants to adjust and stay current with the latest advancements. Furthermore, the unique characteristics of current technology, including industry-specific features, company attributes, owned equipment, and technological infrastructure, influence the path of digital transformation and inform future strategies.

Organizational factors within the TOE framework correspond to the "Internal organizational characteristics" category in the DOI model. Important components consist of organizational size, availability of resources, formal and informal structures, and communication processes, all of which collectively impact the organizational environment's support for or resistance to digital transformation initiatives.

External factors within the TOE framework focus on macro and business environment elements, such as industry characteristics, market dynamics, competitive pressures, technology support, infrastructure, and government influences. Industry-specific attributes like growth rates, developmental stages, and uncertainty levels play a significant role in shaping digital transformation efforts. While a flourishing and steady industry creates favorable conditions for organizational changes, excessively stable environments can breed complacency and opposition to change, whereas unstable conditions may prompt firms to improve their adaptability, competitiveness, and resilience, thereby facilitating technology adoption and digital transformation. Industry competition compels companies to boost their competitiveness and market position, serving as a driving force in the digital transformation journey.

The TOE framework forms a foundational model that underpins subsequent theories and models, providing a consistent set of factors that can be systematically categorized across existing research.

Verhoef et al.'s (2021) study highlights the importance of external factors in propelling digitalization, particularly focusing on digital technology, digital competition, and digital customer behavior. The rapid evolution of technology, diverse options available, and accessibility of innovations mirror the technology availability aspect of the TOE theory. The arena of digital competition has been altered by technological advancements, allowing companies to leverage technology adoption to gain a competitive advantage and alter the market environment. The evolution of digital customer behavior includes shifts in customer expectations, needs, and purchasing patterns as a result of global digitalization, necessitating companies to embrace technologies such as online sales and marketing platforms, big data analysis, and AI to remain competitive.

Verina and Titko (2019) also highlight the essence of digitalization, emphasizing the integration of digital technologies into all aspects of business operations to create value for customers and stakeholders. The outcomes of digitalization, as outlined by the authors, include enhanced customer experience, improved operational efficiency, increased competitiveness, and the ability to adapt to rapidly changing market conditions.

Overall, both Vial (2019) and Verina and Titko (2019) provide valuable insights into the drivers, essence, and outcomes of digital transformation and digitalization within the context of consumer behavior. By understanding these frameworks and models, businesses can better navigate the challenges and opportunities presented by the digital era and leverage digital technologies to drive innovation and growth.

Table 7 represents an analysis of 23 factors related to digitalization. The factors are categorized based on the environment of their influence: internal and external.

Table 7. *List of factors affecting DT of a company.*

		Factor	Source
internal	1	Organizational culture	Osmundsen et al. (2018) Verina and Titko (2019) Mityaeva and Zavodilo (2019) Dolganova and Deeva (2019) Vial (2019)
	2	Readiness to accept changes	Lenkova et al. (2017) Mityaeva and Zavodilo (2019) Deberdieva et al. (2019) Verina and Titko (2019) Albukhitan (2020) Altukhova (2020) Mechikova (2023)
	3	Financial situation in a company	Mityaeva and Zavodilo (2019) Deberdieva et al. (2019) Dolganova and Deeva (2019) Verina and Titko (2019) Albukhitan (2020) Altukhova (2020) Ozornin (2020) Dolonina and Shinkevich (2021) Mechikova (2023)

	4	Staff knowledge and competence	Verina and Titko (2019) Mityaeva and Zavodilo (2019) Dolganova and Deeva (2019) Albukhitan (2020) Altukhova (2020) Dolonina and Shinkevich (2021) Mechikova (2023)
	5	Organizational structure	Lenkova et al. (2017) Mityaeva and Zavodilo (2019) Albukhitan (2020) Ozornin (2020)
	6	Communication and consensus inside the company	Osmundsen et al. (2018) Karapaev and Nureyev (2019) Mityaeva and Zavodilo (2019)
	7	Self-motivation of employees	Verina and Titko (2019)
	8	Support from senior management	Liere-Netheler et al. (2018) Dolganova and Deeva (2019) Karapaev and Nureyev (2019) Altukhova (2020)
	9	Digital strategy of the company	Osmundsen et al. (2018) Verina and Titko (2019) Mityaeva and Zavodilo (2019) Dolganova and Deeva (2019) Dolonina and Shinkevich (2021)
	10	Automation of processes	Verina and Titko (2019) Albukhitan (2020) Mechikova (2023)
	11	Maturity of business processes	Liere-Netheler et al. (2018) Verina and Titko (2019) Dolganova and Deeva (2019)
	12	System of tools to assess digital transformation	Altukhova (2020) Ozornin (2020)
	13	Roadmap of transformation activities	Osmundsen et al. (2018)
	14	Technology adoption	Osmundsen et al. (2018) Albukhitan (2020) Ozornin (2020)
external	15	Data security	Mityaeva and Zavodilo (2019) Albukhitan (2020) Mechikova (2023)
	16	Qualification of external specialists	Osmundsen et al. (2018) Mityaeva and Zavodilo (2019) Deberdieva et al. (2019) Altukhova (2020) Ozornin (2020) Dolonina and Shinkevich (2021) Mechikova (2023)

	17	Customer demand	Liere-Netheler et al. (2018) Osmundsen et al. (2018)
	18	Business specifics, geolocation	Deberdieva et al. (2019)
	19	Number of competitors	Albukhitan (2020) Ozornin (2020) Mechikova (2023)
	20	Availability of domestic digital products	Mechikova (2023)
	21	Development of IT solutions	Verina and Titko (2019)
	22	Economic situation, government policy	Liere-Netheler et al. (2018) Dolonina and Shinkevich (2021)
	23	Technological integration of the company and its counterparties	Ozornin (2020)

Source: author's compilation

When examining the factors that affect labor productivity, they can be categorized in different ways. Goel et al. (2017) identifies five main categories: factors internal to the employee (IE), factors internal to the organization (IO) but external to the employee, factors internal to the industry (II) but external to the organization, factors internal to the nation (IN) but external to the industry, and international factors (INT). The author suggests organizing these factors into two broad groups:

- Internal factors that can be controlled, which include IE and IO factors;
- External factors that cannot be controlled, such as II, IN, and INT factors.

Similarly, Lutchenko et al. (2019) offer a breakdown of the various factors that influence labor productivity. These include aspects such as resource management (including human resources, capital, energy, materials, and information), different forms of interaction (technological, economic, behavioral, political, structural, and process-related), and factors that vary depending on the size of the enterprise unit being analyzed (individual, group, or entire enterprise.

Simachev et al. (2020) draw attention to the fact that, in addition to the size of firms, their youth is a significant factor in labor productivity dynamics, likely due to their more modern technological and organizational levels. Research suggests that labor productivity growth, like current labor productivity levels, is positively correlated with investments, a trend seen in both high-performing and low-performing companies in terms of labor productivity. Additionally, there is a link between enhanced labor productivity and companies' adoption of cutting-edge digital technologies, investment in research and development (R&D), and notably, the escalation of R&D spending.

Thus, a summary of the factors considered by several researchers [Syverson, 2011; Goel et al., 2017; Lutchenko et al., 2019; Kharitonova and Rozanova, 2020; Simachev et al., 2020] is presented in Table 8. Similar to the case of digitalization factors, the presented labor productivity factors are categorized based on the environment of their influence: internal and external.

Table 8. *List of factors affecting labor productivity in a company.*

		Factor	Source
internal	1	Organizational culture	Goel et al. (2017) Lutchenko et al. (2019)
	2	Staff knowledge and competence	Goel et al. (2017) Lutchenko et al. (2019) Kharitonova and Rozanova (2020)
	3	Motivation and enthusiasm	Goel et al. (2017) Lutchenko et al. (2019)
	4	Duration of company activity	Simachev et al. (2020)
	5	Headcount	Simachev et al. (2020)
	6	Innovative activity	Simachev et al. (2020)
	7	Organizational structure	Goel et al. (2017) Lutchenko et al. (2019) Simachev et al. (2020)
	8	Training, learning and development	Goel et al. (2017)
	9	Technology adoption	Goel et al. (2017)
	10	Pay	Goel et al. (2017) Lutchenko et al. (2019)
external	11	Qualification of external specialists	Goel et al. (2017) Simachev et al. (2020) Kharitonova and Rozanova (2020)
	12	Number of competitors	Syverson (2011) Goel et al. (2017) Simachev et al. (2020)
	13	Economic situation, government policy	Goel et al. (2017) Lutchenko et al. (2019) Simachev et al. (2020)

Source: author’s compilation

Based on this list of factors of both concepts of digitalization and labor productivity, the selection factors for the research model would be conducted in the next paragraph.

1.2. Selection of factors

To enhance the significance and exploratory power of the research model, a decision was made to focus on the most influential factors that have the most pronounced impact on both digitalization and labor productivity within a company.

In Tables 7 and 8, a total of 36 factors are presented. Upon deeper analysis, it was observed that some of the analyzed factors are common to both digitalization and labor productivity. In other words, such factors have an influence on both concepts. Therefore, the factors that are most frequently mentioned by researchers as the most influential, and are also common to both concepts, were identified. Additionally, these factors were renamed, and some were grouped together to structure the research model and improve its readability (Table 9).

Table 9. *Factors selected for further in-depth research.*

	Initial factor name	*Proposed factor name*	*Meaning in the research*
1	Availability of domestic digital products; Development of IT solutions; Innovative activity.	Innovative push	The existence of cutting-edge technologies within the industry, either already embraced by competitors or holding the potential to deliver substantial advantages and success to the organization.
2	Number of competitors.	Competition	The degree of competitiveness within the market in which the company operates.
3	Readiness to accept changes; Communication and consensus inside the company; Support from senior management;	Attitude to digitalization and change	The stance towards changes and Digital Transformation (DT) within the organization, as perceived and resisted by top management and personnel.
4	Automation of processes; Technology adoption;	Corporate technology	The distinct characteristics of the existing information systems utilized within the organization in terms of their intricacy, adaptability, and interconnectivity.

5	Business specifics, geolocation.	Market condition	The present state of the market in which the company operates, encompassing its level of economic well-being and stability.
6	Staff knowledge and competence; Qualification of specialists; Training, learning and development.	Employee competence	The level of knowledge and qualifications of the company's employees, as well as the skills they possess.
7	Technological integration of the company and its counterparties; Digital strategy of the company.	Alignment of Business and IS	How well do the company's utilization of information systems (IS) align with its business objectives and strategic direction.

Source: author’s compilation

Based on these factors research hypotheses would be formulated and research model would be constructed.

2. Proposition of research model

2.1. Structural Equation Modeling

Modeling is a well-established method in research and analysis used to explore different phenomena by developing a model that represents the subject of study in a controlled and scaled-down manner. This study focuses on utilizing Structural Equation Modeling (SEM), an advanced statistical technique that integrates regression analysis, path analysis, and factor analysis to examine causal relationships[10]. One key advantage of SEM is its capability to estimate latent variables, which are abstract concepts that are not directly measurable, such as factors influencing a company's digitalization, inferred from indirect indicators for analysis.

SEM uses measurement and analysis models to uncover hidden variables using observable ones. A structural model then shows the relationships between these hidden variables. Through separate regression equations, the connections between the components identified in SEM and real-world data are estimated. This structural modeling framework consists of two main elements: the measurement model, which looks at how hidden variables are linked to their observable indicators to find factor structures, and the structural

[10] Ozherelyeva, T. A. (2017). Structural modeling equations. Prospects of science and education, (2 (26))

model, which evaluates causal relationships between dependent and independent variables affecting the hidden variables in the model, demonstrating how factors interact with each other and with the main phenomena.

The research design encompasses the implementation of five statistical methods: path analysis, exploratory factor analysis (EFA), confirmatory factor analysis (CFA), mediating effect analysis, and moderating effect analysis. Each of these methods serves a specific purpose in understanding the relationships between variables and refining the model structure.

1) Path analysis is used to estimate the direct and indirect effects of digitalization factors on labor productivity. This method is crucial in determining the magnitude and direction of the impact of each factor on digital transformation. The outcome of this analysis is a path diagram that illustrates the relationships between variables in a linear equation form.

2) Exploratory factor analysis (EFA) is employed to identify the underlying latent constructs associated with observed items. The primary objective of EFA is to refine the structure of latent variables by validating or modifying the proposed factor structure. This process is essential in gaining insights into the composition of factors and their relationships with the research subject.

3) Confirmatory factor analysis (CFA) is utilized to validate the proposed connections between observable items and latent constructs. It is applied when the structure of latent variables has been predetermined and needs validation. CFA aims to assess the overall model fit, establish its significance, and evaluate the model's explanatory power. Various coefficients are employed to assess the model's goodness of fit.

4) Mediating and moderating effect analysis is used to identify potential mediating variables that mediate the impact of independent variables on the dependent variable. This analysis also assesses the presence of moderating variables that influence the magnitude and direction of the relationship between other dependent variables and independent variables. These analyses enrich the depth and scope of the research inquiry by unveiling underlying relationships among research variables.

Overall, the combination of these analytical approaches provides a comprehensive understanding of the impact of digitalization on labor productivity and the underlying mechanisms driving this relationship.

Structural Equation Modeling (SEM) offers numerous advantages[11]. Unlike exploratory approaches such as principal components analysis (PCA) and partial least squares (PLS), which primarily focus on exploration rather than hypothesis testing, SEM and Confirmatory Factor Analysis (CFA) are confirmatory in nature. SEM allows for the simultaneous estimation of relationships between latent variables, enabling the statistical testing of multiple hypotheses within a model. It not only evaluates direct relationships but also complex structured models involving mediation, moderation, and grouping. CFA, a component of SEM, provides detailed insights into model issues, aiding researchers in identifying and rectifying problems when model fit is inadequate.

One notable strength of SEM is its ability to analyze error variance separately from unexplained variance in latent constructs, facilitating model refinement. However, SEM does have limitations[12]. The assessment of latent constructs is susceptible to subjectivity owing to their inherent abstractness, which can introduce inaccuracies in estimation. To address this potential bias, scholars have the option to utilize established assessment methodologies or perform initial exploratory examinations of measurement frameworks. Furthermore, Structural Equation Modeling (SEM) demands a substantial sample size and imposes constraints on the number of parameters estimated in relation to known values.

Despite these constraints, SEM remains highly suitable for studies necessitating the examination of structural models involving latent variables. Its confirmatory approach, capability for intricate modeling, and provision of comprehensive insights render it a valuable instrument for hypothesis testing and model enhancement within research settings.

2.2. Hypotheses and research model

To investigate the digitalization of organizations, seven key factors were identified for further examination. However, to assess the influence of these factors not only on digitalization but also on labor productivity, an additional hypothesis was incorporated. Consequently, a research model was developed based on a total of eight hypotheses.

[11] Lahey, B. B., et al. (2012). Using confirmatory factor analysis to measure contemporaneous activation of defined neuronal networks in functional magnetic resonance imaging. NeuroImage, 60(4), 1982–1991. https://doi.org/10.1016/j.neuroimage.2012.02.002

[12] Werner C., Schermelleh-Engel K. Structural equation modeling: Advantages, challenges, and problems [online resource] //Introduction to Structural Equation Modeling with LISREL. – 2009. – Access: http://kharazmi statistics.ir/Uploads/Public/MY%20article/Structural%20Equation%20Modeling.pdf (date:25.03.2024)

H1: *High level of employees competence positively impacts Digitalization of the entire company.*

The hypothesis posits that companies are more likely to succeed in their digital transformation efforts when their employees possess advanced digital skills and competencies. It is believed that having employees with strong digital skills is essential for thriving in today's increasingly digital landscape. To fully utilize digital technologies, companies need employees who can effectively utilize digital tools. The impact of digitalization on employees' future competencies is a crucial factor that influences the overall success of a company's digital transformation. Well-educated employees are able to understand the complexities of their work and can adapt to new digital roles and technologies within the organization. As a result, investing in employee education and development can greatly enhance a company's digitalization process.

H2: *Positive attitude to change in the organization, positively impacts Digitalization of the entire company.*

It is believed that organizations with a positive outlook on change are more likely to effectively carry out digitalization projects. This is due to their willingness to embrace new technologies and procedures, leading to enhanced efficiency, communication, and innovation. The attitude towards change reflects the mindset of top leadership and decision-makers in the organization when it comes to embracing new ideas and practices. It indicates their willingness to embrace innovation and new ways of working. Experts suggest that the successful implementation of digitalization depends on how effectively the organization communicates the need for change to employees and their willingness to adapt, as well as their internal resistance or readiness for transformation processes [Verina & Titko, 2019]. Organizations that are resistant to change face significant barriers to digitalization, as employee resistance can impede progress and undermine the overall perception of digitalization [Vial, 2019].

H3: *High innovative pressure in an industry, where company operates positively impacts Digitalization of the entire company.*

This hypothesis posits that companies operating in industries characterized by high levels of innovative pressure and abundant availability of technology are more inclined to undergo digitalization. This propensity arises from the increased probability of adopting new technologies and processes, leading to enhanced efficiency, improved communication, and heightened innovation. The contemporary landscape is defined by a proliferation of advanced technologies applicable to manufacturing processes (Table 2), such as Big Data, Artificial Intelligence (AI), the Internet of Things (IoT), Cloud Services, and Robotics, alongside industry-specific technologies like Advanced Process Control (APC) and Industrial Internet of Things (IIoT) [Deberdieva et al., 2019; Dolonina & Shinkevich, 2021; Mechikova & Klimachev, 2023]. The dynamic and flexible nature of these technologies enables the transition towards automation and the incorporation of automated guided vehicles at the operational level, leading to improved efficiency and operational fluidity. The presence of these advantageous and promising solutions serves as a catalyst for companies to digitalize their operational workflows [Gillani et al., 2020]. As industry players increasingly adopt these technological innovations, others are compelled to do the same to stay competitive and avoid falling behind. Additionally, the evolving demands, preferences, and expectations of consumers due to digital advancements necessitate a flexible and client-focused strategy for implementing digital transformation. Businesses that prioritize meeting customer needs are more likely to incorporate digital tools, redesigning their operations and leveraging the advantages and possibilities offered by technology to better understand and respond to customer desires.

H4: *Generalized and interconnected technology applied in an enterprise, positively impacts Digitalization of the entire company.*

It is believed that organizations that adopt flexible and interconnected technologies are more likely to successfully undergo digital transformation. This is because these technologies can lead to improved efficiency, communication, and innovation, while also facilitating the integration of different aspects of the business. In his research on the concept of digital transformation, Vial (2019) discusses how inertia can impede the process. Inertia, as described by Vial, occurs when current resources hinder the digital transformation process. This obstacle is particularly problematic when a company has unique and non-traditional technologies that are difficult to integrate due to compatibility issues with other digital technologies. Therefore, organizations using more versatile and commonly used technologies may have an easier time implementing digital transformation. The interconnectedness of technologies within an organization also plays a significant role in influencing the digitalization process.

H5: *High competition in an industry, where company operates positively impacts Digitalization of the entire company.*

This hypothesis posits that a company operating in a highly competitive industry is more likely to exhibit digitalization. The company's dedication to enhancing performance and efficiency in order to stay competitive in the market has led to these results. The impact of competition on different aspects of a company's performance and operations has been closely examined. Scholars have noted competition as a key factor in the digitalization process. Competing fiercely motivates companies to find ways to improve their competitiveness and hold onto their market share. Consequently, competition serves as a motivator in the digitalization process [Oliveira & Martins, 2011; Liere-Netheler et al., 2018; Gillani et al., 2020; Verhoef et al., 2021].

H6: *Instabilities in an industry, where the company operates positively impacts Digitalization of the entire company.*

The hypothesis posits that organizations operating in industries characterized by volatility are more inclined to undergo digital transformation. This inclination is driven by their ability to quickly adjust to market fluctuations and demonstrate increased responsiveness to changing customer needs, leading to improved efficiency and decision-making. In volatile markets, where competition is fierce and conditions are constantly changing, companies must adapt to survive and remain profitable. According to Gillani et al. (2020), organizations facing market instability are more inclined to adopt a proactive and adaptable approach compared to those in consistent environments. In order to achieve this flexibility, businesses employ various techniques and resources, including the integration of digital technologies and the redesign of their operational structures. By incorporating digital tools, companies can create interconnected and open communication platforms, ultimately improving their capacity to adjust and react to changes in the market. This empowers them to make informed decisions, streamline processes, and stay competitive amidst market volatility.

H7: *Alignment of business and information systems (IS) in an enterprise, positively impacts Digitalization of the entire company.*

The proposition states that organizations are more likely to successfully adopt digitalization when they align their business operations with their digital transformation process. This alignment allows companies to effectively utilize technology to improve operations and align strategic goals with market demands. When business and information systems (IS) are aligned, organizations can efficiently use IT and IS to achieve overall business objectives. One common challenge faced by organizations is the lack of coordination between business and IT goals, often pursued through separate frameworks. This lack of alignment can result in project failures and performance delays. To address this issue, organizations must integrate IT functions with core business operations to support digitalization and reach organizational goals. Some companies are recognizing the importance of merging business and IT strategies to develop a comprehensive digital strategy focused on leadership in the digital space, flexible and scalable operations, improved customer experiences, and emerging digital innovations. By prioritizing these aspects, organizations can optimize their digital transformation efforts, align their strategies with market demands, increase productivity, and reach their objectives.

H8: *Digitalization in an enterprise positively impacts Labor productivity of the entire company.*

The hypothesis posits that digitalization within an enterprise has a positive impact on the labor productivity of the entire company. This is supported by research findings [Borovskaya et al., 2020, Varlamova & Larionova, 2020] that demonstrate a promotional effect of digitalization on labor productivity, with a significant portion of this effect attributed to the influence on human capital. Furthermore, prior research underscores a non-linear positive correlation between digitization and corporate labor productivity, underscoring the significance of investing in data-driven innovation capabilities, enhancing training for digital talent, improving financial capacity, and fortifying internal management practices to enhance labor productivity. The hypothesis underscores the need for companies to align their strategies with digital advancements to optimize their digital transformation efforts and align with market demands, ultimately leading to enhanced productivity levels across the organization.

Based on these hypotheses following research model was formulated:

Source: author's compilation

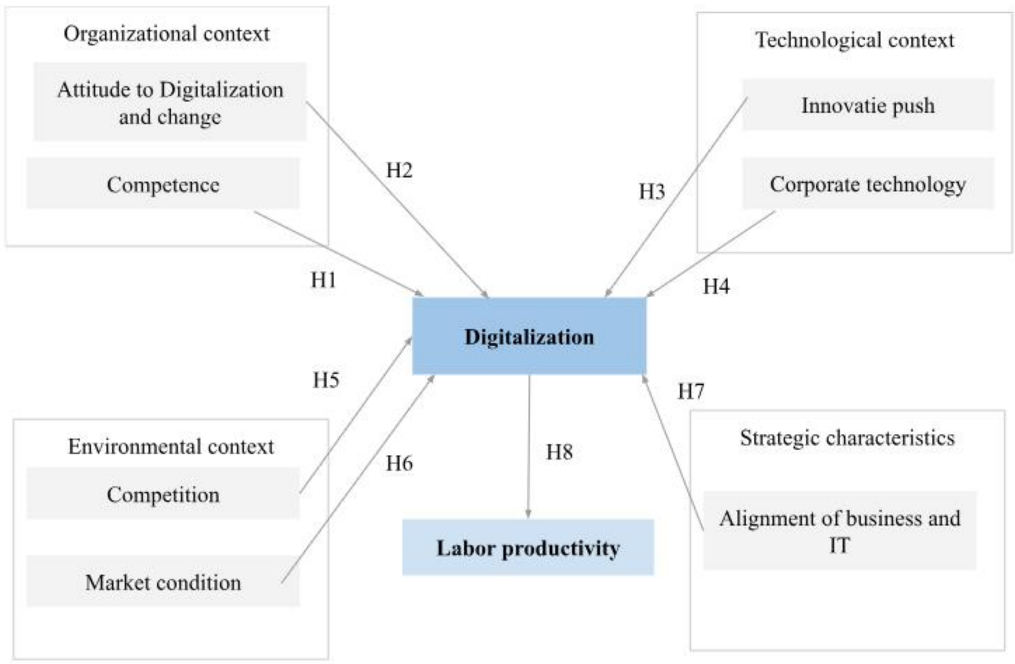

Figure 9. *Visualization of research model.*

This is the structural model which will be used in SEM analysis in order to test research hypotheses.

To summarize, a model with eight factors potentially affecting digitalization and labor productivity was developed. It will be further used for quantitative analysis.

3. Research design development

3.1. Choice of technique

In the previous section, it was decided to use Structural Equation Modeling (SEM) as the primary method for conducting structural modeling in the study. To confirm the validity of their model, the researchers intend to gather primary data through a survey.

Surveys are well-suited for quantitative research as they enable standardized data collection in forms that are simple to analyze using statistical methods. Surveys are also helpful for obtaining crucial data on latent variables that cannot be directly observed[13]. The most common method for assessing latent constructs in surveys is through the use of Likert scales, a widely employed psychometric measurement tool in questionnaire development. Typically, the Likert scale consists of five response options, ranging from one extreme to the other, such as "strongly disagree" to "strongly agree."

By employing SEM and survey methodology, the researchers aim to gather and analyze data in a systematic and statistically robust manner. The use of Likert scales enables the quantification of respondents' attitudes, opinions, and perceptions related to the latent variables under investigation. This approach allows for the collection of standardized data that can be effectively analyzed using statistical techniques, ultimately contributing to the overall validity and reliability of the research findings.

The scale's reliability in the study relies heavily on the careful selection of statements for participants. Therefore, a detailed examination of digitalization and each element in the research framework is essential, taking into account the substance and components of each element. A thorough grasp of the content of each element is vital for crafting questions that effectively measure digitalization and each specific aspect.

1) Digitalization

In the context of digitalization, a topic of significant importance for key market players, there are numerous academic and consulting efforts focused on developing methods for evaluating an organization's digital readiness. Bain & Company has created the Digital Readiness Assessment survey, intended for companies seeking to gauge their level of digitalization. This survey examines companies across various dimensions, including digital strategy, customer engagement, data analytics, and technology infrastructure. In addition, SCOPISM has introduced a similar Digital Transformation Readiness Assessment questionnaire, with a particular focus on automation levels. Therefore, a recommended approach would be to combine these surveys to thoroughly assess and plan for digital transformation initiatives.

2) Organizational attitude to employee’s competence.

[13] Janssens, W., Wijnen, K., De Pelsmacker, P., & Van Kenhove, P. (2009). Marketing Research with SPSS. http://ci.nii.ac.jp/ncid/BB08188838

Competence refers to the skills, knowledge, and abilities possessed by individuals within an organization. In the context of digitalization and labor productivity, competence plays a crucial role in determining how effectively employees can adapt to new technologies, processes, and changes brought about by digitalization. High levels of competence among employees can positively impact labor productivity by enabling them to effectively utilize digital tools, innovate, and contribute to the overall success of digital initiatives.

3) Organizational attitude to digital transformation and change.

The mindset, beliefs, and readiness of an organization to embrace digitalization and adapt to the evolving digital landscape are crucial factors in determining its success. A positive attitude towards digitalization can lead to innovation, agility, and a culture of continuous improvement, ultimately enhancing labor productivity. Conversely, resistance to change can hinder the successful implementation of digital initiatives and negatively impact productivity. The topic of attitude towards change is a significant area of study in organizational psychology, with various survey scales developed to measure this concept.

In a study by Neiva et al. (2005), researchers sought to validate a scale that measures attitudes towards organizational change. Through exploratory factor analysis on a sample of employees from two companies, they identified three primary factors that contribute to attitude towards change in organizations. Firstly, the factor of belief in the likelihood of change that focuses on employees' confidence in the actual implementation of change. In environments where change is met with resistance or remains at the discussion stage without action, this confidence is typically low. Secondly, the factor regarding concerns about potential losses that reflects a negative perspective on change driven by anxieties such as the fear of losing compensation, job security, or other benefits as a result of the change. Thirdly, the factor of perceived benefits of change that assesses how much senior management believes that the proposed changes will benefit the organization and themselves individually. It evaluates whether the changes are perceived as advantageous or not.

This research will use an adapted version of the scale proposed by Neiva et al. (2005), along with measures to evaluate management and employee support specifically for aspects related to digitalization, as these factors are crucial for the successful implementation of digitalization initiatives.

4) Innovative push.

In today's fast-paced business landscape, organizations are increasingly recognizing the significance of fostering innovation to stay ahead of the curve. This emphasis on innovation, particularly in the context of digitalization and labor productivity, is known as "innovative push." It reflects an organization's commitment to exploring novel ideas, technologies, and approaches to drive growth and maintain a competitive edge in the digital age. By prioritizing innovative push, organizations can develop creative solutions, streamline processes, and enhance overall productivity. This idea is closely associated with the TOE theory, which emphasizes the significance of technology accessibility as a critical driver of innovation. Technology availability denotes the existence of recent digital tools that can be integrated into different business functions, including production, sales, distribution, and marketing. These tools are now within reach of companies in terms of affordability, compatibility, and simplicity of integration. Additionally, competitive pressure also plays a role in pushing innovation. As rivals incorporate new technologies to improve their competitive edge, it becomes more difficult for other market participants to sustain their position without adopting digital transformation.

Over time, the pressure to maintain competitiveness and realize full potential drives organizations to adopt and implement digital technologies. The main components of innovative push include availability of digital technologies, pressure from competitors, the intention to maintain competitiveness.

Organizations that prioritize innovative push are more likely to embrace digitalization and achieve higher labor productivity. By actively seeking out and implementing new technologies, they can gain a competitive advantage in the market and stay ahead of the curve.

In conclusion, innovative push is a crucial factor in the success of organizations in the digital age. By fostering a culture of innovation, embracing new technologies, and responding to competitive pressure, companies can drive growth, improve productivity, and maintain their position in the ever-evolving business landscape.

5) Labor productivity.

The momentum of digitalization in the manufacturing sector has been steadily increasing, with diverse and somewhat profound expectations regarding its influence on productivity, management practices, and the design of human work. Jeske et al. (2021) conducted a series of three studies within the German metal and electrical industry to explore the current status of digitalization, along with associated experiences and expectations in the years 2015, 2017, and 2019. The comprehensive analysis of these studies unveiled various trends, encompassing anticipations of productivity enhancements, the adoption of lean methodologies and comprehensive approaches, as well as the implications for employees, their numbers, and their adaptability. The progression of digitalization within the manufacturing sector carries significant implications for productivity, management strategies, and the configuration of human work. It is reshaping managerial approaches, and its effects on employment are multifaceted, encompassing both positive and negative outcomes. As digitalization continues to advance, it is imperative to assess its impact on workers and formulate strategies to address any adverse consequences.

6) Corporate technology.

Corporate technology encompasses the digital tools, systems, and technologies utilized by an organization to support its operations and strategic objectives. The effective integration and utilization of corporate technology play a vital role in driving digital transformation and enhancing labor productivity. By leveraging advanced technologies, organizations can streamline processes, improve efficiency, and create value for both employees and customers.

7) Competition.

Competition refers to the competitive landscape within the industry where an organization operates. Intense competition can drive organizations to innovate, improve efficiency, and enhance productivity to maintain a competitive advantage. Effectively responding to competitive pressures is crucial as it can guide the organization's approach to digital transformation and its impact on labor productivity. Michael Porter's influential work on competition offers valuable insights into the factors that influence competition and its elements. According to Porter's Five Forces framework, competition is shaped by five critical dimensions:

- Overall rivalry. This involves understanding the competitive intensity in the market, market saturation, the number and influence of market participants, diversity among competitors, product differentiation, switching costs, and customer loyalty.
- Bargaining power of suppliers. This refers to the ability of suppliers to influence the prices, quality, and availability of inputs, which can impact an organization's costs and profitability.

- Bargaining power of buyers. This involves the ability of customers to influence the prices, quality, and availability of products or services, which can impact an organization's revenue and market share.
- Threat of substitutes. This refers to the availability of alternative products or services that can satisfy the same customer needs, which can limit an organization's pricing power and market share.
- Threat of new entrants. This involves the ease with which new competitors can enter the market, which can impact an organization's market share and profitability.

By evaluating these five forces, organizations can gain a better understanding of the competitive landscape and develop strategies to enhance their competitive position[14].

8) Market condition.

Market conditions refer to the external factors and dynamics that exert influence on the industry and market within which an organization operates. Variations in market conditions, such as alterations in consumer preferences, technological advancements, or economic trends, have the potential to impact the organization's digital transformation initiatives and labor productivity. By adapting to market conditions and effectively utilizing digital technologies, organizations can enhance their competitiveness and drive productivity. Market stability includes a range of factors. Firstly, volatility levels indicate how quickly market conditions change, with higher volatility suggesting more frequent changes. Secondly, uncertainty levels refer to the difficulty of predicting outcomes in the industry with accuracy[15].

9) Alignment of business and Information technologies.

The synchronization of business and information technologies involves integrating technology solutions with an organization's strategic goals and operational processes. In the context of digitalization and labor productivity, ensuring that business objectives align with technology initiatives is essential for optimizing processes, promoting teamwork, and enhancing productivity. When business goals are well-coordinated with technology efforts, organizations can streamline operations, improve collaboration, and boost productivity levels. The alignment of business and Information Systems (IS) refers to how effectively a

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[14] Porter, M. E.. How Competitive Forces Shape Strategy. Harvard Business Review. Retrieved April 21, 2024, from https://hbr.org/1979/03/how-competitive-forces-shape-strategy

[15] Gillani, F., Chatha, K. A., Jajja, M. S. S., & Farooq, S. (2020). Implementation of digital manufacturing technologies: Antecedents and consequences. International Journal of Production Economics, 229, 107748. https://doi.org/10.1016/j.ijpe.2020.107748

company's use of information systems supports its business objectives and strategy. Various tools can be employed to evaluate this alignment. Luftman's Strategic Alignment Maturity Model, developed in 2000, covers six key areas of maturity in aligning business and IS. Communication maturity focuses on communication levels between the IT department and other units, emphasizing knowledge sharing and mutual understanding. Value measurement maturity assesses how well a company recognizes the value IT brings to its operations. Assessing the maturity of governance involves evaluating compliance and determining the responsible parties for planning IT resources. The maturity of partnerships focuses on the relationships between IT and other functions, with an emphasis on trust and collaboration. Scope and architecture maturity gauges the flexibility and transparency of IT in supporting business operations. Skills maturity measures innovation, adaptability, and contribution to corporate goals[16]. Bourdeau et al. (2019) highlight the significance of verifying whether a company has an IS strategy and if the business strategy is aligned with IT and corporate information systems[17].

3.2. Questionnaire development and data collection

The preceding section delved into key theories and reliable measurement tools that can be used as a foundation for creating a survey instrument. Table 10 compares the techniques for developing scales, distinguishing between established scales that have been tested and proven by other researchers and new scales that are based on theories and crafted by the researcher for the current study, utilizing applicable theoretical frameworks.

Table 10. *Likert Scales development for questionnaire.*

Latent variable	Approach	Theory base for questionnaire
Digitalization	Existing scale	Bain & Company's Digital Readiness Assessment; SCOPISM Digital Transformation Readiness Assessment questionnaire.
Company’s attitude to employee’s	Original scale based on	Kifa (2024)

[16] Luftman, J. N. (2000). Assessing Business-IT alignment maturity. Communications of the Association for Information Systems, 4. https://doi.org/10.17705/1cais.00414
[17] Bourdeau, S., Hadaya, P., & Lussier, J. (2019). Assessing the Strategic Alignment of Information Systems Projects: A Design Science approach. Projectics, n°20(2), 115–154. https://doi.org/10.3917/proj.020.0115

competence	theory	Digital Skills Assessment Guidebook
Company's attitude to digitalization and changes	Existing scale	Neiva et al. (2005)
Labor productivity	Existing scale	Jeske et al. (2021)
Innovative push in the industry	Original scale based on theory	Gillani et al. (2020); TOE.
Corporate information systems and technologies	Original scale based on theory	Vial (2019)
Competition in the industry	Original scale based on theory	Porter (1979)
The state of the industry	Original scale based on theory	Gillani et al. (2020); TOE.
Business and information system alignment	Original scale based on theory	Bourdeau et al. (2019) Luftman (2000)

Source: author's compilation

As a result, a questionnaire of 10 sections with 63 questions in general was developed.

Section 1. General information

1. The industrial sector of the company.
2. Size of the company.
3. Department.
4. Relation to digitalization (direct: realization; indirect: affected by Digitalization; none).
5. Model of business interaction with customers.

Section 2. The digitalization in the company

6. The company has a clear vision for succeeding in the digital future and is taking necessary steps to achieve it.
7. The company has the right people, skills, and culture to realize its digital vision.
8. Digital technologies are used to improve and differentiate products, services, and customization.
9. Digital technologies have been implemented in most aspects of the business.
10. Digital technologies are used in daily tasks.

11. Business process automation capabilities are regularly identified, evaluated, and implemented.
12. A significant part of manual labor is automated.
13. Technologies like Big Data, AI, IoT, Cloud Services, and Robotics are utilized.
14. Industry-specific technologies, such as APC, IIoT, and ERP systems, are used.
15. Digital initiatives involve representatives from IT and other functions.
16. Data and analytics are actively used for decision-making.
17. Major gaps in digital capabilities are identified, and plans are developed to address them.
18. Digital initiatives are successfully transformed from experiments to large-scale projects.

Section 3. Company's attitude to employees' competence

19. Learning and development programs are provided to enhance employees' knowledge of the digitalization process.
20. Senior management supports the improvement of employees' qualifications.
21. Employees are encouraged to improve their qualifications.
22. Employees may receive bonuses for completed development programs or improved qualifications.
23. Employees may take test tasks to prove their level of competence in the digitalization process.

Section 4. Company's attitude to digitalization and changes in general

24. The idea of digitalization is supported by the management.
25. The idea of digitalization is supported by employees.
26. Mechanisms and workarounds to avoid change are not developed.
27. Changes actually happen, not just at the discussion level.
28. Inevitable changes do not cause fear and dissatisfaction among people.
29. Changes are believed to "breathe life" into the organization.
30. Changes are important because they benefit employees.

Section 5. Employee's attitude to digitalization and changes in general (labor productivity)

31. I feel comfortable with the changes that digitalization has brought to my job.
32. Digitalization has improved the efficiency of my work processes.
33. I believe digitalization has positively impacted my job role.
34. I am confident in my ability to adapt to digitalization in the company.

35. I believe the company's digital transformation has been beneficial for the organization as a whole.
36. I am satisfied with the level of support and training provided by the company for digitalization.
37. I believe that digitalization has improved communication and collaboration within the company.

Section 6. Innovative push in the industry

38. Many digital technologies can be applied in the production/sales and distribution process.
39. Many digital technologies can be applied in marketing communications.
40. Many digital technologies can be applied in office work.
41. Competitors are actively using digital technologies.
42. The company strives to be a leader in the use of digital solutions.

Section 7. Corporate information systems and technologies

43. The information systems, applications, and software form a single corporate network.
44. The information systems, applications, and software work well.
45. The information systems, applications, and software are common in the market.
46. The information systems are specially developed by the company's specialists or third-party organizations.
47. The introduction of digital technologies has improved communication and collaboration among employees.

Section 8. Competition in the industry

48. The company belongs to a highly competitive market.
49. There are many active companies in the industry.
50. The market is represented by a lot of large and strong players.

Section 9. The state of the industry

51. The industry is characterized by unstable profitability and high risks.
52. The level of uncertainty in the industry is high.
53. The industry is at a stage of active growth or decline.
54. The industry is not supported by the state.

Section 10. Business and information system alignment

55. IT representatives can easily bring innovative ideas to management.

56. Information systems and IT create great value for the business.
57. The planning of IT resources is carried out with the joint participation of management and IT representatives.
58. Management understands the basics of IT.
59. The IT department understands the basics of business.
60. Employees trust the IT department.
61. IT employees actively communicate with other functions.
62. The company has an IT strategy.
63. Information systems and IT are a component of the business strategy.

To obtain a representative sample, it was crucial to distribute the questionnaire to the appropriate target audience:

- Current or former employees, or individuals with relevant experience in the manufacturing industry;
- Minimum of six months of comprehensive company experience;
- Job position at least at the level of lower-level management or senior specialist;
- Higher education background.

A combination of data collection methods was utilized to gather responses for the study. One part of the responses was intended to be obtained through the researcher's personal network using the snowball sampling technique. This involved sharing the questionnaire with acquaintances and asking them to forward it to their own contacts, creating a chain referral process. The remaining portion of the responses was planned to be collected through paid targeted advertising on the Anketolog survey platform. This allowed the researcher to specify the desired respondent characteristics, facilitating the distribution of the questionnaire to Anketolog's participant pool matching those criteria. By employing this mixed approach, the researcher aimed to ensure a representative sample that met the predefined participant eligibility requirements.

4. Conclusion on Chapter 2

Through a comprehensive examination of available literature, this research uncovered eight crucial elements, which formed the basis for eight research hypotheses. Structural Equation Modeling was utilized to assess these hypotheses, culminating in the creation of a graphical research framework. A survey was then administered to validate this model, utilizing a questionnaire with ten sections, each incorporating well-established Likert scales:

Section 1. General information

Section 2. Digitalization in the company

Section 3. Company’s attitude to employees’ competence

Section 4. Company's attitude to digitalization and changes in general

Section 5. Employee's attitude to digitalization and changes in general (labor productivity)

Section 6. Innovative push in the industry

Section 7. Corporate information systems and technologies

Section 8. Competition in the industry

Section 9. The state of the industry

Section 10. Business and information system alignment

The survey was administered using a multi-pronged strategy, blending focused paid promotion on Anketolog with distribution through personal and professional contacts. The following section will provide an in-depth examination of the primary data that was gathered and an overview of the overall research conclusions.

CHAPTER 3. DATA ANALYSIS AND FUTURE RECOMMENDATIONS

This part of the study will concentrate on analyzing the data collected directly from representatives of manufacturing companies. The analysis will include hypothesis testing and evaluating the importance of the research model. This will lead to the development of practical recommendations for chemical and petrochemical companies seeking to implement digitalization strategies effectively and improve employee productivity based on the research findings.

1. Data analysis

1.1. Sample

To gather authentic data, a survey was developed and disbursed through two varying approaches: the snowball strategy and paid targeting on the Anketolog platform. The snowball technique included sharing the survey among the author's personal and professional circles, as well as social media groups for alumni and postgraduate students from Saint Petersburg State University's Graduate School of Management. Furthermore, responses were obtained through the Anketolog platform, where users could define target audience criteria (such as educational background, managerial positions, and work in manufacturing industries) and establish a cost per response. Anketolog then sends the survey to its pool of participants, who complete it in exchange for payment. The total number of participants in the sample was 258, with the distribution of industries they represented shown in Figure 10.

Source: author's compilation

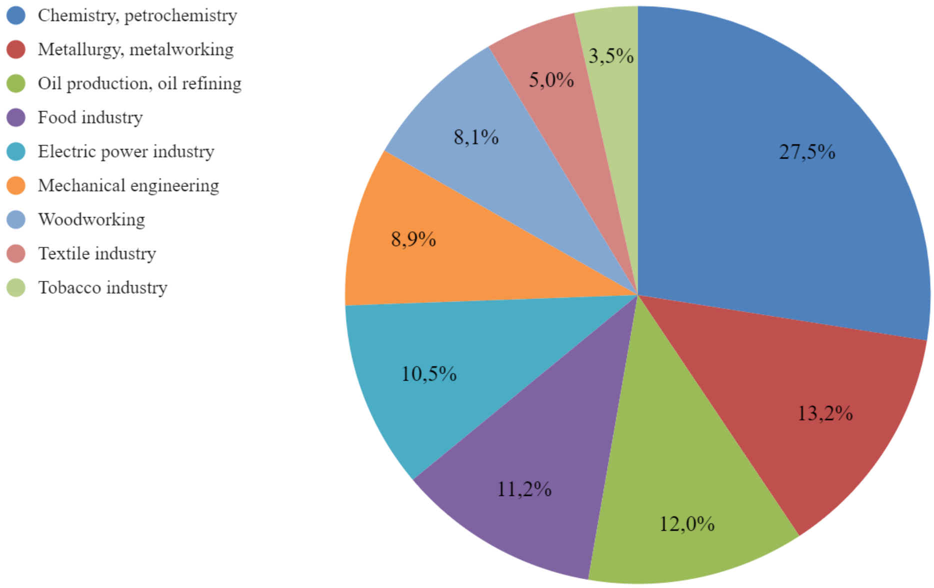

Figure 10. *Sample structure.*

The chemical and petrochemical industry is prevailing among the respondents, with 27,5% of the respondents. Additionally, 13,2% and 12% of the respondents are from the metalworking and oil extraction and refining industries, respectively.

The survey respondents come primarily from large and medium-sized companies. Specifically, 53.8% of participants are from large enterprises, while 45.7% are from medium-sized companies. Only a small fraction, less than 1%, are from small companies. It's important to note that the definitions of small, medium, and large enterprises are based on the number of employees. Small enterprises have between 10 and 49 employees, medium-sized enterprises have between 50 and 249 employees, and large enterprises have 250 or more employees[18].

In conclusion, the sample is representative of the research population, as its structure closely matches the characteristics of the target group. For further analysis, the responses from participants in the chemistry and petrochemistry industry will be used, resulting in a final sample size of 71.

[18] Entrepreneurship - Enterprises by business size - OECD Data. (n.d.). theOECD. https://data.oecd.org/entrepreneur/enterprises-by-business-size.htm

1.2. Exploratory Factor Analysis

After collecting and verifying the data's representativeness, the research advanced to the Exploratory Factor Analysis (EFA) phase. During this stage, the main focus was to validate the questionnaire, assess the importance of the items linked to the underlying concepts, and make any required adjustments to the model.

To prepare for the EFA, the survey questions were coded and renamed to align with the underlying constructs they represent (Table 11).

Table 11. *Structure of measurement model.*

Variable	Item	Related question
Digitalization	D_1	1. The company has a clear vision for succeeding in the digital future and is taking necessary steps to achieve it.
	D_2	2. The company has the right people, skills, and culture to realize its digital vision.
	D_3	3. Digital technologies are used to improve and differentiate products, services, and customization.
	D_4	4. Digital technologies have been implemented in most aspects of the business.
	D_5	5. Digital technologies are used in daily tasks.
	D_6	6. Business process automation capabilities are regularly identified, evaluated, and implemented.
	D_7	7. A significant part of manual labor is automated.
	D_8	8. Technologies like Big Data, AI, IoT, Cloud Services, and Robotics are utilized.
	D_9	9. Industry-specific technologies, such as APC, IIoT, and ERP systems, are used.
	D_10	10. Digital initiatives involve representatives from IT and other functions.
	D_11	11. Data and analytics are actively used for decision-making.
	D_12	12. Major gaps in digital capabilities are identified, and plans are developed to address them.
	D_13	13. Digital initiatives are successfully transformed from experiments to large-scale projects.
Company's attitude to employee's competence	CA_C_1	1. Learning and development programs are provided to enhance employees' knowledge of the digitalization process.
	CA_C_2	2. Senior management supports the improvement of employees' qualifications.
	CA_C_3	3. Employees are encouraged to improve their qualifications.
	CA_C_4	4. Employees may receive bonuses for completed development programs or improved qualifications.

	CA_C_5	5. Employees may take test tasks to prove their level of competence in the digitalization process.
Company's attitude to digitalization and changes	CA_D_1 CA_D_2 CA_D_3 CA_D_4 CA_D_5 CA_D_6 CA_D_7	1. The idea of digitalization is supported by the management. 2. The idea of digitalization is supported by employees. 3. Mechanisms and workarounds to avoid change are not developed. 4. Changes actually happen, not just at the discussion level. 5. Inevitable changes do not cause fear and dissatisfaction among people. 6. Changes are believed to "breathe life" into the organization. 7. Changes are important because they benefit employees.
Labor productivity	LP_1 LP_2 LP_3 LP_4 LP_5 LP_6 LP_7	1. I feel comfortable with the changes that digitalization has brought to my job. 2. Digitalization has improved the efficiency of my work processes. 3. I believe digitalization has positively impacted my job role. 4. I am confident in my ability to adapt to digitalization in the company. 5. I believe the company's digital transformation has been beneficial for the organization as a whole. 6. I am satisfied with the level of support and training provided by the company for digitalization. 7. I believe that digitalization has improved communication and collaboration within the company.
Innovative push in the industry	IP_1 IP_2 IP_3 IP_4 IP_5	1. Many digital technologies can be applied in the production/sales and distribution process. 2. Many digital technologies can be applied in marketing communications. 3. Many digital technologies can be applied in office work. 4. Competitors are actively using digital technologies. 5. The company strives to be a leader in the use of digital solutions.
Corporate information systems and technologies	CIS_1 CIS_2 CIS_3 CIS_4 CIS_5	1. The information systems, applications, and software form a single corporate network. 2. The information systems, applications, and software work well. 3. The information systems, applications, and software are common in the market. 4. The information systems are specially developed by the company's specialists or third-party organizations. 5. The introduction of digital technologies has improved communication and collaboration among employees.
Competition in the industry	C_1 C_2 C_3	1. The company belongs to a highly competitive market. 2. There are many active companies in the industry. 3. The market is represented by a lot of large and strong

		players.
The state of the industry	IN_1 IN_2 IN_3 IN_4	1. The industry is characterized by unstable profitability and high risks. 2. The level of uncertainty in the industry is high. 3. The industry is at a stage of active growth or decline. 4. The industry is not supported by the state.
Business and information system alignment	B_IS_1 B_IS_2 B_IS_3 B_IS_4 B_IS_5 B_IS_6 B_IS_7 B_IS_8 B_IS_9	1. IT representatives can easily bring innovative ideas to management. 2. Information systems and IT create great value for the business. 3. The planning of IT resources is carried out with the joint participation of management and IT representatives. 4. Management understands the basics of IT. 5. The IT department understands the basics of business. 6. Employees trust the IT department. 7. IT employees actively communicate with other functions. 8. The company has an IT strategy. 9. Information systems and IT are a component of the business strategy.

Source: author's compilation

The main purpose of conducting Exploratory Factor Analysis (EFA) throughout the study was to assess the reliability and relevance of the specified items in measuring the underlying construct being investigated. This step is essential because many scales used to assess latent variables are often novel and proposed by the researcher, requiring validation. EFA is used to determine which items should be eliminated from the measurement model to improve its overall significance. The process of performing EFA using the Python programming language is illustrated in Appendix Figure 1.

- EFA for latent variable "Digitalization"

Table 12. *EFA for "Digitalization" variable.*

Item	Factor loading
D_1	0.823
D_2	0.511
D_3	0.199
D_4	0.682

D_5	0.787	
D_6	0.737	
D_7	0.411	
D_8	0.346	
D_9	0.696	
D_10	0.509	
D_11	0.950	
D_12	0.935	
D_13	0.786	
Latent construct Digitalization	Kaiser-Meyer Measure	0.612
	Bartlett's Test significance	0.000
	Cronbach Alpha	0.884

Source: author's compilation

The results of the factor analysis indicate that it can be reliably applied in this particular situation. The Kaiser-Meyer-Olkin measure of sampling adequacy, which evaluates the suitability of factor analysis, is moderately strong at 0.612. While not exceptionally high, this value surpasses the commonly accepted threshold of 0.6, suggesting that factor analysis is appropriate for the dataset. Additionally, Bartlett's Test of Sphericity, which examines if the correlation matrix is an identity matrix, demonstrates statistical significance with a p-value below 0.01. This significant finding supports the use of factor analysis by confirming the presence of correlations among the variables. The internal consistency of the "Digitalization" latent construct, as measured by Cronbach's alpha, is 0.884. This value exceeds the widely accepted minimum threshold of 0.7, suggesting a high level of reliability and internal consistency among the measurement items for this latent variable. The factor loadings, which represent the strength of the relationships between the observed variables (items) and their respective latent constructs, vary in their magnitudes. Some items exhibit relatively low factor loadings (D_2, D_3, D_7, D_8, D_10), indicating that they may have weaker associations with their intended latent constructs compared to other items. These items could be considered for potential removal or refinement in subsequent analyses to improve the overall factor structure.

In summary, the results collectively support the use of factor analysis in this case, with the KMO measure and Bartlett's Test of Sphericity indicating the appropriateness of the technique. The high Cronbach's alpha value suggests a reliable and consistent latent construct, while the varying factor loadings suggest that some items may need further examination or refinement to optimize the factor structure.

- EFA for latent variable “Company’s attitude to employee’s competence”

Table 13. *EFA for “Company’s attitude to employee’s competence” variable.*

Item	Factor loading	
CA_C_1	0.845	
CA_C_2	0.970	
CA_C_3	0.716	
CA_C_4	0.659	
CA_C_5	0.726	
Latent construct Company’s attitude to employee’s competence	Kaiser-Meyer Measure	0.747
	Bartlett’s Test significance	0.000
	Cronbach Alpha	0.857

Source: author’s compilation

The outcomes of the factor analysis suggest that the data is suitable for further examination. The KMO measure of sampling adequacy is 0.747, while Bartlett's Test of Sphericity shows statistical significance (p-value < 0.01), collectively supporting the appropriateness of conducting factor analysis. The Cronbach's alpha coefficient for the latent construct "Company's Attitude towards Employee Competence" is 0.857, showing a strong level of internal consistency among the measurement items. Additionally, the factor loadings, which show the correlations between the observed variables and their related latent constructs, are higher than 0.66, indicating robust relationships. Overall, the findings of the factor analysis suggest that the structure of the latent construct is both dependable and meaningful.

- EFA for latent variable “Company's attitude to digitalization and changes”

Table 14. *EFA for “Company's attitude to digitalization and changes” variable.*

Item	Factor loading	
CA_D_1	0.851	
CA_D_2	0.962	
CA_D_3	0.543	
CA_D_4	0.404	
CA_D_5	0.631	
CA_D_6	0.634	
CA_D_7	0.859	
Latent construct Company's attitude to digitalization and changes	Kaiser-Meyer Measure	0.535
	Bartlett’s Test significance	0.000
	Cronbach Alpha	0.847

Source: author’s compilation

The factor analysis results suggest the following insights. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is 0.535, which falls below the recommended threshold of 0.6. This indicates potential issues with the adequacy of the sample size or composition. The Bartlett's Test of Sphericity yielded a statistically significant result (p-value < 0.01), indicating that the data is appropriate for factor analysis. The Cronbach's alpha coefficient for the latent construct "Company's Attitude to Digitalization and Changes" is 0.847, showing strong internal consistency among the measurement items and suggesting a reliable latent construct with closely related items. However, upon closer examination of the factor loadings, it was found that items CA_D_3 and CA_D_4 have weak correlations with their respective latent constructs. While the overall structure of the latent construct appears reliable and significant, further analysis may be needed to consider removing these items or reassessing the latent variable to enhance the model's fit and validity.

In summary, the factor analysis results highlight some potential limitations in the data, particularly regarding sample adequacy. However, the latent construct demonstrates strong internal consistency. To enhance the model's robustness, it may be beneficial to further investigate the problematic items and consider refining the latent variable structure.

- EFA for latent variable “Labor productivity”

Table 15. *EFA for “Labor productivity” variable.*

Item	Factor loading	
LP_1	0.936	
LP_2	0.910	
LP_3	0.968	
LP_4	0.961	
LP_5	0.922	
LP_6	0.919	
LP_7	0.906	
Latent construct Labor productivity	Kaiser-Meyer Measure	0.764
	Bartlett’s Test significance	0.000
	Cronbach Alpha	0.973

Source: author’s compilation

The results of the factor analysis confirm that the data is suitable for examination. The sampling adequacy measurement (KMO) is 0.764, and Bartlett's Test of Sphericity shows statistical significance ($p < 0.01$), indicating that proceeding with factor analysis is appropriate. The Cronbach's alpha coefficient for the "Labor Productivity" construct is 0.973, indicating high internal consistency among the measurement items. Additionally, the factor loadings, which show the relationships between observed variables and latent constructs, are above 0.906, suggesting strong correlations. Overall, the factor analysis results suggest a reliable and significant structure for the latent construct.

- EFA for latent variable “Innovative push in the industry”

Table 16. *EFA for "Innovative push in the industry" variable.*

Item	Factor loading	
IP_1	0.602	
IP_2	0.967	
IP_3	0.687	
IP_4	0.337	
IP_5	0.739	
Latent construct Innovative push in the industry	Kaiser-Meyer Measure	0.611
	Bartlett's Test significance	0.000
	Cronbach Alpha	0.709

Source: author's compilation

The coefficients obtained indicate that factor analysis is generally appropriate in this scenario. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy stands at 0.611, slightly below the recommended threshold of 0.6, yet still suggesting adequacy for factor analysis. Bartlett's Test of Sphericity yields a statistically significant result (p-value < 0.01), affirming the suitability of conducting factor analysis. The Cronbach's alpha coefficient for the "Innovative Push in the Industry" latent variable is 0.709, indicating strong internal consistency among the measurement items. Additionally, the factor loadings, which represent the relationships between observed variables and their latent constructs, are generally high. However, item IP_4 shows a weak correlation with the latent construct and should be eliminated. Despite considerations for item removal, the results of the factor analysis reveal a dependable and meaningful structure for the latent variable.

- EFA for latent variable "Corporate information systems and technologies"

Table 17. *EFA for "Corporate information systems and technologies" variable.*

Item	Factor loading
CIS_1	0.834
CIS_2	0.893

CIS_3	0.265	
CIS_4	0.792	
CIS_5	0.760	
Latent construct Innovative push in the industry	Kaiser-Meyer Measure	0.632
	Bartlett's Test significance	0.000
	Cronbach Alpha	0.795

Source: author's compilation

The coefficients obtained suggest that factor analysis is generally appropriate in this case. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is 0.632, slightly below the recommended threshold of 0.6 but still indicating suitability for factor analysis. Bartlett's Test of Sphericity is statistically significant (p-value < 0.01), supporting the appropriateness of conducting factor analysis. The Cronbach's alpha coefficient for the "Innovative Push in the Industry" latent construct is 0.795, indicating high internal consistency among the measurement items. The factor loadings, representing the correlations between observed variables and their latent constructs, are generally high. However, item CIS_3 shows a low correlation with the latent construct and should be removed. Despite the need for potential item removal, the factor analysis results suggest a dependable and significant structure for the latent construct.

- EFA for latent variable "Competition in the industry"

Table 18. *EFA for "Competition in the industry" variable.*

Item	Factor loading	
C_1	0.083	
C_2	0.923	
C_3	0.946	
Latent construct Competition in the industry	Kaiser-Meyer Measure	0.448
	Bartlett's Test significance	0.000
	Cronbach Alpha	0.577

Source: author's compilation

The findings from the factor analysis indicate issues with the data quality. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is 0.448, falling below the acceptable threshold of 0.6, suggesting a potential lack of representativeness in the sample. Despite this, Bartlett's Test of Sphericity shows a statistically significant result (p-value < 0.01). The Cronbach's alpha coefficient for the "Competition in the Industry" latent variable is 0.577, suggesting weak internal consistency among the measurement items. Upon examining the factor loadings, it is evident that item C_1 has a very weak correlation with its corresponding latent construct. In summary, the reliability and significance of the latent variable structure are questionable. Further investigation may require considering the exclusion of this latent variable.

- EFA for latent variable "The state of the industry"

Table 19. *EFA for "The state of the industry" variable.*

Item	Factor loading	
IN_1	0.902	
IN_2	0.978	
IN_3	0.864	
IN_4	0.313	
Latent construct The state of the industry	Kaiser-Meyer Measure	0.675
	Bartlett's Test significance	0.000
	Cronbach Alpha	0.820

Source: author's compilation

The findings from the factor analysis indicated several key points. Firstly, the KMO measure of sampling adequacy was found to be 0.675, indicating that the sample size was sufficient for the analysis. Additionally, Bartlett's Test of Sphericity revealed statistical significance (p-value < 0.01), suggesting that the variables were correlated and appropriate for factor analysis. The Cronbach's alpha coefficient for the "The state of the industry" latent variable was 0.820, indicating strong internal consistency among the measurement items. However, upon examination of the factor loadings, it was observed that item IN_4 displayed a weak correlation with its corresponding latent variable. This may suggest that the item is not closely aligned with the overarching construct. While the overall structure of the latent variable appeared reliable and significant, it was recommended that item IN_4 be eliminated from the model due to its low correlation with the latent construct. This decision could potentially enhance the fit and interpretability of the model.

- EFA for latent variable “Business and information system alignment”

Table 20. *EFA for “Business and information system alignment” variable.*

<table>
<tr><td>Item</td><td colspan="2">Factor loading</td></tr>
<tr><td>B_IS_1</td><td colspan="2">0.729</td></tr>
<tr><td>B_IS_2</td><td colspan="2">0.834</td></tr>
<tr><td>B_IS_3</td><td colspan="2">0.689</td></tr>
<tr><td>B_IS_4</td><td colspan="2">0.800</td></tr>
<tr><td>B_IS_5</td><td colspan="2">0.492</td></tr>
<tr><td>B_IS_6</td><td colspan="2">0.831</td></tr>
<tr><td>B_IS_7</td><td colspan="2">0.805</td></tr>
<tr><td>B_IS_8</td><td colspan="2">0.824</td></tr>
<tr><td>B_IS_9</td><td colspan="2">0.944</td></tr>
<tr><td rowspan="3">Latent construct The state of the industry</td><td>Kaiser-Meyer Measure</td><td>0.548</td></tr>
<tr><td>Bartlett’s Test significance</td><td>0.000</td></tr>
<tr><td>Cronbach Alpha</td><td>0.923</td></tr>
</table>

Source: author’s compilation

The results of the factor analysis indicate constraints within the dataset. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy falls below the acceptable threshold at 0.548, suggesting potential data limitations. Bartlett's Test of Sphericity yields a statistically significant result (p-value < 0.01). The Cronbach's alpha coefficient for the "Business and Information System Alignment" latent construct is notably high at 0.923, indicating strong internal consistency among the measurement items. Analysis of the factor loadings identifies item B_IS_5 as having a weak correlation with its corresponding latent construct.

While the overall structure of the latent construct appears reliable and significant, consideration may be given to removing item B_IS_5 for improved alignment.

The exploratory factor analysis (EFA) process identified opportunities to improve the model's structure and fit. Based on the EFA results, several items were removed from the model, including D_3, D_7, D_8, CA_D_4, IP_4, CIS_3, C_1, IN_4, and B_IS_5. Additionally, three other items were flagged for more in-depth examination in future analysis stages. These modifications have enhanced the model, making it more robust and ready for additional evaluation and validation.

1.3. Research model and hypotheses testing

In this study, Confirmatory Factor Analysis (CFA) served two main purposesю The first one is to assess the accuracy of the expected connections between the variables in the research model. The second one is to establish the statistical importance of the overall research model in describing the phenomenon being studied.

Python, a programming language, was utilized alongside appropriate data analysis tools to conduct structural equation modeling (SEM) and evaluate the model's effectiveness. The process and Python code used for implementing CFA can be found in Appendix Figure 2 for further details.

Eight research hypotheses were introduced in Chapter 2 for further investigation.

1. High level of employees' competence positively impacts Digitalization of the entire company.
2. Positive attitude to change in the organization, positively impacts Digitalization of the entire company.
3. High innovative pressure in an industry, where company operates positively impacts Digitalization of the entire company.
4. Generalized and interconnected technology applied in an enterprise, positively impacts Digitalization of the entire company.
5. High competition in an industry, where company operates positively impacts Digitalization of the entire company.
6. Instabilities in an industry, where the company operates positively impacts Digitalization of the entire company.

7. Alignment of business and information systems (IS) in an enterprise, positively impacts Digitalization of the entire company.
8. Digitalization in an enterprise positively impacts Labor productivity of the entire company.

At the beginning of the study, an assessment was carried out to confirm that the key concepts were closely related. The Critical Ratios for all items in the categories met the required value of 1.96, indicating a single dimension and supporting convergent validity. However, one variable, CA_D_6, fell short of this standard with a Critical Ratio of 1.850, which affected the convergent validity of the concept "Company's perspective on digitalization and transformation" as outlined in Table 21.

Table 21. *Critical ratio coefficients for each item of each latent variable.*

Latent variable	Item	Estimate	Standard Error	Critical Ratio
Digitalization	D_1	0.673	0.005	9.518
	D_2	0.473	0.052	2.074
	D_4	0.600	0.038	3.078
	D_5	0.638	0.032	3.567
	D_6	1.092	0.073	4.042
	D_9	1.135	0.074	4.172
	D_10	1.076	0.087	3.648
	D_11	1.510	0.068	5.791
	D_12	0.812	0.026	5.036
	D_13	1.233	0.075	4.502
Company’s attitude to employee’s competence	CA_C_1	0.690	0.043	3.327
	CA_C_2	1.043	0.048	4.761
	CA_C_3	0.858	0.065	3.365
	CA_C_4	1.234	0.092	4.068
	CA_C_5	0.789	0.059	3.248
Company's attitude to digitalization and changes	CA_D_1	0.719	0.041	3.551
	CA_D_2	1.206	0.046	5.623
	CA_D_3	0.599	0.080	2.118
	CA_D_5	1.159	0.093	3.801
	CA_D_6	0.457	0.061	1.850
	CA_D_7	1.197	0.059	4.928
Labor productivity	LP_1	0.802	0.016	6.340
	LP_2	0.912	0.045	4.299
	LP_3	1.524	0.065	5.978
	LP_4	0.996	0.033	5.483
	LP_5	0.424	0.014	3.583
	LP_6	1.104	0.055	4.707
	LP_7	1.232	0.061	4.988

Innovative push in the industry	IP_1 IP_2 IP_3 IP_5	0.529 0.802 0.517 1.309	0.019 0.006 0.002 0.076	3.838 10.354 11.560 4.748
Corporate information systems and technologies	CIS_1 CIS_2 CIS_4 CIS_5	0.616 0.927 1.346 0.774	0.057 0.059 0.083 0.056	2.580 3.816 4.672 3.271
Competition in the industry	C_2 C_3	0.872 0.486	0.052 0.041	3.824 2.400
The state of the industry	IN_1 IN_2 IN_3	1.214 0.707 1.159	0.064 0.031 0.065	4.799 4.015 4.546
Business and information system alignment	B_IS_1 B_IS_2 B_IS_3 B_IS_4 B_IS_6 B_IS_7 B_IS_8 B_IS_9	0.605 0.923 0.601 0.529 1.138 1.110 0.975 1.575	0.041 0.047 0.055 0.038 0.065 0.064 0.061 0.074	2.988 4.257 2.563 2.714 4.464 4.388 3.948 5.790

Source: author’s compilation

Moreover, composite factor reliability and Average Variance Extracted (AVE) coefficients were found for each latent variable (Table 22).

Table 22. *Composite factor reliability and AVE for each latent variable.*

Latent variable	Composite factor reliability (> 0.7)	AVE (>0,5)
Digitalization	0.994	0.954
Company’s attitude to employee’s competence	0.986	0.889
Company's attitude to digitalization and changes	0.987	0.886
Labor productivity	0.994	1.101
Innovative push in the industry	0.990	0.726
Corporate information systems and technologies	0.981	0.912
Competition in the industry	0.952	0.498
The state of the industry	0.983	1.106

Business and information system alignment	0.992	0.977

Source: author's compilation

In the context of composite factor reliability, all latent variables exhibit strong composite factor reliability, with values surpassing the 0.7 threshold. This suggests that the items within each latent variable share high covariances and effectively measure the same underlying concepts. However, for the construct "Competition in the industry," the AVE coefficients, while satisfactory, are not optimal. This implies that the convergent validity of this construct is not as robust as desired. Consequently, the structure of this construct merits further examination and refinement to enhance its convergent validity.

To summarize, while the overall composite factor reliability is commendable, the construct "Competition in the industry" could benefit from additional refinement to improve its convergent validity and ensure it accurately measures the intended underlying concept.

Table 23 presents a summary of the goodness-of-fit coefficients for the initial model, intermediate models, and the final model. The model testing process, conducted using Python programming language, is detailed in Appendix Figure 3.

Table 23. *The summary of goodness of fit coefficients.*

Model	X2/df	p.value	TLI	GFI	CFI	RMSEA
Model 1 (initial after EFA adjustments)	3.25	0.000	0.776	0.710	0.820	0.094
Model 2 (deleted D_2)	3.11	0.000	0.780	0.737	0.831	0.090
Model 3 (deleted D_10)	3.05	0.000	0.791	0.741	0.840	0.087
Model 4 (deleted CA_D_3)	3.01	0.000	0.802	0.768	0.857	0.085
Model 5 (deleted CA_D_6)	2.95	0.000	0.821	0.775	0.864	0.084
Model 6 (deleted D_4)	2.92	0.000	0.846	0.801	0.873	0.083
Model 7 (deleted D_9)	2.91	0.000	0.871	0.828	0.895	0.081
Model 8 (deleted CA_C_4)	2.91	0.000	0.889	0.845	0.921	0.080
Model 9 (deleted CA_D_5)	2.93	0.000	0.906	0.864	0.936	0.072
Model 10 (deleted IP_1)	2.91	0.000	0.934	0.876	0.940	0.066
Model 11 (deleted IP_3)	2.87	0.000	0.950	0.902	0.956	0.060

Source: author's compilation

1) Model 1. The initial model exhibited suboptimal goodness of fit after removing certain items based on EFA results. To achieve a good fit, specific criteria should be met, such as a chi-square to degrees of freedom ratio (X2/df) less than 3, a Tucker-Lewis Index (TLI) exceeding 0.9, a Goodness of Fit Index (GFI) higher than 0.9, a Comparative Fit Index (CFI) greater than 0.9, and a Root Mean Square Error of Approximation (RMSEA) not exceeding 0.08. However, the initial model failed to meet these criteria, suggesting a poor fit. Consequently, the model underwent a series of gradual modifications and adjustments, involving the stepwise deletion of 10 items from various latent constructs, until a satisfactory fit was achieved.

2) Model 2. In the creation of Model 2, item D_2 ("The company has the right people, skills, and culture to realize its digital vision") was deleted due to its low factor loading in the EFA analysis. Following the removal of D_2, the model fit improved but still did not meet the desired standards, leading to additional adjustments.

3) Model 3. For Model 3, item D_10 ("Digital technologies are used in daily tasks") was removed based on the EFA results, which showed an insufficient factor loading. After deleting D_10, the model fit improved, but further adjustments were made to enhance its fit.

4) Model 4. In the development of Model 4, item CA_D_3 ("Mechanisms and workarounds to avoid change are not developed") was removed due to its insufficient factor loading in the EFA and the potential increase in Cronbach Alpha of the latent construct. Following the removal of CA_D_3, the model fit improved, indicating a more satisfactory alignment between the model and the data.

5) Model 5. To develop Model 5, item CA_D_6 ("Changes are believed to "breathe life" into the organization") was removed based on its unsatisfactory factor loading in the EFA analysis. Following the deletion of CA_D_6, the model fit improved, and the chi-square to degrees of freedom ratio reached a good estimation. However, other goodness-of-fit coefficients remained unsatisfactory, indicating the need for further adjustments to achieve a well-fitting model.

6) Model 6. In the subsequent phase of model refinement, item D_4 ("Digital technologies have been implemented in most aspects of the business") was excluded due to an inadequate factor loading of 0.68 identified in the EFA analysis. This removal led to some improvement in model fit, but the overall fit remained unsatisfactory. Consequently, further adjustments were implemented to enhance the model's performance.

7) Model 7. To develop Model 7, item D_9 ("Industry-specific technologies, such as APC, IIoT, and ERP systems, are used") was removed. The EFA analysis indicated a factor loading of 0.69 for this item, which is close to 0.7. Following the exclusion of D_9, there was an improvement in the model fit. However, further adjustments were deemed necessary to refine the model.

8) Model 8. In establishing Model 8, item CA_C_4 ("Employees may receive bonuses for completed development programs or improved qualifications") was eliminated. The EFA analysis revealed a factor loading of 0.66 for this item, close to 0.7. Following the removal of CA_C_4, there was a significant enhancement in the model fit. While the CFI coefficients reached an acceptable threshold, RMSEA, TLI and GFI remained unsatisfactory. Consequently, further adjustments were implemented to refine the model.

9) Model 9. To develop Model 9, item CA_D_5 ("Inevitable changes do not cause fear and dissatisfaction among people") was removed. The EFA analysis indicated a factor loading of 0.63 for this item, which is close to 0.7. Following the exclusion of CA_D_5, there was an improvement in the model fit. RMSEA and TLI coefficients reached an acceptable threshold. However, the GFI remained below the desired level of 0.9. Therefore, additional adjustments were necessary to further enhance the model's performance.

10) Model 10. To establish Model 10, item IP_1 ("Many digital technologies can be applied in the production/sales and distribution process") was eliminated. The EFA analysis revealed a factor loading of 0.6 for this item, which is considered unsatisfactory. Removing IP_1 led to an increase in GFI, but it still did not reach the acceptable threshold. Despite this improvement, further adjustments were required to achieve a well-fitting model.

11) Model 11. To create Model 11, item IP_3 ("Many digital technologies can be applied in office work") was removed. The EFA analysis indicated a factor loading of 0.68 for this item, which is close to the desired 0.7 threshold. Deleting IP_3 resulted in an increase in the GFI to 0.902.

The analysis process culminated in the identification of Model 11 as the final, well-fitting model. This refined model was then employed to test the research hypotheses. Table 24 summarizes the coefficients for the hypotheses and the corresponding final decisions based on the analysis. The Python programming language was utilized to conduct the hypothesis testing, with the details presented in Appendix Figure 4.

Table 24. *The results of testing of research hypotheses.*

	Std. coefficient	Corr. coefficient	p-value	Hypothesis
D ⟵ Competence	0.048	0.687	<0.05	accept
D ⟵ Attitude	0.028	0.561	<0.05	accept
D ⟵ Innovative push	0.018	0.569	<0.05	accept
D ⟵ Corporate technology	0.063	0.83	<0.05	accept
D ⟵ Competition	-0.002	-0.102	<0.05	reject
D ⟵ Market condition	0.017	0.261	>0.05	reject
D ⟵ System alignment	0.114	0.867	<0.05	accept
LP ⟵ D	0.099	0.647	<0.05	accept

Source: author's compilation

The research study examined 8 hypotheses related to factors influencing digitalization in enterprises. 6 out of the 8 hypotheses were accepted, indicating that the following factors positively impact digitalization: company's attitude towards employees' competence, company's attitude towards digitalization and change, high innovative pressure, generalized and interconnected technology, and alignment of business and Information Systems (IS) in an enterprise. The most influential factors were system alignment and corporate technology. Digitalization was found to positively affect labor productivity, with a standardized coefficient of 0.099. Companies with high levels of system alignment and developed corporate technology can more easily and successfully undergo digitalization, which in turn impacts labor productivity.

Two hypotheses were not supported by the data. The rejection of Hypothesis 6 is attributed to a high p-value, indicating a lack of statistical significance. This outcome could be attributed to insufficient sample size or respondents' misconceptions about the market environment in which the company operates. Future studies should delve deeper into the influence of market conditions to gain a comprehensive understanding of this relationship. Additionally, Hypothesis 5 was also rejected, despite showing statistical significance. The findings suggest that industry competition may have a detrimental effect on a company's digital transformation, a phenomenon that warrants further exploration.

In conclusion, this research underscores the crucial factors that facilitate successful digitalization and its positive impact on labor productivity. However, further investigation is necessary to elucidate the role of market conditions and the negative influence of industry competition on digital transformation.

2. Discussion

2.1. Results interpretation and practical recommendations

In the preceding paragraph, research hypotheses were examined along with the significance of the model. Consequently, a model demonstrating strong explanatory capability was derived (Figure 11).

Source: author's compilation

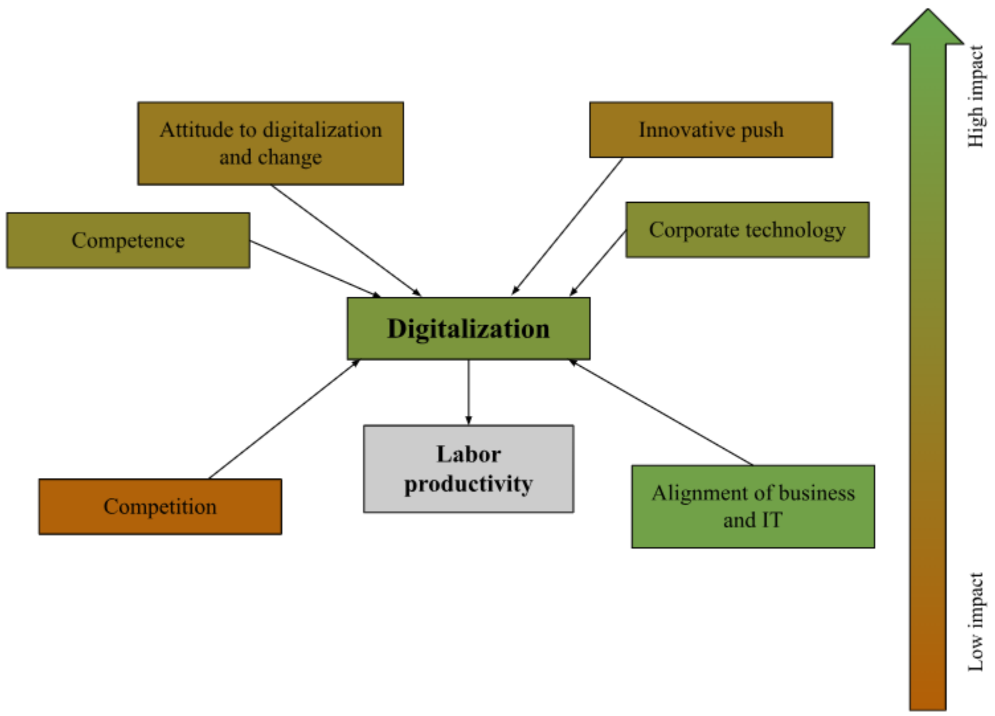

Figure 11. *Obtained model visualization.*

Since in the research obtained results from the respondents of only chemical and petrochemical industry were used, which is 27% of all sample, the following can be concluded. The research identified six primary factors influencing the digitalization process in companies that represent chemical and petrochemical cluster, ranked by their impact strengths in descending order:

1. Alignment of business and Information Systems (IS);
2. Corporate interconnected technology;
3. Company's attitude towards employees' competence;
4. Positive company attitude towards digitalization and change;
5. Innovative push;
6. Intensive competition.

Furthermore, the study revealed a positive correlation between digitalization and labor productivity, with a significant impact strength.

In order to provide actionable suggestions, these results will be combined with the digital transformation strategy. This strategic blueprint serves as a guide designed to innovate the company's existing business approach through the integration and utilization of digital technologies. A clearly outlined digital transformation plan is essential for the comprehensive integration of digital technologies in a manufacturing environment. This plan should encompass all facets of business operations, including production, quality assurance enhancements, distribution, and analytics[19].

Outlined factors that affect digitalization and, consequently, labor productivity can be presented as a matrix in terms of its impact on digitalization and its control over the company (Figure 12).

[19] Albukhitan, S. (2020). Developing digital transformation strategy for manufacturing. Procedia Computer Science, 170, 664–671. https://doi.org/10.1016/j.procs.2020.03.173

Source: author’s compilation

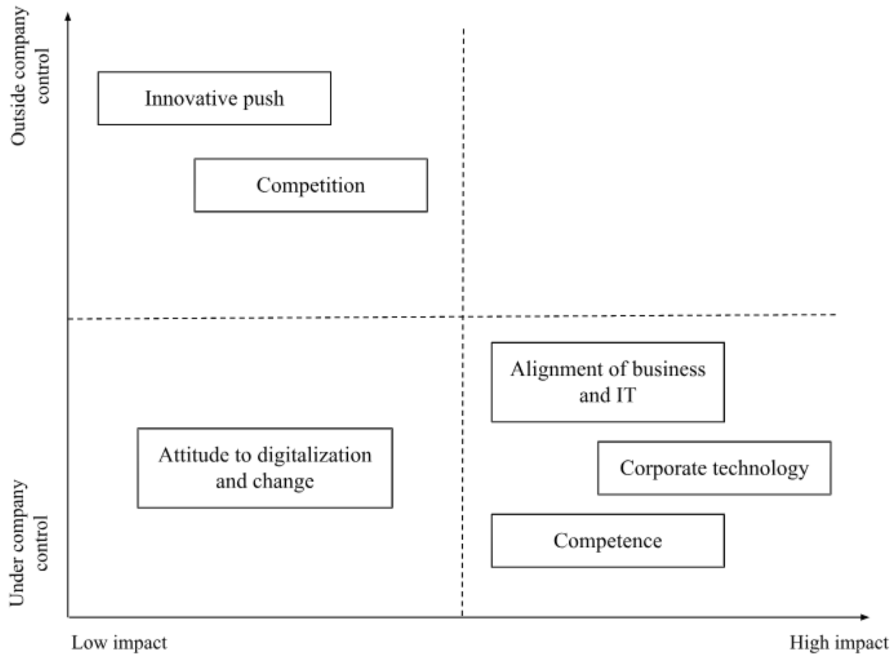

Figure 12. *Matrix of factors affecting digitalization.*

To ensure successful digitalization, companies should incorporate the following four goals into their digital strategy, focusing on factors within their sphere of influence:

1) Aligning the business strategy with the IT strategy of the company.

Aligning business and information systems requires strategically integrating IT and IS to align with the company's business goals and mission. This process involves redefining the business model to treat IT and IS as integral parts of the organization rather than separate entities. Successful alignment of business and IT encompasses the following key areas:

- Enhancing communication;
- Measuring IT impact;
- IT governance;
- Technology infrastructure and architecture;
- Building partnerships;
- Skill development.

2) Enhancing the connectivity of corporate systems.

Many organizations currently operate multiple information systems independently, lacking integration. For example, companies often use distinct software for accounting, budgeting, logistics, marketing, and other functions. This fragmented approach can impede digital transformation efforts, as each system requires individual handling, limiting adaptability and hindering progress. To address this issue, companies should establish a unified corporate network to facilitate cross-departmental collaboration. A consolidated network offers enhanced security, supports diverse functions crucial for operational efficiency, and improves decision-making agility. By fostering a cohesive, interconnected system, companies can streamline operations, enhance data sharing, and make informed decisions, expediting digital transformation and enabling swift adaptation to market dynamics and customer requirements.

3) Transitioning to simplified and integrated technologies.

Successful digital transformation hinges on employing technologies that align with and support the transformation journey. When companies are choosing new technologies, they need to take into account various factors such as how well they will work with current systems, how adaptable and user-friendly they are, as well as the costs and benefits involved. These factors should play a critical role in the decision-making process. If there are incompatible technologies in place, the company should take proactive measures to get ready for digital transformation, which may involve replacing or improving these technologies with the help of a specialized team. By prioritizing technology compatibility and user-friendliness, the company can ensure a smoother transition, reduce disruptions, facilitate the seamless integration of new technologies, and help employees adjust to the ever-changing tech landscape.

4) Establishing a comprehensive employee competency enhancement program.

Implementing a structured competency enhancement program within a digital transformation strategy involves initiatives to enhance employees' skills, knowledge, and capabilities to meet the evolving digital demands. This program focuses on upskilling, reskilling, fostering a culture of continuous learning, and ensuring employees possess the competencies to drive digital transformation. By investing in competency development, organizations empower their workforce to navigate the digital realm effectively, boost performance, and contribute to the successful implementation of digital initiatives.

In summary, the digital transformation strategy's key objectives have been delineated into actionable recommendations for the petrochemical industry to adopt.

2.2. The case of SIBUR

To provide actionable insights, the experience of SIBUR company will be leveraged to illustrate a real-world example of how digital transformation is implemented in a manufacturing company, and how it reflects the four primary recommendations proposed throughout this research.

Among the 10 top-ranked companies in the chemical and petroleum industry, SIBUR is particularly well-known for its expertise in the petrochemical industry, with a particular focus on polymer production. Petrochemical holding SIBUR is one of the first Russian companies to embark on the path of introduction of "Industry 4.0" technologies.

SIBUR's digital transformation strategy is centered around adaptability and a willingness to embrace change. This involves a thorough analysis of existing business processes and the identification of potential areas for expansion. By evaluating various digital initiatives, SIBUR selects projects that will enhance operational efficiency and integrates them into its workflow.

The level of technological equipment of the group's enterprises is currently one of the highest in Russia. In 2022, the digitalization and improvement of end-to-end business processes resulted in a financial impact of 13.2 billion rubles for SIBUR. This was almost a third higher than in 2021[20].

This paragraph would cover exact examples of SIBUR experience in the areas proposed in entire research as recommendations.

- Aligning the business strategy with the IT strategy of the company.

SIBUR aligns its business strategy with its IT strategy to enhance operational efficiency and competitiveness. The company leverages IT to support its business objectives and ensure effective resource utilization. Improving production efficiency while considering safety and environmental principles is another goal of digital transformation. A key aspect of SIBUR's alignment strategy is the integration of digital tools to enhance safety at its production facilities. This initiative demonstrates how the company incorporates IT solutions to support its core business functions, highlighting the importance of aligning technology investments with overall business objectives. SIBUR's focus on sustainability

[20] PJSC SIBUR Holding - official website. PJSC SIBUR. Access: https://www.sibur.ru/ru/press-center/news-and-press/tsifrovizatsiya-i-transformatsiya-protsessov-k-2023-godu-prinesli-siburu-bolee-30-mlrd-rubley/ (date: 25.12.2023)

and environmental responsibility is also reflected in its IT strategy. The company's commitment to reducing its environmental footprint is supported using digital technologies that minimize waste, reduce energy consumption, and promote recycling. Furthermore, SIBUR's IT strategy is influenced by its commitment to diversity and inclusion. The company's digital platforms and tools are designed to foster a culture of diversity and inclusion, ensuring that all employees have equal opportunities for growth and development.

Examining this goal through the example of the company, it can be noted that significant environmental benefits are also provided by the following Industry 4.0 tools:

- The use of drones allows for operational inspections of the territory for damage or deviations from regulations. Flights over technological equipment with infrared cameras enable the detection of local temperature levels on equipment bodies from various angles and in hard-to-reach areas for personnel, increasing informativeness about technical condition;
- A sampling system enables eco-monitoring of river waters;
- Intelligent video surveillance allows for the detection of any visual anomalies in the state of technological equipment, its operating modes, and flame control. All this enables timely decisions on the need for mitigating measures to maintain environmental status and equipment operability;
- The application of Industrial Internet of Things (IIoT) solutions promotes the automation of non-critical production processes and allows for the timely connection of backup equipment in case of technological necessity. Additionally, sensors enable optimal load distribution on equipment.

➢ Increasing the interconnectedness of corporate systems.

SIBUR focuses on increasing the interconnectedness of its corporate systems to enhance operational efficiency and competitiveness. The company leverages digital technologies to integrate its business processes, ensuring seamless communication and data exchange across various departments and locations. One key aspect of SIBUR's interconnectedness strategy is the implementation of Industry 4.0 technologies. The company uses advanced process control systems (SAPC), production management systems (MES), laboratory information management systems (LIMS), and business applications (ERP based) to optimize its production processes and improve decision-making. Another example of SIBUR's interconnectedness strategy is its use of digital platforms for communication and collaboration. The company's digital platforms allow employees to share information, access company resources, and participate in training programs remotely. This increased connectivity enables SIBUR to foster a culture of collaboration and knowledge sharing across its global operations.

The company is committed to automating and digitizing key business processes. This digital transformation covers major end-to-end processes throughout the value chain at SIBUR. The three main processes – sales (from order to cash, O2C), production (from plan to produce, P2P) and procurement (from source to pay, S2P) – collectively contribute to 80% of the overall benefits from digitalization[21].

Table 25 outlines the main digitalization initiatives for these processes in the areas of sales, production, and procurement, as well as providing a brief description for each.

Table 25. *Digitalization and optimization results in the key business processes of SIBUR Holding.*

Business process	Key Projects
Sales	1. GTM program; 2. Cross-sales; 3. Service model; 4. Digital lead generation; 5. Development of demand; 6. Development of digital sales channels.
Production	1. Process simulation; 2. Advanced Process Control (APC); 3. ECONS; 4. Real Time Optimization (RTO); 5. Black Screen intelligent video surveillance.
Procurement	1. Procurement synergy (chemicals, containers, packaging, materials and equipment); 2. Category-based strategies (equipment and materials); 3. Centralization of purchases of the second list in hubs (equipment and materials).

Source: PJSC SIBUR Holding - official website

- Switching to simple and generalized technologies.

SIBUR, together with its partners, is already working on creating industry-specific IT solutions. The company is moving towards the selection of unified platforms,

[21] Ibid.

transparency of requirements for all IT companies, and the development of large pools of developers interacting within common standards. The company has joined two industrial competence centers: "Oil and Gas and Petrochemicals" and "Chemistry." Together with its partners, SIBUR acts as a customer and in some projects, particularly in the creation of an RTO-class technological process simulation system, as a developer, participates in initiatives to create a domestic analogue of the MES production system, digital twins, technological modeling, and reliability management systems, and domestic-based APCS. This is a unique approach to industry partnerships, even by global standards.

Among the IT products at the intersection of mathematics, chemistry, and physics are autopilot systems RTO and APC, which require a strict mathematical model. Until recently, only one company in the world, a French one, was able to build it well. Now the company is looking for a solution to this problem, and once it finds it, the question of the sales market for new IT products created based on its model will arise. For SIBUR's business, this is already a different science, different stages of customization, implementation, integration, and support. Over time, all large industrial companies will be surrounded by partnerships and IT projects that will create new markets for unique solutions with every step.

- Developing and implementing a comprehensive competency enhancement program for employees.

SIBUR places emphasis on enhancing employee skills in working with cutting-edge technology systems and software for data analysis to optimize production processes and fostering the growth of new skills and job roles among staff.

The central component of the employee training and development framework is the Corporate University, which aims to enhance the skills of staff and managers to uphold the company's competitiveness in a dynamic business environment. SIBUR's educational system plays a vital role in staffing the company's operations, fostering a cohesive production and corporate culture across its facilities, and boosting overall production and economic efficiency. Notably, SIBUR's Corporate University achieved accreditation under the CLIP EFMD international quality system, a recognition earned by being the first among Russian industrial firms, developed by the European Foundation for Management Development to evaluate corporate training systems.

Key initiatives and educational projects[22]:

- Competency development. The establishment of the "SIBURINTECH" Center in Tobolsk in 2020, offering a wide array of programs for engineering and workforce development, focusing on both technical and soft skills like critical thinking, change management, and collaboration.
- Digital transformation. Introduction of an IT and digital competencies faculty to educate employees on digitization tools and the principles of the "4.0 industrial revolution."
- Sustainable development. Launch of an online course on sustainable development integrated into SIBUR's new employee adaptation program, accessible to both employees and partners.
- Educational partnerships. Providing educational opportunities to clients, contractors, students, and graduates to enhance the petrochemical industry's knowledge base and promote engineering professions.
- Online learning platform. Development of the "SIBUR Business Practices" platform to share best practices with partners through webinars, video lectures, and online courses.
- Targeted training. Implementation of the "Engineering Standard" document outlining specialized training formats for students at various educational levels, incorporating WorldSkills practices.
- Support for education initiatives. Implementation of programs to enhance IT education, early English language learning, and school infrastructure in regions where SIBUR operates.

The company's digitalization journey commenced with pilot projects in 2018-2019, leading to the consolidation of digital and IT competencies under the SIBUR Digital cluster in 2020. Subsequently, SIBUR Connect was established within the cluster in response to the growing number of IT infrastructure projects. The company's digital transformation strategy involves the active digitalization of core business processes, with organizational changes planned until 2025[23].

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[22] Ibid.

[23] Sibur Digital. SIBUR Digital. Access: https://www.sibur.digital/ (date: 20.02.2024)

To enhance labor productivity, SIBUR is developing labor improvement programs at its production sites, targeting areas such as redundant tasks, inefficient work allocation, and manual labor. Incentive programs have been introduced for blue-collar and white-collar workers to boost motivation and engagement. The universalization of blue-collar professions program, initiated in 2022, enables employees to acquire additional skills, leading to increased productivity, streamlined operations, and enhanced workflow flexibility[24].

In 2024, SIBUR, Sber, and Speech Technology Center (STC) signed a cooperation agreement to jointly develop and implement practical applications of Sber's large language model GigaChat in the field of Artificial Intelligence (AI)[25]. SIBUR is actively integrating Sber's AI technologies to create innovative solutions. For example, AI assistants for various functions:

- Diagnostic engineers: an AI assistant that enables engineers to have dialogues about the causes of equipment malfunctions, providing real-time troubleshooting support.
- Financial specialists: an AI assistant that aggregates company data to answer questions about the dynamics of key factors affecting contribution margin. It helps make data-driven decisions, improves forecasting accuracy, and optimizes processes to increase profits.
- R&D area: an AI assistant for modeling polymers and creating materials with new properties. It aims to predict polymerization processes, polymer properties, formulations, additives, and their impact on the physical and mechanical properties of materials and finished products.
- Procurement: an AI advisor for optimizing the procurement of material and technical resources, transitioning from static records of nomenclature items to parametric cards. The system selects acceptable analogues with advantages in price, quality, and availability.

Vasily Nomokonov, Member of the Management Board and Executive Director of SIBUR, emphasized that as a leader in industrial digitalization, SIBUR is constantly implementing cutting-edge technologies and testing new hypotheses. SIBUR is one of the first companies in Russia to actively implement large language models in key processes,

[24] Kommersant. (2024, May 24). “Review ‘50 years of Tobolsk petrochemistry'". Application. Kommersant. https://www.kommersant.ru/doc/6714689
[25] PJSC SIBUR Holding - official website. (n.d.). PJSC SIBUR. https://www.sibur.com/ru/press-center/news-and-press/cibur-vnedryaet-v-svoi-protsessy-neyrosetevuyu-model-gigachat/

thanks to its partners' openness to joint experiments. Several cases have been developed and tested, including AI assistants for diagnostic engineers, financial specialists, and equipment and materials procurement specialists. These solutions will enable SIBUR to take the next step towards increasing labor productivity by significantly accelerating decision-making across various company processes. SIBUR sees great potential in leveraging tools based on generative artificial intelligence.[26].

In summary, SIBUR showcases a strong alignment between its business and IT strategies. Some noteworthy success factors that can be used as benchmarks by others include the alignment of digital transformation strategy with business strategy, integration of information systems both internally and externally, creation of an IT cluster and in-house solutions, and implementation of a thorough personnel training and development system. In terms of labor productivity incentives, SIBUR consistently strives for enhancement by supporting employees, offering required training and development opportunities, and utilizing contemporary digital tools to streamline operations, enhance safety, and boost efficiency in the production process.

2.3. Limitations and future research

The research presented has several constraints that merit acknowledgment. Firstly, the study is geographically confined to the Russian petrochemical industry, thereby limiting its applicability to the Russian market alone. It is plausible that model testing outcomes may vary when applied to different markets. Secondly, the research is narrowly focused on the manufacturing sector, with each company possessing its own set of digital technologies primarily suited for production processes. This industrial focus restricts the generalizability of the findings. Thirdly, the sample composition lacks representation from small-scale enterprises. Smaller companies often exhibit lower levels of digital adoption compared to larger firms. This underrepresentation warrants further research to delve into the unique aspects of digital transformation within small manufacturing organizations.

Moving forward, there are several avenues for additional research. Firstly, a detailed examination of the relationship between a company's market conditions and its digital transformation process is essential. The research uncovered discrepancies in theory

[26] Ibid.

regarding this factor, notably rejecting the initial hypothesis of industry instability positively impacting digital transformation. An in-depth analysis is needed to explore the effects, both positive and negative, of industry instability on digital transformation within manufacturing companies. Secondly, further research should delve into the impact of competition on digitalization concerning labor productivity enhancement in manufacturing firms. While the research did not confirm the hypothesized relationship, existing theory suggests its significance, necessitating further investigation and analysis. Lastly, exploring the adaptation of the research model to a different industry sector presents a promising avenue for future research.

3. Conclusion on Chapter 3

In the third chapter the research model was tested, and hypotheses were checked. As a result, research revealed six main factors which affect digitalization of petrochemical companies:

1. Alignment of business and Information Systems (IS);
2. Corporate interconnected technology;
3. Company's attitude towards employees' competence;
4. Positive company attitude towards digitalization and change;
5. Innovative push.
6. Intensive competition.

Two hypotheses regarding industry instabilities and competition were rejected due to a high p-value, indicating insignificance and negative impact.

Research has revealed a positive correlation between digitalization and labor productivity, with a significant impact strength. Based on the findings, the following practical recommendations have been proposed:

- To align business and IT strategies: to ensure that the company's business strategy is closely aligned with its IT strategy. This alignment is crucial for maximizing the benefits of digital transformation and enhancing overall operational efficiency.
- To increase interconnectedness of corporate systems: to enhance the interconnectedness of the company's various corporate systems, enabling seamless data flow and integration across different functions and departments. This can lead to improved decision-making, streamlined processes, and increased productivity.

- To adopt simple and generalized technologies: transition towards the use of simple and generalized technologies, rather than complex and specialized solutions. This approach can simplify system maintenance, reduce training requirements, and facilitate broader adoption across the organization.
- To implement comprehensive competency enhancement programs: to develop and implement a comprehensive competency enhancement program for employees, focusing on both technical and soft skills. This can help ensure that the workforce is equipped to effectively leverage digital tools and technologies, driving productivity improvements.

The recommendations mentioned above can be exemplified by the case of SIBUR, the Russian leader in the petrochemical industry. SIBUR's approach to the interconnection between digitalization and labor productivity can be analyzed from the four perspectives outlined:

- Aligning business and IT strategies: SIBUR has consolidated its digital and IT competencies under the SIBUR Digital cluster, ensuring a cohesive strategy for digital transformation.
- Increasing interconnectedness of corporate systems: SIBUR has actively implemented the digitalization of its core business processes, fostering greater integration and data flow across the organization.
- Adopting simple and generalized technologies: SIBUR's digitalization journey has involved a focus on identifying the most suitable tools and technologies, avoiding unnecessary investments and complexity.
- Implementing comprehensive competency enhancement programs: SIBUR's Corporate University has played a pivotal role in developing both technical and soft skills among its employees, supporting the company's digital transformation efforts.

By aligning these four key aspects, SIBUR has demonstrated a comprehensive approach to leveraging digitalization to drive improvements in labor productivity, positioning the company for continued success in the dynamic petrochemical industry.

CONCLUSION

The primary goal of this research study was to investigate how digitalization factors impact labor productivity in the petrochemical industry. In order to achieve this goal, a series of steps were taken.

In Chapter 1, an extensive examination of recent research on the correlation between digitalization and labor productivity in manufacturing firms was conducted, with a particular emphasis on their interdependent nature. This scrutiny brought to light a significant research void, indicating a predominance of qualitative studies and a shortage of quantitative investigations into the relationship between digitalization and labor productivity. Given the limited application of quantitative methodologies, there was a need to delve into the attributes of digitalization and their impact on the growth of labor productivity. The objective was to construct a quantitative framework that could assist organizations in making well-founded decisions and selecting digital technologies to improve labor productivity.

Chapter 2 focused on formulating a research model based on the insights gathered from the literature review, identifying two distinct sets of factors that influence both digitalization and labor productivity. Subsequently, seven key factors influencing digitalization were chosen for detailed analysis based on the literature review:

1) Innovative push;
2) Competition;
3) Attitude to digitalization and change;
4) Corporate technology;
5) Market condition;
6) Employee competence;
7) Alignment of Business and IS.

The research model incorporated Digitalization as a mediating variable between the factors influencing digitalization and labor productivity.

The study utilized Structural Equation Modeling to investigate eight hypotheses, incorporating both Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). Data was collected through a survey questionnaire consisting of 63 questions across 10 sections, distributed to manufacturing companies. A total of 258 responses were received, with 71 from the chemistry and petrochemistry industry used for further analysis.

Chapter 3 focused on data analysis and generating practical recommendations. The initial model was adjusted to create a final model. Goodness-of-fit coefficients confirmed the model's significance and strong explanatory power. Testing of hypotheses resulted in the acceptance of 6 out of 8. The study found that factors like the company's attitude towards employee competence, digitalization and change, high innovation pressure, interconnected technology, and alignment of business and Information Systems (IS) within a company positively influenced digitalization. Particularly, system alignment and corporate technology were noted as the most impactful factors. Digitalization was shown to have a positive impact on labor productivity, with a standardized coefficient of 0.099. Companies with strong system alignment and advanced corporate technology were found to be more successful in implementing digitalization, leading to improved labor productivity. Further research is recommended to delve into the role of market conditions and the potential negative effects of industry competition in the realm of digital transformation.

The study findings led to the development of strategic recommendations for chemical and petrochemical companies to consider in their digitalization strategies. These recommendations focus on four key areas:

1) Harmonizing business and IT strategies. Ensuring that the company's business objectives are closely aligned with and supported by its information technology strategy is crucial for successful digitalization efforts. By integrating these two critical components, organizations can optimize resource allocation, streamline processes, and achieve greater synergy between business goals and technological capabilities.

2) Enhancing system interconnectivity. Increasing the level of interconnectedness among various corporate systems can significantly improve data flow, decision-making, and overall operational efficiency. By breaking down silos and fostering seamless integration, companies can leverage the power of data to drive innovation and gain a competitive edge.

3) Adopting simplified and standardized technologies. Transitioning to simple and generalized technologies can simplify maintenance, reduce complexity, and enable faster adaptation to changing market conditions. By prioritizing standardization and simplicity, chemical and petrochemical companies can optimize their technology stack, reduce costs associated with customization and maintenance, and focus on core business objectives.

4) Investing in employee competency development. Developing and implementing a comprehensive competency enhancement program for employees is essential for successful digitalization. By providing training, resources, and support, companies can

empower their workforce to embrace new technologies, adapt to changing processes, and contribute to the overall success of the digitalization initiative. Investing in employee development not only enhances individual capabilities but also fosters a culture of innovation and continuous improvement.

To further strengthen these recommendations, the study incorporated the example of SIBUR, a leading chemical and petrochemical company, as a benchmark for other organizations in the industry. By analyzing SIBUR's digitalization journey and best practices, the research provides a practical reference point for companies seeking to replicate successful strategies and learn from industry leaders.

In conclusion, the research successfully achieved its goal by formulating strategic recommendations that address the key challenges and opportunities in the digitalization of chemical and petrochemical companies. By aligning business and IT strategies, enhancing system interconnectivity, adopting simplified technologies, and investing in employee competency development, organizations can navigate the digital transformation landscape more effectively and position themselves for long-term success.

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Appendix

Table 1. *The 10 largest companies in the chemical and petrochemical industry from the RAEX-600 2022 rating.*

	Name	Place in the RAEX-600 rating	Sales volume in 2021 (million rubles)	Annual revenue growth rate (%)
1	MHC EuroChem	22	751 581	68,9
2	SIBUR Holding	23	731 176	70,6
3	(PAO) Uralchem	32	474 213	265,5
4	OHK "PhosAgro"	39	420 488	65,6
5	Uralkali	59	305 275	56,4
6	Henkel Rus	196	95 138	13,1
7	KuibyshevAzot	213	87 489	64,9
8	Metafrax Chemicals	227	80 455	64,4
9	Bashkir Soda Company	250	75 036	16,3
10	POLYPLASTIC Group	268	69 493	62,9

Source: RAEX-600 2022

Source: author's compilation

```
!pip install factor_analyzer
!pip install pingouin
```

```
[41] import pandas as pd
     import numpy as np
     import pingouin as pg
     from factor_analyzer import FactorAnalyzer
     from factor_analyzer.factor_analyzer import calculate_bartlett_sphericity, calculate_kmo
```

```
[9]  # Load the csv file
     df = pd.read_csv('data.csv')
     print(df.head())
     print(df.info())
```

```
[35] # Select the columns corresponding to the latent variables
     digitalization = df[['D_1', 'D_2', 'D_3', 'D_4', 'D_5', 'D_6', 'D_7', 'D_8', 'D_9', 'D_10', 'D_11', 'D_12', 'D_13']]
     company_competence = df[['CA_C_1', 'CA_C_2', 'CA_C_3', 'CA_C_4', 'CA_C_5']]
     company_changes = df[['CA_D_1', 'CA_D_2', 'CA_D_3', 'CA_D_4', 'CA_D_5', 'CA_D_6', 'CA_D_7']]
     labor_productivity = df[['LP_1', 'LP_2', 'LP_3', 'LP_4', 'LP_5', 'LP_6', 'LP_7']]
     innovative_push = df[['IP_1', 'IP_2', 'IP_3', 'IP_4', 'IP_5']]
     corporate_tech = df[['CIS_1', 'CIS_2', 'CIS_3', 'CIS_4', 'CIS_5']]
     competition = df[['C_1', 'C_2', 'C_3']]
     industry_state = df[['IN_1', 'IN_2', 'IN_3', 'IN_4']]
     business_alignment = df[['B_IS_1', 'B_IS_2', 'B_IS_3', 'B_IS_4', 'B_IS_5', 'B_IS_6', 'B_IS_7', 'B_IS_8', 'B_IS_9']]
```

```
[52] # Perform EFA for each latent variable
     def perform_efa(df):
         # Calculate Bartlett's Test
         chi_square_value, p_value = calculate_bartlett_sphericity(df)
         print("Bartlett's Test p-value:", p_value)

         # Calculate KMO Measure
         kmo = calculate_kmo(df)
         print("Kaiser-Meyer-Olkin (KMO) Measure:", kmo)

         # Fit the FactorAnalyzer model
         fa = FactorAnalyzer(rotation=None)
         fa.fit(df)

         # Get Factor loadings
         factor_loadings = fa.loadings_
         print("Factor Loadings:")
         print(factor_loadings)

         # Calculate Cronbach's Alpha
         cronbach_alpha = pg.cronbach_alpha(data=df)
         print("Cronbach's Alpha:", cronbach_alpha)
```

```
# Perform EFA for each latent variable
print("EFA for latent variable Digitalization:")
perform_efa(digitalization)
print()
print("EFA for latent variable Company's attitude to employee's competence:")
perform_efa(company_competence)
print()
print("EFA for latent variable Company's attitude to digitalization and changes:")
perform_efa(company_changes)
print()
print("EFA for latent variable Labor productivity:")
perform_efa(labor_productivity)
print()
print("EFA for latent variable Innovative push in the industry:")
perform_efa(innovative_push)
print()
print("EFA for latent variable Corporate information systems and technologies:")
perform_efa(corporate_tech)
print()
print("EFA for latent variable Competition in the industry:")
perform_efa(competition)
print()
print("EFA for latent variable The state of the industry:")
perform_efa(industry_state)
print()
print("EFA for latent variable Business and information system alignment:")
perform_efa(business_alignment)
```

Figure 1. *Exploratory Factor analysis (EFA) using Python Programming language.*

Source: author's compilation

```
from factor_analyzer import ConfirmatoryFactorAnalyzer, ModelSpecificationParser

# Load the data from the CSV file
df = pd.read_csv('data.csv')
# df.info()
# df.head()

df.drop(['D_3', 'D_7', 'D_8', 'CA_D_4', 'IP_4', 'CIS_3', 'C_1', 'IN_4', 'B_IS_5'], axis=1, inplace=True)
# df.info()
```

```
[4] # Define the latent variables and their corresponding items
    latent_variables = {
        "Digitalization": ["D_1", "D_2", "D_4", "D_5", "D_6", "D_9", "D_10", "D_11", "D_12", "D_13"],
        "Company's attitude to employee's competence": ["CA_C_1", "CA_C_2", "CA_C_3", "CA_C_4", "CA_C_5"],
        "Company's attitude to digitalization and changes": ["CA_D_1", "CA_D_2", "CA_D_3", "CA_D_5", "CA_D_6", "CA_D_7"],
        "Labor productivity": ["LP_1", "LP_2", "LP_3", "LP_4", "LP_5", "LP_6", "LP_7"],
        "Innovative push in the industry": ["IP_1", "IP_2", "IP_3", "IP_5"],
        "Corporate information systems and technologies": ["CIS_1", "CIS_2", "CIS_4", "CIS_5"],
        "Competition in the industry": ["C_2", "C_3"],
        "The state of the industry": ["IN_1", "IN_2", "IN_3"],
        "Business and information system alignment": ["B_IS_1", "B_IS_2", "B_IS_3", "B_IS_4", "B_IS_6", "B_IS_7", "B_IS_8", "B_IS_9"]
    }
```

Confirmatory Factor Analysis (CFA)

```
[5] model_spec = ModelSpecificationParser.parse_model_specification_from_dict(df, latent_variables)
    cfa = ConfirmatoryFactorAnalyzer(model_spec, disp=False)
    cfa.fit(df.values)
```

Factor loadings

```
[ ] cfa.loadings_
```

Standard errors

```
[6] cfa.get_standard_errors()
```

Critical ratio coeffitients

```
[15] # Latent variable Digitalization
     d_factor_loadings = [0.673, 0.473, 0.600, 0.638, 1.092, 1.135, 1.076, 1.510, 0.812, 1.233]
     d_errors = [0.005, 0.052, 0.038, 0.032, 0.073, 0.074, 0.087, 0.068, 0.026, 0.075]
     d_critical_ratios = [d_factor_loadings[i] / np.sqrt(d_errors[i]) for i in range(len(d_factor_loadings))]
     print("Digitalization Critical Ratio Coefficients:")
     for i, cr in enumerate(d_critical_ratios):
         print(f"Item {i+1}: {cr:.3f}")

     # Latent variable Company’s attitude to employee’s competence
     ca_factor_loadings = [0.690, 1.043, 0.858, 1.234, 0.789]
     ca_errors = [0.043, 0.048, 0.065, 0.092, 0.059]
     ca_critical_ratios = [ca_factor_loadings[i] / np.sqrt(ca_errors[i]) for i in range(len(ca_factor_loadings))]
     print("Company’s attitude to employee’s competence Critical Ratio Coefficients:")
     for i, cr in enumerate(ca_critical_ratios):
         print(f"Item {i+1}: {cr:.3f}")

     # Latent variable Company's attitude to digitalization and changes
     cad_factor_loadings = [0.719, 1.206, 0.599, 1.159, 0.457, 1.197]
     cad_errors = [0.041, 0.046, 0.080, 0.093, 0.061, 0.059]
     cad_critical_ratios = [cad_factor_loadings[i] / np.sqrt(cad_errors[i]) for i in range(len(cad_factor_loadings))]
     print("Company's attitude to digitalization and changes Critical Ratio Coefficients:")
     for i, cr in enumerate(cad_critical_ratios):
         print(f"Item {i+1}: {cr:.3f}")

     # Latent variable Labor productivity
     lp_factor_loadings = [0.802, 0.912, 1.524, 0.996, 0.424, 1.104, 1.232]
     lp_errors = [0.016, 0.045, 0.065, 0.033, 0.014, 0.055, 0.061]
     lp_critical_ratios = [lp_factor_loadings[i] / np.sqrt(lp_errors[i]) for i in range(len(lp_factor_loadings))]
     print("Labor productivity Critical Ratio Coefficients:")
     for i, cr in enumerate(lp_critical_ratios):
         print(f"Item {i+1}: {cr:.3f}")
```

```
[15] # Latent variable Innovative push in the industry
     ip_factor_loadings = [0.529, 0.802, 0.517, 1.309]
     ip_errors = [0.019, 0.006, 0.002, 0.076]
     ip_critical_ratios = [ip_factor_loadings[i] / np.sqrt(ip_errors[i]) for i in range(len(ip_factor_loadings))]
     print("Innovative push in the industry Critical Ratio Coefficients:")
     for i, cr in enumerate(ip_critical_ratios):
         print(f"Item {i+1}: {cr:.3f}")

     # Latent variable Corporate information systems and technologies
     cis_factor_loadings = [0.616, 0.927, 1.346, 0.774]
     cis_errors = [0.057, 0.059, 0.083, 0.056]
     cis_critical_ratios = [cis_factor_loadings[i] / np.sqrt(cis_errors[i]) for i in range(len(cis_factor_loadings))]
     print("Corporate information systems and technologies Critical Ratio Coefficients:")
     for i, cr in enumerate(cis_critical_ratios):
         print(f"Item {i+1}: {cr:.3f}")

     # Latent variable Competition in the industry
     c_factor_loadings = [0.872, 0.486]
     c_errors = [0.052, 0.041]
     c_critical_ratios = [c_factor_loadings[i] / np.sqrt(c_errors[i]) for i in range(len(c_factor_loadings))]
     print("Competition in the industry Critical Ratio Coefficients:")
     for i, cr in enumerate(c_critical_ratios):
         print(f"Item {i+1}: {cr:.3f}")

     # Latent variable The state of the industry
     in_factor_loadings = [1.214, 0.707, 1.159]
     in_errors = [0.064, 0.031, 0.065]
     in_critical_ratios = [in_factor_loadings[i] / np.sqrt(in_errors[i]) for i in range(len(in_factor_loadings))]
     print("The state of the industry Critical Ratio Coefficients:")
     for i, cr in enumerate(in_critical_ratios):
         print(f"Item {i+1}: {cr:.3f}")
```

```python
[15] # Latent variable Business and information system alignment
bis_factor_loadings = [0.605, 0.923, 0.601, 0.529, 1.138, 1.110, 0.975, 1.575]
bis_errors = [0.041, 0.047, 0.055, 0.038, 0.065, 0.064, 0.061, 0.074]
bis_critical_ratios = [bis_factor_loadings[i] / np.sqrt(bis_errors[i]) for i in range(len(bis_factor_loadings))]
print("Business and information system alignment Critical Ratio Coefficients:")
for i, cr in enumerate(bis_critical_ratios):
    print(f"Item {i+1}: {cr:.3f}")
```

Composite factor reliability and Average Variance Extracted (AVE)

```python
[20] # Latent variable Digitalization
d_n = len(d_factor_loadings)
d_composite_reliability = (sum(d_factor_loadings)**2) / ((sum(d_factor_loadings)**2) + sum(d_errors))
print(f"Digitalization Composite Factor Reliability: {d_composite_reliability:.3f}")

d_ave = sum(np.square(d_factor_loadings)) / d_n
print(f"Digitalization Average Variance Extracted (AVE): {d_ave:.3f}")
print()

# Latent variable Company’s attitude to employee’s competence
ca_n = len(ca_factor_loadings)
ca_composite_reliability = (sum(ca_factor_loadings)**2) / ((sum(ca_factor_loadings)**2) + sum(ca_errors))
print(f"Company’s attitude to employee’s competence Composite Factor Reliability: {ca_composite_reliability:.3f}")

ca_ave = sum(np.square(ca_factor_loadings)) / ca_n
print(f"Company’s attitude to employee’s competence Average Variance Extracted (AVE): {ca_ave:.3f}")
print()
```

```python
# Latent variable Corporate information systems and technologies
cis_n = len(cis_factor_loadings)
cis_composite_reliability = (sum(cis_factor_loadings)**2) / ((sum(cis_factor_loadings)**2) + sum(cis_errors))
print(f"Corporate information systems and technologies Composite Factor Reliability: {cis_composite_reliability:.3f}")

cis_ave = sum(np.square(cis_factor_loadings)) / cis_n
print(f"Corporate information systems and technologies Average Variance Extracted (AVE): {cis_ave:.3f}")
print()

# Latent variable Competition in the industry
c_n = len(c_factor_loadings)
c_composite_reliability = (sum(c_factor_loadings)**2) / ((sum(c_factor_loadings)**2) + sum(c_errors))
print(f"Competition in the industry Composite Factor Reliability: {c_composite_reliability:.3f}")

c_ave = sum(np.square(c_factor_loadings)) / c_n
print(f"Competition in the industry Average Variance Extracted (AVE): {c_ave:.3f}")
print()

# Latent variable The state of the industry
in_n = len(in_factor_loadings)
in_composite_reliability = (sum(in_factor_loadings)**2) / ((sum(in_factor_loadings)**2) + sum(in_errors))
print(f"The state of the industry Composite Factor Reliability: {in_composite_reliability:.3f}")

in_ave = sum(np.square(in_factor_loadings)) / in_n
print(f"The state of the industry Average Variance Extracted (AVE): {in_ave:.3f}")
print()

# Latent variable Business and information system alignment
bis_n = len(bis_factor_loadings)
bis_composite_reliability = (sum(bis_factor_loadings)**2) / ((sum(bis_factor_loadings)**2) + sum(bis_errors))
print(f"Business and information system alignment Composite Factor Reliability: {bis_composite_reliability:.3f}")

bis_ave = sum(np.square(bis_factor_loadings)) / bis_n
print(f"Business and information system alignment Average Variance Extracted (AVE): {bis_ave:.3f}")
```

Figure 2. *Confirmatory Factor analysis (CFA) using Python Programming language.*

Source: author’s compilation

```
[2] !pip install semopy
```

```
[1] import pandas as pd
    import numpy as np
    import statsmodels.api as sm
    import matplotlib.pyplot as plt
```

```
[3] from semopy import Model, semplot, calc_stats
```

```
[6] # Load your data from the CSV file
    df = pd.read_csv('data.csv')
    df.drop(['D_3', 'D_7', 'D_8', 'CA_D_4', 'IP_4', 'CIS_3', 'C_1', 'IN_4', 'B_IS_5'], axis=1, inplace=True)
    df.head()
```

```
df.columns
```

```
df.info()
```

```
[9] # Summary Statistics
    df.describe().T
```

Model 1 initial,after EFA adjustments

```
[8] # Define the SEM model
    model_desc_1 = '''
    Digitalization =~ D_1 + D_2 + D_4 + D_5 + D_6 + D_9 + D_10 + D_11 + D_12 + D_13
    Company_attitude_comp =~ CA_C_1 + CA_C_2 + CA_C_3 + CA_C_4 + CA_C_5
    Company_attitude_digit =~ CA_D_1 + CA_D_2 + CA_D_3 + CA_D_5 + CA_D_6 + CA_D_7
    Labor_productivity =~ LP_1 + LP_2 + LP_3 + LP_4 + LP_5 + LP_6 +LP_7
    Innov_push =~ IP_1 + IP_2 + IP_3 + IP_5
    Corporate_technologies =~ CIS_1 + CIS_2 + CIS_4 + CIS_5
    Competition =~ C_2 + C_3
    Ind_state =~ IN_1 + IN_2 + IN_3
    Alignment =~ B_IS_1 + B_IS_2 + B_IS_3 + B_IS_4 + B_IS_6 + B_IS_7 + B_IS_8 + B_IS_9
    Company_attitude_comp ~ Company_attitude_digit + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
    Company_attitude_digit ~ Company_attitude_comp + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
    Innov_push ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Competition + Ind_state + Alignment
    Corporate_technologies ~ Company_attitude_comp + Company_attitude_digit + Innov_push + Competition + Ind_state + Alignment
    Competition ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Ind_state + Alignment
    Ind_state ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Competition + Alignment
    Alignment ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Competition + Ind_state
    Digitalization ~ Company_attitude_comp + Company_attitude_digit + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
    Labor_productivity ~ Digitalization
    '''
```

```
[9] # Fit the SEM model
    model_1 = Model(model_desc_1)
    sem_results_1 = model_1.fit(df)

    # Print the summary of the SEM model
    print(sem_results_1)
```

```
[10] # Analyze parameter estimates
     ins_1 = model_1.inspect()
     print(ins_1)
```

```
[11] # Calculate additional SEM statistics
     stats_1 = calc_stats(model_1)  # Use calc_stats directly
     print(stats_1)
```

```
[12] ### Visualize Structural Equation Relationship Plot
     # Generate SEM plot and save it to a file
     semplot(model_1, "model.png")
```

Model 2

[13]
```
# Define the SEM model
model_desc_2 = '''
Digitalization =~ D_1 + D_4 + D_5 + D_6 + D_9 + D_10 + D_11 + D_12 + D_13
Company_attitude_comp =~ CA_C_1 + CA_C_2 + CA_C_3 + CA_C_4 + CA_C_5
Company_attitude_digit =~ CA_D_1 + CA_D_2 + CA_D_3 + CA_D_5 + CA_D_6 + CA_D_7
Labor_productivity =~ LP_1 + LP_2 + LP_3 + LP_4 + LP_5 + LP_6 +LP_7
Innov_push =~ IP_1 + IP_2 + IP_3 + IP_5
Corporate_technologies =~ CIS_1 + CIS_2 + CIS_4 + CIS_5
Competition =~ C_2 + C_3
Ind_state =~ IN_1 + IN_2 + IN_3
Alignment =~ B_IS_1 + B_IS_2 + B_IS_3 + B_IS_4 + B_IS_6 + B_IS_7 + B_IS_8 + B_IS_9
Company_attitude_comp ~ Company_attitude_digit + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Company_attitude_digit ~ Company_attitude_comp + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Innov_push ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Competition + Ind_state + Alignment
Corporate_technologies ~ Company_attitude_comp + Company_attitude_digit + Innov_push + Competition + Ind_state + Alignment
Competition ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Ind_state + Alignment
Ind_state ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Competition + Alignment
Alignment ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Competition + Ind_state
Digitalization ~ Company_attitude_comp + Company_attitude_digit + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Labor_productivity ~ Digitalization
'''
# Fit the SEM model
model_2 = Model(model_desc_2)
sem_results_2 = model_2.fit(df)

# Print the summary of the SEM model
print(sem_results_2)
```

```
# Analyze parameter estimates
ins_2 = model_2.inspect()
print(ins_2)

# Calculate additional SEM statistics
stats_2 = calc_stats(model_2)  # Use calc_stats directly
print(stats_2)
```

Model 3

[14]
```
# Define the SEM model
model_desc_3 = '''
Digitalization =~ D_1 + D_4 + D_5 + D_6 + D_9 + D_11 + D_12 + D_13
Company_attitude_comp =~ CA_C_1 + CA_C_2 + CA_C_3 + CA_C_4 + CA_C_5
Company_attitude_digit =~ CA_D_1 + CA_D_2 + CA_D_3 + CA_D_5 + CA_D_6 + CA_D_7
Labor_productivity =~ LP_1 + LP_2 + LP_3 + LP_4 + LP_5 + LP_6 +LP_7
Innov_push =~ IP_1 + IP_2 + IP_3 + IP_5
Corporate_technologies =~ CIS_1 + CIS_2 + CIS_4 + CIS_5
Competition =~ C_2 + C_3
Ind_state =~ IN_1 + IN_2 + IN_3
Alignment =~ B_IS_1 + B_IS_2 + B_IS_3 + B_IS_4 + B_IS_6 + B_IS_7 + B_IS_8 + B_IS_9
Company_attitude_comp ~ Company_attitude_digit + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Company_attitude_digit ~ Company_attitude_comp + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Innov_push ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Competition + Ind_state + Alignment
Corporate_technologies ~ Company_attitude_comp + Company_attitude_digit + Innov_push + Competition + Ind_state + Alignment
Competition ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Ind_state + Alignment
Ind_state ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Competition + Alignment
Alignment ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Competition + Ind_state
Digitalization ~ Company_attitude_comp + Company_attitude_digit + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Labor_productivity ~ Digitalization
'''
```

[14]
```
# Fit the SEM model
model_3 = Model(model_desc_3)
sem_results_3 = model_3.fit(df)

# Print the summary of the SEM model
print(sem_results_3)

# Analyze parameter estimates
ins_3 = model_3.inspect()
print(ins_3)

# Calculate additional SEM statistics
stats_3 = calc_stats(model_3)  # Use calc_stats directly
print(stats_3)
```

Model 4

```
[15] # Define the SEM model
model_desc_4 = '''
Digitalization =~ D_1 + D_4 + D_5 + D_6 + D_9 + D_11 + D_12 + D_13
Company_attitude_comp =~ CA_C_1 + CA_C_2 + CA_C_3 + CA_C_4 + CA_C_5
Company_attitude_digit =~ CA_D_1 + CA_D_2 + CA_D_5 + CA_D_6 + CA_D_7
Labor_productivity =~ LP_1 + LP_2 + LP_3 + LP_4 + LP_5 + LP_6 +LP_7
Innov_push =~ IP_1 + IP_2 + IP_3 + IP_5
Corporate_technologies =~ CIS_1 + CIS_2 + CIS_4 + CIS_5
Competition =~ C_2 + C_3
Ind_state =~ IN_1 + IN_2 + IN_3
Alignment =~ B_IS_1 + B_IS_2 + B_IS_3 + B_IS_4 + B_IS_6 + B_IS_7 + B_IS_8 + B_IS_9
Company_attitude_comp ~ Company_attitude_digit + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Company_attitude_digit ~ Company_attitude_comp + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Innov_push ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Competition + Ind_state + Alignment
Corporate_technologies ~ Company_attitude_comp + Company_attitude_digit + Innov_push + Competition + Ind_state + Alignment
Competition ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Ind_state + Alignment
Ind_state ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Competition + Alignment
Alignment ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Competition + Ind_state
Digitalization ~ Company_attitude_comp + Company_attitude_digit + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Labor_productivity ~ Digitalization
'''
# Fit the SEM model
model_4 = Model(model_desc_4)
sem_results_4 = model_4.fit(df)

# Print the summary of the SEM model
print(sem_results_4)
```

```
[15] # Analyze parameter estimates
ins_4 = model_4.inspect()
print(ins_4)

# Calculate additional SEM statistics
stats_4 = calc_stats(model_4)  # Use calc_stats directly
print(stats_4)
```

Model 5

```
[16] # Define the SEM model
model_desc_5 = '''
Digitalization =~ D_1 + D_4 + D_5 + D_6 + D_9 + D_11 + D_12 + D_13
Company_attitude_comp =~ CA_C_1 + CA_C_2 + CA_C_3 + CA_C_4 + CA_C_5
Company_attitude_digit =~ CA_D_1 + CA_D_2 + CA_D_5 + CA_D_7
Labor_productivity =~ LP_1 + LP_2 + LP_3 + LP_4 + LP_5 + LP_6 +LP_7
Innov_push =~ IP_1 + IP_2 + IP_3 + IP_5
Corporate_technologies =~ CIS_1 + CIS_2 + CIS_4 + CIS_5
Competition =~ C_2 + C_3
Ind_state =~ IN_1 + IN_2 + IN_3
Alignment =~ B_IS_1 + B_IS_2 + B_IS_3 + B_IS_4 + B_IS_6 + B_IS_7 + B_IS_8 + B_IS_9
Company_attitude_comp ~ Company_attitude_digit + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Company_attitude_digit ~ Company_attitude_comp + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Innov_push ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Competition + Ind_state + Alignment
Corporate_technologies ~ Company_attitude_comp + Company_attitude_digit + Innov_push + Competition + Ind_state + Alignment
Competition ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Ind_state + Alignment
Ind_state ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Competition + Alignment
Alignment ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Competition + Ind_state
Digitalization ~ Company_attitude_comp + Company_attitude_digit + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Labor_productivity ~ Digitalization
'''
```

```
[16] # Fit the SEM model
model_5 = Model(model_desc_5)
sem_results_5 = model_5.fit(df)

# Print the summary of the SEM model
print(sem_results_5)

# Analyze parameter estimates
ins_5 = model_5.inspect()
print(ins_5)

# Calculate additional SEM statistics
stats_5 = calc_stats(model_5)  # Use calc_stats directly
print(stats_5)
```

Model 6

```
[17] # Define the SEM model
model_desc_6 = '''
Digitalization =~ D_1 + D_5 + D_6 + D_9 + D_11 + D_12 + D_13
Company_attitude_comp =~ CA_C_1 + CA_C_2 + CA_C_3 + CA_C_4 + CA_C_5
Company_attitude_digit =~ CA_D_1 + CA_D_2 + CA_D_5 + CA_D_7
Labor_productivity =~ LP_1 + LP_2 + LP_3 + LP_4 + LP_5 + LP_6 +LP_7
Innov_push =~ IP_1 + IP_2 + IP_3 + IP_5
Corporate_technologies =~ CIS_1 + CIS_2 + CIS_4 + CIS_5
Competition =~ C_2 + C_3
Ind_state =~ IN_1 + IN_2 + IN_3
Alignment =~ B_IS_1 + B_IS_2 + B_IS_3 + B_IS_4 + B_IS_6 + B_IS_7 + B_IS_8 + B_IS_9
Company_attitude_comp ~ Company_attitude_digit + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Company_attitude_digit ~ Company_attitude_comp + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Innov_push ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Competition + Ind_state + Alignment
Corporate_technologies ~ Company_attitude_comp + Company_attitude_digit + Innov_push + Competition + Ind_state + Alignment
Competition ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Ind_state + Alignment
Ind_state ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Competition + Alignment
Alignment ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Competition + Ind_state
Digitalization ~ Company_attitude_comp + Company_attitude_digit + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Labor_productivity ~ Digitalization
'''
# Fit the SEM model
model_6 = Model(model_desc_6)
sem_results_6 = model_6.fit(df)

# Print the summary of the SEM model
print(sem_results_6)
```

```
[17] # Analyze parameter estimates
ins_6 = model_6.inspect()
print(ins_6)

# Calculate additional SEM statistics
stats_6 = calc_stats(model_6)  # Use calc_stats directly
print(stats_6)
```

Model 7

```
[18] # Define the SEM model
model_desc_7 = '''
Digitalization =~ D_1 + D_5 + D_6 + D_11 + D_12 + D_13
Company_attitude_comp =~ CA_C_1 + CA_C_2 + CA_C_3 + CA_C_4 + CA_C_5
Company_attitude_digit =~ CA_D_1 + CA_D_2 + CA_D_5 + CA_D_7
Labor_productivity =~ LP_1 + LP_2 + LP_3 + LP_4 + LP_5 + LP_6 +LP_7
Innov_push =~ IP_1 + IP_2 + IP_3 + IP_5
Corporate_technologies =~ CIS_1 + CIS_2 + CIS_4 + CIS_5
Competition =~ C_2 + C_3
Ind_state =~ IN_1 + IN_2 + IN_3
Alignment =~ B_IS_1 + B_IS_2 + B_IS_3 + B_IS_4 + B_IS_6 + B_IS_7 + B_IS_8 + B_IS_9
Company_attitude_comp ~ Company_attitude_digit + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Company_attitude_digit ~ Company_attitude_comp + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Innov_push ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Competition + Ind_state + Alignment
Corporate_technologies ~ Company_attitude_comp + Company_attitude_digit + Innov_push + Competition + Ind_state + Alignment
Competition ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Ind_state + Alignment
Ind_state ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Competition + Alignment
Alignment ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Competition + Ind_state
Digitalization ~ Company_attitude_comp + Company_attitude_digit + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Labor_productivity ~ Digitalization
'''
```

```
[18] # Fit the SEM model
model_7 = Model(model_desc_7)
sem_results_7 = model_7.fit(df)

# Print the summary of the SEM model
print(sem_results_7)

# Analyze parameter estimates
ins_7 = model_7.inspect()
print(ins_7)

# Calculate additional SEM statistics
stats_7 = calc_stats(model_7)  # Use calc_stats directly
print(stats_7)
```

Model 8

```
[19] # Define the SEM model
model_desc_8 = '''
Digitalization =~ D_1 + D_5 + D_6 + D_11 + D_12 + D_13
Company_attitude_comp =~ CA_C_1 + CA_C_2 + CA_C_3 + CA_C_5
Company_attitude_digit =~ CA_D_1 + CA_D_2 + CA_D_5 + CA_D_7
Labor_productivity =~ LP_1 + LP_2 + LP_3 + LP_4 + LP_5 + LP_6 +LP_7
Innov_push =~ IP_1 + IP_2 + IP_3 + IP_5
Corporate_technologies =~ CIS_1 + CIS_2 + CIS_4 + CIS_5
Competition =~ C_2 + C_3
Ind_state =~ IN_1 + IN_2 + IN_3
Alignment =~ B_IS_1 + B_IS_2 + B_IS_3 + B_IS_4 + B_IS_6 + B_IS_7 + B_IS_8 + B_IS_9
Company_attitude_comp ~ Company_attitude_digit + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Company_attitude_digit ~ Company_attitude_comp + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Innov_push ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Competition + Ind_state + Alignment
Corporate_technologies ~ Company_attitude_comp + Company_attitude_digit + Innov_push + Competition + Ind_state + Alignment
Competition ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Ind_state + Alignment
Ind_state ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Competition + Alignment
Alignment ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Competition + Ind_state
Digitalization ~ Company_attitude_comp + Company_attitude_digit + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Labor_productivity ~ Digitalization
'''
# Fit the SEM model
model_8 = Model(model_desc_8)
sem_results_8 = model_8.fit(df)

# Print the summary of the SEM model
print(sem_results_8)
```

```
[19] # Analyze parameter estimates
ins_8 = model_8.inspect()
print(ins_8)

# Calculate additional SEM statistics
stats_8 = calc_stats(model_8)  # Use calc_stats directly
print(stats_8)
```

Model 9

```
[20] # Define the SEM model
model_desc_9 = '''
Digitalization =~ D_1 + D_5 + D_6 + D_11 + D_12 + D_13
Company_attitude_comp =~ CA_C_1 + CA_C_2 + CA_C_3 + CA_C_5
Company_attitude_digit =~ CA_D_1 + CA_D_2 + CA_D_7
Labor_productivity =~ LP_1 + LP_2 + LP_3 + LP_4 + LP_5 + LP_6 +LP_7
Innov_push =~ IP_1 + IP_2 + IP_3 + IP_5
Corporate_technologies =~ CIS_1 + CIS_2 + CIS_4 + CIS_5
Competition =~ C_2 + C_3
Ind_state =~ IN_1 + IN_2 + IN_3
Alignment =~ B_IS_1 + B_IS_2 + B_IS_3 + B_IS_4 + B_IS_6 + B_IS_7 + B_IS_8 + B_IS_9
Company_attitude_comp ~ Company_attitude_digit + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Company_attitude_digit ~ Company_attitude_comp + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Innov_push ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Competition + Ind_state + Alignment
Corporate_technologies ~ Company_attitude_comp + Company_attitude_digit + Innov_push + Competition + Ind_state + Alignment
Competition ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Ind_state + Alignment
Ind_state ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Competition + Alignment
Alignment ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Competition + Ind_state
Digitalization ~ Company_attitude_comp + Company_attitude_digit + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Labor_productivity ~ Digitalization
'''
```

```
[20] # Fit the SEM model
model_9 = Model(model_desc_9)
sem_results_9 = model_9.fit(df)

# Print the summary of the SEM model
print(sem_results_9)

# Analyze parameter estimates
ins_9 = model_9.inspect()
print(ins_9)

# Calculate additional SEM statistics
stats_9 = calc_stats(model_9)  # Use calc_stats directly
print(stats_9)
```

Model 10

```
[21] # Define the SEM model
model_desc_10 = '''
Digitalization =~ D_1 + D_5 + D_6 + D_11 + D_12 + D_13
Company_attitude_comp =~ CA_C_1 + CA_C_2 + CA_C_3 + CA_C_5
Company_attitude_digit =~ CA_D_1 + CA_D_2 + CA_D_7
Labor_productivity =~ LP_1 + LP_2 + LP_3 + LP_4 + LP_5 + LP_6 +LP_7
Innov_push =~ IP_2 + IP_3 + IP_5
Corporate_technologies =~ CIS_1 + CIS_2 + CIS_4 + CIS_5
Competition =~ C_2 + C_3
Ind_state =~ IN_1 + IN_2 + IN_3
Alignment =~ B_IS_1 + B_IS_2 + B_IS_3 + B_IS_4 + B_IS_6 + B_IS_7 + B_IS_8 + B_IS_9
Company_attitude_comp ~ Company_attitude_digit + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Company_attitude_digit ~ Company_attitude_comp + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Innov_push ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Competition + Ind_state + Alignment
Corporate_technologies ~ Company_attitude_comp + Company_attitude_digit + Innov_push + Competition + Ind_state + Alignment
Competition ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Ind_state + Alignment
Ind_state ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Competition + Alignment
Alignment ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Competition + Ind_state
Digitalization ~ Company_attitude_comp + Company_attitude_digit + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Labor_productivity ~ Digitalization
'''
# Fit the SEM model
model_10 = Model(model_desc_10)
sem_results_10 = model_10.fit(df)

# Print the summary of the SEM model
print(sem_results_10)
```

```
[21] # Analyze parameter estimates
ins_10 = model_10.inspect()
print(ins_10)

# Calculate additional SEM statistics
stats_10 = calc_stats(model_10)  # Use calc_stats directly
print(stats_10)
```

Model 11

```
# Define the SEM model
model_desc_11 = '''
Digitalization =~ D_1 + D_5 + D_6 + D_11 + D_12 + D_13
Company_attitude_comp =~ CA_C_1 + CA_C_2 + CA_C_3 + CA_C_5
Company_attitude_digit =~ CA_D_1 + CA_D_2 + CA_D_7
Labor_productivity =~ LP_1 + LP_2 + LP_3 + LP_4 + LP_5 + LP_6 +LP_7
Innov_push =~ IP_2 + IP_5
Corporate_technologies =~ CIS_1 + CIS_2 + CIS_4 + CIS_5
Competition =~ C_2 + C_3
Ind_state =~ IN_1 + IN_2 + IN_3
Alignment =~ B_IS_1 + B_IS_2 + B_IS_3 + B_IS_4 + B_IS_6 + B_IS_7 + B_IS_8 + B_IS_9
Company_attitude_comp ~ Company_attitude_digit + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Company_attitude_digit ~ Company_attitude_comp + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Innov_push ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Competition + Ind_state + Alignment
Corporate_technologies ~ Company_attitude_comp + Company_attitude_digit + Innov_push + Competition + Ind_state + Alignment
Competition ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Ind_state + Alignment
Ind_state ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Competition + Alignment
Alignment ~ Company_attitude_comp + Company_attitude_digit + Corporate_technologies + Innov_push + Competition + Ind_state
Digitalization ~ Company_attitude_comp + Company_attitude_digit + Innov_push + Corporate_technologies + Competition + Ind_state + Alignment
Labor_productivity ~ Digitalization
'''
```

```
# Fit the SEM model
model_11 = Model(model_desc_11)
sem_results_11 = model_11.fit(df)

# Print the summary of the SEM model
print(sem_results_11)

# Analyze parameter estimates
ins_11 = model_11.inspect()
print(ins_11)

# Calculate additional SEM statistics
stats_11 = calc_stats(model_11)  # Use calc_stats directly
print(stats_11)
```

Figure 3. *Structural Equation modelling using Python Programming language.*

Source: author's compilation

H1: High level of employees competence positively impacts Digitalization of the entire company.

```
[8] # Define the variables
digitalization = data[['D_1', 'D_5', 'D_6', 'D_11', 'D_12', 'D_13']].sum(axis=1)
company_attitude_comp = data[['CA_C_1', 'CA_C_2', 'CA_C_3', 'CA_C_5']].sum(axis=1)

# Calculate the Pearson correlation coefficient
correlation_coefficient, _ = pearsonr(digitalization, company_attitude_comp)

# Calculate the p-value
p_value = 2 * (1 - pearsonr(digitalization, company_attitude_comp)[1])

# Set the significance level
alpha = 0.05

# Perform the hypothesis test
if p_value < alpha:
    print(f"The null hypothesis that company's attitude to competence positively affect digitalization is rejected. The correlation coefficient is {correlation_coefficient} and the p-
else:
    print(f"The null hypothesis that company's attitude to competence positively affect digitalization cannot be rejected. The correlation coefficient is {correlation_coefficient} anc

# Calculate the standard coefficient
standard_coefficient = correlation_coefficient * np.sqrt((np.var(digitalization) / len(digitalization)) * (np.var(company_attitude_comp) / len(company_attitude_comp)))
print(f"The standard coefficient is {standard_coefficient}.")
```

H2: Positive attitude to change in the organization, positively impacts Digitalization of the entire company.

```
# Define the variables
digitalization = data[['D_1', 'D_5', 'D_6', 'D_11', 'D_12', 'D_13']].sum(axis=1)
company_attitude_digit = data[['CA_D_1', 'CA_D_2', 'CA_D_7']].sum(axis=1)

# Calculate the Pearson correlation coefficient
correlation_coefficient, _ = pearsonr(digitalization, company_attitude_digit)

# Calculate the p-value
p_value = 2 * (1 - pearsonr(digitalization, company_attitude_digit)[1])

# Set the significance level
alpha = 0.05

# Perform the hypothesis test
if p_value < alpha:
    print(f"The null hypothesis that company's attitude to digitalization and change positively affect digitalization is rejected. The correlation coefficient is {correlation_coeffici
else:
    print(f"The null hypothesis that company's attitude to digitalization and change positively affect digitalization cannot be rejected. The correlation coefficient is {correlation_c

# Calculate the standard coefficient
standard_coefficient = correlation_coefficient * np.sqrt((np.var(digitalization) / len(digitalization)) * (np.var(company_attitude_digit) / len(company_attitude_digit)))
print(f"The standard coefficient is {standard_coefficient}.")
```

H3: High innovative pressure in an industry, where company operates positively impacts Digitalization of the entire company.

```
[10] # Define the variables
digitalization = data[['D_1', 'D_5', 'D_6', 'D_11', 'D_12', 'D_13']].sum(axis=1)
innov_push = data[['IP_2', 'IP_5']].sum(axis=1)

# Calculate the Pearson correlation coefficient
correlation_coefficient, _ = pearsonr(digitalization, innov_push)

# Calculate the p-value
p_value = 2 * (1 - pearsonr(digitalization, innov_push)[1])

# Set the significance level
alpha = 0.05

# Perform the hypothesis test
if p_value < alpha:
    print(f"The null hypothesis that high innovative pressure in an industry positively affect digitalization is rejected. The correlation coefficient is {correlation_coefficient} anc
else:
    print(f"The null hypothesis that high innovative pressure in an industry positively affect digitalization cannot be rejected. The correlation coefficient is {correlation_coefficie

# Calculate the standard coefficient
standard_coefficient = correlation_coefficient * np.sqrt((np.var(digitalization) / len(digitalization)) * (np.var(innov_push) / len(innov_push)))
print(f"The standard coefficient is {standard_coefficient}.")
```

H4: Generalized and interconnected technology applied in an enterprise, positively impacts Digitalization of the entire company

```
# Define the variables
digitalization = data[['D_1', 'D_5', 'D_6', 'D_11', 'D_12', 'D_13']].sum(axis=1)
corp_techn = data[['CIS_1', 'CIS_2','CIS_4', 'CIS_5']].sum(axis=1)

# Calculate the Pearson correlation coefficient
correlation_coefficient, _ = pearsonr(digitalization, corp_techn)

# Calculate the p-value
p_value = 2 * (1 - pearsonr(digitalization, corp_techn)[1])

# Set the significance level
alpha = 0.05

# Perform the hypothesis test
if p_value < alpha:
    print(f"The null hypothesis that generalized and interconnected technology applied in an enterprise positively affect digitalization is rejected. The correlation coefficient is {c
else:
    print(f"The null hypothesis that generalized and interconnected technology applied in an enterprise positively affect digitalization cannot be rejected. The correlation coefficier

# Calculate the standard coefficient
standard_coefficient = correlation_coefficient * np.sqrt((np.var(digitalization) / len(digitalization)) * (np.var(corp_techn) / len(corp_techn)))
print(f"The standard coefficient is {standard_coefficient}.")
```

H5: High competition in an industry, where company operates positively impacts Digitalization of the entire company.

```
[12] # Define the variables
digitalization = data[['D_1', 'D_5', 'D_6', 'D_11', 'D_12', 'D_13']].sum(axis=1)
competition = data[['C_2', 'C_3']].sum(axis=1)

# Calculate the Pearson correlation coefficient
correlation_coefficient, _ = pearsonr(digitalization, competition)

# Calculate the p-value
p_value = 2 * (1 - pearsonr(digitalization, competition)[1])

# Set the significance level
alpha = 0.05

# Perform the hypothesis test
if p_value < alpha:
    print(f"The null hypothesis that high competition in an industry, where company operates positively affect digitalization is rejected. The correlation coefficient is {correlation_
else:
    print(f"The null hypothesis that high competition in an industry, where company operates positively affect digitalization cannot be rejected. The correlation coefficient is {corre

# Calculate the standard coefficient
standard_coefficient = correlation_coefficient * np.sqrt((np.var(digitalization) / len(digitalization)) * (np.var(competition) / len(competition)))
print(f"The standard coefficient is {standard_coefficient}.")
```

H6: Instabilities in an industry, where the company operates positively impacts Digitalization of the entire company.

```
[13] # Define the variables
digitalization = data[['D_1', 'D_5', 'D_6', 'D_11', 'D_12', 'D_13']].sum(axis=1)
ind_state = data[['IN_1', 'IN_2', 'IN_3']].sum(axis=1)

# Calculate the Pearson correlation coefficient
correlation_coefficient, _ = pearsonr(digitalization, ind_state)

# Calculate the p-value
p_value = 2 * (1 - pearsonr(digitalization, ind_state)[1])

# Set the significance level
alpha = 0.05

# Perform the hypothesis test
if p_value < alpha:
    print(f"The null hypothesis that instabilities in an industry, where the company operates positively affect digitalization is rejected. The correlation coefficient is {correlatior
else:
    print(f"The null hypothesis that instabilities in an industry, where the company operates positively affect digitalization cannot be rejected. The correlation coefficient is {corr

# Calculate the standard coefficient
standard_coefficient = correlation_coefficient * np.sqrt((np.var(digitalization) / len(digitalization)) * (np.var(ind_state) / len(ind_state)))
print(f"The standard coefficient is {standard_coefficient}.")
```

H7: Alignment of business and information systems (IS) in an enterprise, positively impacts Digitalization of the entire company.

```
[14] # Define the variables
digitalization = data[['D_1', 'D_5', 'D_6', 'D_11', 'D_12', 'D_13']].sum(axis=1)
alignment = data[['B_IS_1', 'B_IS_2', 'B_IS_3', 'B_IS_4', 'B_IS_6', 'B_IS_7', 'B_IS_8', 'B_IS_9']].sum(axis=1)

# Calculate the Pearson correlation coefficient
correlation_coefficient, _ = pearsonr(digitalization, alignment)

# Calculate the p-value
p_value = 2 * (1 - pearsonr(digitalization, alignment)[1])

# Set the significance level
alpha = 0.05

# Perform the hypothesis test
if p_value < alpha:
    print(f"The null hypothesis that alignment of business and information systems (IS) in an enterprise positively affect digitalization is rejected. The correlation coefficient is {
else:
    print(f"The null hypothesis that alignment of business and information systems (IS) in an enterprise positively affect digitalization cannot be rejected. The correlation coefficie

# Calculate the standard coefficient
standard_coefficient = correlation_coefficient * np.sqrt((np.var(digitalization) / len(digitalization)) * (np.var(alignment) / len(alignment)))
print(f"The standard coefficient is {standard_coefficient}.")
```

H8: Digitalization in an enterprise positively impacts Labor productivity of the entire company.

```
# Define the variables
digitalization = data[['D_1', 'D_5', 'D_6', 'D_11', 'D_12', 'D_13']].sum(axis=1)
labor_productivity = data[['LP_1', 'LP_2', 'LP_3', 'LP_4', 'LP_5', 'LP_6', 'LP_7']].sum(axis=1)

# Calculate the Pearson correlation coefficient
correlation_coefficient, _ = pearsonr(digitalization, labor_productivity)

# Calculate the p-value
p_value = 2 * (1 - pearsonr(digitalization, labor_productivity)[1])

# Set the significance level
alpha = 0.05

# Perform the hypothesis test
if p_value < alpha:
    print(f"The null hypothesis that digitalization in an enterprise positively impacts Labor productivity of the entire company is rejected. The correlation coefficient is {correlati
else:
    print(f"The null hypothesis that digitalization in an enterprise positively impacts Labor productivity of the entire company cannot be rejected. The correlation coefficient is {c

# Calculate the standard coefficient
standard_coefficient = correlation_coefficient * np.sqrt((np.var(digitalization) / len(digitalization)) * (np.var(labor_productivity) / len(labor_productivity)))
print(f"The standard coefficient is {standard_coefficient}.")
```

Figure 4. *Hypotheses testing using Python Programming language.*

Source: author’s compilation

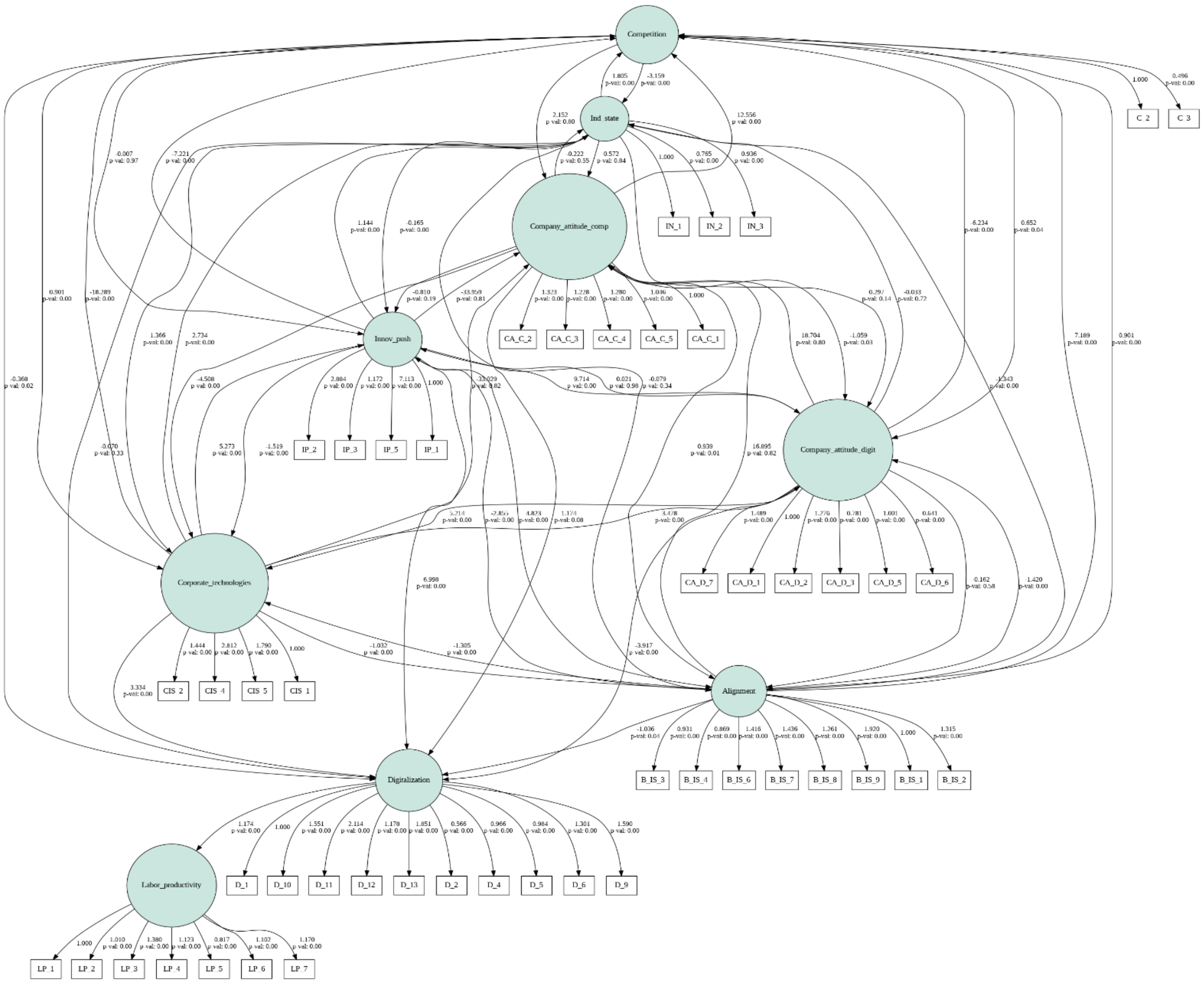

Figure 4. *Initial structural model.*