The role of digital transformation in enhancing innovation within SMEs in Food Industry

Master of Engineering Management

2023 – 2025

Submitted in partial fulfillment of the requirements for the degree of Master of Engineering Management

School of Engineering and Digital Sciences

In partnership with

Graduate School of Business

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May, 2025

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May, 2025

Declaration

We, Gulshat Yerbolatova, Dinmukhammedali Narbayev, Adilbek Oralbek, Akerke Nurmukhambetova and Mirlan Tuleugaliyev, declare that the research contained in this thesis, unless otherwise formally indicated within the text, is the author's original work. The thesis has not been previously submitted to this or any other university for a degree and does not incorporate any material already submitted for a degree.

Signature (s):

Date: 05.05.2025

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Abstract

Restaurant business in Kazakhstan operates in a dynamic environment with fast changing trends and consumer demands. This creates numerous operational and economical challenges for the SMEs, despite the growing market. Thus, continuous innovation stands as a key for survival. This study aims to assess the digital transformation's impact on the innovation capabilities of SMEs in Kazakhstan. After careful literature review, key factors chosen as enablers of innovations are 'technology adoption', 'data analytics', 'supply chain integrity', 'operational efficiency', 'employee skills & training'. Data was collected from 57 SMEs in Astana through an online survey. Structural Equation Modeling with Partial Least Squares (SEM-PLS) was utilized for relationship analysis between key factors. The results indicated a significant effect of digital transformation on innovation performance. The strongest relationships were defined between pairs of technology adoption - operational efficiency (r = 0.687) and data analytics - employee skills & training (r = 0.583). Additionally, SMEs refer to the limited overall budget for DT initiatives as the most significant barrier. Limitations of the study are small sample size and few indicators for each latent variable.

1. Introduction

1.1 Research Problem & Justification

The restaurant industry in Kazakhstan, particularly in major cities like Almaty and Astana, plays a vital role in the economy, contributing significantly to SMEs' share of GDP (35.4% in 2023). However, despite the market's growth, challenges persist in restaurant sustainability, as evidenced by survival rates - only 62% of restaurants in Almaty and 67% in Astana last beyond the first year, with steep declines to 17% and 19% respectively after five years. This reflects the volatile nature of the industry, which is further influenced by evolving food tech trends, such as the rise of food delivery services, increasing investments in food technology, and innovations like digitization, meal kits, and 3D food printing. Given these market dynamics, understanding the factors affecting restaurant success and sustainability is crucial for business owners, investors, and policymakers.

1.2 Objectives of the Study & Research Questions

This research aims to analyze the effects of digital transformation on innovation capabilities of small and medium-sized enterprises (SMEs) operating in Kazakhstan's food service industry. The research investigates five fundamental aspects of digital transformation which include 'technology adoption' and 'data analytics' and 'supply chain integration' and 'operational efficiency' and 'employee training and skill development'.

The research aims to establish how much digital capabilities improve SMEs' research and development capabilities and their ability to create new products and business models. The study investigates the factors which support or hinder small and medium-sized enterprises during their digital transformation process. The research uses Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze both direct and mediating effects including how operational efficiency improvements and supply chain flexibility might indirectly boost innovation.

The study uses survey data and empirical modeling to deliver practical findings which help SME leaders and policymakers and other stakeholders use digital transformation for economic resilience and competitive advantage. The research delivers a complete analytical report together with strategic recommendations and a concise presentation for business and government stakeholders.

2. Literature Review

2.1 What is Digital Transformation?

Steam power was the technology that revolutionized the world during the first of the four industrial revolutions. It was the assembly line in the second and the computer in the third. The fourth industrial revolution is currently underway, and digital technologies are at its center. Artificial intelligence (AI), machine learning, robots, advanced analytics, the Internet of Things (IoT), and machine learning are digital technologies that are revolutionizing how businesses operate and engage with the public and their clients.

For our topic it is important to identify key terminology and the way they are used in order to not get confused on our topic. So our objective is to examine the role of digital transformation in enhancing innovation within SMEs in Kazakhstan. We first define digital transformation. In order to give an exact definition of DT we analyzed 6 studies on this topic. According to Verhoef et al. (2021) multidisciplinary reflection on the topic of digital transformation, there are three stages of digital transformation: digitization, digitalization, and digital transformation. Nowadays a lot of people get confused by these terminologies and that is why we should clearly identify what is what. So in their work they identified DT as changing the way a firm uses digital technologies to develop a new digital business model that helps create and capture greater value for the firm (Verhoef et al. 2021). Vial (2021) identifies three key observations from definitions of digital transformation. First, digital transformation is largely defined in relation to organizations. Second, there are differences in the types of technologies and the nature of the transformation itself. Third, common terms such as “digital technologies” provide some consistency across definitions.

2.2 The phases of digital transformation

In their work Verhoef et al. (2021) conducted a scoping review approach to understand how different disciplines conceptualize and define digital transformation. They identified three phases: digitization, digitalization, and digital transformation, with the first two phases being incremental steps towards a more comprehensive transformation.

Digitization is the simple process of converting analog information into digital form. Some other research on this topic refers to digitization as the process of changing analog to digital tasks or as the incorporation of IT into existing processes, and more generally as facilitating the creation of cost-effective resource settings through the use of IT (Vrana & Singh, 2021). Based on the above, digitization is defined as the act of converting analog information into digital information (Verhoef et al. 2021). For example, scanning the physical document and converting them into digital files, converting printed books into electronic formats. So digitization only affects the internal and external documentation processes without changing the value creation activities.

Digitalization is recognized as a significant trend transforming society and business, driven by the adoption of digital technologies within organizations or their operating environments (Reis et al., 2020). For example, digitalization of government is becoming a mainstream focus of governance reforms, with high expectations to improve the public value delivered by governments, increasing both the efficiency and effectiveness of public administration. Such changes often involve the introduction of new digital platforms and systems that would not be possible without digital technologies (Dobrolyubova, Klochkova, & Alexandrov, 2019). Digitalization is found at some point between digitization and DT (Calderon-Monge & Ribeiro-Soriano, 2023). Pagani and Pardo (2017) claim that digitalization enables businesses to leverage digital technologies to improve user experiences, streamline corporate operations, and increase coordination—all of which offer value for their clients. Along with major improvements in customer interactions and general corporate procedures, this method involves cost reductions. Based on the previous data, we may define digitalization as the process of incorporating digital technology into current company procedures in order to boost productivity, enhance client communications, and produce new value.

Digital transformation phase is the most extensive stage of change, marked by changes that affect the entire organization and result in the creation of new business models (Verhoef et al. 2021). Vial (2021, p. 118) also identifies digital transformation as the process meant to enhance an entity by bringing about major changes via the integration of computer, connection, information, and communication technologies.

Digital transformation (DT) refers to the adoption and integration of digital technologies into business operations, fundamentally reshaping how companies operate and deliver value to customers (Romanello & Veglio, 2022). For small and medium-sized enterprises (SMEs), digital transformation plays a crucial role in enhancing competitiveness, efficiency, and innovation (Liu et al., 2024). DT is not just about digitizing existing processes but also about creating new business models, improving operational efficiency, and enabling data-driven decision-making (OECD, 2022).

In the context of SMEs, particularly those in the food industry, DT encompasses multiple aspects, including 'technology adoption', 'data analytics', 'supply chain integrity', 'operational efficiency', and 'employee skills & training' development. These components are central to our study and align directly with the survey questions designed to assess how digitalization impacts business performance and innovation.

2.3 Technology Adoption

Business processes optimization through digital solutions such as ERP systems and AI-based automation and CRM software and cloud computing defines 'technology adoption'. Omrani et al. (2022) found that SMEs which implement digitalization strategies achieve better operational efficiency and cost reduction together with enhanced customer service.

The adoption of technology stands as a crucial element for business transformation because it enhances operational efficiency and strengthens competitive position while improving decision-making quality. Small and medium-sized food industry businesses can optimize their operations through digital solutions that include automated order processing systems and electronic payment platforms and smart kitchen equipment and data-driven inventory management systems. The research Mariam (2023) shows that rapid technology implementation into business operations strongly affects company growth and customer satisfaction and innovation levels.

Thakur and Maurya (2024) indicate that artificial intelligence and blockchain technology together with big data analysis and Industry 4.0 are transforming food product development by enhancing supply chain efficiency and transparency and product development capabilities. The combination of predictive analytics with machine learning algorithms allows companies to adjust their products for changing consumer demand patterns while blockchain technology delivers supply chain visibility to establish customer trust. Big data analytics transforms decision-making through its ability to deliver behavioral insights about consumers which enables SMEs to develop targeted innovative products.

In addition, Industry 4.0, which combines the Internet of Things, robotics, and intelligent manufacturing systems, has significantly transformed the food industry. It enables monitoring of production processes for the first time, increases the level of output, and reduces costs associated with operational inefficiencies. These technological changes have led to increased flexibility in enterprises, which has become a prerequisite for maintaining their competitiveness within the framework of a grand strategy (Thakur & Maurya, 2024).

However, contrary to the impressive growth of the food industry, sustainability in this sector is lagging behind its growth. One of the most alarming problems of the food system is the amount of food waste generated at various stages in the supply chain of the food system. Despite efforts to solve this issue, the prevalence of food waste undermines both economic efficiency and environmental sustainability. According to the Food and Agriculture Organization (FAO), 14% of the world's total food produced is wasted. This wastage happens in multiple stages in the food system, from harvesting and processing to distribution and consumption. In developing countries, the situation is even worse when up to 40% of food production never reaches the final customers. According to a United Nations report, the world throws over 1 billion meals per day, whereas 787 million people are living in hunger.

These challenges from 'technology adoption' can be categorized as internal factors and external factors (Shah, 2023). As suggested by Shah (2023), internal factors are within the organization and encompass internal aspects like leadership, organizational culture, and employee skill sets, which are unique in the organization. External factors, on the other hand, stem from the outside environment and include elements such as market fluctuations, government regulations, and the availability of technological infrastructure (Shah, 2023). Internal factors have received a strong interest from researchers. For example, Abd Rahman, Kamarulzaman, and Sambasivan (2013) conducted research on the relationship between technology adoption and organizational culture and performance. But the majority of the research was addressing the measurable factors of a firm, such as costs, performance metrics, etc.

2.4 Data Analytics

'Data analytics' implies a set of techniques and tools to extract and analyze data. Data can be collected from day-to-day business operations or human activities. In this context, all the collected information can be a very useful tool for generating insights and identifying growth opportunities, but to do it in a structured way might be challenging. Moreover, 'data analytics' can help to identify patterns, relationships, and interactions between many variables in the business. However, only the collection of raw data is insufficient for value generation, and there is evidence that data collection in itself does not bring the anticipated results in terms of productivity growth (Bianchini & Michalkova, 2019).

With the fast growth of digital technologies, digital transformation has led to a huge increase in digital data, which businesses use to improve their production processes and make quick, flexible decisions. The businesses that achieved successful implementation of digital technologies such as 'data analytics' in the context of business are suitable for reshaping their business models or streamline their business operations (Frau, Moi, & Cabiddu, 2022).

When considering the role of 'data analytics' in SMEs performance, the impact of 'data analytics' and data-driven decision-making mostly happens through five channels: enhancing research and development (data-driven R&D); developing new goods and services by using data either as a product or as a major input (data products and data-intensive products); optimizing production or delivery processes (data-driven processes); improving marketing through targeted advertisement (data-driven marketing); and developing new organizational and management approaches or significantly improving existing practices (data-driven organization). With all this data, companies are increasingly faced with the challenge of processing them and are therefore looking for more effective and meaningful ways to collect and use this data. This data processing can be done internally within the organization or externally with the help of business partners and third parties. Therefore, using large data in a suitable way means analysing the collected data to derive valuable information and gain valuable insights which can be used for improving the product and services to better meet market needs (Frau, Moi, & Cabiddu, 2022).

Decision-making means assessing different options and alternatives to choose the best one for achieving a certain goal that business considers. In the context of data-driven decision making is choosing an alternative or making a decision based on the factual information, assessing quantitative metrics and data analysis. With data-driven decision making, the company's heads and managers are able to make strategic decisions based on the facts rather than opinions and feelings. In the digital world, data-driven decision making is an important aspect and can provide many advantages as it helps to improve efficiency, reduce costs, improve the products and drive innovations. Today, being a data-driven company means that you can tackle challenges, stay competitive and grow sustainably in the fast-changing world (Ulrich et al., 2018).

Data analysis helps SMEs discover fresh insights and growth opportunities which are backed by concrete evidence. The outcome leads to better strategic decision making through informed choices. Data analytics becomes essential for industries which experience both high market competition and numerous companies operating in the market. SMEs can achieve higher profitability through data-driven decision making when they implement such practices in highly competitive markets (Žilka et al., 2024).

Small and medium-sized enterprises (SMEs) can use data analysis to discover hidden patterns which lead to better strategic choices. The manufacturing sector presents a specific case where SMEs need data analysis because they maintain thin profit margins while facing strong market competition. Through DDDM implementation small and medium-sized manufacturers can detect operational inefficiencies and optimize their processes to make strategic decisions that boost profitability.

The economy of companies becomes stronger through data-driven innovation which represents a fundamental element of digital transformation. The approach enables businesses to maintain market leadership while outperforming their competitors. Companies need to use advanced methods including big data analytics and AI and machine learning technologies to convert data into valuable information when they want to become data-driven organizations that implement innovations. Firms can enhance their operations, research and development, new product and service development, improve marketing strategies and achieve a competitive advantage. Overall, it allows businesses to respond effectively to market opportunities and challenges (Sultana, Akter, & Kyriazis, 2022).

In summary, the integration of data analytics, data-driven decision-making, and digital transformation plays a crucial role in enhancing business performance and driving innovation. As SMEs continue to adopt these technologies, their ability to remain competitive and agile in a rapidly evolving digital economy will largely depend on how effectively they leverage data for strategic growth.

2.5 Supply chain

A well-organized supply chain is one of the significant competitive advantages of SMEs, allowing companies to innovate. Therefore, companies put special emphasis on developing their logistics system. Within this system, the food industry collaborates tightly with raw materials and semi-finished products suppliers such as agricultural, meat producers, forestry and fishing companies (Manzini & Accorsi, 2012). There are key characteristics of the food supply chain that differentiates it from other industries. First is traceability due to the customer's increased demand for the safe, healthy and high quality products (Trienekens et al., 2011). Restaurants that care about brand reputation should adhere to these basic standards of quality and safety. Second feature is the perishable nature of products (Kumar et al., 2020). Food service products have very limited shelf life that sometimes causes food wastages and losses. Thirdly, regulatory requirements set by the government affect the supply chain. (Sharma et al., 2009). Some constraints impact above mentioned quality aspects and types of the products supplied that may harm overall welfare of consumers. Finally, the seasonality feature affects demand patterns causing demand fluctuations and requires proper forecasting (Eksoz et al., 2014).

Persistent challenges faced by the food supply chain are the perishable nature of the product, ineffective demand management, poor pre-harvest management, lack of government support, high operation costs and lack of cold chain infrastructure (Kumar et al., 2020).

Digital technology integrated into the food supply chain has to solve the existing challenges considering inherent characteristics. One of the most used digital tools is the Internet of things (IoT). Opportunities of IoT can start with automatic manual work and spread to real-time monitoring, autonomous coordination, gaining adaptability and agility (Ben-Daya et al., 2020). For the pursuit of a decentralized data server that ensures transparency and consequent increase in brand trust, blockchain technology has been proposed for many years (Ehsan et al., 2022). Neglecting infrastructural challenges, the implementation of the system benefits all the stakeholders, suppliers, distributors, vendors, restaurants, and end clients. Moveover, the recent boom in artificial intelligence (AI) became a ready solution that can resolve problems in the

Food supply chain (Wang et al., 2024). Lastly, enterprise Resource Planning (ERP) and Cloud-Based Platforms also benefit the efficiency of managing supply chain processes.

Integration of digital technologies and restructuring the whole system require reasonable strategic drivers. Some significant drivers are Real-time Tracking, adaptability to market changes, and supply chain systems for collaboration between suppliers (Patidar et al., 2021). There are studies investigating the importance of three. By implementing IoT for real-time tracking, companies can do better in visibility, efficiency, cost reduction and risk management (Adeusi et al., 2024). Optimization of logistics allows experiments with new delivery models and to develop innovative solutions for better supply chain responses. Thanks to the second driver, need for adaptability, supply chains can quickly respond to demand fluctuations, disruptions, and new regulations to be more resilient and reliable (Holloway, 2025). AI-driven demand forecasting helps the restaurants to respond quickly to market needs and optimize seasonal offerings, including innovative product offerings (organic, plant-based, etc.). Collaboration between companies is a preferred strategy for accelerating innovative solutions, including supply chain (Shin et al., 2019). In the Food Industry, enterprises can use Integrated ERP, EDI, and cloud-based platforms enhance information sharing and coordination between suppliers. Strong supplier relationships allow companies to test and implement innovative technologies faster, such as smart inventory systems or automated replenishment models.

2.6 Operational efficiency

Incorporating ‘operational efficiency’ as a latent variable in Structural Equation Modeling (SEM) framework is well-supported in the context of Digital Transformation (DT), especially for SMEs in the food industry. DT projects frequently seek to improve operational efficiency, which measures how well a company uses its resources to achieve desired results.

Research shows that small and medium-sized enterprises (SMEs) in the food sector apply digital transformation (DT) techniques to enhance productivity by minimizing input usage and optimizing available resources (Kahraman & Rigopoulos, 2024).

Digital solutions adoption by SMEs leads to a 25% productivity boost and 30% reduction in operating costs through automation and better resource management according to the World Economic Forum (2024).

The success of DT activities depends heavily on operational efficiency which serves as a vital component in digital transformation preparedness assessment models (Naji, Gunduz & Al-Henzab, 2024).

The SEM model used operational efficiency estimation based on the following observed variables:

Digital tools and process automation represent the implementation of automated systems and digital technology to enhance workflow efficiency and reduce manual labor and streamline business operations. The system includes tools that optimize task performance and decision processes through cloud-based software and AI systems and process automation solutions.

Businesses can enhance their operational performance through automation technologies which include artificial intelligence (AI) and machine learning and robotic process automation (RPA) to reduce errors and optimize operations (Sheth, 2021).

Cost Efficiency & Waste Reduction: This refers to a company's capacity to reduce operating costs and wasteful use of resources by using digitalization and streamlining procedures. Businesses may decrease wasteful spending, improve resource use, and enhance overall financial performance by combining automation and data-driven insights.

Digital tools implementation can significantly reduce labor costs and operational expenses by minimizing manual intervention and errors. Additionally, technologies like AI and IoT help optimize energy usage and reduce material waste, leading to improved sustainability and cost savings (Edstellar, 2025).

Speed & Productivity Improvements – This captures the extent to which digital transformation enhances the speed of operations and boosts overall productivity. It includes reductions in production cycle time, faster decision-making, and increased output due to improved coordination and digital workflow management.

Digital technologies accelerate the carrying out of routine tasks, significantly reducing the possibility of human error and increasing operational efficiency by speed and productivity improvements (Lo, Yang, Zhang & Li, 2024).

The rationale behind observed variables designed to measure operational efficiency through digital adoption is that digital tools are highly effective in improving workflow (operational) efficiency within the organization (e.g., cloud storage, accounting software, etc.).

Adoption of digital technology, like accounting software and cloud storage, can enhance collaboration, expedite procedures, and enable real-time data access. According to research, companies that invest in digital transformation projects exhibit improvements in decision-making skills and process optimization, which enhance operational efficiency levels (Xu et al., 2023).

The implementation of digitalization leads to substantial cost reductions because it automates processes while reducing human mistakes and maximizing resource utilization. Digital tools boost operational performance through cost reduction according to research on digitalization effects on operational efficiency (Liu et al., 2024).

Digital technologies shorten cycle times through process optimization and delay minimization. Digital transformation enables businesses to boost productivity through operational time efficiency improvements (Gurumurthy, 2020).

The variables serve to obtain data about digital adoption impacts on workflow effectiveness as well as cost reduction and time savings and other operational efficiency aspects. The collected data will enable a complete understanding of both benefits and development opportunities within the company's digital transformation projects.

2.7 Employee Training & Skills

In the era of rapid technological advancement, digital transformation has become a critical focus for businesses striving to maintain competitiveness and foster innovation. However, technological investment alone does not guarantee success. Human capital, particularly employee skills & training, plays a pivotal role in driving digital transformation and innovation (Small Business Economics, 2024). Research indicates that organizations investing in upskilling programs experience increased productivity and enhanced talent acquisition and retention. Specifically, 93% of CEOs who introduced upskilling initiatives reported these benefits (PwC, 2024).

Human capital theory supports the significance of employee skills in digital transformation because it shows that education and training investments boost employee productivity and adaptability (Becker, 1964). According to Becker human capital includes education and on-the-job training which produces substantial effects on economic results. Research shows that organizations which focus on continuous learning achieve better results than their competitors because employee training investments lead to a 49% higher chance of surpassing competitors in performance metrics (Psico-Smart, 2023).

The implementation of automation technology serves as a main force behind digital transformation because it boosts employee productivity and enables staff members to concentrate on process enhancement. According to Dong and Mcintyre (2014) automation cuts down on repetitive work so employees can dedicate their time to innovative tasks and problem-solving. McKinsey (2020) reports automation results in employee efficiency improvements between 30-50% while Deloitte (2016) discovered RPA implementation led to employees spending more time on process optimization and resulted in 70% of companies identifying 30% more inefficiencies for improvement.

The connection between digital transformation and innovation depends heavily on employee digital competence. Huu (2022) investigates the relationship between employee digital competence and their autonomy with digital tools and their innovative work behaviors. The research shows that digital skill development through specific training programs enhances employee innovation capabilities which drives successful digital transformation projects.

Digital upskilling receives its importance from various case studies. Accenture collaborated with Henkel to develop a complete digital upskilling initiative for their 52,000 employees who work across consumer and industrial product sectors worldwide. The program started by evaluating employee skills and then determined training needs before delivering specialized educational programs for different roles which resulted in better operational performance and sustained innovative practices (Accenture, 2024). Through its Cloud Skills Initiative Microsoft dedicated substantial resources to employee training which helped the company sustain its technological market dominance and drive innovation (Digital Experience, 2024).

Digital adaptability is a competitive necessity, and organizations embracing digital inclusivity are better positioned to foster innovation. Research suggests that companies integrating accessibility in their digital strategies are more likely to achieve innovation and competitive advantage (Forbes, 2024). Peter Senge’s Learning Organization Theory supports this perspective, emphasizing that fostering a culture of continuous learning and adaptability is essential for organizational success. By promoting collaboration through digital technologies, companies can create an environment conducive to ongoing development and responsiveness to change (Senge, 1990).

'Employee skills & training' is an essential latent variable in measuring digital transformation and innovation within SMEs. Empirical evidence and theoretical foundations demonstrate that investing in human capital, fostering automation-driven efficiency, and promoting digital adaptability are crucial for driving successful digital transformation initiatives. Companies prioritizing employee upskilling and digital competence development will be better positioned to enhance innovation and sustain competitive advantage in an evolving digital landscape.

2.8 Interconnectedness of DT elements and Innovation

The non-linear process of digital transformation depends on how different organizational capabilities interact through mutual influence and reinforcement. The adoption of digital transformation in SMEs particularly in food service resource-constrained industries depends heavily on workforce readiness and operational design features and supply chain flexibility and data-driven decision-making practices. This section explores the theoretical connections between these factors to explain their impact on innovation performance before establishing the structural model for the study.

'Technology adoption' is a basic element of transformation processes. However, the effectiveness of these solutions in the economy depends on the level of training of employees (Omrani et al., 2022) and the quality of the company in terms of analysis and reliable data. For example, the use of cloud inventory systems or ERP platforms will be ineffective if the staff does not have the necessary skills to work with them or if operational processes are not adapted to new digital forms. Overall, *'technology adoption'* is one of the main drivers of innovation. According to Radicic (2023), SMEs that use digital tools like mobile apps, automation systems and electronic platforms have a higher probability to create new products and improve their services. In the food service industry, technology helped many companies to offer online ordering services, digital menus and online payment of the bills.

'Operational efficiency' is also an important driver of innovations in different industries. Research highlights that '*operational efficiency'* plays a key role in this process, helping to increase agility, reduce waste, and create conditions for scaling innovation (Gurumurthy, 2020;

Xu et al., 2023). Kahraman (2023) in his research stated that SMEs use digital technologies to make the work faster and decrease costs and labor work. These improvements help to enhance internal processes, which can be considered as process innovation. Also, there is much more room for testing new ideas and products when the process runs smoothly and with minimal human effort.

Likewise, *'data analytics'* alone does not lead to innovation. Its potential is realized when organizations are able to use the insights gained to optimize operational processes (Liu et al., 2024), adapt supply chains (Ehsan et al., 2022), and develop customer-centric innovations. Even small restaurants can use data to update their menu, improve delivery times, or plan promotions.

'Supply chain integrity' is a consequence of these effects, which cause early coordination, improved traceability, and consistent responses to market changes, which enables organizational agility and innovation capabilities (Shin et al., 2019). However, effective supply chain digitalization often depends on previous investments in technology and a skilled workforce, which ensures the interrelationship of the components of digital transformation.

'Employee skills and training' play an important link. Research shows that SMEs that invest in employee skills not only show higher productivity, but also determine innovation outcomes through improved adaptability and experimentation (Nasir et al., 2022). Cadden (2021) shows that when employees have good digital skills, they can use new technologies more effectively and help bring new ideas into the business. Without training, SMEs might have digital tools but not know how to use them well. Training also supports the culture of constant learning and innovation inside the company.

These relationships are well documented in the literature and form a theoretical model that we intend to test using partial least squares structural equation modeling (PLS-SEM). Specifically, our model examines both direct and mediated paths between five core DT variables and their impact on SME innovation. The following table summarizes the survey items, associated constructs, and corresponding research hypotheses.

Table 1

Survey Variable Codebook

№	Short name	Statement/Definition
Q1	Digital tool utilization	Our business consistently utilizes digital tools (e.g., POS systems, CRM software, QR codes, Kaspi, loyalty programs) for daily operations.
Q2	Online sales presence	We actively sell our products through online platforms such as Glovo, Wolt, and our website.
Q3	Impact on profitability	The adoption of digital technologies has improved our business profitability.
Q4	Workflow efficiency	Digital tools are highly effective in improving workflow (operational) efficiency in our organization (e.g., cloud storage, accounting software).
Q5	Cost reduction	The adoption of digital solutions helped reduce our operational costs.
Q6	Time savings	Time saved per production cycle due to digital solutions is significant.
Q7	Structured data collection	Our business does not have a structured approach to data collection.
Q8	Customer insight utilization	We use data-driven customer insights to develop new products and services that better meet market needs.
Q9	Market responsiveness	Our business leverages data analytics to anticipate market trends and develop innovative solutions.
Q10	Training opportunities	The company provides employees with learning opportunities to improve business processes.
Q11	Automation support	The automation of routine tasks has allowed employees to focus on improving work processes.
Q12	Digital collaboration	The use of digital technologies in our company has contributed

		to a work environment where employees with different backgrounds and skill levels can collaborate effectively.
Q13	Real-time tracking	We use digital tools to track supply chain operations in real time.
Q14	Adaptability	Digitalization of the supply chain enables us to adapt to market changes faster and implement new products.
Q15	Supplier collaboration	Digital platforms for supplier collaboration (EDI, cloud systems) facilitate joint development and implementation of innovative solutions.

2.9 Empirical Studies & Theoretical Framework

For the data analysing purpose, multiple tools can be useful for gaining different insights. After collecting data, this research aims to identify the relationship between study variables. Use of multiple regression methods is common among enterprises with being used for 75% of the cases (Manley et al., 2020). However, in the past decade partial least squares structural equation modeling (PLS-SEM) is gaining popularity. PLS-SEM is widely accepted due to its user-friendly interface, allowing researchers to analyze relationships between observed and latent variables while conducting robustness tests and accounting for measurement error (Memon et al., 2021). Guenther et al. researched the relevance of using the tool for marketing management and found a positive trend in its application (2023). PLS-SEM is applicable in these cases below: prediction is the primary statistical objective of the research; conducting exploratory research to develop or extend theory; the research includes multi-item latent variables; one or more of the latent variable measurement models are measured formatively; the scaling method is non-parametric, such as ordinal or nominal measurements; the data consists of financial ratios or similar types of secondary/archival data; the research focus is on a small population sample that results in a small sample size, such as in business-to-business research; large samples are available (10,000+); the structural model is complex and includes many constructs, indicators, and/or causal relationships; data are not normally distributed, as is typical of social sciences and survey data (Manley et al., 2020).

Considering the advantages, this paper uses PLS-SEM for analysing gathered data.

2.10 Model fit Test Indices Choice Justification

In Structural Equation Modeling (SEM), selecting appropriate fit indices is crucial for evaluating how well your model aligns with the observed data. Because of its clarity and reliability, the Comparative Fit Index (CFI), among the widely used indices of Standardized Root Mean Square Residual (SRMR), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Comparative Fit Index (CFI), is frequently suggested.

Justification for Choosing CFI:

A user-specified model's fit is assessed by the CFI in comparison to a more constrained baseline model, usually the "independence model," which makes the assumption that all variables are uncorrelated. Because it adapts to sample size and works effectively even with smaller samples, it is especially beneficial. Furthermore, the CFI is less susceptible to the data's distributional assumptions, which makes it a flexible option for a range of research settings.

Newsom (2023) highlights that the CFI is a popular fit index that evaluates how well a target model fits against an independent model, taking sample size and model complexity into consideration. According to Sathyanarayana and Mohanasundaram (2024), the CFI is one of the most well-known fit indices in SEM and is prized for its capacity to provide an unbiased evaluation of model fit.

A thorough assessment of the model's performance will be ensured by selecting the CFI, which is in line with accepted SEM procedures that place a high value on establishing a balance between model complexity and goodness-of-fit.

3. Methodology / Research design

3.1 Survey design

The survey was carefully developed to capture the information on five latent variables related to digital transformation implementation and innovation capabilities of SMEs. *The survey consists of 15 likert-scale questions* in total with 3 questions for each latent variable. *The likert scale questions* were designed to indicate the level of agreement of respondents from “1” = strongly disagree to “5” = strongly agree. Also, some questions were reverse coded to avoid response bias and to ensure that respondents thoroughly understood the questions and took time when answering.

Each of the five latent variables correspond to a specific dimension of digital transformation affecting innovation capabilities in SMEs, which are ‘technology adoption’, ‘data analytics’, ‘supply chain integrity’, ‘operation efficiency’ and ‘employee skills & training’. Each variable was measured by a set of three questions that were formulated based on DT literature tailored to SMEs. For instance, ‘technology adoption’ is explained by the extent to which an enterprise uses digital tools and software, while ‘employee skills & training’ items assess the enterprise’s efforts to upskill staff in terms of digital transformation. By mapping three observable items to each latent variable, the survey ensures that each variable is measured by multiple indicators enabling reliable assessment for each latent construct. The total of 15 questions keeps the survey concise and manageable for respondents, while still gathering rich information across all five DT dimensions.

3.2 Sampling

Our target population are *SMEs in the food service industry in Astana,* specifically businesses such as cafes and restaurants. This sector was chosen because it comprises many SMEs that are influenced the most by digital technologies in recent years (digital tools and software for maintaining orders in and out, online ordering systems, data analytics, etc.). However, the level of digital transformation of cafes and restaurants in Astana varies and some of them may be much behind the others. The SMEs targeted fall under the definition of small and medium enterprises, and typical respondents are owners or managers who have insight into both the business’s innovation efforts and its use of digital technologies.

To contact survey participants and get their answers a *non-probability convenience sampling approach* was used. The cafes and restaurants available in Astana were parsed via 2GIS with all their contact information. Data collection was performed via an online survey platform and the link was distributed directly to respondents (enterprise representatives) through direct message in WhatsApp and Telegram. Participation was *voluntary and anonymous,* and respondents were assured that their answers would be kept confidential and used for academic purposes only.

As of the current phase of the project, 57 responses have been collected from SME owners/managers. This sample provides an initial dataset for analysis. While 57 is a relatively modest sample size, it is within acceptable bounds for exploratory analysis in Structural Equation Modeling. The survey remains open to collect additional responses, with the goal of reaching a larger sample to improve statistical power.

3.3 SEM/PLS-SEM

Given the study's goal to identify the innovation capabilities of SMEs, we employed **Structural Equation Modeling (SEM)** to test the relationships between digital transformation dimensions and innovation capabilities. SEM is a good choice here as it allows simultaneous examination of the *measurement model* (the relationship between observed items and latent variables) and the *structural model* (the linking paths between latent variables). In this research, the structural model includes five DT-related latent variables as independent variables that have an effect on the *outcome variable representing innovation capabilities*. To identify the dependencies on outcome, the literature is analyzed where the effect of DT-related dimensions is identified on the innovations capabilities of different enterprises. Using SEM enables us to identify the correlations between DT factors and their interconnection and impact on innovation capabilities in one unified analysis.

We specifically chose to use *Partial Least Squares SEM (PLS-SEM),* implemented with the SmartPLS software package, due to the nature of our data and research objectives. PLS-SEM is a variance-based approach to SEM that is used for predictive and exploratory research models. In our case, the goal is to *identify the key "driver" of innovation capabilities and determine whether there is interconnection among latent variables,* rather than purely confirm an existing theory. – a scenario where PLS-SEM is recommended. Additionally, PLS-SEM is advantageous given our **sample size (n = 57)**. PLS-SEM can accommodate relatively small samples and still produce robust estimates by focusing on explained variance and using resampling techniques (Fong & Law, 2013). Unlike covariance-based SEM, it does not rely on large-sample theory and makes fewer assumptions about data distribution. This flexibility is important for our study, as the sample is moderate and the latent variables are measured by Likert scales. Furthermore, the model includes five latent variables with three indicators each and PLS-SEM can handle such *complex models with a limited sample size* effectively by iterative estimation of latent variable scores (SmartPLS GmbH, n.d.) .

Using SmartPLS software we were able to construct the path model connecting latent variables with each other and generated factor loadings for each observable item and path coefficients for each relationship computed by the PLS-SEM algorithm. The choice of SmartPLS is justified by its user-friendly interface and its capability to provide extensive outputs for *latent variable scores, R^2 values,* which are useful for evaluating the results. In summary, the use of SEM (and specifically PLS-SEM with SmartPLS) allows us to assess the measurement quality of our survey and the strength of the DT-innovation links, even with a relatively small sample.

SmartPLS is a widely used software for conducting PLS-SEM analysis. Due to its user-friend;y interface and ability to provide factor loadings, latent variable scores, R^2 values and other outputs for analysis makes it a good choice for software. Moreover, SmartPLS supports bootstrapping methods, which can be used to improve the statistical significance of the relationship and make the data more reliable (Yim, 2019).

3.4 Bootstrapping

Bootstrapping stands as one of the methods to boost response numbers. The non-parametric resampling technique of bootstrapping generates repeated samples with replacement from a given dataset to create an approximation of the sample distribution. The method allows researchers to calculate variability and confidence intervals and bias without requiring strict parametric assumptions and provides a way to boost small sample sizes through resampling with replacement (Brownlee, 2019). The algorithm selects random samples from the dataset before returning them to their original position. The selection process enables each observation to appear multiple times in the bootstrapped generated dataset. The method of selecting samples through replacement is known as sampling with replacement (Brownlee, 2019).

The research used bootstrapping because the available data was restricted and most cafes refused to participate. Bootstrapping generates additional observations known as "pseudo-observations" which stabilize variance estimates and enhance confidence intervals. The statistical power of the data becomes stronger through bootstrapping which results in more representative findings. Recent studies have employed bootstrapping as a method to expand their datasets. For instance, Bello et al. (2015) applied a bootstrap nonlinear-regression method to an experiment with very few observations, generating additional bootstrap samples that augmented the design and improved the accuracy of approximated response functions. Smith and Jones (2018) developed a bootstrap-based framework to assess sampling sufficiency of ecological network metrics, effectively treating bootstrap replicates as additional observations to judge when sampling efforts are adequate.

4. Results

4.1 PLS-SEM model

The survey responses were collected on the qualtrics platform and then downloaded as an Excel file. In total, 78 responses were gathered in one month of active distribution. After eliminating partial answers, 57 full answers were used for the further analysis. The items were measured on a 5-point Likert scale. Table 2 shows the descriptive statistics, including means, median, observed min and max, and standard deviation of the data for PLS-SEM analysis.

Table 2

Collected Data's Descriptive Statistics

Item	Mean	Median	Observed min	Observed max	Standard deviation
Q1	4.586	5.000	2.000	5.000	0.696
Q2	4.263	5.000	2.000	5.000	0.883
Q3	4.162	4.000	3.000	5.000	0.677
Q4	3.960	4.000	3.000	5.000	0.618
Q5	4.010	4.000	3.000	5.000	0.628
Q6	4.081	4.000	3.000	5.000	0.646
Q7	2.869	3.000	1.000	5.000	0.895
Q8	4.212	4.000	2.000	5.000	0.729
Q9	3.586	4.000	1.000	5.000	0.841
Q10	3.657	4.000	1.000	5.000	0.955
Q11	3.848	4.000	3.000	5.000	0.520
Q12	3.990	4.000	2.000	5.000	0.628
Q13	3.616	4.000	2.000	5.000	0.907
Q14	3.606	4.000	2.000	5.000	0.633
Q15	3.374	3.000	2.000	5.000	0.719

The Excel file containing answers in numerical values for the 15 questions (observed variables) was converted into a csv file. In order to verify correct loading's groupings, an EFA was conducted first. Aim was to check if observed items aligned with the prearranged latent constructs. The results are presented in Table 3. 15 items were grouped into 4 factors and most factors were above an acceptable value of 0.5. Presented uniqueness value shows to what extent the item is unique to the variable and not shared with others.

Table 3

Factor Loading and Groupings by EFA

Item	Factor 1	Factor 2	Factor 3	Factor 4	Uniqueness
Q3	0.810				0.318
Q4	0.756				0.417
Q2	0.740				0.442
Q5	0.662				0.515
Q15	0.618				0.452
Q14		0.949			0.084
Q13		0.597			0.539
Q6		0.419			0.758
Q11			0.800		0.343
Q10			0.771		0.322
Q7				0.859	0.252
Q12				0.477	0.585
Q1				0.454	0.607
Q8				0.445	0.616
Q9					0.615

However, these findings did not match with literature findings and theoretical consistency. It is hard to determine practically meaningful common relationships between items Q2, Q3, Q4, Q5, and Q15. Item 9 was indicated as excessive. Therefore, the study proceeded with the original model structure, that is well explained and supported by evidence. Following that, the results were uploaded into SmartPLS and categorized under the predefined latent variables: ‘Technology adoption’, ‘operational efficiency’, ‘data analytics’, ‘employee skills & training’, and ‘supply chain integrity’. The connections between latent variables and justifications are given on Table 4.

Table 4

Connections Between Latent Variables and Justifications

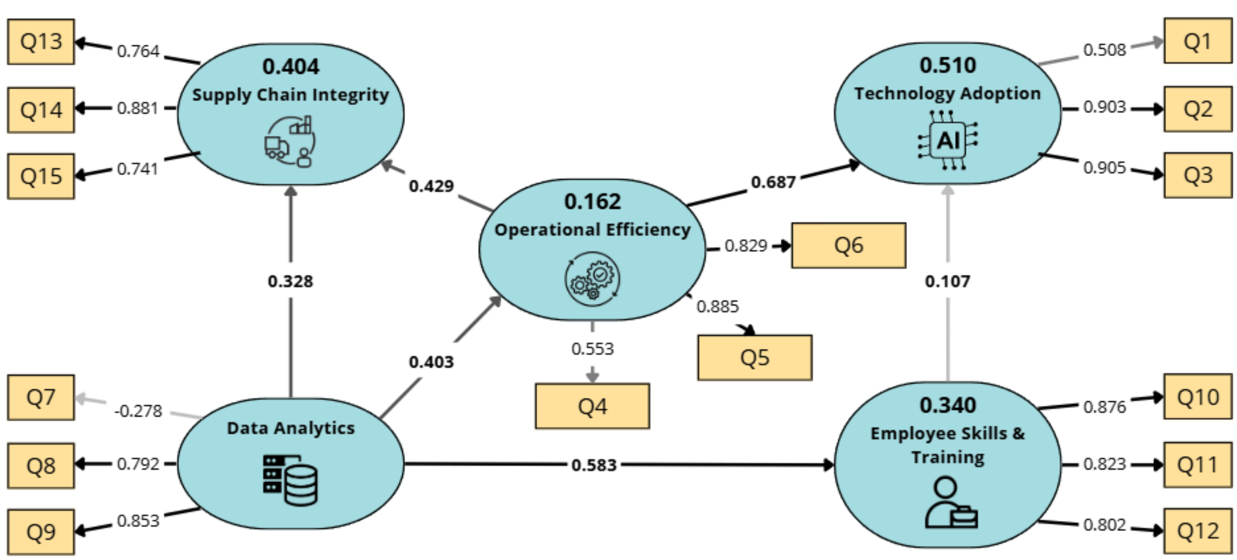
Connections	Explanations
Data analytics - > Employee skills & training	Upskilling employees is positively impacted when data analytics are used to assess their performance (Akdere & Egan, 2020).

Data analytics - > Operational efficiency	Data analytics adoption leads to significantly higher one-year ahead operational efficiency (Kausar et al., 2025).
Data analytics - > Supply chain integrity	Good data management enables businesses to use organizational learning and big data analytics to achieve sustainable supply chain management results (Bag et al., 2019).
Employee skills & training - > Technology adoption	Upgrading employee's skills and knowledge fosters their intentions to embrace digital technology (Chaudhuri et al., 2023).
Operational efficiency - > Supply chain integrity	Supply chain integration has a positive and noteworthy impact on customer value generation and the operational effectiveness of the business (Iranban, 2019).
Operational efficiency - > Technology adoption	Product/service-related technologies positively affect the flow practices on performance (Tortorella et al., 2019).

Graphical representation of the calculations by the PLS-SEM algorithm are shown in Figure 1.

Figure 1

Graphical Output of Structural Model Calculated by PLS-SEM Software



Loadings

The results show high indicator loadings in the majority of latent variables. Loadings are recommended to be above 0.708, which indicates that the model explains more than 50 percent of the indicator's variance (Hair et al., 2018). All the observed variables of 'employee skills & training' and 'supply chain integrity' meet recommendations, thus indicating the observed variable as a strong indicator of the latent construct). 'Operational efficiency' and 'technology adoption' are explained not that well by only Q6 and Q1, respectively. But still, the numbers are acceptable. 'Data analytics' variable contains negative loading of Q7 meaning that the observed variable moves inversely with the latent factor. The reason can be explained by the nature of the question where reverse coding was used. Overall, measurement model assessment shows satisfactory outcomes indicating relevance of the responses.

Collinearity

Collinearity values in Table 5 reveal no bias in the regression results. According to Hair et al. (2018), VIF values close to 3 or lower indicate the absence of collinearity issues among the predictor constructs, thereby supporting the reliability of the results.

Table 5

Collinearity Statistics (VIF)

Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15
1.12	2.37	2.22	1.64	1.74	1.10	1.10	1.16	1.21	2.09	1.83	1.42	1.77	2.19	1.32

R-square

The next values that indicate the model's explanatory power are R-square, which measures the variation explained by each endogenous component (Rigdon, 2012). The R-square values range from 0 to 1, where 0.75, 0.5, 0.25 are considered as substantial, moderate and weak (Hair et al., 2018). Too high R-square as 0.9 indicates overfitting of the model to the data. The results of 'supply chain integrity' (0.404) and 'technology adoption' (0.510) show moderate explanatory power. The latent constructs 'operational efficiency' (0.162) and 'employee skills & training' (0.340) are relatively weakly explained by the predictor variables. However, the r-square values have to be interpreted in relation to the design and context of the study. This study could use more numbers of predictors, and data that would result in higher r-square. Despite that, the structural model is acceptable to interpret the results as reliable.

Path coefficients

Path coefficients are the other important values generated by the PLS-SEM and represented in the white boxes in Figure 1. Higher path coefficient shows more strength and right direction of the relationship (Sarstedt et al., 2017). The highest path coefficients are ‘operational efficiency’ → ‘technology adoption’, ‘data analytics’ → ‘employee skills & training’ and constitute 0.687 and 0.583, respectively. The path coefficients ‘data analytics’ → ‘operational efficiency’ (0.403), ‘operational efficiency’ → ‘supply chain integrity’ (0.429), ‘data analytics’ → ‘supply chain integrity’ (0.328) show moderate effect between them. The lowest effect between latent variables are between ‘employee skills & training’ and ‘technology adoption’ making up 0.107. To evaluate the effects of bias, Sarstedt et al. (2017) suggest using significance assessment based on bootstrapping standard errors. A path coefficient is considered significant at the 5% error probability level if zero is excluded from the 95% bias-corrected and accelerated confidence interval. For example, 0.1 can be considered significant if lower bound is 0.5 and upper bound is 0.15 of the 95% confidence interval. Bootstrapping of the results are given on Table 6. P values lower than 0.05 indicates significance of the effects inbetween. The model does not show considerable effect between ‘employee skills & training’ and ‘technology adoption’.

Table 6

Path Coefficients of the Structural Model and Significance Testing Results

	Path coefficient	P values	Significant (p<0.05)?
Data analytics - > Employee skills & training	0.583	0.000	Yes
Data analytics - > Operational efficiency	0.403	0.000	Yes
Data analytics - > Supply chain integrity	0.328	0.004	Yes
Employee skills & training - > Technology adoption	0.107	0.140	No
Operational efficiency - > Supply chain integrity	0.429	0.000	Yes
Operational efficiency - > Technology adoption	0.687	0.000	Yes

4.2 Correlation matrix

Figure 2

Correlation Matrix Using Heat Map

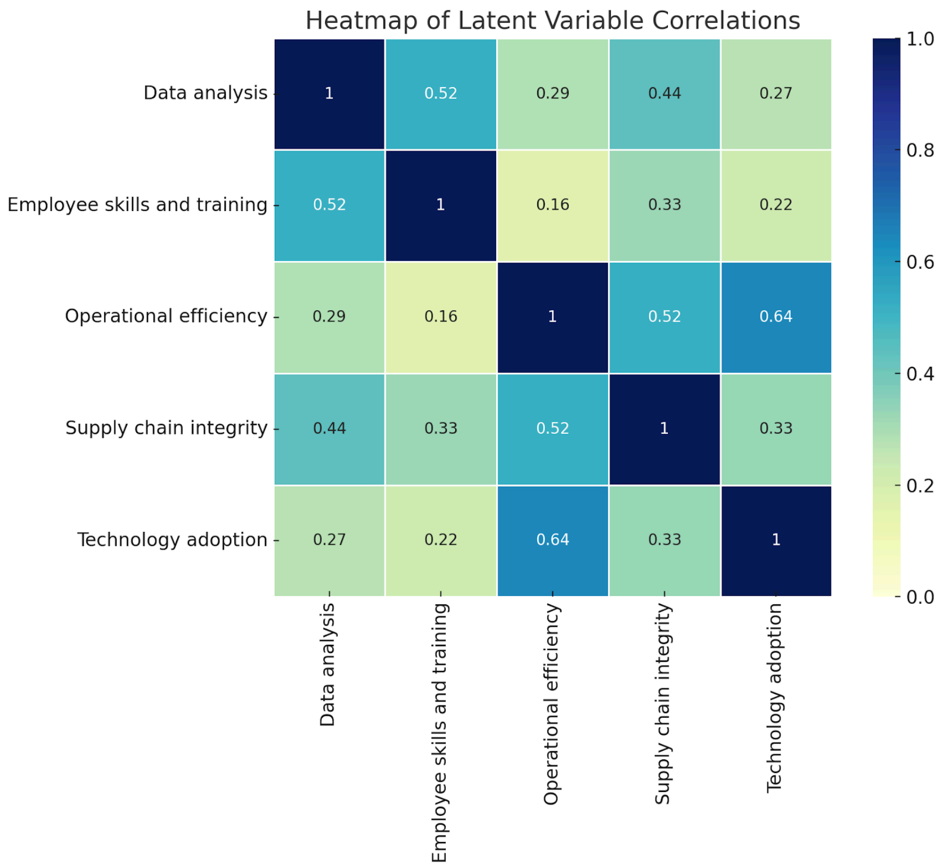


Figure 2 shows correlation matrix extracted by PLS-SEM, that presents the interrelationships among five latent variables: 'Data analytics', 'employee skills & training', 'operational efficiency', 'supply chain integrity', and 'technology adoption'. The strongest observed correlation is between 'operational efficiency' and 'technology adoption' (r = 0.642), suggesting a strong positive relationship. This implies that as organizations adopt more advanced technologies, they tend to experience a significant improvement in operational efficiency. Additionally, 'operational efficiency' is moderately correlated with 'supply chain integrity' (r =

0.523), indicating that a more robust and reliable supply chain contributes positively to operational performance.

‘Data analytics’ also plays a significant role, showing a moderate positive correlation with both ‘employee skills & training’ (r = 0.523) and ‘supply chain integrity’ (r = 0.438). These relationships highlight the importance of data-driven decision-making in enhancing workforce capability and ensuring a dependable supply chain. Although ‘data analytics’ has a lower correlation with ‘technology adoption’ (r = 0.273), it still reflects a meaningful link that supports the idea that analytics capability may influence or benefit from technological advancement.

‘Employee skills & training’ shows its strongest correlation with ‘data analytics’ (r = 0.523), which could reflect the interdependence between analytical capabilities and workforce development. However, its correlations with ‘operational efficiency’ (r = 0.159) and ‘technology adoption’ (r = 0.224) are relatively low, suggesting that training programs may not be directly tied to these outcomes unless supported by other factors. Lastly, ‘technology adoption’ shares moderate correlations with ‘supply chain integrity’ (r = 0.330) and ‘employee skills and training’ (r = 0.224), reinforcing the idea that adopting new technologies might also necessitate or result in enhancements to training and supply chain practices. Overall, the matrix highlights several critical interdependencies, with ‘operational efficiency’ and ‘technology adoption’ emerging as central, strongly linked factors in organizational performance.

4.3 Indirect, mediating effects

The correlation matrix reveals several potential indirect relationships among the latent variables that provide deeper insight into how certain organizational capabilities influence others through mediating factors. These indirect pathways are particularly valuable in understanding complex interdependencies that may not be fully captured by direct correlations alone.

One notable indirect effect is the pathway from ‘data analytics’ to ‘operational efficiency’ through ‘supply chain integrity’. Although the direct correlation between ‘data analytics’ and ‘operational efficiency’ is relatively low (r = 0.289), ‘data analytics’ shows a stronger correlation with supply chain integrity (r = 0.438), which in turn has a significant relationship with ‘operational efficiency’ (r = 0.523). This suggests that improved data analysis practices may not directly boost operational performance but do so indirectly by enhancing the integrity and reliability of the supply chain.

A second important mediated pathway is observed from ‘employee skills & training’ to ‘operational efficiency’ through ‘technology adoption’. While the direct relationship between ‘employee skills & training’ and ‘operational efficiency’ is quite weak (r = 0.159), the correlation between ‘employee skills & training’ and ‘technology adoption’ (r = 0.224), and between ‘technology adoption’ and ‘operational efficiency’ (r = 0.642), indicates a substantial indirect effect. This implies that when organizations invest in skill development and training, they may better facilitate the adoption of new technologies, which in turn leads to improved operational outcomes.

Another insightful pathway involves the influence of ‘data analytics’ on ‘technology adoption’ through ‘operational efficiency’. Although the direct link between ‘data analytics’ and ‘technology adoption’ is modest (r = 0.273), ‘data analytics’ is moderately associated with ‘operational efficiency’ (r = 0.289), which itself is strongly correlated with ‘technology adoption’ (r = 0.642). This suggests that effective use of ‘data analytics’ enhances operational capabilities, which then supports greater integration of new technologies.

These indirect effects highlight the importance of considering intermediary variables when analyzing organizational dynamics. In particular, ‘supply chain integrity’, ‘operational efficiency’, and ‘technology adoption’ serve as crucial mediators that amplify the influence of other foundational capabilities such as ‘data analytics’ and ‘employee skills & training’. Organizations aiming to enhance performance should recognize and leverage these indirect pathways for more strategic planning and investment.

Table 7

Indirect Effects

Connections	Specific indirect effects value
Data analysis -> Operational efficiency - > Supply chain integrity	0.125
Data analysis - > Operational efficiency - > Technology adoption	0.180
Data analysis - > Employee skills & training - > Technology adoption	0.065

The results (Table 7) show that ‘data analytics’ does not just impact things directly—it plays a behind-the-scenes role in improving other areas of the organization. For example, better data analysis leads to more efficient operations, and that, in turn, helps the company adopt new technologies more effectively (with an indirect effect of 0.180). It also helps build a stronger, more reliable supply chain by first improving how operations run (indirect effect of 0.125). There’s even a smaller but still interesting effect where data analysis supports employee skill development, which then helps with adopting new technology (0.065). All of this points to one clear message: investing in ‘data analytics’ can quietly but powerfully influence multiple parts of a business, especially when it works hand-in-hand with other areas like operations and training.

4.4 Innovation barriers

As a final step, descriptive statistics were planned to be applied to analyze the dataset obtained from the CIS Database. This method offers concise summaries of the sample and key metrics, aiding in the description and interpretation of the data’s characteristics (Hayes, 2024). The identified patterns for European countries were intended to be compared with results from Kazakhstani SMEs, collected through surveys, to identify barriers to digital transformation that hinder innovation.

The following barriers which can hinder an enterprise's ability to digitally transform and innovate were retrieved from CIS database (Eurostat, n.d.) and Kazakhstani SMEs were asked to assign the degree of importance to each of these barriers, in order to be able to obtain comparable results.

- Limited overall budget for digital transformation initiatives
- High costs associated with adopting specific digital technologies
- Shortage of employees with necessary digital skills
- Insufficient access to external digital knowledge and expertise
- Strong competition from digitally advanced firms
- Organizational resistance to change or conflicting strategic priorities

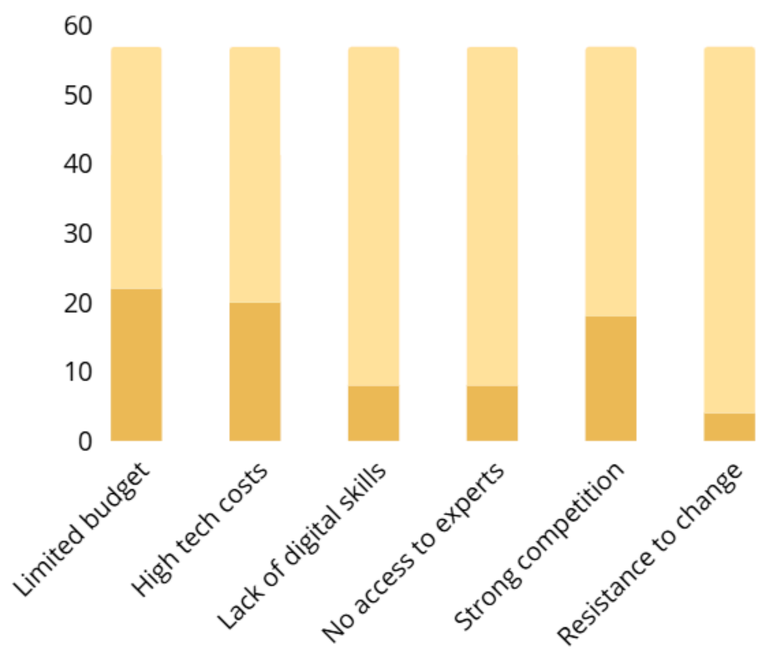
Degree of importance contained 5 points from *Not a barrier* to *Very high importance* (5 - Very High | 4 - High | 3 - Moderate | 2 - Low| 1 - Not a barrier).

However, this comparative analysis was ultimately not conducted. The survey results from Kazakhstani SMEs covered only the last three years of their operations, while the most recent CIS database—published in 2022 and conducted every three years—did not include the question related to hindering factors of innovation. As a result, relevant data for European countries were unavailable, making direct comparison between the two datasets infeasible.

Nevertheless, the survey conducted among Kazakhstani SMEs yielded valuable insights. Out of 57 respondents, 22 (38.6%) identified a *limited overall budget for digital transformation initiatives* as the most significant barrier. In contrast, 15 respondents (26.3%) indicated that *organizational resistance to change or conflicting strategic priorities* was not a barrier at all. This suggests that financial constraints are the most pressing obstacle, while internal organizational factors are perceived as less critical. The following figure presents the results of survey data collected from Kazakhstani SMEs regarding innovation barriers.

Figure 3

Innovation Barriers with Significance Based on Survey Data Collected from SMEs



5. Discussion of results

The results of this study provide strong support for the central hypothesis: different dimensions of digital transformation (DT) significantly affect innovation performance among

SMEs in the food service industry in Kazakhstan. Based on survey responses and a structural equation model (SEM), this section analyzes the main findings and interprets their theoretical and practical implications.

The analysis revealed that ‘technology adoption’ shows the highest direct relationship with ‘operational efficiency’ (r = 0.687). The findings align with research that demonstrates how cloud solutions and ERP systems and AI-based automation enhance operational efficiency in SMEs (Omrani et al., 2022; Liu et al., 2024). The direct access to resources through operational efficiency enables innovation because it optimizes processes and frees up resources. The research supports this finding because operational efficiency acts as both a direct innovation driver and a crucial mediator in multiple pathways.

The variable ‘data analytics’ maintains its moderate connections with other variables while acting as a supporting element. The system enables innovation and enhances operational efficiency and supply chain integrity which supports technology adoption. For example, the path from ‘data analytics’ to ‘technology adoption’ via ‘operational efficiency’ (indirect effect = 0.180) illustrates how improved data processing capacity enables better decisions and smoother workflows—prerequisites for the successful integration of new digital tools. This multi-level relationship is consistent with the broader literature on data-driven innovation (Frau et al., 2022).

The supply chain also emerged as an important factor, particularly as a facilitator. The data show that effective data analytics improves supply chain integration (r = 0.328), which subsequently improves operational efficiency (r = 0.523). This indirect path (indirect effect = 0.125) suggests that supply chain resilience and transparency can enhance the benefits of data capabilities for innovation outcomes – particularly relevant in the perishable food sector, where timeliness and traceability are critical.

Employee training and digital skills development were positively correlated with ‘data analytics’ and ‘technology adoption’, but had a weaker direct effect on operational performance. However, their indirect effect through ‘technology adoption’ (indirect effect = 0.065) supports the idea that a skilled workforce facilitates smoother digital adoption, which ultimately supports innovation. This supports theories of human capital investment and digital competence as critical factors in transformation (Becker, 1994).

However, finding the reason for low correlation coefficient is because many SMEs training programs focus on broad digital proficiency rather than specific platforms or tools being adopted, leading to skills-technology mismatch (Shahadat et al., 2023). Also, Varela in his research “Employee training strategies for new technology implementation in small business” (2022) identified 2 potential challenges that employees can face during the training: too generic training where the individual capabilities and current needs of employees are not considered and poor selection of third-parties learning resources and training centers, which provide insufficient knowledge transfer to employees. These challenges come from the limited resources that SMEs have. However, the inability to select the best learning resources might be constrained by the internal resources, the case-by-case approach of identifying the improving zones of employees can boost the learning efficiency and therefore positively affect technology adoption level inside the organization.

Taken together, these results show that innovation does not arise from any single digital transformation factor in isolation. Instead, it is the interaction – especially through the mediating effects – of ‘data analytics’, ‘operational efficiency’, ‘technology adoption’, and ‘supply chain integrity’ that drives innovation potential. This systemic view of innovation provides important practical insights for SME owners and policymakers: investments in fundamental capabilities such as learning or analytics can drive broader organizational improvements when strategically integrated with operational and technological upgrades. Finally, the results justify the use of PLS-SEM in modeling complex, multi-level relationships between latent constructs, especially with moderate sample sizes. By capturing indirect effects and intervariable dependencies, this approach provided a detailed picture of how digital transformation drives innovation in SMEs.

6. Recommendations and Future Work

Foodservice SMEs in Kazakhstan operate under significant constraints – limited financial resources, gaps in digital skills, and unstable supply chains (Bekmurat & Satpayeva, 2025; Chen & Wang, 2024). These challenges require a targeted approach to digital transformation (DT). Table 7 below ranks key DT factors by their overall impact on innovation (including both direct and indirect impacts on firm innovation). These rankings, which show which areas have the biggest impact on innovation when enhanced, are based on the findings of a structural equation model. SME managers can better deploy their limited resources and governments can focus support on areas that have the most potential for driving innovation by knowing these priorities.

Table 8

Total Effects of Digital Transformation Factors on Innovation

Rank	DT factor	Direct effect	Indirect effect	Total effect
1	Technology adoption	High	Moderate	Highest
2	Operational efficiency	High	-	High
3	Data analytics	Moderate	Moderate	High
4	Employee skills & training	Low-moderate	Moderate	Moderate
5	Supply chain integrity	Low	Low-moderate	Lower

Note: The total effect is the sum of the direct and indirect standardized coefficients of the path to innovation.

The results show that 'technology adoption' has the largest overall impact on innovation, followed by 'operational efficiency' and 'data analytics'. 'Employee skills & training' and 'supply chain integrity' factors also make significant contributions, but are more supporting than primary in their impact.

This section outlines a comprehensive set of recommendations and future directions aimed at enhancing innovation through digital transformation (DT) within Kazakhstan's food service SME sector. These recommendations are based on the findings of this study and the structural relationships identified through the PLS-SEM analysis. The recommendations are categorized into three core areas: strategic actions for SME leaders, institutional support strategies for policymakers, and opportunities for future research and implementation projects.

The first step for SME management should be to direct digital transformation efforts according to the ranked overall status of each innovation driver. The evidence from empirical research demonstrates that operational efficiency and technology adoption and data analytics capabilities serve as essential drivers for innovation both directly and through spillover effects. A phased and prioritized implementation approach should be adopted to help SMEs effectively manage their distributed resources and decision-making processes.

The first recommendation is to invest in high-impact technologies. The research indicates that "external technologies" drive SME innovation through their immediate benefits to service quality and operational processes. The tools connect to cloud-based point-of-sale (POS) systems, QR code ordering platforms, and mobile payment integrations. The implemented technologies enhance productivity levels and enable service innovations through online ordering systems and loyalty programs and multi-channel customer interactions. The research findings match global studies which demonstrate that digital tools boost SMEs' market engagement and product innovation capabilities (Bilal et al., 2024; World Economic Forum, 2023).

Second, improving efficiency should be a priority for SMEs, especially in the competitive and cost-sensitive foodservice industry. Digital tools can improve inventory management, planning, and automation processes, reducing overhead costs and freeing up focus on innovation. Current research confirms that increased efficiency creates space—time, budget, and opportunity—to experiment with new ideas and services (Chen and Wang, 2024; Bekmurat and Satpayeva, 2025).

Third, leveraging data analytics strategically is essential. Although its direct effect on innovation is moderate, 'data analytics' plays a significant indirect role by supporting better decision-making and enhancing other DT elements, including operational efficiency and technology usage. SMEs should be encouraged to systematically collect and analyze business data, ranging from sales trends and customer feedback to supply chain metrics. Basic dashboards and digital platforms such as Kaspi or Glovo offer built-in analytics features that SMEs can utilize as a starting point to build internal data literacy (WEF, 2023).

Fourth, workforce digital skills and training must not be overlooked. Although the effect of employee training on innovation is less pronounced than other variables, it is nonetheless a foundational enabler. A digitally literate workforce is essential for successful technology adoption and data utilization. Therefore, SME leaders should organize regular digital literacy workshops tailored to their specific operational tools and platforms. When employees are equipped to effectively use new technologies, the broader DT process becomes more cohesive and innovation outcomes more likely (Bilal et al., 2024; WEF, 2023).

Lastly, securing supply chain stability through digital means is increasingly critical in Kazakhstan's volatile market environment. While 'supply chain integrity' had the lowest total effect on innovation in the model, its importance as a risk buffer cannot be overstated. SMEs should adopt low-cost digital tools—such as supplier coordination platforms, shared order sheets, and instant messaging applications—to enhance visibility and resilience in their supply chains. This is especially pertinent given the logistical disruptions in the region (S&P Global, 2022).

In tandem with firm-level strategies, coordinated policy support is crucial to enabling the digital transformation of SMEs. At the institutional level, government action can address systemic challenges and create an ecosystem in which small businesses can thrive. The first recommended policy measure is the provision of financial incentives to lower the barriers to technology adoption. Subsidies, tax credits, or micro-grants could significantly ease the burden of investing in DT infrastructure such as software subscriptions, automation tools, or e-commerce platforms (Bekmurat & Satpayeva, 2025; WEF, 2023).

Second, investment in national digital infrastructure remains a pressing need. Policymakers should ensure that all regions, including rural and peri-urban areas, have access to reliable and affordable internet. This infrastructure is foundational for SMEs aiming to adopt cloud technologies, implement real-time tracking, or participate in online marketplaces (Chen & Wang, 2024; Bekmurat & Satpayeva, 2025).

Third, skills development must be a national priority. The government, in collaboration with vocational institutions and private sector actors, should offer accessible digital upskilling programs focused on SME-relevant technologies. These may include digital marketing, data analytics, inventory management systems, and cybersecurity. Public-private partnerships can deliver such training efficiently, ensuring that both business owners and employees have the competencies required for sustained innovation (Bilal et al., 2024).

Fourth, policy efforts should aim to improve supply chain resilience through coordinated platforms and networks. This could involve the development of shared logistics infrastructure, cold-chain distribution systems, and digital procurement platforms that allow SMEs to pool demand and engage more effectively with suppliers. These initiatives would buffer food service businesses from shocks in supply availability or pricing (S&P Global, 2022).

Finally, the establishment of dedicated SME innovation support centers is recommended. These hubs can offer mentorship, technical support, and demonstration areas where business owners can test emerging technologies before implementation. By embedding such support within programs like “Digital Kazakhstan,” the government can ensure that innovation is accessible not only to tech startups but also to traditional businesses like cafes, bakeries, and restaurants (Bekmurat & Satpayeva, 2025).

In addition to these practical and policy-level strategies, the research findings point to several important directions for future academic and applied work. First, longitudinal studies should be conducted to assess how digital transformation progresses over time and how its effects on innovation evolve. Such studies would provide insights into causality and the durability of outcomes across different phases of DT implementation. Second, future research could explore the moderating role of variables not included in the current model, such as organizational culture, customer engagement, or leadership orientation. Including these factors may uncover additional insights into how and under what conditions digital transformation most effectively drives innovation.

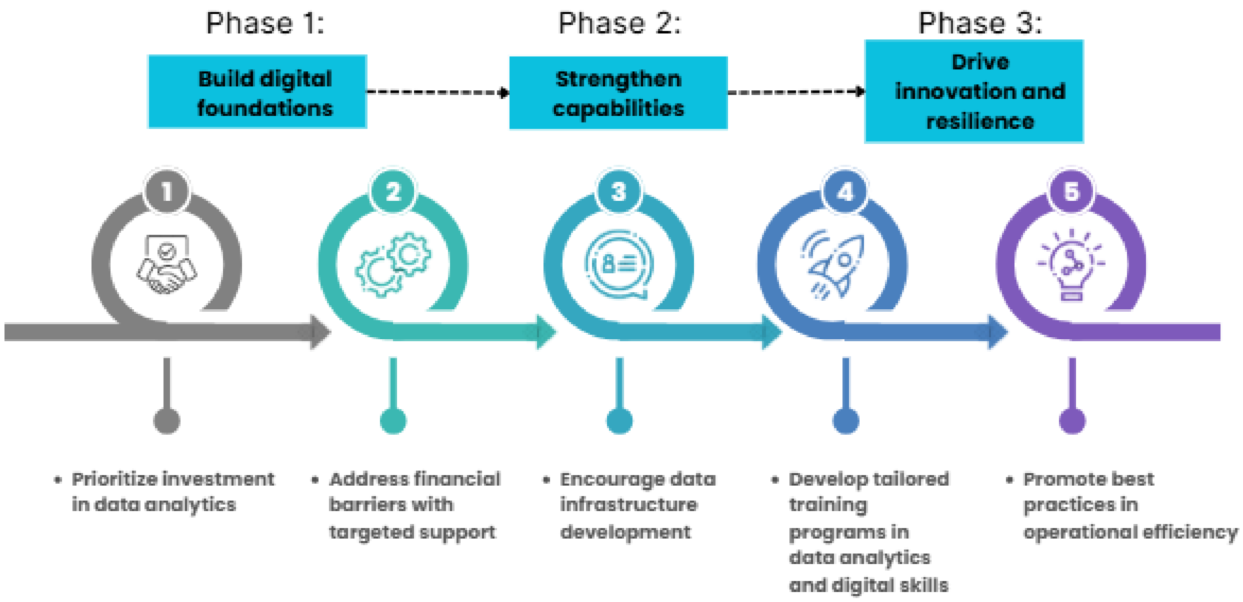
Moreover, qualitative research—such as interviews and case studies—could supplement the current quantitative findings by offering deeper insight into the barriers and success factors SMEs encounter in practice. These narratives can uncover context-specific solutions, such as adaptive strategies for overcoming staff resistance or financial constraints, thereby enriching the theoretical framework with practical knowledge.

SMEs should establish pilot programs to test phased digital transformation technologies in standard operations before practical implementation. The first phase of chains should begin with efficiency tools before progressing to analytics dashboards in the second phase and finishing with an online ordering platform in the third phase. The monitoring of innovation results during each stage ensures that the preferred direction remains healthy. Digital transformation hubs or sandboxes enable SMEs to safely test technologies like AI menu design and cable-based shipment tracking in a learning environment with minimal risk.

The research directions and recommendations presented offer a definitive roadmap (Figure 4) which supports evidence-based innovation enhancement through digital transformation for Kazakhstani SMEs in the food service industry. SMEs can effectively tap into digital transformation innovation through operational process improvements and technology investments and data development and human capital enhancement and supply chain stability and institutional support. Ongoing research and pilot projects should continue to improve and validate knowledge about digital transformation while ensuring its long-term sustainability and scalability and inclusivity.

Figure 4

Strategic Framework for SME Digital Transformation and Innovation



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