Kitti Dióssy

From Youth Perspectives to Leadership Influence

Does the act of shaping the leadership context of digital transformation lead to superior operational performance?

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DOCTORAL DISSERTATION

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CHAPTER I - Introduction

In the rapidly evolving landscape of the contemporary, industrialised business world, the interconnected dynamics of HR, leadership styles, digital transformation, and operational performance have become pivotal factors in determining an organisation's success (Tortotella et al., 2023). Leadership styles reflect leadership philosophies and practices. Moreover, employees’ perceptions play a crucial role in steering a company through the complexities of the digital era (Berman et al., 2020). Digitalisation and digital transformation, on the other hand, refer to the strategic integration of technology to reshape business processes, enhance efficiency, and drive innovation (Zhong et al., 2017). In order to maintain competitiveness in the digital era, companies shall improve their operational performance via Industry 4.0 (I4.0) (Liao et al., 2017; Culot et al., 2020). Through three research papers, my dissertation explores the intricate relationship between human resources issues and I4.0, leadership styles, digital transformation, and their direct and indirect impacts on operational performance.

I.1. Research goals and practical relevance of the research

I have *personal* and *professional* goals with this research.

The goal of the research outlined in the three chapters appears to be multifaceted, aiming to explore and comprehend the interplay between artificial intelligence (AI) and HR from the perspectives of the youth (Generations Y and Z); moreover, the connection between digital transformation, leadership styles, and operational performance, particularly within the context of Hungarian manufacturing companies (SMEs). The most significant added value of my dissertation is its holistic perspective and multidisciplinary approach. The study examines generational differences, attitudes towards digitalisation, digital skills, leadership styles and their interactions in the context of companies' operational performance.

My *personal* objective of my doctoral dissertation is to ascertain the opinions from a variety of viewpoints on the subject of digitalisation. As an HR consultant and digital tool user (current employee), my curiosity towards the conquest of globalisation and digitalisation stems from a professional and an everyday private life perspective. Over the years, I have developed a keen interest in the psychological aspects of economics and aspire to gain a more profound comprehension of the advantages and disadvantages associated with this subject matter. Accordingly, the objective is to examine and comprehend the opinions, attitudes, and perceptions of young economists from Generations Y and Z concerning AI. This encompasses their confidence, motivation, interest in AI, and perspectives on AI's impact on various aspects of work, including the relationship between AI and human resources and the balance between soft and hard skills. The objective is to provide insights that can assist organisations in aligning their AI strategies with the expectations and attitudes of the younger workforce, thereby ensuring enhanced engagement and preparedness for current and future challenges.

I have adopted a top-down approach after conducting a thorough analysis of this topic from a bottom-up perspective. This decision is based on my strong interest in pursuing further education or taking on a leadership role in a familiar environment. As mentioned earlier, the decision served as the foundation for my ongoing research.

As an ambitious economist, my *professional* objective is to examine the impact of diverse *leadership styles* on the *digital transformation* process within Hungarian *manufacturing* companies. This entails investigating how leadership approaches focusing on performance, relationships, goals, and implementation influence the efficacy of digital transformation strategies and activities. The aim is to identify effective leadership practices that can enhance digital transformation outcomes, assisting organisations in navigating and implementing digital changes in a more effective manner. Furthermore, it would be advantageous to conduct an investigation into how digital transformation acts as a mediator in the connection between leadership styles and improvements in operational performance. This necessitates an understanding of the manner in which leadership exerts an influence on operational outcomes through the implementation of digital transformation initiatives. The objective is to comprehensively understand the factors that contribute to successful operational performance improvements in a digitalised environment. This will provide leaders with a strategic framework to optimise digital and operational performance.

The principal objective of the research is to contribute to the corpus of knowledge on the role of digital transformation in organisations of SMEs, with a particular focus on the manner in which it interacts with leadership styles and affects operational performance. The research aims to provide practical guidance for organisations striving to exploit the benefits of digital transformation while effectively managing human resources and leadership skills.

This comprehensive research approach seeks to provide practical solutions for organisations pursuing success in an increasingly digital and AI-driven world.

The research presented in the three chapters (Chapter II., III., IV.) offers valuable insights that have significant *practical implications* for a range of industries, particularly manufacturing companies engaged in digital transformation. The findings of each paper could be applied in practice.

I introduce my research approach through my papers. The articles are the followings:

Dióssy, K. (2024). Y és Z generációs fiatal közgazdászok vélekedése a mesterséges intelligenciáról, *Köz-Gazdaság – Review of Economic Theory and Policy, 19*(1), 114-131. https://doi.org/10.14267/RETP2024.01.08

Dióssy, K., Losonci, D. I., & Városiné Demeter, K. (2023). Vezetési stílusok hatása a digitális transzformációra, *Vezetéstudomány / Budapest Management Review, 54*(10), 2–14. https://doi.org/10.14267/VEZTUD.2023.10.01

Dióssy, K., Losonci, D. I., Aranyossy, M., & Városiné Demeter, K. (2025). The role of leadership in digital transformation – a paradox way to improve operational performance, *Journal of Manufacturing Technology Management, 36*(9), 88-113. https://doi.org/10.1108/JMTM-07-2024-0386

Organisations can tailor their talent acquisition and recruitment campaigns by understanding the confidence, motivation, and interest of Generation Y and Z economists in connection to AI with the expectations and aspirations of younger professionals, ensuring a more engaged and motivated workforce. By understanding which areas of AI young economists view as most impactful, companies can prioritise the integration of AI in those areas. The multidisciplinary perspective of these professionals can provide a comprehensive range of perspectives on the ideal approach to digital transportation. Their education has instilled in them a holistic approach, and their openness to new technologies and technological experience sets them apart. Notably, the younger generations exhibit an innovative approach to digital tools. This could guide investment decisions and focus on AI applications more likely to be accepted and utilised effectively by the future workforce. Insights into the perceived importance of soft and hard skills in the AI-driven workplace can help organisations develop and enhance both technical and interpersonal skills, preparing their employees for the future of work.

Companies can also use the findings to design management development programs that emphasise the leadership styles most conducive to successful digital transformation. This could include management training that proves more effective in driving digital initiatives. Understanding how different leadership styles affect digital transformation can also help companies refine their digital strategies, ensuring that management teams are equipped to lead successful digital transformations. This could lead to more efficient production processes, reduced downtime, and improved productivity. Consulting firms can use the research to advise clients on best practices for digital transformation tailored to their leadership styles and organisational culture. By understanding how digital transformation mediates the relationship between leadership and operational performance, companies can optimise their leadership practices and digital strategies to achieve better operational outcomes. This includes enhancing productivity, reducing costs, and improving product or service quality.

The practical implications for *leaders* concerning the management and acceleration of innovative manufacturing applications, digital transformation initiatives, and Industry 4.0 adoption are also discussed. Leaders can use the results to shape their company’s digital strategy, ensuring that it aligns with the workforce’s expectations and the prospective domains where AI can benefit most. They can then adapt or modify their management approaches to endorse digitalisation efforts, leading to smoother transitions and more effective implementation of new technologies. Leaders can be trained to recognise the critical role that digital transformation plays in operational success, adjusting their leadership styles to support digital initiatives that lead to measurable performance improvements. It is incumbent upon leaders to develop a more profound comprehension of their employees' attitudes towards digitalisation. This enhanced understanding will empower managers to formulate personalised digital strategies.

Overall, the research provides practical insights that industries can use to enhance their digital transformation efforts, optimise the development of leadership styles, and better align their workforce strategies with the expectations of younger generations. These findings offer a roadmap for companies seeking to stay competitive in an increasingly digital marketplace, ensuring they can attract top talent, effectively manage change, and achieve operational performance excellence.

I.2. Main concepts

The centre of my research is the interaction of *digital*- and *human* factors in an organisation. I study this phenomenon from the perspectives of both the employees and the management at the microeconomic level.

This chapter sets forth the principal concept that underlies my doctoral dissertation. Furthermore, the papers employ a variety of perspectives. My initial research question was whether the digital solution was an inevitable outcome. In order to respond to this question at the microeconomic level, my research commenced with a bottom-up approach, focusing on the employees' perspective. Having gained insight into their perceptions and positive attitudes, I adopted a top-down approach, gathering information from SMEs' top management.

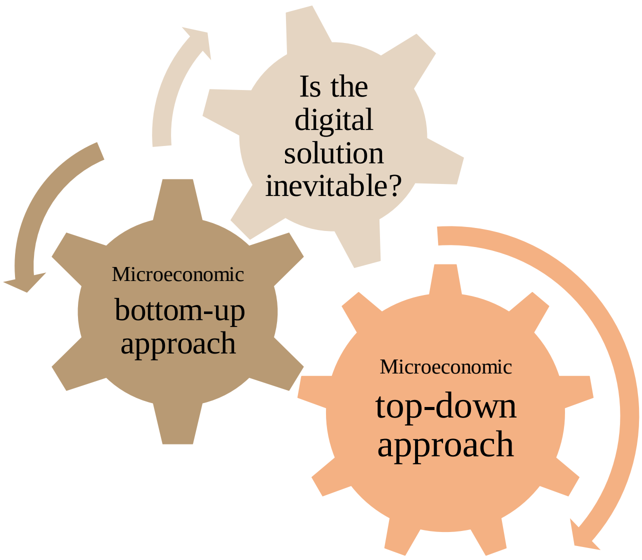
The *bottom-up approach* was employed to study the opinions of young generations about AI and robotics and ascertain their potential impact on the future workforce and HR practices. This will probably entail the implementation of grassroots or foundational strategies, whereby digital solutions will emerge from the lower levels of an organisation driven by individuals. The approach emphasises organic growth and innovation from the employees themselves.

The *top-down approach* is typified by strategic decisions that originate from higher levels of an organisational structure. This study examines the role of leadership styles in driving digital transformation within Hungarian SMEs and investigates how leadership styles influence operational performance improvements through digital transformation.

The central concept connects these two approaches, suggesting that the inevitability of digital solutions may depend on how the *digital* and *human* factors interact and complement each other within an economic or organisational context. The interplay between the bottom-up and top-down methods may determine the effectiveness and acceptance of digital transformation efforts and company competitiveness through operational performance.

Figure 1 demonstrates the point of view and main concept of my research.

Figure 1: The main concept of the research



Source: Author’s work, 2024

I.3. Research gaps and research questions

The younger generations are born into the digital age (Tari, 2010; 2011) and are, therefore, best placed to understand the relationship between human and digital factors (Menezes & Malhotra, 2022), as they will be the leaders of the future (Yılmaz et al., 2024). The most significant areas of impact, encompassing both soft and hard skills that can be cultivated (Bencsik et al., 2016), as well as the interconnection between AI and HR (Zhong et al., 2017; Semeraro et al., 2023), serve as pivotal points for managerial guidance in investment and development decisions (Frank et al., 2019). Subsequently, I examine the role of top management in digital transformation, investigating the impact of leadership styles on this process and the skill sets that can facilitate more effective outcomes. Nevertheless, the most crucial inquiries pertain to the manner in which the results can be expressed in terms of competitiveness, the leadership style that manufacturing companies should adopt, and the manner in which the results can be enhanced through digital transformation.

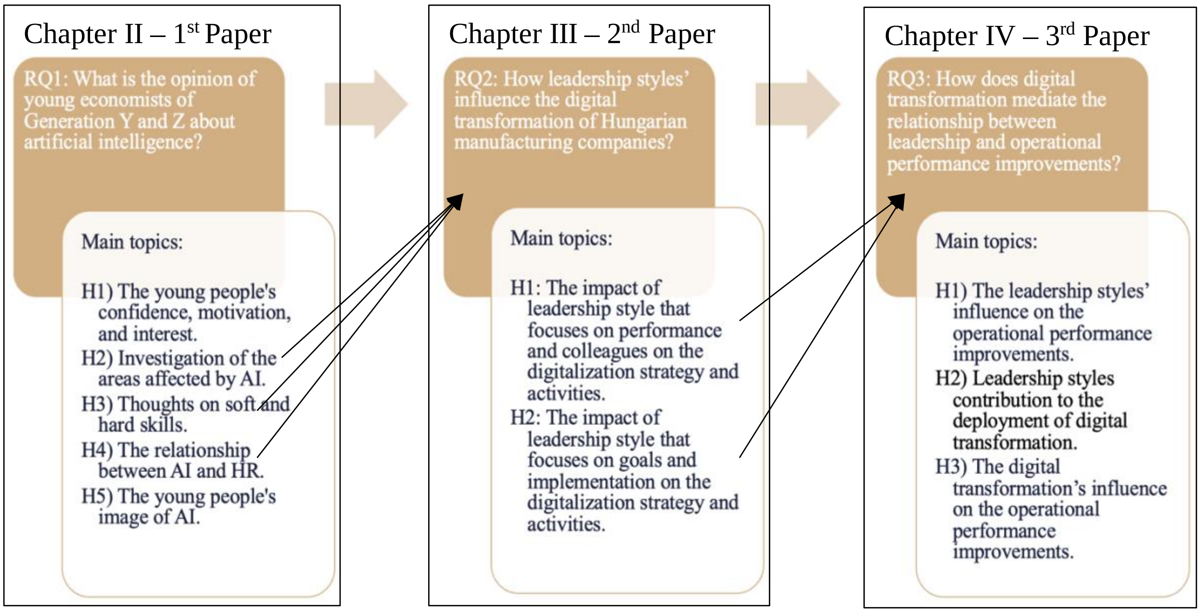
Manufacturing in Hungary is one of the most significantly impacted sectors by the advent of digitalisation (Központi Statisztikai Hivatal, 2021). My comprehensive understanding of both soft and hard skills and the relationship between AI and HR (Bencsik et al., 2016) enables me to elucidate the significance of digital transformation and leadership (Inversini, 2025) and their impact on SMEs’ operational performance (Tortorella et al., 2023).

Different leadership styles adopt distinct approaches to digital transformation and operational performance, assigning varying ratings to specific leadership styles (Tortorella et al., 2023). It can also be argued that the combination of relationship-oriented (e.g., recognition, setting an example, support, development, motivation, employee well-being) and task-oriented (e.g., scheduling obligations, monitoring, control, short-term planning, goal-oriented, accurate communication) leadership styles are the most convenient option in case of digital transformation as both have a predominantly positive effect, although the focuses of the effects are different and literature is not explicit in terms of results (Tortorella et al., 2018; 2019; 2023; Mikkelson et al., 2019). It is also uncertain how strong the effect is on digital transformation and whether leadership styles directly affect operational performance. Some literature mentions that leadership which supports technology and changes correlates to higher financial performance (Berman et al., 2020; Dubey et al., 2020); on the other hand, according to others, leadership has an indirect effect on organisational performance in the digital transformation context (Wu et al., 2021).

Whilst there has been some research into the effectiveness of task-oriented and relationship-oriented leadership styles separately (Tortorella et al., 2018; 2019; 2023; Mikkelson et al., 2019), there has been little research into their integrated application (Tortorella et al., 2023). It is possible that leaders will be able to apply different styles at different stages of digital transformation, but it is not yet clear what combinations work best. It is also unclear how each leadership style specifically affects innovation and employee engagement during digital transformation (Henkel et al., 2019). The human challenges of digital transformation (Semeraro et al., 2023), such as technological resistance, employee training and adaptation (Chardonnens, 2025), have not yet received sufficient attention in the study of leadership style effectiveness. Digital tools, such as AI, robotics and automated systems, play an important role in digital transformation (Chu & Kurup, 2025). However, the operational performance outcomes (Akçay Kasapoğlu, 2018) and successful adaption depend on how well they can align human leadership with technological tools (Lemaignan et al., 2017). The paucity of research in this area, particularly concerning the optimal integration of technology systems and human resources in the light of operational performance (González-Mohíno et al., 2024), is a glaring lacuna in the extant literature. The challenge for future leaders will be to find the right balance between leveraging digital tools and maintaining human-centred leadership in a rapidly evolving technological environment.

Figure 2 outlines the research hypotheses and research questions in every research paper and the progression of research through three interconnected chapters. Each is represented by distinct papers focusing on varying aspects of digital transformation, leadership styles, and their influence on operational performance improvements. Given that the dissertation comprises three research papers, the hypotheses are divided into three chapters in accordance with the nature of the paper-based dissertation.

Figure 2: Research hypotheses and research questions



Source: Author's work, 2024

The initial research gap identified in the initial paper is the dearth of comprehensive knowledge regarding the opinions of young economists from Generations Y and Z on AI and the connection between AI and HR. The objective is to gain insight into the perception of AI among young economists, specifically those belonging to Generations Y and Z. The hypotheses are derived from the various topics addressed in the paper's main body. The confidence, motivation and interest of the younger generation in AI are not well understood in the digital environment, particularly in relation to how these factors influence their perception of AI's role in the workplace and society. Furthermore, there is a dearth of research exploring the specific and most crucial areas of AI application that these young economists are concerned about (Frank et al., 2019). Additionally, there is a need for investigation into the impact of AI on both soft and hard skills, as well as the broader implications for HR. The final areas of investigation are the perception of the relationship between AI and HR practices and the overall image of AI among young economists.

The second research gap arises from the need to understand how different leadership styles influence digital transformation within Hungarian manufacturing SMEs (He et al., 2023; Imran et al., 2021). The relationship between leadership styles and digital transformation activities lacks depth, particularly concerning how leadership styles translate into successful digitalisation efforts. While digital transformation is a prominent and widely discussed topic in contemporary business and technology discourse (Weber et al., 2022; Tabernero et al., 2009; Mikkelson et al., 2019; Ardi et al., 2020). However, despite its prevalence, there remains a paucity of comprehensive understanding surrounding its underlying principles, particularly about the role of information, integration, and impact. The specific ways in which leadership styles (Fiedler, 1978) that emphasise either performance and colleague relations or goal setting and implementation impact the digital strategy and activities remain underexplored.

The third research gap pertains to the nexus between digital transformation, leadership styles, and operational performance improvements. Although there is an acknowledgement that leadership is a pivotal factor in digital transformation (Weber et al., 2022), the mediating effects of digital transformation on the relationship between leadership styles and operational performance necessitate further investigation (Tortorella et al., 2023). This should take into account the direct or indirect relationship between leadership and operational performance, leadership and digital transformation, and digital transformation and operational performance (Berman et al., 2020; Dubey et al., 2020; He et al., 2023; Imran et al., 2021; Tortorella et al., 2023; Wu et al., 2021). The specific nuances of how digital transformation contributes to or enhances operational performance beyond the traditional scope of leadership influence represent a critical area that has not been fully addressed in existing literature, which is already complex.

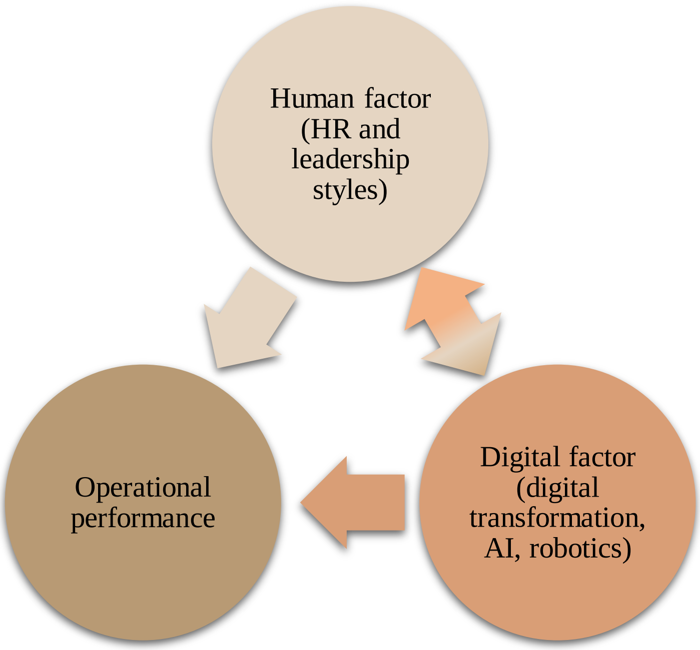
The outlined research gaps and questions emphasise a structured approach to investigating the intersection of digital transformation, leadership, and operational performance, starting with the perspectives of young economists on AI. This progression highlights the need for a deeper understanding of leadership styles' role in digital transformation and how these transformations mediate the impact of leadership on operational success. The scientific results have significantly added value to the existing body of knowledge, offering valuable insights for academic research and practical applications in the industry.

I.4. Research framework and outline

In this chapter, I present the framework of the doctoral dissertation: the connection between *human* and *digital factors* and improvements in corporate *operational performance*. An examination of the viewpoints of young experts – on the relationship between human resources (HR), AI and robotics – is the starting point of this dissertation. A well-established model is presented in the subsequent analysis to examine the interrelationship between leadership styles and digital transformation. This is supplemented with a more comprehensive examination of leadership styles, digital transformation, and corporate operational performance.

Figure 3 presents the research framework and the connections between the factors.

Figure 3: Research model and connection of impact analysis between the factors



Source: Author's work, 2024

Production, distribution and communication methods are currently undergoing a significant transformation. The *manufacturing* processes are becoming increasingly flexible, productive, faster, and of higher quality (Gerbert et al., 2015). Since the advent of the steam engine, which signalled the beginning of the Industrial Age, humanity has been engaged in gradual mechanisation. However, the emergence of the Internet, mobile technologies, advancements in electronics, nanotechnology, and progress in medicine, healthcare, and digital applications have notably accelerated the development of mechatronics (Dirican, 2015). The integration of information technology (IT) systems across the entire value chain is optimising manufacturing processes (Nagy et al., 2018), replacing isolated manufacturing operations with fully automated, integrated production lines (Gerbert et al., 2015) and enabling e-business through advanced technologies such as the Internet of Things (IoT), 3D printing, cloud computing, artificial intelligence, and big data analytics (Frank et al., 2019).

Recent advancements in novel *technologies* have led to the automation of particular manufacturing processes that were previously conducted exclusively by *human* operators (Liao et al., 2017; Culot et al., 2020). Consequently, this transition has resulted in enhanced efficiency, superior quality, diminished waste, and heightened precision, reinforcing the mechanisation imperative. The attainment of efficient manufacturing is contingent upon the efficacious interaction between machinery and human operators (Semeraro et al., 2023). The utilisation of machinery facilitates the execution of specific technological processes, thereby rendering the efficient operation of such machinery a crucial aspect of the manufacturing process. The effective operation of a company is contingent upon the synergy between human work and machine operations (Dvorsky, 2017). In the context of *Industry 4.0*, a collaborative relationship between humans and machines will emerge, facilitated by cognitive technologies in the industrial environment (Frank et al., 2024). Intelligent machines will be capable of performing tasks through the utilisation of speech recognition, computer vision, machine learning, and advanced synchronisation models. It is, therefore, essential to develop sophisticated learning models for machines, such as robots, in order to ensure that *humans and machines* develop mutually beneficial skills in all work settings (Lemaignan et al., 2017; Zhong et al., 2017).

It is of paramount importance to gain an understanding of the perception of this relationship from the perspective of *Generation Z and Y*, as this will significantly influence the potential for cooperation between *human*- and *digital* factors. This generation will constitute the future managerial class and form the opinion on acceptance of digitalisation (Al-Okaily et al., 2024). In the contemporary digital age, these generations are the first to have been born into a world where digital tools are ubiquitous, both in their private and professional lives. They possess a substantial corpus of knowledge regarding technology. It is they who will shape the future of digital transformation (Bencsik & Machova, 2016). The present study explores new sociological aspects of generational issues.

By today, the main components of the organisation-wide digital transformation are widely recognised (Erboz, et al., 2022; Karippur & Balaramachandran, 2022). Namely, besides the technology (Gill & VanBoskirk, 2016; Heini & Heikki, 2015) a successful digital transformation also requires a digital strategy (Gill & VanBoskirk, 2016; Matt et al., 2015), a significant change in the organisational structure and resources (Ivan et al., 2019; Karippur & Balaramachandran, 2022) and cultural adjustments (Gill & VanBoskirk, 2016; Ivan et al., 2019). A model was employed (see Figure 3) to study digital transformation in the context of organisational transformation and its pillars (Eirich et al., 2019). It has been demonstrated to be applicable and offer significant added value in today's rapidly evolving global environment (Liu, 2020).

To achieve a successful digital transformation based on empirical results, two elements are needed: a digital strategy and digital activities that facilitate the change process (Dióssy et al., 2023). The alignment of business strategy with the integration of digital technologies and the management of transformed operations is essential to ensure that the organisation's efforts are coordinated, coherent, and effective in achieving its objectives (Matt et al., 2015). A less hierarchical organisational structure is recommended (Imran et al., 2021), and a stable financial background is required (Wu et al., 2021). Furthermore, the attitude and mindset of employees (He et al., 2023), their willingness to embrace change and implement new technologies (Ivan et al., 2019), and their training (Akçay Kasapoğlu, 2018) are also critical factors.

Digital transformation is not merely about adopting the latest technologies. It represents a holistic shift in the way organisations operate and deliver value (Galbraith & Kates, 2010). The integration of artificial intelligence, data analytics, robotics, cloud computing, and other emerging technologies has the potential to revolutionise business processes, customer interactions, and even business models (Zhong et al., 2017). However, achieving successful digital transformation requires more than technological investment (Csiki et al., 2023). It demands a well-defined strategic vision, cultural support (Karippur & Balaramachandran, 2022), aligned organisational structure and resources (Alshehab et al., 2022; Ivan et al., 2019), a solid technological foundation (Dubey et al., 2020; He et al., 2023) and effective leadership (Teece, 2016).

The role of *leadership* in digital transformation is multifaceted (Tortorella et al., 2023). Leaders must possess visionary qualities to steer the organisation effectively through a comprehensive digital strategy. They must act as catalysts for change, instigating cultural transformations (Berman et al., 2020) that encourage adaptability and a willingness to embrace digital advancements (He et al., 2023). Moreover, leaders should be enablers, providing the necessary resources, information, and support for employees to enhance their skills and effectively navigate the digital landscape (Imran et al., 2021).

Effective leadership is the base of organisational success, and different leadership styles shape a company's culture, decision-making processes, and overall functioning (Berman et al., 2020). Traditional task-oriented styles, characterised by top-down decision-making, hierarchical organisational structures, and a rigid chain of command, have been replaced by more collaborative approaches and efficient monitoring processes (Fiedler, 1971; Mikkelson, 2019; Tabernero et al., 2009). Task-oriented leadership, for instance, emphasises inspiring and motivating employees to exceed their anticipated performance. Relationship-oriented leaders focus on building strong connections and fostering collaboration among team members to align organisational culture (Ardi et al., 2020; Fiedler, 1971; Mikkelson, 2019). They create a collaborative work environment. Through collaboration and communication, relationship-oriented leaders can ensure that digital strategies are developed with input from various stakeholders, leading to more comprehensive and effective plans (Imran et al., 2021).

In the context of digital transformation, leadership styles need to be performance-driven, employee-centred and adaptable. Leaders must be open to change, encourage experimentation, and empower employees to embrace new technologies (Frank et al., 2024). My results indicate that the shift towards more task-oriented leadership styles in conjunction with a relationship-orientated approach is crucial for effectively managing the challenges and capitalising on the opportunities digital disruption brings (Dióssy et al., 2023). This collaborative approach facilitates the adoption of new technologies and nurtures a culture of innovation and resilience (Imran et al., 2021).

The role of leaders in enhancing *operational performance* is of utmost importance. Decisions based on strategy can directly or indirectly influence business performance. Leaders can contribute to operational-level performance implications (Akçay Kasapoğlu, 2018). The successful execution of a digital transformation strategy hinges on procedural aspects that demand clear and dedicated responsibilities (Wu et al., 2021). Designating an experienced professional aligned with strategy goals is crucial (Matt et al., 2015). Leaders need to have cognitive-, interpersonal-, strategic- and business leadership skills to be able to lead a successful digital transformation in the manufacturing industry (Guzmán et al., 2020) for the purpose of establishing management credibility and avoiding decision-making bias (Matt et al., 2015).

Examining the interrelationship between leadership, digital transformation, and operational performance reveals ample evidence of the significant impact of digital manufacturing on improvements in operations performance (Felsberger et al., 2020). Furthermore, both academic and practical experience underlines the potential direct influence of leadership on financial business performance (Berman et al., 2020). The interdependent relationship between leadership styles and digital transformation significantly influences operational performance. Organisations that align their leadership styles to meet digital transformation requirements are better positioned to thrive in the digital age. Results show that task-oriented leadership fosters a culture that is favourable to innovation and adaptability, which are crucial factors for achieving success in today's dynamic business environment (Imran et al., 2021). However, our knowledge about how leadership drives digital transformation and operational performance is limited (Tortorella, et al., 2023). I focus on this issue by approaching digital transformation as a complex organisational change with crucial sociotechnical foundations.

In conclusion, the youth's opinion and the intersection of human-, digital factors, and operational performance is a critical nexus that determines the success of organisations in the manufacturing business landscape (as a prominent sector of digital transformation in Hungary). Positive, adaptable employees and supportive management attitude, as well as effective leadership that embraces change, fosters innovation and guides the organisation through a seamless digital transformation journey, are fundamental to achieving improved operational performance. As businesses navigate the complexities of the digital age, understanding and leveraging this interplay will be pivotal for sustained success and competitiveness.

I.5. Research structure and introduction of the papers

Chapters II, III and IV show the papers that are published. In this chapter phase, I explain the connections between the research ideas and publications.

The research connects the evolving views of young economists on the connection between AI, robotics, and HR with the importance of leadership and digital transformation within Hungarian manufacturing SMEs, culminating in an exploration of how these factors together impact operational performance improvements. The connection suggests a holistic approach where understanding the workforce's views, adopting the right leadership styles, and strategically managing digital transformation can lead to improved operational performance.

Figure 4 introduces the connections between the papers and visualises the ideas followed between the research papers.

Figure 4: Connections of the research papers and publications

Chapter	Main topic	Key points
Chapter II 1st Paper	Youth's opinion on AI, robotics, skills, and HR relationship	- AI, robotics and digitalisation are expanding internationally, putting pressure on Hungarian SMEs. - Young economists (employees) have an ambitious, positive attitude towards AI. - M**anagerial perspectives on AI shall be explored.** **- Implementing digital opportunities for better performance. What outcomes are expected from these changes?**
Chapter III 2nd Paper	Leadership styles' effect on digital transformation	**- Hungarian manufacturing SMEs need digital transformation to remain competitive.** - Digital transformation affects complex organisational transformation: strategic planning, organisational structure, resources, culture, and technology. - Change must come from top management; leadership style is crucial. - Leaders mainly focus on performance and colleagues, but goals and implementation are also important. **- If digital transformation improves operational performance — what factors are key?**
Chapter IV 3rd Paper	Leadership's role in the connection between digital transformation & operational performance	- **Leaders play the most critical role** in transformation. - Task-oriented leadership yields the best transformation results in this context. - Relationship-oriented leadership has direct adverse effects on operational performance. - Digital transformation is a mediator between leadership styles and operational performance. - **Benefits**: **Cost improvement** and **flexible servicing (no quality effects), but relationship-oriented leadership is less effective.**

Source: Author's work, 2025

The main question of my first research concerns employees' opinions on the interaction between HR, AI, and robotics. Based on my results, which are further elaborated upon in Chapter II, I express some concerns. We shall exploit the opportunities in Hungary because the extensive expansion of AI and digitalisation has already been put through most SMEs. The question is rightly raised: are we in a setback? The opinions and attitudes of young employees (economists) on AI changes are very ambitious and positive both domestically and internationally. Do we need to look for answers at the top management level? How can we implement the opportunities for digital change and more effectively exploit digital transformation? What results can be expected due to the changes? These questions were raised to answer in my second paper. Understanding young economists' positive attitudes towards AI and robotics sets the stage for effective digital transformation (Chapter III), particularly in how leadership styles should be adapted to harness this potential. The need for management to address the ambitions and expectations of the younger workforce is echoed in the strategic leadership decisions discussed in Chapters III and IV.

Domestic (Hungarian) manufacturing SMEs make up a significant part of our economy, and this needs to be dealt with digitally. The digital approach in Hungary is positive. How can leaders take advantage of this? The digital transformation affects the whole company: within the digital transformation, two pillars can be separated: I. strategic planning and II. Organisation, resources and technological approach and condition. Digital transformation is inevitable, and all manufacturing companies need to go through it, and change will come from the top managerial level. Which leadership style should they focus on? The manufacturing leaders primarily concentrate on completing tasks and their quality; however, the relationship orientation cannot be missed. Hungarian domestic manufacturing managers also focus on performance. What kind of effects (outputs) can be expected if we digitally transform our firm? Is digital transformation an inevitable tool to acquire improved operational performance? What is the real key in the process? The answers are in the third paper. Exploring how leadership styles influence digital transformation directly connects to how this transformation impacts operational performance (Chapter IV). Chapter III sets the foundation for the paradox discussed in Chapter IV, where the right leadership style can positively and negatively influence performance improvements depending on how digital transformation is managed. Digital transformation affects the entire company, including strategic planning and technological adaptation. Leadership styles, especially those from top management, play a critical role in steering digital transformation. Manufacturing leaders must balance task completion with relationship orientation.

Leaders clearly have the most crucial role in digital change. What should they put the most emphasis on to have higher operational performance? Managers play a vital role in driving change, emphasising task-oriented leadership, yielding better results. The best digital transformation results can be achieved by focusing on the task-oriented leadership style. A relationship-oriented leadership style has a negative effect on operational performance. Digital transformation is the most critical mediator tool in the relationship between leadership styles and operational performance improvement: with the direction of strategy, the digital transformation tasks (from the organisation and technology point of view) can be carried out. The findings in Chapter IV on how digital transformation mediates leadership and performance outcomes are linked to the importance of addressing youth opinions and leadership adaptability, which are discussed in Chapters II and III. The results also show a positive effect of digital transformation regarding cost improvement and flexible services (no positive impact on quality) and a negative effect of a relationship-oriented leadership style on operational performance.

I.6. Literature background

In this chapter I introduce the literature background of my dissertation and highlight the most essential conceptual ideas developed in my research papers. As my doctoral dissertation consists of various research papers, instead of a systematic literature review, I collected, evaluated, organised relevant literature, and draw a framework of my research based on the selected topics. I collected the relevant literature based on keyword searches, and using the snowball method, I analysed the relevance of the literature and drew the literature framework of the topics of my three papers and subsequently composed a critical literature review of the designated topics analysing the abstracts and research papers.

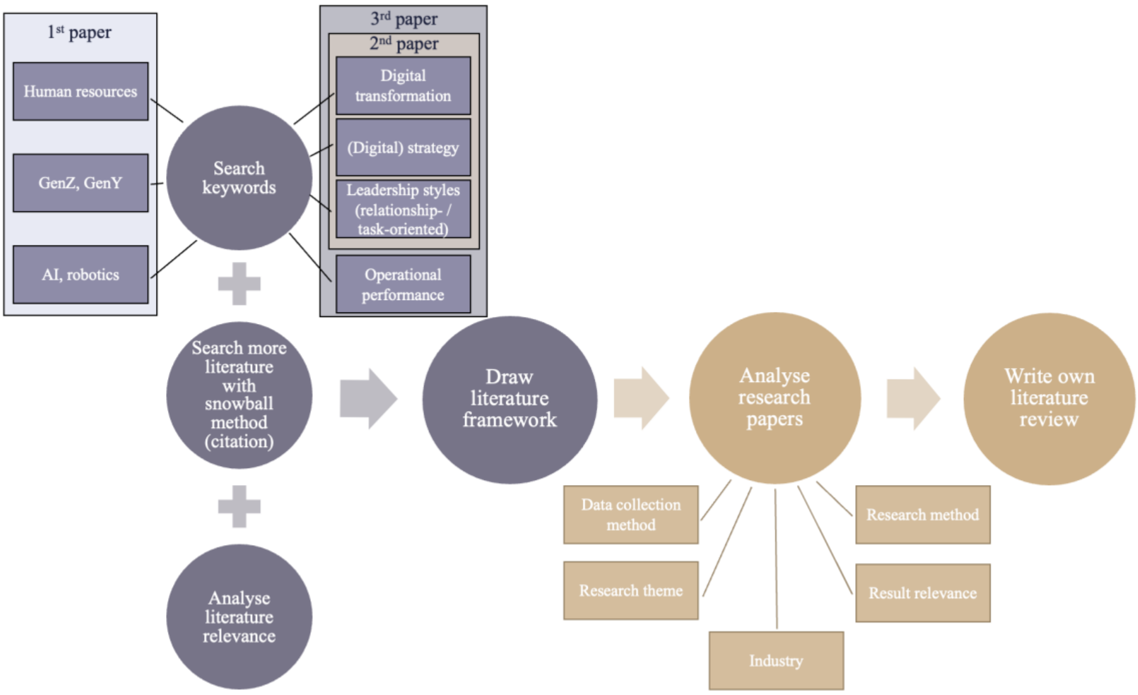
The dissertation consists of three main concepts. Firstly, the *human factors* encompass HR aspects of AI and robotics, as well as the perception of young generations regarding the connection and the characteristics of leadership styles.

The second is the *digital* realm, including areas of AI, mainly the impact of robotics and digital transformation in manufacturing companies, which are the leading sectors.

The third one pertains to the improvements of *operational performance*. Through my dissertation, I analyse the interrelationships and impacts of these three main factors. The impact of leadership competencies on the digital transformation process, particularly in the context of Industry 4.0 and robotics, remains a subject of ongoing research.

Figure 5 outlines the process and methods used in conducting the literature review for my papers.

Figure 5: Literature review process and methods



Source: Author’s work, 2024

I.6.1. Human factors: GenY and GenZ, leadership

The values and attitudes of younger generations are shaping the future prospects. It is crucial to examine the phenomenon of the digital aspects from the vantage point of younger generations for several reasons. Primarily, they are frequently the principal agents and beneficiaries of technological advancement. Members of the Millennial (Tari, 2011) and Generation Z (Tari, 2010) cohorts have been socialised in an environment characterised by pervasive digital technology (Menezes & Malhotra, 2022). They are digital natives who, by their upbringing, have become adept at integrating technology into their daily lives (Yılmaz et al., 2024). Their perspective can provide insights into how digital tools and platforms can be leveraged more effectively, given that they tend to be early adopters and heavy users of new technologies. Young people will be the ones implementing and working within digitally transformed environments (Tari, 2010; 2011).

The concept of generational cohorts has been in use since the 20th century. The term "veterans" is used to describe those individuals born between the 1920s and the conclusion of the Second World War, which encompasses the period following the First World War. At this particular juncture, four generations are engaged in collaborative endeavours. The term "*Baby Boomers*" describes those born from the end of the Second World War to the 1960s. The term '*Generation X*' describes individuals born from the 1960s onwards, while the term '*Millennials* or *Generation Y'* describes those born from the 1980s until 1994. The term '*Generation Z*' represents the youngest working generation, born between 1995 and early 2010s (Zemke et al., 2000; Howe & Strauss, 1992).

This research focuses on current economics students from prestigious higher education institutions, as it is anticipated that within the next decade or so, these individuals will assume positions of leadership. By examining their current expectations and concerns, as well as their aspirations for the future, insights can be gleaned regarding both current trends and future directions. The defining characteristic of generations is rather their technological experiential knowledge, not their age. This experiential knowledge is the primary factor in determining the target group for my study. In the contemporary workplace, it is becoming increasingly common for employees from different generations to collaborate and adapt to new technologies in a relatively short space of time, which can present a significant challenge for some individuals. Generation Y employees exhibit a marked tendency to engage with digital technologies in comparison to their Generation X counterparts, perceiving these technologies as intuitive and straightforward to utilise. Conversely, while most Generation X employees recognise the potential benefits of digital technologies, they frequently encounter difficulties in seamlessly integrating them into daily operations (Annosi et al., 2024). These divergent perspectives on digital adoption can be attributed to disparities in prior knowledge, which contribute to the uneven development of digital capabilities between the two generations. While members of Generation X may have been among the first to encounter the introduction of electronic messages and the World Wide Web (WWW), members of Generation Y have been the ones to benefit most from the development of Windows 95, Google, PayPal, Hotmail, and Wikipedia. For Generation Z, being raised in a technological era has meant that they have grown up with smart tools and applications being a key part of their lives (Chardonnens, 2025). In the context of SMEs, younger generations have the capacity to explore innovation opportunities associated with digitalisation. The analysis demonstrates that younger entrepreneurs have adopted various digital transformation strategies, yielding a range of benefits in terms of competitiveness, decision-making effectiveness, visibility and communication, and new opportunities for value creation (Del Vecchio et al., 2024). The Baby Boomers are approaching retirement age and are thus attempting to maintain their employability in the face of rapid technological change in the workplace (Schneider, 2024). In order to prepare employees for an AI-enabled workplace, it is incumbent upon organisations to adopt comprehensive training and development programmes (Oyekunle & Boohene, 2024).

Generation Y is the inaugural cohort to mature in an epoch characterised by the pervasiveness of digital technologies, with these instruments integral to their quotidian existence (Tari, 2010). As a result of their comprehensive digital training, they can rapidly adapt to and excel in using new IT tools (Bencsik et al., 2016). This generation is distinguished by a proclivity for embracing change, a tendency to prioritise the present, and a reluctance to engage in long-term planning. They prefer immediate gratification and tend to prioritise immediate enjoyment over future goals. Their social interactions frequently occur in virtual spaces, and they are typically receptive to cultural differences (Bencsik & Machova, 2016).

Generation Z, in contrast, is characterised by robust career aspirations and professional ambition, coupled with advanced technical and linguistic abilities, rendering them highly proficient in their roles (Yılmaz et al., 2024). It is incumbent upon employers to prepare themselves to engage with this generation effectively, integrating them into the organisation's culture and supporting their transition into productive employees (Elmore, 2014). They are intuitive, expect rapid responses, are proactive, and demonstrate a fast pace in information processing and content research. They seek instant feedback and resist long-term commitments (Tari, 2011). This tendency can result in an inaccurate self-perception due to a lack of awareness of their limitations. Generation Z also embraces the principle of "living for today," often blurring the lines between work and leisure (Törőcsik et al., 2014).

The two generations under discussion have been selected based on their distinctive traits and characteristics, as they represent the future workforce, either as employees or managers, in the short and long term (Yılmaz et al., 2024). In the context of the labour market, the success of a company is contingent upon its capacity to recruit individuals who possess the requisite competencies, skills and experience, in addition to a personal motivation (Tari, 2010; 2011) and value system that is aligned with the organisation’s goals. It is, therefore, of paramount importance to ensure that the expectations and needs of the labour force are aligned with those of the recruiting organisations.

Consequently, there is a pronounced focus on aligning training programmes with the labour market requirements. The available evidence suggests that managers should give close attention to the integration of different generations within the organisation, ensuring that the specific needs of each group are addressed. This is crucial for developing a motivated and well-rounded workforce (Gabrielova & Buchko, 2021). Both Generation Y and Generation Z are well-positioned to adapt to changes brought about by AI, given their extensive familiarity with IT and technology, which they have grown up with (Bencsik et al., 2016). They are inclined to conduct a significant proportion of their lives online and tend to prefer email communication over face-to-face interactions. It is, however, essential to create a productive atmosphere and conducive working conditions for them (Tari, 2011). In light of their penchant for short-term planning, it is recommended that their work assignments comprise challenging tasks that stimulate them and provide opportunities for learning (Menezes & Malhotra, 2022). They possess considerable expertise across various disciplines and take pride in applying their knowledge. In both their personal and professional lives, they tend to favour straightforward and efficient solutions (Tari, 2010). Furthermore, they are often willing to volunteer for innovation tasks, such as implementing AI (Yılmaz et al., 2024). They typically anticipate prompt feedback and recognition from their supervisors (Tari, 2010). They are oriented towards the present and derive satisfaction from their current circumstances. For this cohort, achieving a healthy work-life balance is of paramount importance, and they place a high value on workplace flexibility (Menezes & Malhotra, 2022).

The principal distinction between Generation Y and Generation Z is that the former is more inclined to pursue leadership roles than the latter (Gabrielova & Buchko, 2021). Generation Y is also more engaged in the learning process, whereas Generation Z tends to focus on topics that align with their personal interests. Furthermore, Millennials are more dedicated to teamwork than Generation Z (Zhong et al., 2017).

Generation Y and Generation Z economists are poised to become tomorrow's leaders (Yılmaz et al., 2024). Consequently, their perceptions and opinions will inform our ideologies on leadership and management (Gabrielova & Buchko, 2021). It is indubitable that the younger generation will assume the role of future leaders and decision-makers. Involving them in discussions about digital transformation at the present time helps to foster leadership abilities. It guarantees that they will be adequately prepared to direct organisations through forthcoming technological alterations (Al-Okaily, 2024).

It is crucial to examine leadership from the perspective of its styles, as distinct approaches to leadership profoundly impact how leaders interact with, inspire, and direct their teams (Frank et al., 2024). This, in turn, influences the development of organisational culture, decision-making processes, and performance outcomes. The different *leadership style* presents a distinct pattern of skills and behaviours (Lovelance et al., 2019) that managers apply to influence their subordinates in order to achieve goals (Hersey et al., 2001; Weber et al., 2022). Managers are key people in the company's change management process (Teece, 2016). By examining leadership through the lens of leadership styles (Rüzgar, 2018), organisations can gain a deeper understanding of how different approaches impact performance and innovation (Henkel et al., 2019). This enables leaders to evolve and adopt the most effective strategies. By leadership style, I mean the toolset that a manager uses to influence the employees in order to achieve company goals (Gandolfi & Stone, 2018). Researchers usually differentiate a few distinct and, in some cases, extreme patterns in their leadership models, such as transactional- and transformational leadership styles (Burns, 1978; Rousseau, 1995; Bass, 1990) and relationship- and task-oriented leadership styles pair (Katz et al., 1950; Fiedler, 1978; 1971), democratic- and autocratic leadership styles (White & Lippitt, 1960) or situational leadership (Hersey & Blanchard, 1977).

The contingency leadership approach claims no 'one fits all' leadership style (Nahavandi, 2002; Teece, 2016; Müller et al., 2024). In other words, finding the appropriate leadership style that supports the envisioned organisational path is crucial. The role of leadership in fostering a positive attitude towards artificial intelligence, robotics, digital transformation and, in general, I4.0 is particularly salient for older employees (Schneider, 2024). The democratic leadership style, which is characterised by a greater degree of autonomy being afforded to employees, is conducive to the digital transformation process. This approach is aligned with the company's mission and strategic objectives. (Porfírio et al., 2021). However, it is important to note that over-reliance on AI may potentially hinder the development of critical thinking and self-regulatory skills (Chardonnens, 2025).

For example, task-oriented leaders use top-down communication and specify how to carry out the required job (Tabernero et al., 2009). They emphasise short-term planning, personnel efficiency, role and objective clarification, and performance monitoring (Mikkelson et al., 2019). Employees in this context show higher levels of group efficacy, productivity and positivism. Relationship-oriented leaders are employee-focused, give social and emotional support, and provide special attention. They focus on empowering, supporting, and motivating followers (Ardi et al., 2020). They aim to develop trust, commitment, motivation, cooperation and cohesion in teams (Mikkelson et al., 2019).

As leadership effectiveness is considered, studies usually examine the individual and team level (performance) implications. Some evidence suggests that relationship-oriented leadership behaviour positively impacts employee (individual) performance (MacKenzie et al., 2001). Other scholars (Hater & Bass, 1998) found that relationship-oriented leadership contributes more to predicting the followers' performance than task-oriented leadership. According to Jung and Avolio (2017), individual performance increases, and employees contribute to giving more ideas under a task-oriented leader. However, collective performance will be more significant when they work under a relationship-oriented leader.

Several studies concluded that task and relationship-oriented styles can influence the effective deployment of Operations Management (OM) paradigms. Regarding Total Quality Management (TQM), authors underline leadership skills in setting vision and strategy, developing commitment, recognising people, nurturing a process-based culture and creating an open and learning-focused culture (Zairi, 1994; Beer, 2003). In the lean context, Gelei et al.'s (2015) studied production managers and found that micromanagerial and communicative attributes could contribute to the extensive use of lean techniques. Van Dun et al. (2017) showed a less balanced picture; they claim that lean middle managers are significantly more engaged in relationship-orientated (e.g., active listening, agreeing) than task-oriented behaviour. Further studies emphasise the potential influence of external factors. Januszek et al. (2024) drew attention to different characteristics of the effective top (e.g., guiding through vision) and middle management (e.g., applying standards and defining tasks) in lean transition.

I.6.2. Digital factors: AI, robotics, and digital transformation

The field of *artificial intelligence (AI)* has made considerable progress since the seminal question posed by Alan Turing in 1950, which sought to ascertain whether machines could exhibit intelligent behaviour. The field of AI has a long history, with the first developments occurring in the 1950s, when logic-based systems were created. However, the most transformative development occurred in 2011 with the rise of "machine learning" (ML) (Nakayama et al., 2020). This branch of AI employs statistical techniques to enhance a machine's capacity to anticipate future outcomes by examining historical data. The implementation of ML, frequently achieved through utilising neural networks, is contingent upon the availability of extensive datasets (Semeraro et al., 2023), which are employed to model intricate patterns. The range of applications for AI is growing rapidly, encompassing robotics, autonomous vehicles, consumer goods, and services such as smart appliances and home security systems (Soori et al., 2024). One of the most developed areas of AI and ML is in medicine and healthcare (Balahurovska, 2023; Koebe, 2025), where opportunities for adaptive and precision learning, improved skills in complex care coordination and continuous professional development are important (Chu & Kurup, 2025). While these innovations offer enhanced security, they also introduce new practical and legal challenges for product security frameworks (OECD, 2019).

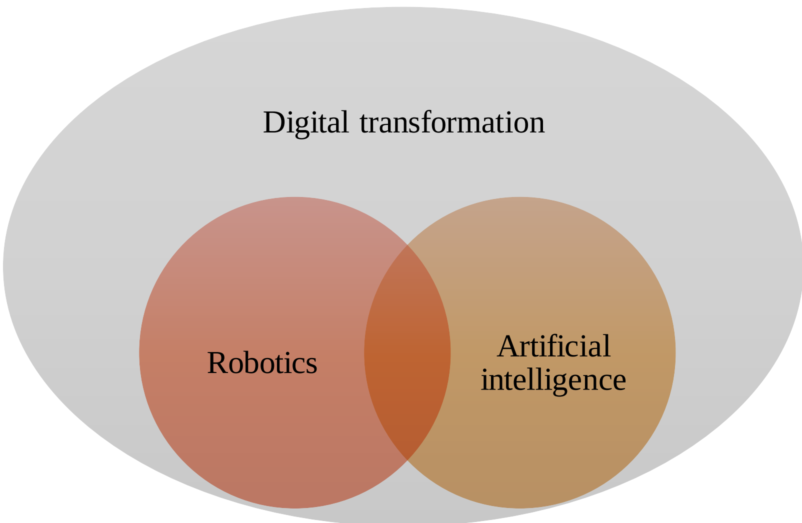
Robotics represents one of the most prominent applications of AI. The integration of AI with robotics has the potential to facilitate substantial scientific advancement (Soori et al., 2024). To illustrate, laboratory automation systems can be programmed with AI to conduct scientific experiments (OECD, 2019). Robots have historically been employed in production settings to perform repetitive, complex, and monotonous tasks by following pre-programmed instructions. However, the advancement of robotics is progressing towards greater autonomy, flexibility, and collaboration (Semeraro et al., 2023). It is reasonable to posit that in the future, robots will be capable of sensing changes in their environment and the operations of other robots, thereby enabling them to adapt to new situations autonomously (Lemaignan et al., 2017).

The impact of AI and robotics on decision-making and productivity is irrefutable (Zhong et al., 2017). However, this raises the question of job displacement (Frey & Osborne, 2013), which in turn gives rise to ethical considerations regarding data protection and fairness, further complicating the landscape (Balahurovska, 2023; Farina et al., 2025).

The concept of *'digital transformation'* is not merely the digitisation of processes; it also encompasses the utilisation of AI and AI tools. Digital transformation is predicated on a more holistic perspective, with the objective of enhancing a business's competitiveness. In this approach, artificial intelligence and robotics are considered instrumental tools (Chu & Kurup, 2025). For SMEs, the adoption of information and communication technology (ICT) tools and digitalisation is of paramount importance for maintaining competitiveness in a rapidly evolving market. Therefore, nations such as Hungary and the United States give priority to investments in digitalisation (Digitális Jóléti Program, 2020). It is of the utmost importance to engage in long-term planning to fully leverage AI’s potential in the context of digital transformation. The digitalisation of processes allows for the more efficient management of information resources (Al-Okaily et al., 2024), which in turn leads to a reduction in costs and an enhancement in customer satisfaction. In the contemporary manufacturing environment, the proliferation of digital devices interconnected via internet-based networks has accentuated the significance of digital transformation. This exponential growth has rendered digital transformation a pivotal element in advancing manufacturing systems. The advent of digital and virtual manufacturing and the emergence of sophisticated modelling, simulation and presentation tools have enabled the rapid and flexible design, production, and delivery of bespoke products (Zhong et al., 2017).

Figure 6 explains the relationship between robotics, AI and digital transformation.

Figure 6: Relationship between robotics, AI, and digital transformation



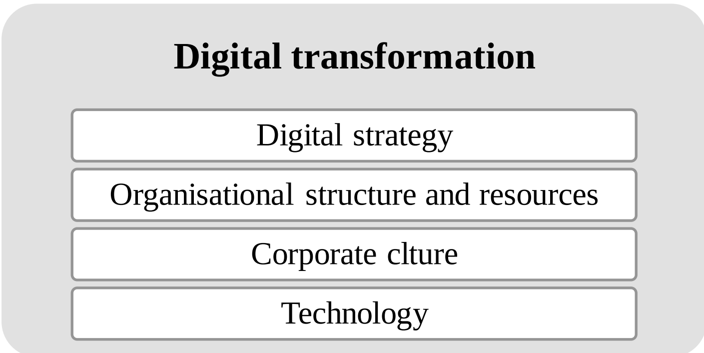
Source: Author’s work, 2024

Digital transformation is not simply ‘digital’. It requires systematic and organisational transformation as well.

The models Galbraith (5 Stars) and McKinsey (7s) proposed to address the structural, functional, transformational and change-related aspects of organisational design. The 5 Star model encompasses five key areas: strategy, structure, remuneration, processes, and people (Galbraith & Kates, 2010). However, McKinsey goes beyond the traditional scope of strategy and structure to encompass a more comprehensive view of organisational systems, employees, skills, style or culture and the company’s value (McKinsey, 2008). The two approaches share several similarities. The initial element is the strategic plan, which delineates the direction, objectives, value proposition, mission, and typically the product or service to be produced or marketed, market, and customer value (Galbraith, 2002) that the company adheres to. It enables the company to gain a competitive advantage (Hanafizadeh & Ravasan, 2011). As evidenced in the literature, this is the most crucial aspect of managing a company, enabling it to make informed decisions. In contrast, quantitative research conducted in the early 2000s among large Spanish companies has already demonstrated that there is no direct, significant impact of strategy on corporate performance (Avella et al., 2001). Conversely, research corroborating the significance of strategy (Brunetti et al., 2020) indicates that strategy is a pivotal factor in digital transformation. The second element is the organisational structure, which determines the location of decision-making authority and facilitates the navigation of the company's internal hierarchy (Galbraith & Kates, 2010). It is the manner in which individuals comprehend the organisational structure and ascertain the appropriate point of contact (Hanafizadeh & Ravasan, 2011). The third aspect is the processes associated with the flow of information, which serve as the conduit for responding to information technologies. Additionally, they facilitate decision-making processes, either vertically or horizontally (Habidin et al., 2016). The system processes, in particular, warrant attention (McKinsey, 2008). The fourth aspect is remuneration and reward systems, which influence motivation, affect performance, and contribute to the achievement of organisational goals (Galbraith & Kates, 2010). The McKinsey model encompasses the informal roles within an organisational structure, which are significant to employees in terms of their characteristics (Hanafizadeh & Ravasan, 2011). The fifth category of the model is that of people (human resources), which exerts a significant influence on the selection processes and, consequently, the mindset and skills of employees (Habidin et al., 2016). The McKinsey model identifies the employees, talents, and opportunities within the firm as essential elements (Hanafizadeh & Ravasan, 2011). One of the primary areas of focus during the transformation process is the development of individual and institutional skills, as well as the manner in which these skills are applied in a collaborative setting. The middle element of the McKinsey 7S model represents the core value that the company strives to uphold throughout its lifespan.

Digital transformation can be understood as a continuous change, the creation of a digital culture by applying digital and other technologies and organisational practices in order to provide better services, gain competitive advantage, profitability and respond effectively to challenges in a complex environment (Westerman et al., 2012). It is indisputable that digitalisation's core is around technology. However, successful organisational turnaround requires firms to approach it as a complex organisational phenomenon (Erboz et al., 2022). Digitalisation's (i) technological toolset must be accompanied by organisation-wide changes shaping (ii) digital strategy, (iii) organisational resources and structure, and (iv) culture (Móricz, 2022; Karippur & Balaramachandran, 2022). This multidimensional approach of digitalisation at the firm level is called digital transformation (DT). The pillars of digital transformation are indicated in Figure 7.

Figure 7: Digital transformation pillars



Source: Author's work, 2024, based on Móricz, 2022 and Karippur & Balaramachandran, 2022

A *digital strategy*, linked to business strategy, is crucial from the very early stages of digital transformation (Akçay Kasapoğlu, 2018; Matt et al., 2015). The digital strategy sets clear and quantifiable goals (Karippur & Balaramachandran, 2022) that guide individual and team efforts (Alshehab et al., 2022). Elaboration of the strategy is followed by execution (Gill & VanBoskirk, 2016; Heini & Heikki, 2015), which is monitored throughout the digital transformation. The key prerequisite here is to define clear and quantifiable goals. Finally, gained experience in digital roll-out influences strategy renewal processes (Karippur & Balaramachandran, 2022; Tortorella et al., 2019).

Organisational resources and structure shall be the foundation for the process. Once the direction is defined by the strategy, knowledge accumulation and structural adjustments are the prerequisites for the exploitation of technological knowledge and capabilities (Heini & Heikki, 2015; Alshehab et al., 2022; Ivan et al., 2019; Tavoletti et al., 2021). The development of resources is especially critical since an ongoing digital transformation has different phases, and each has distinct requirements (e.g., managing implementation or a mature firm). Individuals supporting digital transformation in terms of technological expertise should come from the most capable organisational units (Akçay Kasapoğlu, 2018). Their presence assigned formal roles and training (and recruitments) together ensure that digital skills are pervading the organisation (Karippur & Balaramachandran, 2022). The ongoing development of knowledge is critical since digital transformation has different maturity phases, and each of them has distinct requirements (e.g., managing implementation or a mature firm). The underlying assumption is that firms undergoing digitalisation possess the necessary financial resources (Móricz, 2022).

Culture considerably determines the success of digital transformation. An effective culture reconciles top-down and bottom-up directions. A firm cultivating digital transformation reconciles top-down (e.g., supportive management attitude) and bottom-up (e.g., employee involvement, perception and attitude to digitalisation, and idea generation) directions of organisational culture development facilitates the employee-driven idea generations (Karippur & Balaramachandran, 2022). Several key actions support the transformation of culture and help the adjustment of the organisation to the emerging business challenges. Internal and external communication of the digital vision is an essential activity (Gill & VanBoskirk, 2016), education and training at all levels (Akçay Kasapoğlu, 2018; Tay & Low, 2017). It ultimately nurtures capability and resource development as well (Ivan et al., 2019; Tavoletti et al., 2021). Finally, beliefs related to risk-taking and willingness to take responsibility are also critical elements since new digital practices behave as a kind of innovation with significant potential to fail (Gill & VanBoskirk, 2016; Móricz, 2022; Karippur & Balaramachandran, 2022; Akçay Kasapoğlu, 2018).

The technology approach is crucial for manufacturing companies in digital transformation (Akçay Kasapoğlu, 2018). Digital transformation is a technology-driven initiative, the main emphasis of which is the deployment of technological solutions. As firms engage in new technologies, they face several crucial decisions in this regard. First, path dependency theory or the concept of absorptive capacity (Karippur & Balaramachandran, 2022) suggest that a firm's current technology serves as a basis for further developments. Technologies such as AI, robotics, cloud computing, blockchain or the Internet of Things (IoT) represent distinct categories within this overarching framework (Inversini, 2025). It leads to a colourful technological landscape mixing more traditional e-business solutions with recent technological advancements. Second, sensing capabilities related to exploring new technological solutions bring benchmarking to the forefront (Heini & Heikki, 2015). Firms might examine digitalisation in the industry by scrutinising buyers, suppliers, competitors, or lead firms (Gill & VanBoskirk, 2016; Móricz, 2022). Third, assessing technological advancement is key to continuous improvement (Karippur & Balaramachandran, 2022). The key pillars of digital transformation depend on each other; e.g., lack of resources constrains digital skill development and hence slows down the digital journey.

In addition to the beneficial impacts, artificial intelligence has emerged as a disruptive force in education, primarily due to its capacity to transform the roles and responsibilities of teachers, and educational institutions (Reeves Huapaya et al., 2025). The integration of AI with legacy systems, the inherent challenges of cybersecurity, and the absence of standardisation are significant impediments to its widespread adoption in business (Pal et al., 2025). Farina et al. (2025) posit that the repercussions of artificial intelligence may encompass deleterious effects, including human displacement, diminished wages, and an augmentation of power and income inequality. The substantial volume of data produced by digital transformation has the potential to surpass the capacity of the company's information infrastructure. This, in turn, can lead to a heightened risk of data, information, and knowledge leakage, which has the capacity to nullify the anticipated benefits of innovation. Consequently, this can act as a deterrent to corporate innovation (Xue et al., 2025). Integrating robots is projected to enhance efficiency and productivity. However, this transition may also introduce challenges, including high costs, skill gaps, and organisational shifts. Future leaders will be required to effectively balance the roles of service robots and human staff (Xu et al., 2020). In order to capitalise on the disruptive potential of AI and robotics and overcome the challenges associated with its implementation, businesses must address organisational leadership, culture, resource availability, perceived benefits, regulatory considerations, data security, technology evaluation, and workforce readiness (Oyekunle & Boohene, 2024).

I.6.3. Operational performance

A multidimensional approach ensures that all aspects of a company's performance are measured and managed effectively. *Operational performance* is critical for measuring the effectiveness and competitiveness of an organisation's core business processes; a comprehensive evaluation of performance should include a balanced mix of financial, customer, employee, and strategic metrics. While *market performance* is important for understanding a company's competitive position and financial success (Chikán et al., 2022), operational performance offers a more controllable and actionable set of metrics that directly influence the efficiency, cost-effectiveness, and quality of a company's output. In many cases, it represents a superior indicator when the objective is to guarantee that a company's internal processes are optimised. While both metrics are important, operational performance is frequently the foundation upon which market success is built.

Operational performance refers to the process of measuring a firm's performance against standard or prescribed indicators. They differ from company to company based on the industry they operate in (Tortorella et al., 2019). It comprises quality of products/services, new product development, customer satisfaction, employee retention, and speedy delivery (Tortorella et al., 2023).

Operational performance is a critical aspect of a firm's overall performance, and it has long been recognised that manufacturing and competitive strategies play a crucial role in shaping how well a company operates and competes in the market (Amoako-Gyampah & Acquaah, 2008). Firms' ordinary capabilities result in outcomes (performance) (Chikán et al., 2022) such as cost, reliability, flexibility and services, speed, dependability, and quality (Slack et al., 2010; Teece, 2016).

Research by Avella et al. (2001) suggests that competitiveness priorities (or capabilities) and cultural program decisions or practices (in key decision areas) and their internal coherence may be the most important factors for companies to maintain their performance in the long term. Three primary operational capabilities are identified - flexibility, supply chain integration, and organisational capability - that positively impact business performance in general, specifically on competitiveness, financial performance, and operational performance. These capabilities are crucial for organisations to gain a competitive edge and achieve operational excellence (Chahal et al., 2020). Digital solutions with substantial leadership help manufacturing companies improve quality and provide more responsive operations (Akçay Kasapoğlu, 2018). Operational performance is a multidimensional concept that includes factors like flexibility, supply chain integration, and organisational capability. These operational capabilities are essential for organisations aiming to achieve and maintain a competitive advantage and improved business performance (Chahal et al., 2020).

I.7. Research problem and relevance of research

The current understanding of the relationship between the human factor, digital factor, and operational performance is somewhat limited. In this chapter I express the connection and the research problem.

I.7.1. Connection of HR and technologies

The relationship between human resources (HR) and technologies represents a pivotal concern that permeates the entire field of management and organisational studies. One of the most pressing challenges currently facing the field of management and organisation is the advent of the fourth industrial revolution, or Industry 4.0 (Nagy, 2018). Technological advancements have enabled specific manufacturing processes, which were previously conducted exclusively by humans, to be completed more rapidly, efficiently, with higher quality, and with less waste through the utilisation of machines. These advantages serve to highlight the necessity of mechanisation. It is of the utmost importance that machines and humans interact effectively in order for production to be productive (Semeraro et al., 2023). Machinery plays a pivotal role in enabling specific technological processes, and it is of paramount importance that individuals efficiently operate these machines. The optimal functioning of a company is contingent upon the harmonious integration of human labour and machine operation (Dvorsky, 2017). In the future, there will be a continuous requirement for highly proficient professionals to oversee the software of machines, guaranteeing that humans and machines work in conjunction rather than in opposition (Nagy, 2018). The accelerated propagation of digitalisation and AI has precipitated a demand for employees to enhance their skill sets in order to adapt to these emergent technologies. This has engendered considerable challenges for both employees and employers. In this context, the importance of human interaction in technology is indisputable, as evidenced by research findings demonstrating human interaction's efficacy in engendering favourable outcomes. It is evident that leaders play a pivotal role in the acceptance of technology, including AI, cloud computing, IoT, Big Data and robotics (Inversini, 2025).

In the context of Industry 4.0, the collaboration between humans and machines will be enhanced by applying cognitive technologies in industrial settings (Semeraro et al., 2023). The advent of intelligent machines equipped with capabilities such as speech recognition, computer vision, machine learning, and advanced synchronisation models will enable them to perform their tasks with greater autonomy (Frank et al., 2019). To this end, it is vital to develop sophisticated learning models for machines such as robots, thereby ensuring that human and machine capabilities are mutually reinforcing in various operational contexts (Lemaignan et al., 2017).

In their study, Frey and Osborne (2013) identified several occupations that they classified as 'high risk', including those that require direct, face-to-face interaction. The research indicates that while the employment of robots will not result in the complete elimination of human jobs, it will nevertheless lead to significant changes in the nature of work. Those with limited skill sets may encounter difficulties maintaining their employment status, as their roles may be susceptible to automation. This presents a challenge for employers to provide training and education that will ensure the long-term employability of their workforce. Combined with data from the 2010 Bureau of Labour Statistics, Frey and Osborne estimated that 47% of US workers are at high risk of job displacement. However, they also observed that not all jobs, but rather specific tasks within jobs, might be replaced by digital solutions. Notwithstanding these challenges, the research offers some grounds for optimism. The question is whether AI will ultimately result in the elimination of more jobs than it creates remains a topic of contention.

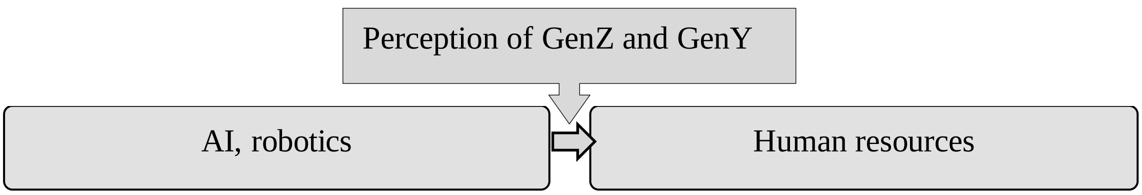
However, in order to remain competitive in the context of Industry 4.0, companies must adapt to new structural interactions among employees, focus on additional qualities for human capital, and recognise different ways of assessing workforce competencies (Flores et al., 2020). Managers must engage with these changes in order to keep pace with the technological advancements that are transforming the nature of work (Al-Okaily et al., 2024).

Research indicates that the impact of AI in Hungary is anticipated to become notable. Among others, the Hungarian manufacturing, transport, and construction industries will likely undergo significant technological transformation (Demeter & Losonci, 2020). In the context of Industry 4.0, future research in smart manufacturing is expected to focus on areas including data-driven innovative manufacturing models, integrated manufacturing systems (IMS), human-machine collaboration and the overarching framework for the application of smart manufacturing practices (Zhong et al., 2017). In the context of Industry 4.0, there is a pressing need for significant shifts in human capital, with a particular emphasis on a human-centred perspective for companies navigating this industrial revolution (Flores et al., 2020).

The current digital transformation of Hungary can be observed in three main phases (Endrődi-Kovács & Stukovszky, 2022). Phase 1 (early 2020s): Computational tasks and the analysis of structured data have been the primary focus, with noticeable changes occurring primarily in the financial and information communication sectors. The second phase, which is projected to span the mid-2020s to 2030, will see the continuation of the aforementioned developments. This phase will witness transformations in business support functions, simple decision-making tasks, and general data retrieval and reconciliation functions, including those related to human resources and accounting. Additionally, autonomous movement in warehouses is likely to become more prevalent. Phase 3 (from 2030 onwards): It is anticipated that substantial changes will occur in physical work and manual precision tasks in assembly and transport, particularly in manufacturing areas (PWC, 2019). This focus on manufacturing is the primary reason for its central role in my research in Hungary.

Figure 8 illustrates how AI, robotics and human resources are related to the perception of GenZ and GenY.

Figure 8: Perception of GenZ and GenY on the relationship between AI, robotics, and human resources



Source: Author’s work, 2024

I.7.2. Leadership styles and operational performance improvements

Our knowledge is limited on how task- and relationship-oriented leadership styles influence operational performance. Some literature mentions transformational and transactional leadership (Hater & Bass, 1998; Bass, 1990), but there are few task- or relationship-oriented leadership styles research. Strong transformation-focused leadership can lead to successful transformation in SMEs (He et al., 2023). Also, digital transformation executives directly affect a firm's financial performance (Berman et al., 2020). Managers can improve operational performance by creating new products or services, reducing risk, improving product or service quality, and reducing cost (Dubey et al., 2020). Also, manufacturing strategy (developed by managers) that drives operational decisions influences performance outcomes (Amoako-Gyampah & Acquaah, 2008).

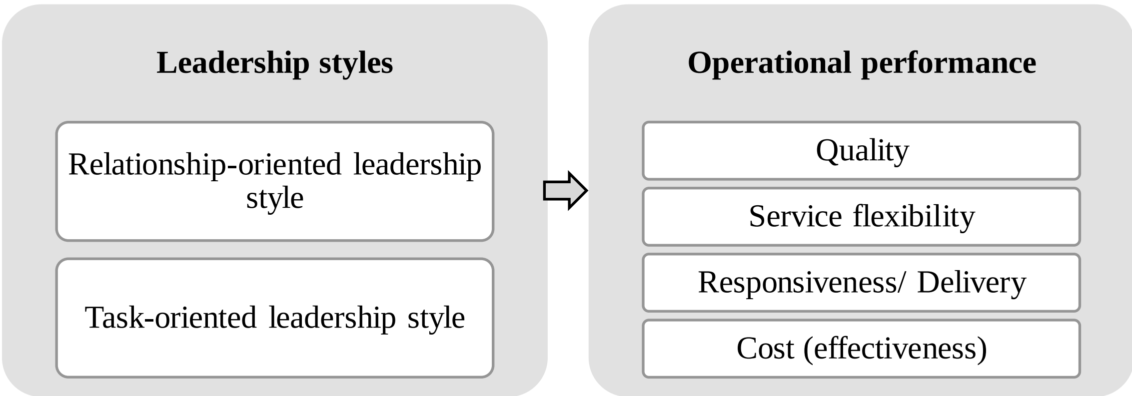
Undoubtedly, leaders must possess certain skills (Lovelance et al., 2019; Weber et al., 2022) to achieve performance improvements. Such as agility, competency of adaptability, innovativeness, flexibility, pro-activeness and the KPI mindset and long-term direction sense, which resonate with task-oriented leadership (Dubey et al., 2020). Task-oriented leaders have a significant impact on a firm's operational performance by facilitating service flexibility and maintaining quality standards. Their emphasis on task completion and performance monitoring can contribute to cost savings and improve operational agility and service quality within the organisation (Tortorella et al., 2023). Leaders who aim to concentrate on relations can improve firms' operational performance by enhancing cost savings and flexibility in service delivery and improving the quality of products or services through strong relationships with all stakeholders (Imran et al., 2021).

Somewhat different marks are assigned to a specific leadership style. Both have a decisively positive effect, although the direction of the impact is different (Mikkelson et al., 2019). Researchers often look at the individual or group level, less often at the organisational level performance indicators (Kretschmer & Khashabi, 2020). Also, the short- and long-term results can differ (Weber et al., 2022). Nevertheless, while task-oriented leaders may approach leadership differently from relationship-oriented leaders, we might assume that managers with both task-oriented and relations-oriented skill sets can achieve a positive impact on the same operational performance incentives (Henkel et al., 2019).

Organisational level implications are directly linked to operational and financial performance. To fulfil business operations, companies need to have suitable organisational and financial structures (Matt et al., 2015).

Figure 9 outlines the interplay between leadership styles and operational performance.

Figure 9: Relationship between leadership styles and operational performance



Source: Author's work, 2024

I.7.3. Leadership styles and digital transformation

Exemplary leadership capabilities are essential to developing strategy and driving digital transformation in the organisation (Westerman et al., 2012; Akçay Kasapoğlu, 2018). The successful implementation of digital tools and practical applications is contingent upon the workforce of Generation Y and Generation Z, as they are the primary consumers of digital technologies and the most capable of spearheading the process (Tari, 2010; 2011).

Knowledge management (KM) can be defined as the process of creating, sharing, organising, and using knowledge effectively within an organisation to improve decision-making, efficiency, and innovation. It involves the capture of both explicit knowledge (documented information such as reports and manuals) and tacit knowledge (personal insights, skills, and experiences) to ensure that valuable expertise is retained and utilised (Nonaka et al., 1996). It is imperative to adjust one's skills and knowledge in the era of AI (Inversini, 2025). KM strategies frequently encompass technology-driven solutions, such as databases and AI-powered systems, in addition to collaborative practices, including mentorship and knowledge-sharing, to encourage continuous learning (Padeli et al., 2025). In the context of digital transformation, knowledge management assumes particular significance. It facilitates the transfer of professional expertise from seasoned professionals to their successors, thereby ensuring the continuity of knowledge and skillsets across generations. This dynamic also enables the younger generation to reciprocate, offering technological competencies to their elders, thus fostering a continuous learning environment (Jones, 2024). In the context of organisations comprising employees from multiple professional disciplines, knowledge management assumes even greater significance. This is particularly evident in scenarios where personnel are drawn from fields as diverse as engineering, information technology and economics. In order to engage Generation Z ("Zoomers"), it is essential that companies enhance their digital capabilities and strategic adaptation. Integrating AI technologies facilitates personalised learning pathways and real-time feedback, enabling a more effective and efficient learning environment (Chardonnens, 2025). It is imperative for leaders to demonstrate proficiency in the effective creation, transformation, storage and application of knowledge resources in order to foster innovation, improve operational performance and maintain a competitive edge (González-Mohíno et al., 2024).

The Hersey-Blanchard situational leadership model is particularly useful in the context of I4.0 and digital transformation because it emphasises adaptability in leadership based on employees' readiness and competence levels (Hersey & Blanchard, 1997). Digital transformation introduces rapid technological changes and adaptation of AI and robotics that affect employees from different generations differently; some may be highly skilled and confident with new technologies, while others may struggle with adoption (Hersey et al., 2001). By employing situational leadership, leaders can assess their teams' development levels and adjust their leadership style accordingly, whether through directive guidance for older generations who require support (Annosi et al., 2024; Del Vecchio et al., 2024; Schneider, 2024) or delegation for highly competent employees such as younger generations (Tari, 2010; 2011). This flexible approach ensures a smoother transition, enhances employee engagement, and accelerates the successful implementation of digital initiatives (Hersey et al., 2001).

There is strong evidence of the crucial importance of leadership in the successful deployment of Operations Management programs like TQM or lean management. Beer (2003) underlines the importance of leadership skills and quality of management in TQM that sets directions, develops commitment, and creates an open and learning-focused culture. Zairi (1994) identifies similar key ingredients of TQM leadership by underlying vision and strategy, recognition of people and nurturing process-based culture. Van Dun et al. (2017) claim that lean middle managers engage significantly more in relations-oriented (e.g., active listening, agreeing) and less in task monitoring behaviours.

The impact of transformational- and transactional leadership styles on digitalisation is not always direct; innovation capability serves as a mediating factor in this relationship. Innovation capability has been identified as a key factor in this regard. Therefore, organisations should focus on fostering innovation at all levels and allowing leaders to develop their skills to make effective decisions (AlNuaimi et al., 2021). The appropriate leadership styles in the context of Industry 4.0 are termed 'Leadership 4.0', a term which encompasses identifiable key characteristics and skills. (Puhovichova & Jankelova, 2021). Strong leadership is essential with the capability of innovativeness, a sense of creativity, effective teamwork and clear communication of the identified strategy (Akçay Kasapoğlu, 2018). In the case of manufacturing companies, task completion monitoring can lead to the required outcome of the transformation (Kretschmer & Khashabi, 2020). On the other hand, clear vision and purpose communication from top management with intervention only when it is needed can drive the transformation. Relationship-oriented actions can contribute to the exploitation of digital transformation (Tay & Low, 2017). Managers’ responsibilities include overseeing the allocation of necessary resources for implementing a digital transformation strategy (Imran et al., 2021).

A task-oriented leader's emphasis on goal setting, efficient processes, and performance monitoring can shape the development and execution of a firm's digital strategy. By aligning digital initiatives with organisational goals, optimising processes for digital implementation, and monitoring, they can drive the success of digital initiatives and contribute to the overall competitiveness and growth of the firm in the digital age. Task-oriented focus with attention to employee well-being, long-term strategic investments, and the human aspect of technology adoption is essential for fostering a supportive organisational culture and technological innovation within the firm (Tortorella et al., 2019; 2023).

The relationship-oriented leaders can also have a significant impact on a firm's digital strategy, albeit through a different approach compared to task-oriented leaders (Tortorella et al., 2018; 2023). Relationship-oriented leaders focus on building strong connections and fostering collaboration among team members, stakeholders, and external partners. They put more emphasis on cultural alignment that can shape the development and execution of a firm's digital strategy. They can have a profound impact on a firm's organisational culture, resource allocation, and adoption of technologies as they can create a positive work environment, optimise resource allocation, and facilitate the successful adoption of technologies (Mikkelson et al., 2019).

Furthermore, the leader shall spread awareness of digital transformation, AI and robotics topics, promote collaboration and innovation, be value-driven, drive digital change, drive cultural aspects of digital transformation, lead by example, take risks, be data-driven, be a promoting mentor/coach-style leadership and bring transparency (Imran et al., 2021; Dubey et al., 2020), which skills belong to the relation-oriented leaders' skill set. In the context of ethical issues and moral dilemmas, human intuition should be retained within the purview of leadership, with a focus on relationship orientation. Conversely, the utilisation of AI algorithms and the periodic updating of standards can ensure high accountability, which is indicative of task orientation. Digital leadership necessitates the cultivation of diverse forms of intelligence (emotional, social, cognitive, and ethical) to demonstrate a strategic approach and the capacity to engage effectively with technological systems (Balahurovska, 2023). I assume that task-oriented leaders have more impact on strategy (Pfeffer, 1987); on the other hand, relationship-oriented leaders have more effect on teams, organisational culture, and resources (Mikkelson et al., 2019).

The concept of 'Leadership 4.0' encompasses a multifaceted set of attributes and practices. These include effective communication, the dissemination of knowledge and understanding, the establishment of clear standards (KPIs) and methodologies, the provision of coaching, the establishment of expectations, the promotion of openness and transparency, the cultivation of trust, the orientation of employees, and the fostering of a culture that embraces and learns from mistakes (Puhovichova & Jankelova, 2021) which is the combination of relationship- and task-oriented leadership styles. Nevertheless, Puhovichova and Jankelova (2021) posit that the most effective Leadership 4.0 approach is relationship-oriented: to concentrate on the capacity to comprehend how technology influences human beings and how the organisational model corresponds with human nature. However, the responsibility assigned to leaders varies according to their leadership level. Specifically, leaders at the strategic level are expected to demonstrate creativity in developing digital transformation, while leaders at the operational level, predominantly technical staff, are expected to demonstrate proficiency in the technological application (Kwiotkowska et al., 2021).

Weber et al. (2022) proposed the existence of two digital transformation-oriented managers: task-oriented and relationship-oriented managers. The empirical study concluded that although the combination of the two styles does not give the highest efficiency, task-oriented leaders and relationship-oriented skills cannot be ignored since they soften the downsides of the task-oriented style. Tortorella et al. (2018; 2023) studies also show similar results, although they mainly focused on digitalisation in a lean environment: managers can achieve greater efficiency with task orientation, but with their relational style traits, they can achieve more favourable results in the long term.

A paucity of research has been conducted on analysing leadership competencies that *negatively* affect effectiveness. To the best of my knowledge, no study has been carried out on negative leadership competencies in the I4.0 environment. The influence of leadership on digital transformation is undoubtable, and findings suggest that skills in both task and relationship-oriented styles could have a *positive* impact on digital transformation (Kwiotkowska et al., 2021). As is evidenced, leadership constitutes the fundamental element of digital transformation, including the acceptance of artificial intelligence and robotics. The leader must possess a clear vision that can be communicated to employees and support innovation within the organisation to facilitate a seamless transition process (Müller et al., 2024). Nevertheless, there is a considerable amount of debate surrounding the most efficacious leadership style in terms of effecting transformation.

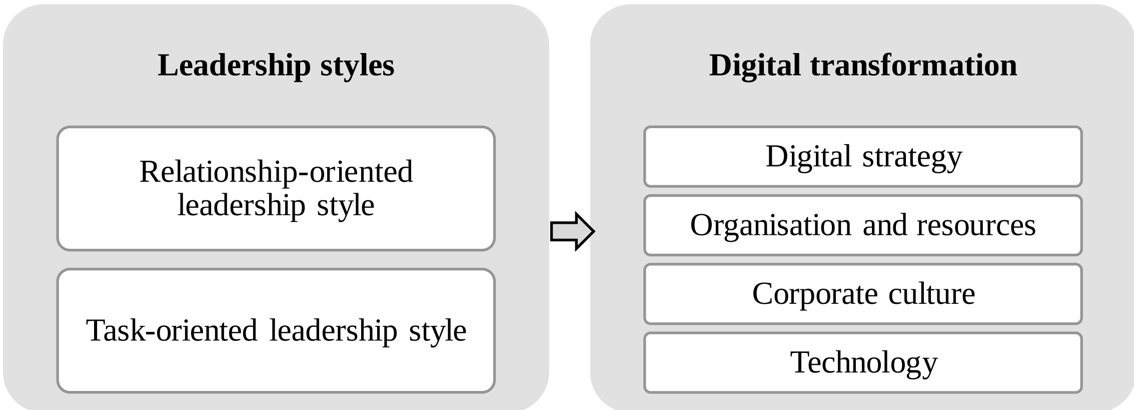
Some argue that task orientation should be the primary focus, with leaders concentrating on KPIs. In the context of digital transformation, task-oriented leaders have been shown to demonstrate a high level of proficiency, owing to their emphasis on efficiency, clear objectives, and practical outcomes. These leaders tend to perform well in environments where measurable progress, process optimisation, and structured frameworks are paramount, such as manufacturing areas (Tortorella et al., 2018; 2023). This congruence with the systematic nature of digital technologies facilitates their rapid adoption and implementation of new digital tools to streamline operations.

Conversely, others posit that the emphasis should be on the individual's value, communication, collaboration, team dynamics and relationships in order to facilitate acceptance and a more personalised experience with digital tools (Tay & Low, 2017; Puhovichova & Jankelova, 2021). They are adept at fostering innovation by ensuring that technology adoption is aligned with company culture and stakeholder needs (Mikkelson et al., 2019).

A third perspective, which is supported by the notion of a 'no-one-fit-for-all' (Hersey & Blanchard, 1997), proposes a “digital leadership” style or “Leadership 4.0” (Puhovichova & Jankelova, 2021) that combines task and relationship orientation (Dióssy et al., 2023; 2025) and incorporates technical, sociological, strategic and business skills (Balahurovska, 2023; Imran et al., 2021; Dubey et al., 2020) with a special focus on employees and implementation success. The advantage of mixing these two styles lies in their complementary strengths: task-oriented leaders drive the technical implementation and optimisation of digital solutions (Tortorella et al., 2018; 2023), while relationship-oriented leaders ensure these changes are accepted and effectively integrated across teams (Mikkelson et al., 2019). Together, they create a balanced approach to digital transformation efforts (Weber et al., 2022).

Figure 10 portrays the link between leadership styles and digital transformation.

Figure 10: Relationship between leadership styles and digital transformation



Source: Author’s work, 2024

A number of conflicting opinions have been expressed with regard to the role of future leaders in the context of digital transformation - AI and automation (Tegmark & Werner, 2018). While some argue that these technologies can increase productivity and generate new employment opportunities (Sufian et al., 2025; Tortorella et al., 2023; Xu et al., 2020), others contend that machines could potentially usurp human employment, rendering many jobs obsolete (Frey & Osborne, 2017; OECD, 2019). The debate encompasses a range of perspectives on the relative merits of AI and robots in decision-making, with some asserting that AI can make faster and more accurate decisions than humans (Xue et al., 2025; Yukl et al., 2002; Habidin et al., 2016), while others contend that human intuition and creativity are irreplaceable, and that leadership requires human guidance (Balahurovska, 2023). The utilisation of AI and robots gives rise to a number of ethical dilemmas (Farina et al., 2025), including data protection, fair decision-making and machine liability (Balahurovska, 2023). Conversely, others argue that digital transformation and the use of technological tools are necessary to maintain global competitiveness (Liao et al., 2017; Culot et al., 2020). The capacity of artificial intelligence to empower managers to respond with greater adaptability to a dynamic environment is widely acknowledged (Imran et al., 2021; Hersey & Blanchard, 1977). However, there are those who contend that the excessive reliance on digital solutions such as AI or robotics in business operations can render company practices opaque (Chardonnens, 2025) and result in an undue prioritisation of technological solutions over human factors.

I.7.4. Digital transformation and operational performance improvements

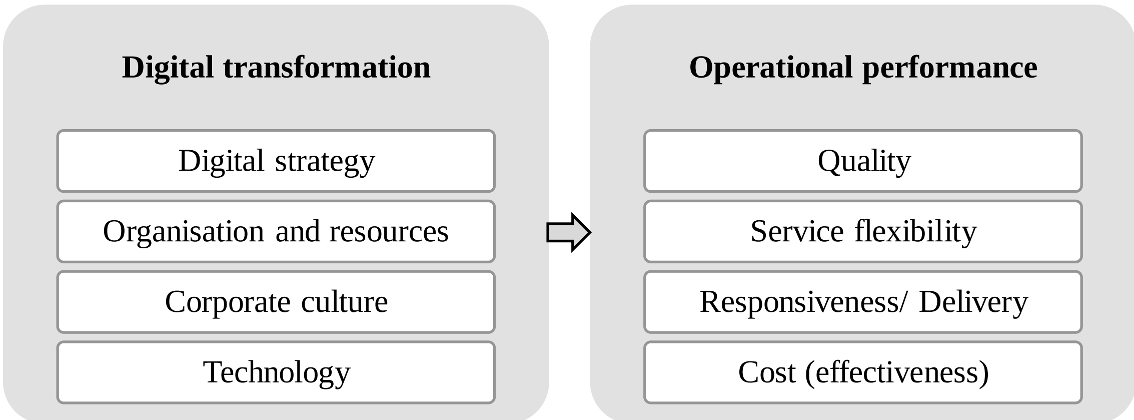
The advent of Industry 4.0 has engendered a paradigm shift in the manufacturing sector, offering enterprises the prospect of attaining a competitive advantage through enhanced productivity, flexibility, ROI, cost reduction, and accelerated processing speeds (Sufian et al., 2025). The potential for applications of digital transformation tools - AI, Big Data, cloud computing - to improve operational efficiency is significant (Xue et al., 2025). Digital transformation can bring great benefits to an organisation, including enhanced organisational performance, better business operations and processes (Kretschmer & Khashabi, 2020). Digital transformation has been used to change business operations, business models and affect products, services, processes, and organisational structures (Westerman et al., 2012). A strongly identified digital strategy can lead to greater operational performance (Matt et al., 2015). Manufacturing firms start their digital journey as it promises improvements in all dimensions of the triple bottom line (Felsberger et al., 2020). Studies examining different 'layers' (e.g., projects, applications, firm-level) of digital transformation in the manufacturing context reached very similar conclusions. Empirical evidence underlines that there is a positive relationship between digital transformation and operational performance. Quality and inventory are the key vehicles to improve perceived cost efficiency (Büchi et al., 2020; López-Gómez et al., 2018). Firms' digital transformation can positively correlate to the boost of financial performance (Berman et al., 2020; Dubey et al., 2020). Moreover, it can improve firms' operating flexibility with quicker response (Tian et al., 2022) and quality through a high level of service and sustainable production (Akçay Kasapoğlu, 2018).

In general, digital transformation can have a profound positive impact on a firm's operational performance by enhancing efficiency, increasing flexibility, improving quality, cost-effectiveness and optimising their services. Primary strategy can have a transformative impact on a firm's operational performance: strategy aligns the firm's goals and technology initiatives with organisational goals, culture and resources, leading to tangible improvements (Berman et al., 2020; He et al., 2023; Tortorella et al., 2023; Wu et al., 2021). Organisations that successfully embrace digital transformation can gain a competitive edge, drive growth, and achieve long-term success in today's rapidly evolving business landscape (Chikán et al., 2022).

The findings of the study of Müller et al. (2024) indicate that in circumstances where there is a limited adoption of robotics, companies utilise robots with the objective of reducing costs through process innovation. Conversely, when adoption levels are high, the technology is employed to enhance revenue through product innovation.

Figure 11 reveals the connection between digital transformation pillars and operational performance indicators.

Figure 11: Relationship between digital transformation and operational performance



Source: Author's work, 2024

I.7.5. The relationship between leadership styles, digital transformation, and operational performance

The dissertation's most significant added value lies in its holistic and multidimensional approach to the topic of the relationship between leadership styles, digital transformation, and operational performance.

There are a limited number of studies investigating the relationship between leadership and management studies, digital transformation (with particular reference to AI and robotics), and operational performance. While there are case studies giving insight into the context of these relationships (Imran et al., 2021; Tay & Low, 2017), many of them use surveys for the investigation (Dubey et al., 2020; He et al., 2023). There is only one study using clearly defined leadership styles (Tortorella et al., 2023); other studies only provide some characteristics that they consider essential for leaders. The term '*digital transformation*' is a broad concept that can be described in a number of ways in the academic literature. Some studies grasp the digital transformation purely with technology-related aspects, utilisation of specific digital tools, such as AI, Big Data, ML, or robotics (Dubey et al., 2020; He et al., 2023; Tay & Low, 2017), while other articles use cultural measures (Akçay Kasapoğlu, 2018; Imran et al., 2021). Others, however, employ the term more expansively to denote a comprehensive organisational transformation with multiple facets: a combination of technology, culture, or even strategic-related items is applied (Berman et al., 2020; Tortorella et al., 2023). Regarding the operational measures, mainly business-level measures are used, such as financial measures, market share, and RoI. Classical operations measures are less frequent, although digital technologies most probably have a more direct impact on operational measures than business-level ones (Csiki et al., 2023). There are only two studies focusing on a larger sample of manufacturing companies (Dubey et al., 2020; Tortorella et al., 2023).

The positive impact of digital technologies on various operational performance measures was analysed in the study of López-Gómez et al. (2018). Manufacturing firms pursue digital transformation to provide better services (products), gain competitive advantage, and increase profitability (Westerman et al., 2012). Managers' contribution to digital transformation and higher operational performance is also acknowledged, at least with a defined digital strategy (Hess et al., 2016). Digital solutions with substantial leadership help manufacturing companies improve quality and provide more responsive operations (Akçay Kasapoğlu, 2018).

It is incumbent upon leaders to proactively incorporate digital technologies into their business processes, as this enables overcoming technology limitations, enhancing collaboration, and fostering innovation. Digital tools, such as the Internet of Things (IoT), have the capacity to streamline production processes. Trust in tools like robots and AI, in conjunction with effective leadership, is of pivotal significance in the context of enhancing operational efficiency. Integrating advanced digital technologies through a knowledge-oriented leadership paradigm can potentially contribute to enhanced operational performance. This integration offers practical perspectives to managers on managing digital transformation within organisations (González-Mohíno et al., 2024). Furthermore, firms must meticulously select and adjust their technology portfolios based on operational needs, especially when evaluating the practical value of emerging technologies, such as blockchain. Hence, it is imperative to strike a balance between resource efficiency and organisational resilience, as digital technologies have the potential to enhance both of these aspects by improving adaptability, risk resistance, and decision-making agility in changing environments (Xue et al., 2025). Investing in entrepreneurial traits, such as proactiveness, risk-taking and innovativeness, is pivotal for numerous organisations. It is imperative for managers to embody an entrepreneurial spirit to capitalise on these traits and achieve a competitive advantage. The ability to construct and leverage AI is paramount, and environmental dynamism can significantly influence the adoption of AI and organisations' operational performance (Dubey et al., 2020).

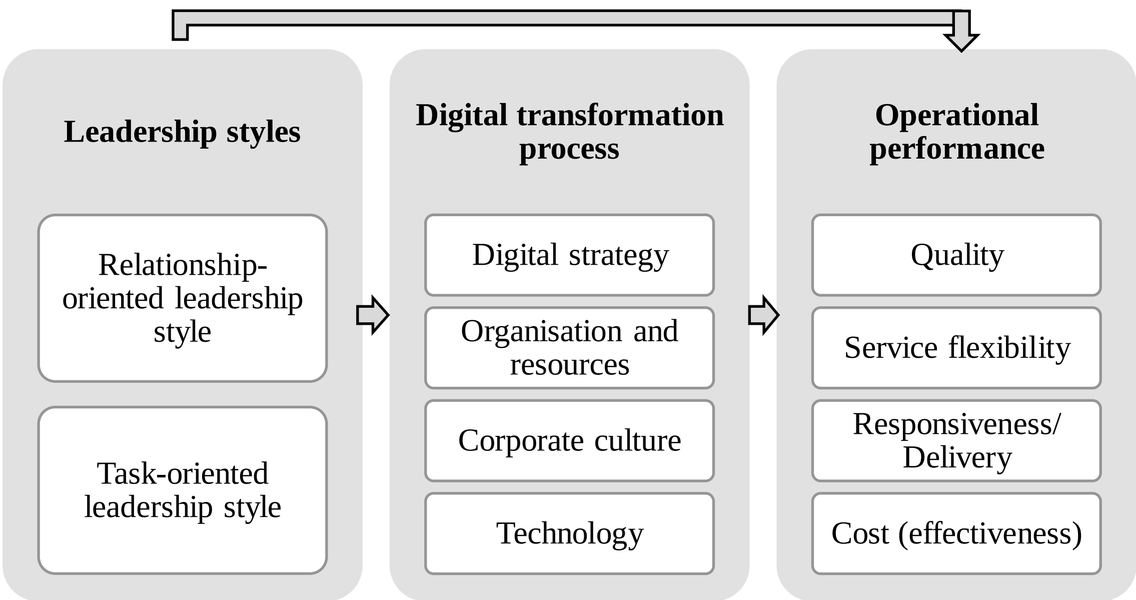
A recent study by Tortorella et al. (2023) analysed leadership's moderating influence on the relationship between digital transformation and performance. It found a positive influence on task-oriented behaviours (moderating the impact of technology) and a negative influence on relationship-oriented behaviours (moderating the impact of employee and culture). The study of Tortorella et al. (2023) examines moderating implications of leadership; however, we believe that leadership does drive digital transformation. Furthermore, they did not consider the aspect of resources (especially organisational issues) in their paper.

Digital transformation-oriented managers can be categorised into two types: task-oriented and relationship-oriented managers (Weber et al., 2022). In the empirical study, it is revealed that although the combination of the two styles does not give the highest efficiency, task-oriented leaders, relationship-oriented skills cannot be ignored since they soften the downsides of the task-oriented style. Studies (Tortorella et al., 2019; 2023) also show similar results, although they mainly focused on lean management in a digital environment: managers can achieve greater efficiency with task orientation, but with their relational style traits, they can achieve more favourable results in the long term. Müller et al. (2024) identified that the digital transformation leadership competency portfolio is contingent upon analysing the transformation drivers and goals. A comprehensive exploration of market innovation, operational efficiency, active stakeholder involvement, and enhanced competitiveness is imperative to ensure the efficacy of the portfolio.

The precise characterisation of leadership, the complex approach to digital transformation, and the focus on more direct operational measures in the manufacturing industry distinguish my research.

Figure 12 maps out the connection between leadership styles, digital transformation pillars and operational performance indicators.

Figure 12: Relationship between leadership styles, digital transformation, and operational performance.



Source: Author's work, 2024

The evolution of the relationship between digital tools, leadership, and operational performance reflects a transition from basic automation to a fundamental reimagining of business operations (Tortorella et al., 2023). From the perspective of efficiency, cost reduction, and enhanced communication (Slack et al., 2010; Teece, 2016) through competitive advantage (Avella et al., 2001; Chikán et al., 2022) to the current state of smart tools (Soori et al., 2024), AI leadership, and decision-making partners, the trajectory is intriguing, and the future remains uncertain (Smith & Green, 2018; Krishnan, 2024). The prospect of robot leaders in the near future is a fascinating one. In the contemporary digital age, success is contingent on leaders who are not only adept at adopting the most recent technological tools but also possess a profound understanding of their impact on human beings and operational performance outcomes (Tortorella et al., 2023; Dióssy et al., 2023; 2024; 2025). Therefore, the future of digital transformation - AI, robotics - and leadership entails a broad spectrum of opinions and challenges and ascertaining the optimal balance will be a pivotal task for leaders (Puhovichova & Jankelova, 2021). It is suggested by these trends that the future of leadership will be characterised by a delicate balancing act between the embrace of technological advancements and the maintenance of a human-centred approach (Zhong et al., 2017). The challenge for leaders will be to identify innovative methods of leveraging artificial intelligence and robotics while ensuring that leadership practices are ethical, transparent, and inclusive (Smith & Green, 2018; Krishnan, 2024).

I.8. Research methods and research setting

In my doctoral dissertation, I used quantitative research methods. I chose a questionnaire survey to collect the data as it is the most frequently used primary research technique because it furnishes the researcher with a plethora of objective data. (Mikkelson et al., 2019).

In the *first paper*, I utilised the data obtained from the questionnaire survey, comprising a 252-item cleaned sample from the USA and Hungary. Both developed countries have prioritised investment in digitisation, although the approach and level of digitisation differ. The data were subjected to an association test, correlation test, a difference between variables test ($\chi 2$ test), categorical principal component analysis (CATPCA), homogeneity test and ordinal logistic regression (o-logit) study following pre-tests and examinations. The chosen analyses followed a pre-set method. The association test reveals which elements are related to each other (see Table 2). The correlation test shows which elements are correlated to each other: in this matter, in the long term, Americans believe that robots will be more likely to do the jobs. With the homogeneity test, I examined the difference between the thinking of generations Y and

Z, as well as Americans and Hungarians. As the result of the aforementioned $\chi2$ tests, there was no significant difference between the generations' opinions or the nations' thinking. I used CATPCA for the purpose of attitude investigation (see Table 1). With regression analysis, I managed to determine the function-like positive or negative relationships of the variables in a multivariate approach and the relationship between AI and HR (see Table 3). Results indicated that young economists support the use of AI in their workplace.

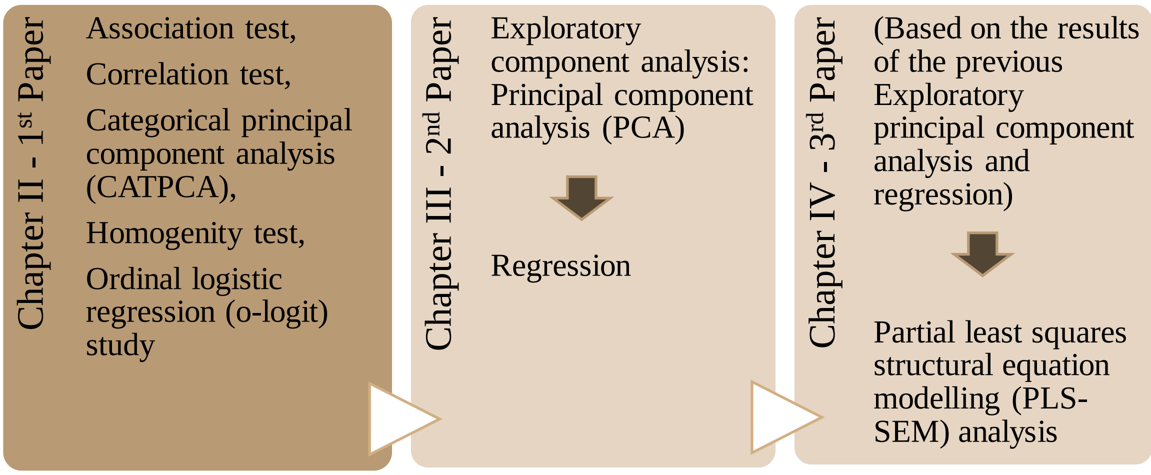
The *second and third papers* are based on the identical database obtained from TÁRKI during the period of 2018-2019. In contrast, the first paper is based on a different database – data collected by me in 2020 – analysed with a different statistical approach. The survey was focused on SMEs, and thus, the 84% participation rate in Hungary is representative of the sampling rate. The largest proportion of respondents were from the manufacturing sector (51%), followed by trade (24%). The sample also included companies from a range of other sectors, including construction, transport, storage, catering, and information and communication. Domestic private owners own a substantial majority of the enterprises in question. The majority of these enterprises are headquartered in Budapest and Central Hungary. A total of 234 companies completed the questionnaire, and financial data were also requested. In total, approximately 1,000 questionnaires were distributed. A further stage of data processing was cleaning the data set to ensure its reliability. The final sample comprised 209 companies. The sample processed during the research was limited to companies operating in Hungary, and only manufacturing companies were included in the analysis. The rationale behind the data reduction was to concentrate the research efforts, and one of the most effective methods for achieving this was to focus on the manufacturing sector during the data collection period (2018-2019). Prior research has demonstrated that the manufacturing sector is a significant area of focus in the context of digitalisation. In addition to its status as a significant contributor to the Hungarian economy in 2018 and 2019, the manufacturing sector represents the largest segment of the industrial sector. The number of registered manufacturing companies increased from 74,212 in 2018 to 74,927 in 2019, representing a 1% growth compared to previous years. In 2018, the manufacturing sector constituted 23.1% of Hungary's gross domestic product (GDP), while in 2019, it accounted for 21.5% of the country's GDP. The industry demonstrated a 3.7% growth in 2018 and a 5.5% growth in 2019 in comparison to the previous year. Notably, the manufacturing sector exhibited a 16.1% growth from 2018 to 2019. In 2018, the manufacturing sector accounted for 26.3% of national investment in the economy, while in 2019, this figure reached 26.8% (Központi Statisztikai Hivatal, 2021). In light of the presented data, it can be concluded that the Hungarian manufacturing sector appropriately represents the area under analysis and provides sufficient data for the study. In total, 113 manufacturing firms were included in the database. However, this was subject to further data cleaning, resulting in a final sample of 94 items.

In the *second paper*, I used the SPSS system and exploratory component analysis: Principal component analysis (PCA) to identify the digital transformation pillars (see Table 7) and the leadership styles groups (see Table 9). Moreover, I used regression to analyse the relationship between the two digital transformation pillars and two leadership attributes (see Table 10).

In my *third study*, I used the same exact data sample as in my second research. I built on the previous quantitative research data. I employed a more complex and comprehensive statistical method, partial least squares (PLS), utilising the same data set as in the preceding SPSS study. This software program uses a graphical user interface for variance-based structured equation modelling (SEM) utilising the PLS path modelling method (Wong, 2013). The method may be employed to analyse the relationships between variables and determine their nature. The PLS method entails the execution of multiple OLS (ordinary least squares) sequential regressions. Given that PLS does not estimate parameters using maximum likelihood, a normal distribution is not a prerequisite. The use of OLS is justified on the grounds that it is the most consistent method for small samples. The partial least squares approach is based on variance and requires the appropriate use of relatively small samples (in my case: 94). Furthermore, this method was selected due to the absence of constraints on sample size. This approach can be employed as an efficient method when the sample size and measurable factors are limited and the distribution of variables is uncertain. The PLS employs multiple regression, whereby the coefficient R, the t-value and the coefficients R^2 (see Table 14) are calculated for each regression model component (Saghafi, 2016). The figure illustrates the extent to which the variance of the latent variable is explained by the other latent variables. Furthermore, it elucidates the strength of the effect of one variable on another. The relative statistical importance of the different path coefficients can be determined by their respective weights. These determine the strength of the effect of each item on a given variable (Wong, 2013) (see Table 15 and Figure 17).

Figure 13 presents the statistical research methods that I used in the research papers.

Figure 13: Research methods and their connection



Note: the lighter brown cells are based on the same database, and the dark brown cell based on a different database were analysed with different statistical approaches.

Source: Author's work, 2024

I.9. Structure of the dissertation

The doctoral dissertation comprises three main chapters: research introduction, research papers and conclusion.

In the first chapter, I introduce my goals, research framework and structure, the literature foundation of the dissertation, the research problem, its relevance, the existing research gaps, and the research questions. I used several databases, employed specific research methods, and established the foundation of the research structure.

The second chapter involves the presentation of my three papers which constitute the body of my dissertation.

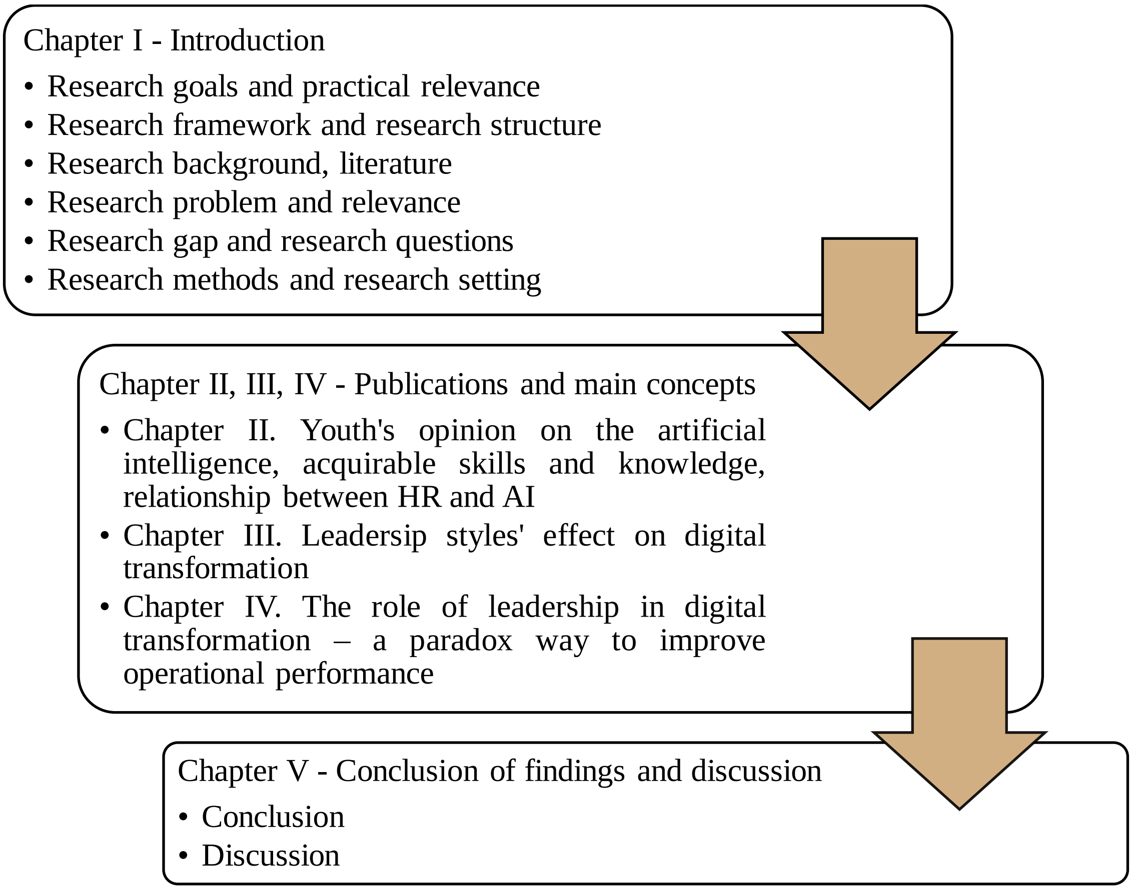
I outline the methodology involving interviews with the Hungarian and American workforce, explicitly targeting young economists who are or will probably be future managers and leaders. Their opinion on artificial intelligence and robots, acquirable skills and knowledge, and the alignment between HR and AI are crucial in the near future as utilisation of digital tools represents the initial step towards enhanced effectiveness and competitiveness in both domestic and international markets. Their acceptance by employers and employees is a fundamental prerequisite for digitalisation success.

Recognising the prevailing positive and trusting perception among current employees (and future managers) regarding the relationship between HR and AI raises concerns about whether Hungarian small and medium-sized enterprises (SMEs) are keeping pace with the rapid expansion of AI and digitalisation (Dióssy, 2024). I adopted a top-down perspective regarding the influence of leadership on digital transformation by analysing (survey) data from top leaders in the context of manufacturing SMEs which dominate the Hungarian economy (Dióssy et al., 2023). I studied the direct and indirect (mediator) effects of different leadership styles on digital transformation and improvements in operational performance (Dióssy et al., 2025).

In the last chapter, I elucidate the correlation between the findings and my conclusions, and I discuss the three papers.

Figure 14 visualises the structure of my doctoral dissertation.

Figure 14: Structure of the dissertation



Source: Author's work, 2024

CHAPTER II – 1st Article

The opinion of young economists of Generation Y and Z about artificial intelligence

Abstract

An increasing part of our everyday lives is influenced by artificial intelligence (AI). The motivation and attitude of Generations Y and Z, who are already present in the labour market, have a long-term effect on the competitiveness of companies. In addition to recognising the advantages of AI, applying it and adapting to its possible disadvantages is also a significant task. In my research, I focus on exploring the way of thinking of young economists regarding AI and robotics using anonymous questionnaires (147 Hungarian, 105 American respondents). In order to do this, I interviewed young people from the United States (a developed economy and leader in AI) and Hungary (a developed economy but not significant in the field of AI). My research revealed that no significant difference can be discovered between the thinking of the economists of the two nations. There are clearly positive and optimistic perceptions about AI and its short- and long-term impact.

II.1. Introduction

In our lives, we often encounter artificial intelligence (AI) in some form. By this, we mean that computers are capable of thinking and performing tasks. They interact with other devices and act as humans in areas that only humans could previously (Dirican, 2015). There is no doubt that the topic is relevant, but its short-term (5-10 years) and long-term (10-30 years) outcomes raise many questions. Both ordinary people and researchers are divided by the question of how human resources (HR) and AI will relate to each other in the future. There will be jobs that disappear and transform, but there will also be jobs that will not change significantly in the foreseeable future.

The intelligent robot, as a technology of the fourth industrial revolution, automates rule-based, repetitive, labour-intensive tasks instead of human labour, for example, in an office environment (Demeter et al., 2020a, b). The main motive behind combining AI with robotics is to try to optimise its level of autonomy through learning. Although the creation of a system exhibiting human-like intelligence remains elusive, robots can perform specialised autonomous tasks using AI.

I conducted a comparative empirical study related to my research topic in Hungary and the United States (USA). The USA is an economic superpower, and Hungary is a relatively small country. Therefore, I am presenting the experiences of two countries with significantly different characteristics. Young generations are represented in large numbers in the labour market in both countries, and both countries are classified as developed ones (OECD, 2019). AI investments are a priority in both the USA and Hungary, but the difference is that this preference has been felt in the USA for a significantly longer time, while in Hungary only in recent years (Digital Wellbeing Program, 2020). According to research by PriceWaterhouseCoopers, the impact of AI in Hungary will begin to intensify in the 2030s. AI will have a greater impact on jobs where men work in the majority, while women will face smaller changes between 2020 and 2030 (PWC, 2019).

I researched the two youngest generations of economists about their opinions and expectations regarding AI. By using the research results, the actors in the economy can prepare for the changes, which is also important because the jobs with the greatest potential deal with AI and data. Economics students can be regarded as lay observers; however, the purpose of my research is precisely to examine the views and experiences of the actors in the labour market.

Given that the chosen target group will definitely face the challenges under investigation, I am looking for the answer to whether they can be more successful by following the American model, creating a completely new action plan, or applying a domestic strategy. The research question explores the connections between young economists' thinking about AI, which serves as the basis for formulating hypotheses.

The article first reviews the framework of AI in the context of the literature review and then analyses the characteristics of nations and generations. After that, it presents the methodology and results of the empirical research. Finally, it summarises findings that are also useful for practice and future research opportunities.

II.2. The conceptual and literary background of the research

This section evaluates the relationship between Industry 4.0, AI, robotisation, and digitalisation. After that, it describes the characteristics of the investigated research object in the USA and Hungary and presents the characteristics of Generation Y and Generation Z in the labour market. Finally, the hypotheses to be investigated will be formulated.

II.2.1. The connection between Industry 4.0, AI, robotisation, and digitalisation

As a result of the fourth industrial revolution, smart products and services were created to transform the business model, the economy, and the functioning of society. Industry 4.0 is a subset of the fourth industrial revolution, within which humans and machines work together in an industrial environment using cognitive technologies (Lemaignan et al., 2017). Individual production and its creation as efficiently as possible have come to the fore. As a result, those companies that are able to satisfy individual customer needs at a low cost can remain competitive and achieve greater profits (Deloitte, 2014).

The manufacturer-supplier-customer relationship, production methods, distribution, and communication fundamentally change (Gerbert et al., 2015). The transformation of Industry 4.0 goes beyond simple process innovation, which is highly dependent on the digitisation of products and the construction of new digitally supported business models. Although physically dominant technologies play a decisive role in production, digital solutions and intangible capital are the main driving forces behind development (Demeter & Losonci, 2020). According to Keszey and Zsukk (2017), innovations are gaining ground primarily in the fields of finance, commerce, the automotive industry, education, healthcare, government, and info-communications.

The digital technology, AI, cognitive technologies, and the Internet of Things (IoT), the world of work and society is changing (Buzurovic et al., 2014). There are still many debates about whether AI will replace human work. Robots capable of performing pre-programmed sequences of tasks have been used in production for a long time, performing repetitive, complex, and monotonous operations. However, the development of robots is moving in the direction of autonomy, flexibility, and cooperation (Lemaignan et al., 2017). According to Tegmark and Werner (2018), within 20 years, 50% of jobs will be automated. These phenomena raise additional questions for HR. What will the relationship be between AI and HR? What skills and abilities will be important?

The technological transformation has accelerated significantly in recent years, with digitisation at its core. Publications of recent years (Demeter, 2020; Demeter & Losonci, 2020; Demeter et al., 2020; Szerb et al., 2020) unambiguously claim that international technological innovations have also reached our country; the only question is which company, when and how successfully it can carry out the digital transformation.

There will be a need for highly qualified specialists in the future to manage the software of the machines. It is a question of how machines and humans can cooperate with each other. Due to automation, jobs will disappear, and low-skilled people are most threatened by the change (OECD, 2019). For this reason, it is important to constantly train and retrain the workforce in order to be able to switch to another task if a work process is replaced by machines.

II.2.2. Generation Y and Z, the young workers

From the 20th century onwards, we can talk about generations, so we distinguish veterans (from the 1920s to the end of World War II), baby boomers (from the end of World War II to the 1960s), Generation X (from the 1960s to the 1980s), Generation Y, the millennials (from the 1980s to the 1990s), and Generation Z (from the second half of the 1990s until the turn of the millennium). In addition, we can discuss the youngest, known as the alpha generation (those who were born after 2010) (Meretei, 2017). There is no uniform agreement on the sharp age limit between the generations in the literature. Therefore, I take the Zemke, Raines & Filipczak (2000) article as a basis, based on the fact that people who were born between 1980 and 1994 belong to Generation Y, and the people who were born between 1995 and 2009 are called Generation Z.

Gen Y, or the first digital generation, was the first to be born into the world of technology. They are highly skilled in digital skills; therefore, it is easy for them to quickly get used to using these IT tools (Bencsik et al., 2016). The majority of Generation Y is already present in the labour market; they are characterised by multitasking and divided attention. For them, the concepts of success, career, and money are primely important. They are committed to their work but not to their workplace. The balance of free time and relaxation is essential to them. Their communication occurs primarily in the virtual space; their online presence never ends (Bencsik et al., 2016).

Gen Z is the first global generation. This age group is flexible, tolerant of different cultures, content- and knowledge-oriented (Tari, 2010). Technology is in the blood of those who were born in this generation. They grew up in an uncertain, complex environment that determines their opinion about work, learning, and the world (Bencsik et al., 2016). They are intuitive; they expect a quick reaction to everything. They are initiators, brave, and fast flow of information and content research characterise their everyday lives, and immediate reward and freedom are necessary for their comfort without commitment (Bencsik & Machova, 2016).

Several multinational companies have conducted research on how Generations Y and Z choose their workplace. It can be concluded that in 2018, both generations clearly had a negative opinion of their business motivation (Deloitte, 2018). The reason for this, in my opinion, can be inadequate communication, as well as the fact that companies are not equipped for the young workforce. With the spread of the fourth industrial revolution, soft skills are becoming more valuable. A company can be successful in the labour market if its employees are employed based on their competencies, skills, proficiency, and experience, supplemented by taking into account their personal and individual motivation and principles (Bencsik et al., 2016). Both generations are the perfect "base material" for embracing the changes brought about by Industry 4.0, as they are most at home in the field of IT and technology, as they were born into it.

II.2.3. Formulation of hypotheses

After mapping the theoretical background, I divided the research question into several groups.

1) young people's confidence, motivation, and interest; 2) investigation of the areas affected by AI; 3) thoughts on soft and hard skills; 4) the relationship between AI and HR; and 5) young people's image of AI. Along these groups, I formulated the following hypotheses:

H1: Economists are confident in the labour market.

H2: There is a difference between the motivation of Hungarian and American economists.

H3: AI and robotisation will have a motivating effect on people's work.

H4: Young Hungarian and American people have different opinions about which areas are most affected by AI in the short term.

H5: Young Hungarian and American people have different opinions about which areas will be most affected by AI in the long term.

H6: Both soft and hard skills are essential from the economists’ perspective.

H7: Both soft and hard skills can be developed from the economists’ perspective.

H8: Human work will not completely disappear; it will just change.

H9: There is a difference in the vision of American and Hungarian economists in the short term and the long term regarding how similar robots will be to us.

H10: According to both American and Hungarian economists, there is a difference between short-term and long-term forecasts in the relationship between robots and HR in the labour market.

H11: Hungarian and American economists think differently about the effects of AI.

II.3. Applied research method and data collection

The chosen research method was an anonymous questionnaire in order to get an authentic picture of how American and Hungarian Generation Y and Z economists think about AI and its influencing factors. The questionnaire survey is the most frequently used primary research technique (Mikkelson et al., 2019).

I am looking for the answer to what similarities and differences are in the thinking and attitude of millennial and global generation economists regarding AI in each country. According to my preliminary assumption, there might be differences between the employees' opinions of the countries due to generational differences.

The questionnaire was completed in Hungarian and English, and I sent it out on social media and in private messages. Most of the domestic applicants are current and former economists from the Corvinus University of Budapest and students from the University of Debrecen. In addition to these, I published the questionnaire in Hungarian university groups where university questionnaires are specifically published, so participants in the most important Hungarian economics training courses answered my questions. A significant part of the American applicants is from California, primarily current and former students at California State University, Sacramento. In addition, I posted the English questionnaire in relevant Facebook groups such as the University of California, Los Angeles, University of California, Long Beach, University of San Francisco, Harvard University Business School, Boston Business School groups, as well as other American questionnaire filling sites and such into groups that engage in academic and business conversations.

The questionnaire has three main parts.

In the first one, I assessed data and opinions about work, such as whether the person filling in is studying or working, in what position and in what field. For example, ‘Do you plan to look for a new job in the next 1-2 years? Do you consider yourself confident in this regard, and what motivates you when working?’

In the second part, I assessed opinions about AI and robots. The questions, formulated on a 1-5 Likert scale, focused on the short- and long-term use of AI, the relationship between robots and HR, and the importance of soft and hard skills. There were short, opinion-explaining questions regarding the AI in order to reveal the personal opinions of the respondents. This also revealed that the respondents have an extremely high knowledge of the subject and are very interested.

In the third part, I asked for general demographic data. Thus, I assessed the age group (generation Y and Z), gender, country of employment, and place of residence by type of settlement, highest completed education, language skills, and income situation.

Of those who filled out the questionnaires, a total of 252 people remained after data cleaning, of whom 147 were Hungarian and 105 were American. Out of the 252 people, a total of 122 are part of Generation Y (56 Hungarians and 66 Americans) and 130 from Generation Z (91 Hungarians and 39 Americans). The distribution of respondents was 112 men (58 Hungarians and 54 Americans) and 139 women (89 Hungarians and 50 Americans), 1 American did not answer the gender question. Based on the sample size, few general statements can be made since the number of respondents is small compared to the population of young economists in the countries. The sampling is not representative, as it was not done by random selection from the young economist population. Despite all this, it can be argued that the results can draw the attention of those involved in the changes.

II.4. Empirical results

I conducted the analysis along the 5 groups formulated in the first section by evaluating the 12 hypotheses. I present the results of the research in the following section.

II.4.1. Examination of hypotheses

I got clear results from the answers to the questions about self-confidence, motivation, and interest belonging to the first hypothesis group. Hungarian applicants are more confident in the labour market than Americans, as 88% of domestic economists and 82% of Americans stated that they would definitely or probably find a job if they looked. 10% of Hungarians are unsure, and 2% believe that they will certainly not find a job if they are looking. Generation Z is in the majority among those who are uncertain. 13% of Americans are not sure they will find a job, and 5% say they won't find a job if they are looking for it. This rate is higher than among Hungarians. Among the indecisive Americans, Generation Z and Generation Y are represented in a half-half ratio.

It is surprising that among Hungarians, Generation Z is remarkably confident about their qualifications: 57% stated that they will definitely find a job if they look, while only 36% of Americans said the same. The ratio was reversed among Generation Y, 50% of American millennials and 39% of Hungarians believed that they would definitely find a job. Overall, according to more than 80% of the respondents, they think that they will definitely or probably find a job in the labour market if they look for it. I therefore accept the first hypothesis, that *economists are confident in the labour market.*

It can be concluded that the two most important motivational factors in both nations are salary and learning and development opportunities. However, Hungarians prefer salaries, while Americans prefer development and learning. In addition to these, the balance between work and free time, the workplace atmosphere and challenging tasks play a prominent role. The latest IT tools were nominated as a motivational factor in a negligible proportion. Therefore, I reject the hypothesis that *there is a difference between the motivations of Hungarian and American economists since* there is hardly any difference between the motivations.

The majority of respondents would not change their attitude toward work as a result of the application of AI (42% for Hungarians, 34% for American respondents), and a small proportion of respondents stated that the application of AI is very motivating for them (6% of Hungarians and 5% of American respondents). 32% of Hungarians and 37% of Americans said that it would be more motivating. 4% of Hungarians and 9% of Americans thought the use of AI was particularly demotivating. There was no difference in the distribution of motivation between Generations Y and X: economists are clearly indifferent. The standard error for the USA is 0.090; 0.075 in the case of Hungary, 0.079 for Gen X, and 0.085 for Gen Y. It can be said that the respondents are optimistic about this topic, but it does not affect their motivation during their work. Therefore, I reject the hypothesis that *AI and robotisation will have a motivating effect on people's work.*

In the second hypothesis group, I examined the areas affected by AI. In the short term, the judgments of Hungarians and Americans are very similar regarding which areas will be most influenced by AI. The reason for this is that the influence of AI can already be felt in these areas, and it is easier to comment on the near future. The image of the call center robot is already present in our lives (telecommunications for Hungarians 63%, for Americans 68%), in transportation (59% for Hungarians, 55% for Americans), the developments of self-driving cars, for example, Tesla. Our easily traceable packages in logistics (42% for Hungarians, 43% for Americans), VR and AR games (38% for Hungarians, 43% for Americans) and robots made by various engineers (33% for Hungarians, 42% for Americans).

In accordance with the above, I reject the fourth hypothesis, according to which *Hungarian and American young people have different opinions about which areas are most affected by AI in the short term,* since there is hardly any visible difference between them.

The opinion is already more divided among the countries' respondents in the long term. According to the Hungarian economists, space research (49%), healthcare (48%), education (44%), followed by logistics (40%), transport (40%), and telecommunications (39%) in that order are the most probable to be AI-affected. There was no area that we believe would not be affected by AI in some form in the long term. According to American respondents, AI will have the greatest impact on healthcare (59%), followed by transport (51%) and engineering (51%), telecommunications (49%) and space research (48%) was marked. Logistics (43%) and national security (42%) are also worth mentioning. According to the Americans, AI will have little impact on tourism in the long term. Long-term visions can also differ from country to country because states can support different projects, and different areas are more prominent in each country (OECD, 2019).

Therefore, I accept the fifth hypothesis, that *Hungarian and American young people have different opinions about which areas are most affected by AI in the long term* since there is no consistent similarity.

In the third group of hypotheses, I examined the difference in opinions regarding soft and hard skills. Both American and Hungarian economists claimed that both skills are equally important when working (54% of Hungarians and 66% of Americans). However, more than a quarter of Hungarians (29%) indicated that soft skills are more important, while in the case of Americans, less than a quarter (25%) thought that soft skills are more important: that is, the ability to solve problems, emotional intelligence, behavioural and communication style, attitude or motivation. 55% of Hungarian Gen Y economists, 54% of Gen Z economists, 73% of American Gen Y, and 54% of Gen Z also think that both types of skills are equally important. This contradicts to Bencsik et al.

(2016), on that Generation Y employees significantly underestimate the importance of soft skills in the field of work.

Based on the above, *I clearly accept the sixth hypothesis, that both soft and hard skills are important from the perspective of economists.*

Regardless of geographic location, young economists believe that both soft and hard skills are important (Hungarians 54%, Americans 66%). In addition, 44% of the Hungarian respondents believe that only the hard skills of AI can be developed, while 49% of the Americans, in contrast, believe that both can be learned and developed. AI is capable of learning human skills, such as emotional intelligence, behavioural and communication style, or motivation, thereby creating even greater competition in the labour market. AI algorithms can also develop soft skills through learning, but people must also be aware of the consequences of this and provide them with opportunities for development and training. Based on the above, *I do not reject the seventh hypothesis, that both soft and hard skills can be developed from the viewpoint of economists, both in the case of the Americans and in the case of the Hungarians. Hence, I reject the hypothesis as a whole.*

The fourth group of hypotheses covers the relationship between AI and HR. Those who completed the survey agreed with the statement that human work will not completely disappear but will rather be transformed in the long term. 74% of Hungarians fully or rather agree that jobs are changing rather than disappearing. More than a third of Americans tend to agree with this, with 23% saying that they strongly agree or tend to disagree. Therefore, I can state that they agree with this only in the case of the Hungarian respondents. In the case of the American respondents, slightly more than half of the respondents agree with this. Only 3-4% of respondents do not agree with the statement, so they think that a significant part of the jobs will disappear. I make it probable that this smaller part will take action against robotisation and AI.

Considering everything, *I accept the eighth hypothesis, that according to the respondents, human work will not completely disappear; it will only be transformed.* Based on the research results, *I accept the ninth hypothesis, according to which there is a difference in the vision of both the American and Hungarian economists in the short- and long-term in terms of how similar robots will be to us* since it is clear that according to the young people of both nations, in the short term, robots will be medium (35-39%) or less (33-34%), while in the long term they will be significantly similar to us (43-45%).

Based on the above, *I accept the hypothesis that, according to both American and Hungarian economists, there is a difference between short-term and long-term forecasts in the relationship between robots and HR in the labour market.* In the short term, the largest part of all respondents said that there will be tasks or parts of tasks that will be performed by robots (34% of Hungarians, 43% of Americans), and 26% of Hungarians and 31% of Americans think that they will only supplement HR. It is interesting that according to 27% of Hungarians, even in the short term, there will be tasks that will be performed entirely by robots, in contrast to only 15% of Americans. In the long term, there is already a more unanimous opinion that there will be tasks completely performed by robots (53-59%).

The eleventh hypothesis, within the framework of which I examine the overall picture of AI, requires further analysis, which is explained in more detail in the next section, but at this point in the research it can be argued that no significant difference can be observed *in the opinions of American and Hungarian young economists regarding AI, and they have a positive opinion.*

II.4.2. Statistical analysis

I continued the research with a more complex, multivariate statistical analysis, supplementing the fourth and fifth hypothesis groups. During the data analysis, I cleansed the sample from data I did not mention during the analysis, transformed the variables into values, and finally performed the pre-tests and examinations. I performed an association test, a correlation test, a difference between variables test (χ^2 test), a categorical principal component analysis (CATPCA), and a regression test on the 252-item cleaned sample.

II.4.2.1. CATPCA

During the CATPCA, based on the 20 questions asked in the questionnaire, I formed groups for the purpose of attitude investigation, supplementing the results of the fourth hypothesis group. The first 10 questions related to the relationship between AI and HR, and the second 10 questions related to the relationship between AI and society. On the Likert scale, I originally converted options 1-5 (with 0 additions) to 1-3 (with 0 additions).

The size of the sample is adequate since 252 (number of sample elements) / 15 (number of final variables) ≈16.8, which is more than the 10 threshold. The value of the Kaiser-Meyer-Olkin test was 0.833 > 0.5, and the p value of the Bartlett test was 0.000.

When determining the number of components, I took into account only those components with an eigenvalue of at least 1.

I ran CATPCA with both 4 and 3 components. Question 10 clearly stood out from the others, so I excluded it. Out of the 19 questions, the correlation coefficient of Q3, Q7, Q9, and Q15 was close to that of another group, so it was not possible to clearly determine which one they belong to, and their correlation coefficient individually did not reach the threshold of 0.5, which is why these questions are also excluded from the research. Since the added value of the fourth group was extremely low based on the CATPCA run on 15 questions, I continued the research with 3 components, the results of which are shown in Table 1.

Table 1: The role and weight of the factors based on CATPCA

Principal component weights			
	Dimension		
	1	2	3
Q1	0.760	0.071	0.048
Q2	0.675	0.205	-0.025
Q4	-0.272	0.607	0.104
Q5	-0.332	0.738	0.134
Q6	-0.153	0.753	-0.133
Q8	-0.027	0.714	-0.012
Q11	0.801	-0.006	0.002
Q12	0.744	0.156	-0.095
Q13	0.769	0.145	-0.137
Q14	0.782	0.107	-0.293
Q16	0.693	0.087	-0.041
Q17	0.555	-0.284	0.156
Q18	0.606	0.177	-0.237
Q19	0.450	-0.027	0.655
Q20	0.297	0.160	0.761

Source: Author's work, 2022

The 3 groups created as a result of the CATPCA were formed as follows:

Group 1

– Q1 I would like to work for a company that uses AI
– Q2 I would like to learn how to work with robots
– Q11 Personally, I am optimistic and positive about the application of AI
– Q12 Our daily lives are beneficially influenced by AI
– Q13 Humanity must adapt to robots and accept the future
– Q14 AI will have a positive impact on society in the long term
– Q16 In the long term, the quality of life will increase as a result of AI
– Q17 Personally, I do not feel threatened by AI
– Q18 The government should better support AI research

Group 2
– Q4 I would voluntarily change jobs because I feel threatened by AI
– Q5 I feel my job is threatened because of AI
– Q6 Could a robot take over my own work?
– Q8 My salary will change with the application of AI

Group 3
– Q19 As a result of AI, the protection of our personal rights will be more emphasised in the future
– Q20 Our consumption habits will change over the long term due to AI

The first group included positive questions affecting our lives and society. Both the Hungarian and the American respondents had a positive opinion of AI, but there were somewhat different opinions on many issues. According to the Americans, the government should support the developments aimed at AI better, yet the Hungarian applicants feel less threatened by AI. American youth depicted a more positive vision of AI's social effects and social responsibility than Hungarians.

The second group included negative questions about working. In the case of questions Q4, Q5, and Q6, the respondents did not agree with the statements. In the case of question 8, they could not clearly assess whether their salary would change or not. Overall, the respondents have an overwhelmingly positive attitude towards AI.

The third group incorporates issues that are relevant to our society in the long term. According to young economists, our lives will clearly change in a positive direction as a result of AI, as our quality of life and shopping habits will also change in a positive direction.

During the research, a fourth group emerged, with question 10, which concerns the long-term operation of companies in light of AI. It is interesting that based on this, according to the respondents, the company can be functional even without investing in AI.

II.4.2.2. Association study

I used an association test to reveal which elements are related by expanding the results of the fifth hypothesis group. Based on the χ^2 test, there is an association between two variables if the Pearson χ^2 p-value is below 0.05. The strength of the relationship can be evaluated according to the Cramer V indicator: weak between 0.00 and 0.30, medium up to 0.70, and strong relationship above 0.70. I present the results of the association study in the table below. Only the significant statistical results are shown in the table below.

Table 2: The variables analysed during the association study

Relationship between examined variables	**Cramer V values**
Income x generations	0.274
Generations x in the long term, how similar will robots be to us	0.209
Income x the long-term relationship between AI and HR	0.298
Nationality x how similar robots will be to us in the long term	0.218
National affiliation x long-term relationship between AI and HR	0.737
Generations x the relationship between AI and HR: you feel threatened by AI	0.245
Generations x the long-term relationship between AI and HR: jobs are only changing	0.210
National affiliation x the long-term relationship between AI and HR: jobs are only transformed	0.226
Nationality and employment support AI	0.232
Generations x AI and society: the government should better support AI	0.213
National affiliation and social responsibility will play a greater role	0.249
Nationality x quality of life will increase	0.218
Nationality and the government should support AI more	0.229
Nationality and the protection of personal rights become more important as a result of AI	0.288

Source: Author’s work, 2022

The Cramer V indicator showed a significantly strong relationship between the variables in only one case. There was a strong relationship between the nationality of the respondents and their opinion of the long-term relationship between AI and HR. A further correlation test showed (Pearson correlation coefficient = -0.541 < 0.01) that in the long term, according to the American respondents, there will be more jobs that will be performed entirely by robots than according to the Hungarian respondents. In the other cases, no significant relationship can be observed with the other variables in terms of income, generation, and nationality.

II.4.2.3. Homogeneity test

With the χ^2 test, I examined the difference between the thinking of generations Y and Z, as well as Americans and Hungarians, supplementing the results of the fifth hypothesis group.

It can be concluded that Gen Y employees are not more motivated if AI were used in their workplace than Gen Z (χ^2 =3.425, p=0.180). Generation Y employees do not support AI in their workplace more than Generation Z (χ^2 =2.904, p=0.234). The motivation of the Hungarian respondents would not change to a greater extent under the influence of AI than that of the Americans (χ^2 =0.372, p=0.830). Hungarian employees do not support the use of AI in their workplace more than Americans (χ^2 =1.068, p=0.581).

As the result of the aforementioned χ^2 tests, there was no significant difference between the opinions of the generations or the thinking of the nations. The result supports my previous statement that the opinions of the respondents do not differ in terms of generation or nationality.

II.4.2.4. Ordinal logistic regression (o-logit) study

With regression analysis, we can determine the function-like positive or negative relationships of the variables in a multivariate approach. The conducted investigation deepens the results of the fifth group of hypotheses. Based on the questionnaire, I designated 10-10 attitude questions as independent variables. The dependent variable of the model is the extent to which *young economists support the use of AI in their workplace.*

According to the model significance test χ^2 =217.255 (p=0.000), the model provides a significant result. The significance level of the estimated parameters was less than 0.05 for four variables: Q1, Q2, Q7, Q12, so they were included in the final model.

I examined the multicollinearity with the variance inflating factor (VIF), wherein a VIF value above 2.5 indicates multicollinearity. The highest VIF value in the data set of the sample was only 1.531, so there is no multicollinearity among the variables. In the model built according to the 5% entry criterion, the significance level of all parameters is close to zero (<0.05), so the input variables have a significant effect on the target variable.

Table 3: Parameters and testing of the o-logit model

		Parameter	Standard error	Wald test	p-value	95% confidence interval	
						Lower limit	Upper limit
Threshold	(= 1)	5.566	0.715	60.684	0.000	4.166	6.966
	(= 2)	8.669	0.893	94.191	0.000	6.918	10.420
Variable	Q12	0.948	0.200	22.406	0.000	0.555	1.340
	Q1	1.215	0.241	25.415	0.000	0.742	1.687
	Q2	0.980	0.210	21.701	0.000	0.568	1.393
	Q7	0.340	0.144	5.538	0.019	0.057	0.623

Source: Author's work, 2022

In the model, the following four variables significantly explain how much the respondents personally support the application of AI in the workplace:

– Q1 I would like to work for a company that uses AI
– Q2 I would like to learn how to work with robots
– Q7 Workplace supports the use of AI
– Q12 Our daily lives are beneficially influenced by AI

The four variables have a significantly positive influence on the extent to which the respondents support AI in the workplace. So, all other variables being equal, the respondents prefer to work for a company that uses AI, or they would prefer to learn how to work with robots, the workplace supports the use of AI more, or even according to the respondents, our daily lives are more beneficially influenced by AI, which induces a greater support for the use of AI in the workplace by the respondents.

In the model, the first question affects the dependent variable most significantly. *How willing the respondents are to work for a company that uses AI* has the greatest impact on how much young economists support AI at work. Thus, I reject the last hypothesis that *Hungarian and American Z and Y generation economists think differently about the effects of AI.*

II.5. Conclusion

As a summary, it can be argued that my experience was generally consistent with the research with only a minor deviation due to generational differences. Based on the results, there is no significant difference in the short term, but in the long term, the American respondents are more optimistic about the long-term benefits of AI than the Hungarians, who feel safer in the short term.

The young people agreed that learning and development opportunities are especially motivating for them during their work. However, AI and its understanding are not yet at the centre of their interest, but they find it exciting. In addition, they do not feel threatened in the labour market. According to the young people of each nation, both soft and hard skills are equally important, and both can be developed. Furthermore, they agreed that it can only be decided, depending on the position in the labour market, whether AI can function as a full-time workforce, which will only perform entire jobs or tasks in the long term.

According to young economists, human work will not completely disappear. It will only be transformed, and they do not feel threatened by AI. It is thought-provoking that, according to young economists, a company can be functional in the long term without AI and that AI and robotisation have no motivating effect on human work. It is surprising that, according to their confession, 24% of young Hungarian and American economists have not yet met AI. Nevertheless, they would like to work for a company that uses AI and learn how to work with a robot.

Hungarian and American young people have different opinions about which areas are most affected by AI in the short- and long term. There is a difference in the vision of the American and Hungarian economists in the short- and long term in how similar the robots will be to humans.

The research showed that Hungarian and American economists from Generation Y and Z have a significantly positive and optimistic opinion about the effects of AI. It is recommended to strengthen this vision among employees through education so that the application and adaptation of AI takes place smoothly in the workplace since its application is inevitable in the near future.

Empirical results of this research demonstrate that people do not have a clear vision of the future, but it can be regarded as favourable and prospective that most of them, regardless of generation and geographical area, are optimistic about this issue. The results are also important because this kind of comparison has not yet been made on the subject either by generation or by asking economists. In my opinion, the short-term and long-term vision of the employees of the current and future years can contribute to a successful technological transformation; we can learn this through research. Additionally, companies can engage in state-of-the-art HR trainings to strengthen the formulation and implementation of their digital strategy in the short term, even in line with the leading American model. In the long term, based on their experience, Hungarian companies can prepare for the development of their domestic strategy, future-shaping factors can be identified, and scenarios can be prepared in order to provide groundwork for novel futures literacy and strategy formation.

Among the limitations of this research, it can be mentioned that the sample is not representative of the entire American and Hungarian population, and the anonymous questionnaire did not precisely define what we call AI, which may have caused uncertainty among the respondents. In addition, I think it is likely that if I had asked employees from a different generation or even people working in a different field (not economists), I could have gotten different results. In the further stages of the research, it is important to use qualitative research methods and analyse the data, for which this exploratory empirical study can be a suitable starting point. Being a field that develops rapidly and brings significant changes even in the short term, the research must be repeated over time so that the results show the current real conditions.

CHAPTER III – 2nd Article

The effect of leadership styles on digital transformation

Abstract

The latest industrial revolution is transforming the business world and prompting many companies to embrace digital transformation. In digital transformation, a company implements changes in their organisational operation (e.g., strategy, organisation, technology) to support the corporate institutionalisation of digital solutions. Based on the literature, leadership style is a key factor in companies' transformation. This research examines the impact of leadership styles on digital transformation using data from the company surveys of the Competitiveness Research Center. The authors found that the digital transformation of Hungarian manufacturing companies has two pillars: the digital transformation strategy and the digital transformation activities. The characteristics of the task-oriented and relationship-oriented leadership styles appear mixed: one focuses on goals and implementation, and the other on performance and people. Both leadership styles have a significant positive impact on the digital transformation strategy; however, only the goals and implementation-focused style has a positive effect on activities.

III.1. Introduction

Because of the latest industrial revolution - the embodiment of which is Industry 4.0 in the manufacturing industry - digitalisation is completely permeating companies. The changes brought about by digitisation affect all essential dimensions of organisational functioning. Many researchers emphasise the role of digital strategy in successful transformation (Matt et al., 2015; Ghobakhloo, 2018; Gill & VanBoskirk, 2016). In addition, the literature also deals with individual technologies (Ivan et al., 2019; Móricz & Drótos, 2019; Gill & VanBoskirk, 2016), the organisation and its resources (Ivan et al., 2019; Kim & Lee, 2007), and the effects of corporate culture (Brunetti et al., 2020; Ivan et al., 2019; Gill & VanBoskirk, 2016). While it is treated as a fundamental principle that the adaptation of digital technology also depends on human resources (Tilson et al., 2010).

In the models analysing the digital transformation, in addition to all these topics, leadership style appears as the success factor shaping digitalisation (Ruel et al., 2021). Leadership style covers the skills and behaviours (Lovelance et al., 2019) that managers possess and use in different ways to manage and influence their subordinates in order to achieve company goals (Hersey et al., 2001; Nahavandi, 2002; Weber et al., 2022). Based on the workshop study of Dunavölgyi (2022), organisational culture and leadership are also important factors in the digitisation environment, since the leader's style has an impact on the implementation of digital changes and the functioning of the organisation.

However, not all leadership styles lead to a better organisation, therefore choosing the right style is important (Gandolfi & Stone, 2018). Several types of leadership styles (pairs) are known, such as the transformational-transactional or the task-relationship-oriented leadership style. While transformational-transactional leadership styles differ in the depth of the changes (Cortellazzo et al., 2019), task-oriented and relationship-oriented leadership styles differ in the focus and orientation of the changes (tasks or people) (Weber et al., 2022). In our article, we conducted our research based on the latter pair of leadership styles. Based on the results of international empirical research, a task-oriented leadership style is typically more effective than a relationship-oriented one, but the latter is also indispensable in digital transformation (Weber et al., 2022).

Focusing on the relationship between leadership and digital transformation, it is also worth considering the characteristics of the domestic context. Only limited domestic results are available on leadership styles, and research does not focus on task- and relationship-oriented leadership styles. Among the leadership characteristics of domestic production managers, good communication, micromanagement, and performance orientation contribute to the deepening of the lean production paradigm (Gelei et al., 2015). According to Hortványi et al. (2020), today's Hungarian managers are generally not prepared for digital transformation or for managing the effects of transformation. The sporadic empirical studies, not only at the domestic but also at the international level, certainly justify a deeper examination of the relationship between leadership styles and digital transformation.

In the domestic corporate environment, a double "movement" is unfolding in the digital transformation. Compared to international trends, the phenomenon is not very dynamic in this country (Szalavetz, 2020); only a small number of companies have the conditions for digital transformation. This is a very consciously digitising and resourceful circle of companies (Móricz, 2021), which can also show results in terms of performance

(Wimmer & Csesznák, 2021). It is beyond dispute that the further expansion of the phenomenon can be greatly supported by strengthening the digital ecosystem or ensuring the availability of qualified and competent labour (Szerb et al., 2020).

Our research complements the results so far in relation to the human side - from the direction of leadership styles - and can provide handholds to those thinking about digitisation. The aim of the research is to provide a comprehensive picture of how leadership styles influence the digital transformation of Hungarian manufacturing companies.

The study consists of four main sections. In the first section, we present the literature background. After exploring the pillars of digital transformation and the characteristics of different leadership styles, we will evaluate their relationships. The subsequent section discusses the research methodology and the research model. We will then present the results of the analyses. In the last section, the conclusions of the research are explained.

III.2. Pillars of the digital transformation process

Digital transformation is a process involving significant organisational transformation. In the literature, several classic models deal with organisational planning and transformation pillars. Galbraith's 5 STAR model (Galbraith & Kates, 2010) and McKinsey's 7S model (McKinsey, 2008) highlight similar factors in relation to organisational changes: strategy, structure, systems/processes and people, the staff and their skills, as well as remuneration and leadership style.

Based on an overview of international and Hungarian works examining the digital transformation of companies (Table 4), it can be established that in this literature as well, generally prominent aspects of organisational transformation are in the centre, such as strategy, organisation and resources, corporate culture, and technology.

Table 4: Literature summary on the pillars of the digital transformation process

Pillars	Factors	Heini & Heikki, 2015	Gill & VanBoskirk, 2016	Ivan et al., 2019	Móricz & Drótos, 2019	Tavoletti et al., 2021	Alshehab et al., 2022	Karippur & Balaramachandran, 2022
Strategy	Digital challenges and opportunities		*		*			*
	Defining a digital business strategy		*	*	*	*	*	*
Organisation and resources	Dealing with digitisation projects		*		*			*
	Availability of material resources			*	*		*	*
	Technological knowledge, ability	*	*	*	*	*	*	*
	Involvement and integration of resources					*	*	*
Corporate culture	Encouraging digitalisation ideas from the bottom		*		*			*
	Adapting to business challenges		*	*	*		*	*
	Innovative risk taking		*		*			*
	Digitisation education		*	*		*		*
	Attitude to change	*		*				*
Technology	Industry tracking		*		*			*
	New technology is consciously tried	*	*		*		*	*
	They are ahead of their competitors in innovation		*		*			*

Source: Author's work, 2023

As shown in Table 1, during the review we preferred works that examined several pillars together. In the works of Ivan et al., 2019 and Tavoletti et al., 2021, technology is known as a fundamental factor, so they are not examined in the light of transformation.

When developing the framework of the research based on four pillars, we considered research of Karippur and Balaramachandran (2022) and Móricz and Drótos (2019) as guidelines. Based on this, we organised the further work. It can be concluded that, although at different depths, at least three pillars were investigated by all reviewed publications. The study of Móricz and Drótos (2019) also confirms that the framework outlined on the basis of international works is also used in Hungary. In the following, we review the most important findings related to the four pillars.

III.2.1. Digital strategy

In relation to digital transformation, the "main message" of this pillar is how much and in what manner the company's management plans. Based on Móricz and Drótos (2019), Gill and VanBoskirk (2016), Karippur and Balaramachandran (2022) and Ivan (et al., 2019) works two questions arise: does it understand the digital challenges and opportunities facing the company, and does it clearly define the organisation's digital business strategy? From the point of view of the digital strategy, it is also extremely important that managers shall be aware of the daily implementation of the digital strategy (Karippur & Balaramachandran, 2022; Gill & VanBoskirk, 2016; Heini & Heikki, 2015). The key issue of implementation is to name clear and quantifiable goals. All employees must understand how their performance relates to the company's digital goals (Alshehab et al., 2022). They also measure how different organisational units work together to achieve the desired result. Additionally, the experiences of digital programs and collaborations are fed back into their strategy because the competitive strategy may depend on digital technology (Tavoletti et al., 2021). Another aspect is that the digital strategy must fit the company strategy (Karippur & Balaramachandran, 2022; Ivan et al., 2019) so that business processes, standardization, and IT integration can support digitalisation solutions within the company.

III.2.2. Organisational structure and resources

As part of this pillar, projects related to digital transformation are implemented in a specific way (not randomly) (Gill & VanBoskirk, 2016; Móricz & Drótos, 2019) so that the given organisation has the appropriate technological knowledge and capabilities (Heini & Heikki, 2015; Alshehab et al., 2022; Tavoletti et al., 2021) and material resources (Móricz & Drótos, 2019). It is also necessary to match the resources to the different phases of the digital transformation (e.g., implementation and management). Staff supporting critical digital functions should come from the best organisational units, thus ensuring that digital skills are embedded in the organisation (Alshehab et al., 2022; Karippur & Balaramachandran, 2022; Ivan et al., 2019).

In the organisational structure, the use of functional silos must be avoided because this can cause isolation and hinder the flow of information (Ivan et al., 2019). The incentive effect of the organisational model focuses on cross-functional collaboration, process development, and digital program management (Karippur & Balaramachandran, 2022; Gill & VanBoskirk, 2016).

III.2.3. Corporate culture

The corporate culture fundamentally determines the execution of the digital transformation. Within the framework of the pillar, it becomes clear how the corporate culture supports digital transformation. Does it provide opportunities for the emergence and support of bottom-up digitisation ideas in order to involve employees and users in the transformation (Karippur & Balaramachandran, 2022)? Whether managers support the digital strategy (Alshehab et al., 2022) and whether they show a supportive attitude towards change within the organisation (Heini & Heikki, 2015; Ivan et al., 2019). Additional definitions of the pillar include how digital culture is managed and integrated into virtual teams with different cultures (Tavoletti et al., 2021). Also, whether they can quickly change digital solutions according to business challenges and whether they are willing to take risks compared to existing practices in order to enable innovation (Gill & VanBoskir, 2016; Móricz & Drótos, 2019; Karippur & Balaramachandran, 2022). The role of whether targeted educational development is ensured within the organisation or whether companies invest in it at all levels of the organisation is considered essential by the literature (Ivan et al., 2019; Tavoletti et al., 2021). It is also important to clearly communicate their digital vision both internally and externally (Gill & VanBoskirk, 2016).

III.2.4. Technology

This pillar includes the company's current technological readiness and its willingness to adopt new technologies. A primary question is whether they follow the leading digital solutions of the industry (Gill & VanBoskirk, 2016; Móricz & Drótos, 2019). Whether they try these new digital technologies consciously in order to examine their applicability in the organisation (Alshehab et al., 2022). Are they using an iterative and collaborative approach to technology development? The availability and trial of technological resources, as well as the strength of current technological activity, are important because of intra-firm activities (Karippur & Balaramachandran, 2022; Heini & Heikki, 2015). In addition to these, the issue of measurement and evaluation is also important. In addition, it is important for the company to consider how it compares to its competitors in terms of digital technological innovations (implementation and application of Big Data, robotisation, and digitalisation solutions) (Gill & VanBoskirk, 2016; Móricz & Drótos, 2019), which position can significantly influence the nature of the digital transformation (Alshehab et al., 2022; Ivan et al., 2019).

The four pillars that make up digital transformation are the strategy, the company's technological approach, the company's culture supporting digitalisation, and the distribution of the organisation and resources. Digital transformation in the company can be characterised by these pillars.

III.3. Leadership style in digital transformation

Based on the literature, one of the most important factors influencing digital transformation is the leader and the employed leadership style (Lovelance et al., 2019; Weber et al., 2022) - since the transformation must be controlled and managed in order to be successful (Alshehab et al., 2022). In addition to managing the technological processes, it is also necessary to manage the organisation, allocate resources and develop the strategy (Keller & Weibler, 2014). For this, where appropriate, their style and working methods must be adapted to the new digital era (Fouad, 2019). During the digital transformation, people-centeredness and a technical attitude are also needed for leadership (Cortellazzo et al., 2019).

Researchers deal with leadership styles, the grouping of style features, their impact on the organisation, and their transformation in several approaches (Henkel et al., 2019). The most well-known models are transactional-transformational (Burns, 1978; Rousseau, 1995; Bass, 1990) and relationship- and task-oriented leadership styles (Katz et al., 1950; Fiedler, 1951). Empirical research on relationship- and task-oriented leaders is summarized in Table 5.

Table 5: Characteristics of task-oriented and relationship-oriented styles and the effects of the styles – empirical works and their methodology

Author(s)	Relationship-oriented leadership style		Task-oriented leadership style		Is digital transformation investigated?	Methodology used, number of respondents	Examined country	Sector / industry
	Characteristics	**Its effects**	**Characteristics**	**Its effects**				
Weber et al., 2022	Trustworthy manager-subordinate relationship Supportive attitude Recognition Existence of trust Developing skills Prioritizes solving challenges in the workplace Mentoring	Greater affective and cognitive trust Greater tendency to innovate	Professionally reliable Directs the work Shows direction to achieve specific goals A good strategist	Greater cognitive trust in the manager, they are considered reliable and a better professional They can also trigger organisational resistance	Yes	Scenario-based experiment, pretest with 97 participants, then questionnaire with 718 participants, total: 815, with two-way multivariate (MANCOVA) analysis of covariance	Germany	Not specified
Tortorella et al., 2018	Focuses on employee relations Problem solving support	Negative impact on implementation	Exact work and task definition,	Positive impact on implementation	Partly, lean is in focus	225 completed questionnaires, tested with confirmatory factor analysis and linear least squares regression	Brazil	Manufacturing industry
Tortorella et al., 2019	Commitment and support Development and training of employees Creating an environment supporting the personal needs of employees, Setting an example Openness recognition of success intellectual support	Long-term positive effects	Accurate communication of goals and expectations Commitment to self-development Communication of information Monitoring and evaluation examination Personal presence and control	Positive impact on implementation	Partly, lean is in focus	107 peer-reviewed articles, systematic literature review, Application of a mixed, multivariate data analysis technique with the participation of 12 experts, with a longitudinal study	Brazil	Manufacturing industry and healthcare
Yukl et al., 2002	Provides support and encouragement, Recognises employees, Develops the skills and abilities of employees, Consults on decision-making and problem-solving	Most style features have a positive effect on efficiency	Short-term planning Communicate goals and expectations clearly Monitor work and performance	Most style features have a positive effect on efficiency	No	275 completed questionnaires, analysed with exploratory and confirmatory factor analysis	USA	Not specified
Henkel et al., 2019	Coaching Exploitation of talent Help Encouraging employees to express their emotions Problem solving Listening to ideas	It should be used in the advanced stages of a project	They are meticulous Direction indicator Determines in advance what work should be done and how it should be done Definition of roles and tasks, Achieving goals Meeting deadlines	It is more effective to apply at the beginning of a project	No	Simulated team project with the participation of 129 managers (based on Fiedler's leadership style self-assessment questionnaire) Pearson's chi-square	US HQs, multiple international locations	Not specified
Tabernero et al., 2009	Employee welfare Employee evaluation and support	Greater team cohesion	Goal oriented Follows specific communication patterns,	Greater group effectiveness	No	3 groups * 24 people = simulation program with 72 participants	Spain	Psychology students

			Assigns the roles of subordinates exactly			(case study), analysed with t-test and regression analysis		
Mikkelson et al., 2019	Building trust Commitment Effectiveness of group work Encouragement Motivation Help	Greater team cohesion Greater satisfaction Motivation increase	Communication from above Monitoring Short-term planning Efficiency increase	Higher productivity A more positive attitude	No	307 completed questionnaires, evaluated by hierarchical regression analysis	US HQs	Not specified
Storm, 2018	Job satisfaction focus Motivation Striving for work-life balance It supports and develops its employees He is in favour of teamwork and cooperation Encourage communication Conflict management Encouragement of other workplace benefits Improving the workplace atmosphere The importance of employee well-being	Greater workplace motivation Better teamwork	Task orientation Development of action plans Exact job description Specific information for employees High level administration Quality assurance Rigorous design Results oriented	Greater focus More accurate, more determined work, Better schedule planning Lack of creativity Reduction in risk taking	No	96 completed questionnaires (Fiedler's least preferred co-worker scale) evaluated with factor analysis and regression analysis	Turkey	Tourism

Source: Author's work, 2022

III.3.1. The relationship-oriented leadership style

Relationship-oriented leaders express their commitment and provide support to their subordinates (Katz et al., 1950; Fiedler, 1951). They focus on the development (Yukl, 2012) and education of employees, create such an environment, and support the personal needs of employees. They are open, recognise the success of their employees, and provide intellectual support (Tortorella et al., 2019). They are constantly motivated (Tortorella et al., 2018). They focus on job satisfaction, strive for a balance between work and private life, support and develop their employees (Rüzgar, 2018). The relationship-oriented leader shows direction (coaches), exploits talents, encourages employees to express their emotions, solves emerging problems, and listens to ideas (Henkel et al., 2019). Such leader consults in decision-making and problem-solving (Yukl et al., 2002). They favour teamwork and cooperation, encourage communication, manage workplace conflicts well, support workplace benefits and improve the workplace atmosphere (Rüzgar, 2018). It is important to facilitate coordination, promote cooperation and activate resources (Behrendt et al., 2017). They motivate, encourage, and support their employees in order to achieve their goals (Mikkelson et al., 2019).

Relationship-oriented leaders create greater cohesion among group members (Mikkelson et al., 2019; Tabernero et al., 2009). On the other hand, relationship-oriented leaders focus on developing trust, commitment, and collaboration through work teams. They are employee-oriented. They provide social and emotional support to those who need it. For relationship-oriented managers, a positive effect was also measured in terms of job satisfaction. They emphasise the development of trust, commitment, motivation, and cooperation in work groups (Mikkelson et al., 2019). According to Van Dun (et al., 2017), efficient (lean) managers who support digital transformation devote more time to communication and problem-solving, which is the hallmark of a relationship-oriented manager.

The advantage of this leadership style is that it increases productivity and risk-taking while creating team cohesion, cooperation, and an excellent work environment. It minimises conflicts and dissatisfaction within the team. However, this can be at the expense of employees putting their daily tasks in the background and not completing their work tasks accurately (Rüzgar, 2018). In addition, too much responsibility can fall on the individual employee (Tabernero et al., 2009).

III.3.2. The task-oriented leadership style

Leaders focus primarily on the task to be performed, the goals, and what is required for this (Katz et al., 1950; Fiedler, 1951). Precise task definition (Tortorella et al., 2018) and short-term (Yukl et al., 2002) action plans are necessary (Tortorella et al., 2019) to ensure quality. They are meticulous, assign roles and tasks in advance, determine how work should be done, how to achieve goals, and strictly adhere to deadlines (Henkel et al., 2019). The day-to-day activities of this manager include organising work, assigning responsibilities, scheduling activities, and allocating resources among different activities. As well as explaining job responsibilities, communicating goals, priorities and deadlines, defining performance standards, and explaining relevant rules, guidelines, and standard procedures (Yukl, 2012). It is important to increase understanding, strengthen motivation and promote implementation (Behrendt et al., 2017). They focus less on their employees and more on tasks and their completion (Rüzgar, 2018). Managers are open to communication, but mainly so that employees understand their tasks exactly, thereby increasing efficiency (Mikkelson et al., 2019). As a result, greater focus, more precise, more determined work and better time planning can be accomplished, so greater productivity can be achieved (Rüzgar, 2018). Task-oriented leaders use top-down communication. They help their subordinates achieve their goals (Mikkelson et al., 2019) through short-term planning, personal efficiency improvement, role and goal clarification, and performance monitoring (Tortorella et al., 2019).

Based on Tabernero's (et al., 2009) case study in the case of task-oriented managers, employees showed high group efficiency, productivity, and positivity within the group. These leaders led their organisation to a more successful digital transformation (Porfírio et al., 2021) than their relationship-oriented counterparts. Jung and Avolio (2017) found that individual performance increases, and employees are more willing to brainstorm under a task-oriented leader. Rüzgar (2018) argues that the accepted leadership styles have a great impact on the exchange of ideas between managers and subordinates; however, the task-oriented leadership style, in contrast, has no effect on the self-orientation of the manager-subordinate relationship.

The strength of this leadership style is that the employees know exactly what they have to do, they can manage their time well, and they can do their work accurately. Everything is completed on time according to exact specifications. However, this can also cause a lack of creativity and reduce risk-taking within the team (Rüzgar, 2018).

III.3.3. The relationship between the two leadership styles

Several studies have found conflicting evidence regarding the effectiveness of task- and relationship-oriented leadership styles and a combination of them. According to Mikkelson (et al., 2019), mixing the two styles is the most effective. According to Tortorella (et al., 2017, 2018, 2019), Lovelace (et al., 2019) and Bunjak (et al., 2022), there is no single most effective leadership style. Leadership rather depends on the context, responds to organisational needs and preferences, and mutually includes related factors that can be controlled to improve organisational performance. This is especially true for leaders of technological transformation (Bunjak et al., 2022).

Weber et al. (2022) argue that both task- and relationship-oriented leaders are in a digital transformation environment. In their empirical study, the authors reveal that although the highest efficiency is not given by the combination of the two styles by task-oriented leaders, relationship-oriented skills cannot be ignored since they soften the downsides of the task-oriented style. Tortorella et al. (2018, 2019) demonstrated similar results, although they mainly focused on lean management in a digital environment, whereby managers can achieve greater efficiency with task orientation, but with their relational style traits, they can achieve more favourable results in the long term.

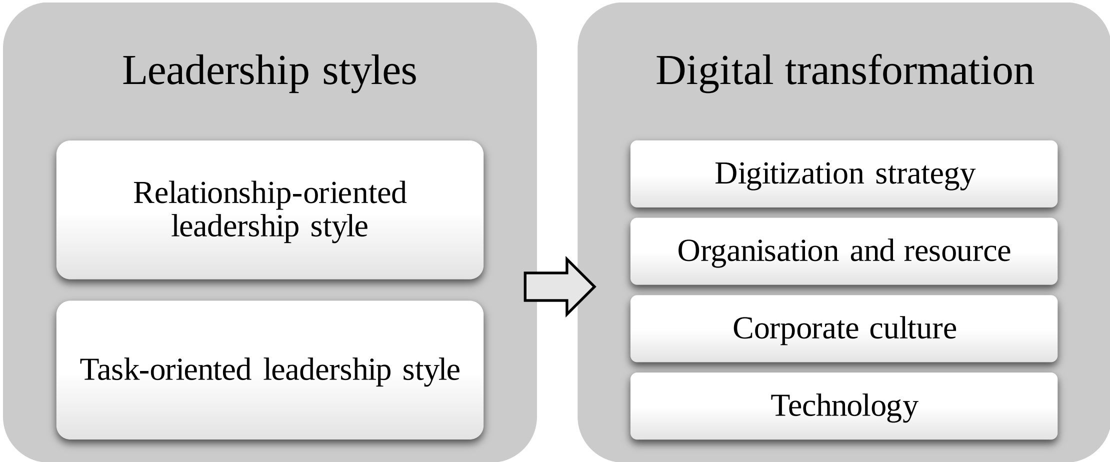
Based on Table 5, it can be concluded that individual research assigns somewhat different marks to a specific leadership style. While it can also be recognised that relationship-oriented (e.g., recognition, setting an example, support, development, motivation, employee well-being) and task-oriented (e.g., scheduling obligations, monitoring, control, short-term planning, goal-oriented, accurate communication) leadership styles can mutually coexist. It is typical that when taking into account the effects of the two styles on performance (results), they come to the conclusion that both have a decisively positive effect, although the focus of their effects is different. In terms of effects, they often think on an individual or group level, less often on organisational level performance indicators. Also, the short- and long-term results can be different. During the research, we focused on digital transformation and the manufacturing industry. The sixth column of Table 5 clarifies that we have limited empirically based knowledge regarding the digital context, and the research conducted in the manufacturing industry (last column) is not extensive either. There is no such complex domestic research on the topic, either (penultimate column).

III.4. Presentation of the research model

Our research connects the pillars of digital transformation and leadership styles identified in the literature. Based on the literature review, our expectation is that leadership styles (Isensee et al., 2020; Obermayer et al., 2021) have a significant impact (Bowman et al., 2019; Eller et al., 2020) on digital transformation. Our research model is presented in Figure 15.

The main hypothesis of the research is that leadership styles have an impact on digital transformation. This main hypothesis is broken down into hypotheses that can be analysed independently. The hypotheses are presented in the statistical analysis.

Figure 15: Research model



Source: Author's work, 2022

III.5. Presentation of the database

For the analysis, we used data from the company survey of the Competitiveness Research Center (VKK) operating at Corvinus University in Budapest (Chikán et al., 2019). The questionnaire used for the survey consisted of five parts, which were aimed at managers responsible for one area of the company in addition to the number one manager (production, marketing and sales, finance, senior management). The data was collected between October 2018 and July 2019 by TÁRKI Ltd.

Based on stratified sampling, the survey targeted companies with at least 50 employees in some selected sectors (Chikán et al., 2019). Based on data from the Központi Statisztikai Hivatal (2021), the sampling frame includes 4,295 Hungarian companies, of which more than 2,000 companies were contacted in connection with the survey. A total of 234 companies filled out the questionnaire. After data cleansing (e.g., deletion of incomplete information, deletion of companies with negative equity based on reports), in order to increase the reliability of the data, 209 companies are included in the final sample. The final sample can be considered representative based on the sectoral and size characteristics of the companies contacted (Szukits, 2022).

We planned to examine the research question on a more homogeneous sample of companies, so we narrowed the research to the manufacturing industry (113 companies). The concepts that are the focus of our research question (leadership styles and digital transformation) were included in the questionnaires filled out by the top managers of the companies. The variables mapping the concepts (Füstös & Tárnok, 2017) were measured on a 1-5 Likert scale. Examining the availability and quality of the data included in the research, we deleted the companies in which at least 50% of the variables related to the given concept were missing or were too monotonous (e.g., the respondent gave each question a number 3 on the 1-5 Likert scale). The data of 94 manufacturing companies were included in the sample to be analysed. For these companies, we replaced the missing data with the average of the variable. In total, less than 10 data had to be replaced.

III.6. Operationalisation and results

In this section, we present the empirical analysis of the hypotheses-examination. Regarding the methodology, it can be highlighted that we first conducted an exploratory principal component analysis for the two groups of variables (digital transformation and leadership styles). We used exploratory instead of confirmatory principal component analysis because the separation of the two leadership styles was not clear based on previous literature. Afterwards, we ran a regression analysis to examine the relationships. Articles using a questionnaire on the topic prefer to use regression analysis to explore relations (Tortorella et al., 2018; Yukl et al., 2002; Tabernero et al., 2009; Mikkelson et al., 2019; Rüzgar, 2018), which is the common methodology in the research we use it. SPSS 25 was used for the analyses.

III.6.1. Operationalisation of the digital transformation process

The four pillars of the digital transformation process were operationalised with the variables in Table 6 (see Móricz, 2022).

III.6.1.1. Sample characteristics

The strategic variables related to digital transformation reflect a contradictory situation. Among all the variables, the highest average value (3.94) can be linked to strategy, which indicates that companies typically understand digital challenges and opportunities. At the same time, the other variable related to strategy shows one of the lowest averages (3.40), drawing attention to the fact that companies do not have a digital strategy. The lowest average (3.24) can be linked to technology, indicating that, based on the managers' perception, their company is not ahead of its competitors regarding new technologies. Based on the Variance, even the largest differences can be attributed to the technology.

Overall, averages between 3 and 4 indicate that respondents tend to agree with the statements.

Table 6: The digital transformation process pillars and variables (N=94)

Pillars	Questionnaire variables	Average	Variance
Strategy	The company management understands the digital challenges and opportunities facing the company.	3.94	1.179
	The management of our organisation clearly defines the organisation's digital business strategy.	3.40	1.297
Organisation and resource	Projects related to digital transformation are implemented in a specific way (not randomly).	3.39	1.360
	We have adequate financial resources to plan and implement digital business transformation.	3.55	1.497
	Our organisation has the technological knowledge and capabilities required for digital business transformation.	3.53	1.241
Corporate culture	In our organisation, there is an opportunity to arise and embrace digitisation ideas coming from below.	3.54	1.412
	We can quickly change our digital solutions according to business challenges.	3.40	1.276
	We are willing to take risks compared to our existing practice by introducing innovative digital solutions.	3.63	1.570
Technology	We track the industry's leading digital solutions.	3.59	1.471
	We consciously test new digital technologies to examine their applicability.	3.41	1.579
	We are ahead of our direct competitors in digital technological innovations.	3.24	1.628

Note: Measured on a 1-5 Likert scale, where 1- least agree with the statement and 5- most agree with the statement

Source: Author’s work, 2022

III.6.1.2. Results of principal component analysis

Exploratory principal component analysis was employed to analyse the 11 variables of the digital transformation process, with Varimax rotation method and Kaiser normalization. During the analysis, we paid attention to the fact that the correlation coefficients between the variables cannot be lower than 0.200. We made this decision so that, in light of the difference, it is clear which component belongs to which variable. Moreover, the value of the minimum correlation coefficients within the components individually exceeds 0.500.

All items in our model have significant factor loadings (>0.600) (Hair et al., 2014). The explained value of the model is higher than 80%, the KMO=0.84. As a result of the model testing, the p-value converges to zero, so the model has significant explanatory power. Table 7 shows that the nine variables belong to two main components: digital strategy and digital transformation activities are the two pillars of digital transformation. The elements of the main component of the digital strategy can be matched to the variables according to the principal categories. At the same time, it is a marked deviation compared to the principal consideration that all the variables related to the other three pillars were included in the main component of digital transformation activities.

Table 7: The rotated component matrix of the digital transformation process

Variables	**Components**	
	Digital transformation activities	**Digital strategy**
We are willing to take risks compared to our existing practice by introducing innovative digital solutions.	0.890	0.306
In our organisation, there is an opportunity to arise and embrace digitisation ideas coming from below.	0.873	0.333
We consciously test new digital technologies to examine their applicability.	0.870	0.330
We have allocated adequate financial resources to plan and implement the digital business transformation.	0.770	0.452
We track the industry's leading digital solutions.	0.766	0.469
We can quickly change our digital solutions according to business challenges.	0.763	0.473
Our organisation has the technological knowledge and capabilities required for digital business transformation.	0.734	0.507
The company management is aware of the digital challenges and opportunities facing the company	0.293	0.927
The management of our organisation clearly defined the organisation's digital business strategy.	0.543	0.743

Source: Author’s work, 2022

Out of the 11 variables 2 were not included in the components ('The implementation of projects related to digital transformation takes place in a specific way (not randomly)'; and 'We are ahead of our direct competitors in digital technological innovations').

After identifying the main components of the digital transformation, we continued the investigations with a statistical analysis of leadership styles.

III.6.2. Operationalisation of leadership styles

Variables related to leadership styles were also analysed using exploratory factor analysis. Based on the literature, we expected two components: relationship- and task-oriented styles (Weber et al., 2022).

III.6.2.1. Sample characteristics

It can be seen from the statistics describing leadership styles (Table 8) that the highest average (4.44) belongs to the variable classified as task-oriented style. It is, therefore, typical for companies that the leader clearly sets the goals, carefully monitors the implementation and intervenes if necessary. This variable also has the lowest standard variance, so respondents tended to agree on this. The other extreme is also a variable linked to the task-oriented style: managers least thought (3.37) that key performance indicators (KPIs) basically convey the company's goals to managers and subordinates. The task-oriented variable with the highest variance is that due to high responsibility, trust is based on control and follow-up. This was the least agreed upon by the respondents.

Table 8: Variables of leadership styles according to the questionnaire (N=94)

Leadership styles	**Tickets**	**Average**	**Variance**
Task-oriented style	The manager clearly sets the goals, carefully monitors their implementation, and intervenes if it seems necessary.	4.44	0.571
	The manager's tasks are largely aimed at ensuring that his/her colleagues perform their tasks as best as possible.	3.19	0.788
	The task of the manager is professional management, precise guidance, and control.	4.18	0.644
	Basically, the key performance indicators (KPIs) convey the company's goals to managers and subordinates.	3.37	0.989
	Because of the great responsibility in the work organisation, trust is based on control and follow-up.	3.83	1,111
Relationship-oriented style	The task of the manager is to make the goals personal, to set an example and to mobilize them in the direction of their implementation.	4.11	0.612
	The manager's duties include the emotional and professional support and development of his/her colleagues.	3.95	0.868
	Building trust is an important managerial task, because it is the way to achieve innovative solutions.	4.01	0.806
	The key performance indicators (KPI) are only part of the managerial toolbox, it is necessary that managers and employees feel that the goals belong to them.	3.85	0.988

	The manager communicates the goals clearly and convincingly, discusses the tasks together and entrusts the implementation to his colleagues, who can turn to him if they feel the need.	4.22	0.691

Note: Evaluated on a 1-5 Likert scale, where 1- least agree with the statement and 5- most agree with the statement

Source: Author's work, 2022

III.6.2.2. Results of principal component analysis

The analysis classified the variables into two main components (Table 9). All elements in the model have significant factor loadings (>0.600), there are no cross-loadings, and the difference between two factor loadings is nowhere less than 0.200 (Hair et al., 2014). The preserved variance ratio of the main components is 66% and the KMO=0.707, which can be concluded to be satisfactory. Four variables were excluded due to their low correlation coefficient (<0.500).

Table 9: Rotated component matrix of traits related to task- and relationship-oriented leadership styles

	Related leadership style	**Components**	
		Leadership style that focuses on performance and colleagues	**Leadership style that focuses on goals and implementation**
Basically, the performance indicators (KPIs) convey the undertaken goals to managers and subordinates.	Task	0.812	-0.036
The manager's tasks are largely aimed at ensuring that his/her colleagues perform their tasks as best as possible.	Relationship	0.723	0.325
The performance indicators (KPI) are only part of the managerial toolbox, it is necessary that managers and employees feel that the goals belong to them.	Relationship	0.707	0.203
Because of the great responsibility in the work organisation, trust is based on control and follow-up.	Task	0.694	0.399
The manager clearly sets the goals, carefully monitors their implementation, and intervenes if it seems necessary.	Task	0.122	0.890
The manager communicates the goals clearly and convincingly, discusses the tasks together and entrusts the implementation to his colleagues, who can turn to him/her if they feel the need.	Relationship	0.234	0.791

Source: Author's work, 2022

A leadership style that focuses on goals and implementation includes the manager communicating the goals clearly and convincingly, discussing the tasks together and entrusting the implementation to colleagues, who can turn to the manager if they feel the need. In our opinion, this style is closer to the relationship-oriented style, despite the fact that it has task-oriented elements.

A leadership style that focuses on performance and colleagues, its main component includes the variables that aim to comply with the KPIs. As well as ensuring that employees perform their tasks in the best possible way, and the manager monitors this through inspection and follow-up. This style is more similar to the classic task-oriented style.

After the numbers of the main components emerged, we continued the research with regression analysis to explore the relationships between the variables along the hypotheses.

III.6.3. Digital transformation and leadership styles – regression analysis

We can measure both the process of digital transformation and leadership styles with two main components. The main hypothesis of the research was thus transformed into four hypotheses:

Main hypothesis: Leadership styles have an impact on digital transformation.

H1: The leadership style that focuses on performance and colleagues has an impact on the digital strategy.

H2: The leadership style that focuses on performance and colleagues has an impact on digital transformation activities.

H3: The leadership style that focuses on goals and implementation has an impact on the digital strategy.

H4: The leadership style that focuses on goals and implementation has an impact on digital transformation activities.

Regression analysis is a proven statistical method for testing the relationships between data and their strength. In the regression analyses, neither multicollinearity nor homoscedasticity was a problem for the examined factors, and there were no outliers in the sample.

Table 10 summarizes the results of the regression analysis. The R-squared indicator indicates the fit of the model is close to 90%. The results were tested at a significance level ($p < 0.050$). The explanatory value of the regression equations is close to 20%.

Table 10: Regression models on the influence of leadership styles on the digital transformation process

	Constant	**Leadership style that focuses on performance and colleagues**	**Leadership style that focuses on goals and implementation**	**R^2**	**p**	**F**
Digit strategy	-1.047E -17	0.384 (p=0.000)	0.216 (p=0.024)	0.194	0.000	10.974
Digital transformation activities: Corporate culture Organisation and resources Technology	6.755E -17	0.425 (p=0.000)	0.114 (p=0.231)	0.193	0.000	10.914

Source: Author's work, 2022

Based on the results, the performance and colleague-focused leadership style has a statistically significant positive effect on the digital transformation activities and the digital strategy. Based on these, we accept the first and second hypotheses.

We see different results regarding the leadership style that focuses on goals and implementation. We also accept the third hypothesis because the leadership style focusing on goals and implementation has a significantly positive effect on the digital strategy. We do not accept the fourth hypothesis because the leadership style focusing on goals and implementation has no significant effect (p=0.231) on digital transformation activities.

Based on the statistical results, both the performance and colleague-focused leadership style and the goals and implementation-focused leadership style have a positive effect on digital transformation, so we accept the main hypothesis. Regarding the styles, we can see that a leadership style that focuses more on performance and colleagues has an impact on digital transformation and, more significantly, on the strategic perspective.

It can also be concluded that based on the opinion of the managers of the examined manufacturing companies, digital transformation is more supported by a leadership style that focuses on performance and colleagues because it affects both digital pillars.

III.6.4. Presentation of relationships

Based on the literature analysis, we expected that the digital transformation would be organised into four pillars - a) digital strategy, b) technology, c) organisation and resources, and d) corporate culture.

Based on the exploratory principal component analysis, the digital transformation is concentrated in two pillars: the digital strategy and the digital transformation activities encompassing all the other principal pillars. These results suggest that decision-making (strategy) and implementation (activities) would be separated. The research highly focuses on the importance of strategy within the digital transformation (Avella et al., 2001). Among the variables, the highest average value can also be linked to a strategic element, therefore the companies understand the change in context. At the same time, based on the low averages related to implementation and technology, the question legitimately arises whether Hungarian companies have the necessary technological background for digital transformation (Móricz, 2022). Although our results confirm that the progress of digital transformation is relatively underdeveloped in this country (e.g., Szalavetz, 2020; Lőrincz et al., 2023), it can also be concluded that managers understand the directions determined by the context.

It is usual in the literature that task- and relationship-oriented leadership styles are examined separately (Tabernero et al., 2009; Henkel et al., 2019). The exploratory analysis of the characteristics of the two styles revealed that leadership styles that combine these characteristics also describe the practice of managers well. Of the two styles we have identified, the leader who focuses on performance and colleagues, i.e., possesses more task-oriented style traits, has a greater impact on digital transformation. At the same time, our research and the literature emphasise that success cannot be attributed to a single leadership style (Lovelace et al., 2019; Bunjak et al., 2022); the best way is to apply leadership styles and style traits simultaneously the appropriate way (Tortorella et al., 2017, 2018, 2019). This may depend on the level and progress of digitisation, the team's size and the leader's personality and experience (Tortorella et al., 2018). As a result of our research, we can argue that by supplementing task-oriented leadership style traits with relationship-oriented style traits, the leader can achieve the greatest results in the process of digital transformation (Tortorella et al., 2019).

Based on previous research, a task-oriented leader was more efficient in the initial stages of the digital transformation, and a relationship-oriented leader had better results in the more advanced stage (Henkel et al., 2019; Tabernero et al., 2009). Given that, based on domestic research, digital transformation is still in its infancy (Demeter et al., 2021), our results are in line with these international results. It can also be seen that a pure task- or relationship-oriented leadership style is not usual, managers like to combine them (Gelei et al., 2015).

III.7. Conclusions, limitations, and continuation of the research

The present research examined the digital transformation, as well as the leadership styles affecting it. In order to carry out the study, we created groups of variables along the lines of digital transformation and leadership styles using principal component analysis and then looked at the impact of leadership styles on digital transformation with regression analysis. Overall, our results show that leadership styles have an impact on digital transformation. We found that the digital transformation requires a performance- and colleague-focused leader who has more task-oriented leadership styles.

The research has several added values:

1) based on the literature, it measures digital transformation on a more complex scale than before.

2) It points out that task- and relationship-oriented styles are mixed in practice, at least domestically.

3) Perhaps the most important result is that it reveals the relationship between leadership styles and digital transformation in the manufacturing industry, which has not yet happened in our country or internationally either. In this regard, it points out that digital transformation is better supported by task-oriented style features.

In light of our results, we can state that strategy and implementation are separated during the digital transformation. Companies are more advanced in formulating strategy, at least in understanding the challenges, compared to its implementation. The transformation is mainly supported by a leadership style that focuses on performance and colleagues, which is closer to classic task-oriented leadership styles. Therefore, it is worthwhile for managers to focus on formulating performance goals that support both strategy and implementation, and their communication and acceptance. Our research is also valuable because we worked with a scale that can be put into practice, which managers can try on themselves. Our results can help them to evaluate their own work and, where appropriate, improve their skills.

An important limitation of the research is that the data comes from the period before Covid-19. However, the pandemics could have been a powerful driving force for some companies to start digital transformation; and those already in progress could be spurred to much faster development. Therefore, in our view, the "digitalisation gap" may now be larger between companies that have already digitised and those that are starting up, which may also cause differences in leadership styles. That is why we intend to repeat the research in the future.

CHAPTER IV – 3rd Article

The role of leadership in digital transformation – a paradox way to improve operational performance

Abstract

Purpose – Leadership has been identified as a crucial driver of efficient deployment of any Operations Management (OM) paradigm. Our work focuses on digitalisation, a recent OM paradigm, and analyses the mediating effect of digital transformation (DT) on the relationship between task-oriented and relationship- oriented leadership styles (LSs) and operational performance (OP) improvements in the manufacturing context. Design/methodology/approach – The authors employed survey data from Hungarian manufacturing firms. Hypotheses are tested using structural equation modelling.

Findings – Task-oriented and relationship-oriented LSs exert distinct influences on DT and OP improvements. The results indicated that task-oriented LS drives OP improvements through its impact on DT. The relationship- oriented LS does not influence DT. Regarding the implications for OP improvements, we revealed a leadership paradox as the indirect positive impact of task-oriented LS may be offset by the direct negative influence of relationship-oriented LS.

Research limitations/implications – The results are most pertinent to manufacturing firms that have already started their digital journey. Further studies must clarify how managers' cultural embeddedness (i.e. general perceptions about efficient leadership in their country or region, national culture) could influence findings. Finally, to learn about the effective long-term behaviours of leaders might require different empirical methods.

Originality/value – To the best of the authors' knowledge, this study represents one of the first survey-based examinations of CEOs on the ways how LSs drive the effective deployment of DT in manufacturing firms. Our findings demonstrate a leadership paradox at the nascent stages of DT in manufacturing firms.

Keywords: Digital transformation, Leadership styles, Operational performance improvements, Manufacturing firms

Quick value overview

Interesting because: As firms engage with technology-driven change it is increasingly necessary to explore factors influencing successful digital transformation (DT). We investigate the role of leadership styles (LSs) in driving DT and improving operational performance (OP) in manufacturing firms. The study uniquely explores how task-oriented and relationship-oriented LS influence DT and OP, revealing a paradoxical relationship.

Theoretical value: The study examines the complex relationships between task- and relationship-oriented LSs, DT and OP. The results show how task-oriented LS exerts a direct and positive influence on DT, which in turn affects the cost efficiency and service flexibility indicators of OP. On the other hand, relationship-oriented leadership has no impact on DT, and it negatively affects OP, particularly in terms of quality and delivery and cost. This deviation challenges conventional wisdom and existing literature, which typically promotes relationship-oriented traits in DT.

Practical value: In order to navigate the digital world and improve OP, leaders must adopt the appropriate LS at each stage of DT. Our findings suggest that task-oriented LS should be emphasised during the early stages of DT. In addition, managers should be cautious of over- reliance on relationship-oriented LS, which may have an adverse effect on OP improvement.

IV.1. Introduction

Over the past decade, a new wave of digitalisation has spread in the manufacturing sector. This phenomenon is referred to as digital manufacturing or Industry 4.0 (I4.0), among others (Culot et al., 2020). As firms engage with this technology-driven change, they usually combine augmented techniques of e-business (e.g. enterprise resource planning, customer relationship management) with advanced technological solutions (e.g. IoT, 3D printing, cloud, artificial intelligence, big data analytics) (Frank et al., 2019).

To realise the potential benefits of digitalisation, firms must approach it as a complex organisational phenomenon (Erboz et al., 2022) that combines both technical and socio elements of organisations. This implies that digital transformation (DT) extends beyond the "pure" adaptation of technological solutions. It also encompasses the elaboration of digital strategy (Gill and VanBoskirk, 2016; Matt et al., 2015), adjustments to the organisational structure and knowledge (Karippur and Balaramachandran, 2022) and changes in cultural traits Ivan et al., 2019; Gill and VanBoskirk, 2016).

Experience related to previous Operation Management's (OM) socio-technical paradigms (e.g. Advanced Manufacturing Technology (AMT), lean production, Total Quality Management (TQM)) has demonstrated that leadership has a critical role in these complex organisational transformations (Beer, 2003). However, studies on previous OM paradigms do not converge towards a clear pattern of supporting leadership behaviour.

One might posit that the rapid expansion of digitalisation in the manufacturing sector would have motivated lively debates on the interplay among leadership (styles) (LSs), DT and operational performance (OP) improvements. Surprisingly, studies rarely focus on the complex web of these concepts (Tortorella et al., 2023). Furthermore, the empirically supported knowledge base on the interplay is incomplete and fragmented. It clearly limits the effective interventions of firms.

Findings on the influence of leadership on DT conclude that leadership fosters DT. It is also highlighted that managers could exhibit traits and behaviours resembling different LSs (Imran et al., 2021; Akçay Kasapoglu, 2018). However, these studies rarely rely on well-established LSs concepts. To propose viable perspectives on the effective deployment of DT, our study distinguishes task-oriented and relationship-oriented LSs. It is a widely used differentiation in leadership studies (Katz et al., 1950; Fiedler, 1971, 1978) with a footprint in the OM context (van Dun et al., 2017).

Works on performance implications of DT or leadership are mature, but multi-focused. In the OM stream, studies on the performance implications of DT are dominated by OP improvements (Szász et al., 2021) and less emphasis is given to financial measures (Alkaraan et al., 2022). Literature on leadership is dominated by detailing improvements in soft measures (primarily on the individual and team levels) and business performance indicators (Berman et al., 2020). Our work integrates these fragmented orientations at the OP improvements level.

Although, the complex web of links between LSs, DT and performance outcomes is seldom addressed, a common point is that both DT and performance could be influenced by leadership (Dubey et al., 2020; Imran et al., 2021). However, studies rely on different assumptions regarding the "driver" factor in the interplay. For example, authors claim either moderator role of LSs (Tortorella et al., 2023) or mediator role of DT

(Dubey at el., 2020).

Our empirical study expands current knowledge on the role of leadership in DT. We approach leadership via LSs and assume that it is a key driver of organisations' digital transformations. Relying on the elaborated research question, our main objective is to identify the direct and indirect impacts of LSs on OP improvements via DT:

RQ: How does DT mediate the relationship between LSs and OP improvements?

The paper is structured as follows. In the literature review section, we introduce the task-oriented and relationship-oriented LSs. Subsequently, a multi-pillar approach of DT is described. As the research model is developed, three main hypotheses are formulated. The methodological section starts with the operationalisation and proceeds with explanatory analyses resulting in the elaboration of sub-hypotheses. The result section summarises the analysis of manufacturing firms' data. After discussing the revealed patterns of perceived effective LSs in DT, our work is concluded with a discussion of future research and managerial implications.

IV.2. Literature review

IV.2.1. Leadership styles

LS defines a distinct pattern of skills, capabilities and behaviours that managers apply to influence their subordinates in order to achieve organisational goals (Weber et al., 2022). Researchers typically differentiate a few distinct, and in some cases extreme, patterns in their leadership models such as transactional and transformational leadership styles (Rousseau, 1995; Bass, 1990), relationship- and task-oriented LSs (Katz et al., 1950; Fiedler, 1971, 1978) democratic- and autocratic LSs (White & Lippitt, 1960) or situational leadership (Hersey & Blanchard, 1977).

The contingency approach of leadership asserts (Fiedler, 1978) that LS needs to be aligned with the desired organisational trajectory. For instance, task-oriented leaders utilise top-down communication and provide clear instructions on how to complete the requisite tasks (Fiedler, 1971). They emphasise short-term planning, personnel efficiency, role and objective clarification and performance monitoring (Mikkelson et al., 2019). Relationship-oriented leaders are employee-focused, provide social and emotional support and offer unique attention to their employees (Fiedler, 1971). Such leaders focus on empowering, supporting and motivating followers (Ardi et al., 2020). Their goal is to foster trust, commitment, motivation, collaboration and cohesion within teams

(Mikkelson et al., 2019).

As the effectiveness of leadership is considered, studies typically examine the individual (Hater and Bass, 1998) and team level (performance) implications (Imran et al., 2021), concluding that collective performance will be greater when they work under a relationship- oriented leader (Jung and Avolio, 2017). Different levels of performance are also discussed. For example, relationship-orientation positively impacts OP indicators like flexibility, quality, cost and delivery (Tay and Low, 2017) or task-oriented leadership has positive influence on financial performance (He et al., 2023). In general, OP implications of leadership attract less academic attention (Tortorella et al., 2023).

This study examines the effects of task-oriented and relationship-oriented LSs. Our scales are consistent with those employed in other studies (Tortorella et al., 2023; van Dun et al., 2017).

IV.2.2. Key pillars of digital transformation

Successful transformation requires firms to approach DT as a complex organisational phenomenon. In addition to (1) technological developments, digitalisation's organisation-wide changes are marked by (2) digital strategy, (3) organisational resources and structure and (4) corporate culture.

IV.2.2.1. Technology

While firms strive to keep pace with the ever-evolving technological landscape, they need to achieve a balance between exploration and exploitation (Kane et al., 2017; Karippur and Balaramachandran, 2022). Path dependency theory (Teece et al., 1997) or the concept of absorptive capacity (Zahra and George, 2002) posits that firm's current exploitation of technology determines the basis for further advancements. When looking for novel solutions, the exploration of technology helps to reconcile external and internal resources (Csiki et al., 2023). Benchmarking competitors, lead firms and buyers are key aspects of such explorations (Gill and VanBoskirk, 2016). The practical consequence of this balancing effort is that firms eventually combine traditional e-business solutions with recent technological innovations (Frank et al., 2019).

IV.2.2.2. Digital strategy

A digital strategy, aligned with business strategy, is crucial from the early stages of DT (Matt et al., 2015). The digital strategy provides clear directions and defines quantifiable goals (Karippur and Balaramachandran, 2022) that guide individual and team efforts (Alshehab et al., 2022). Elaboration of digital strategy is also a signal of competent management. Its elaboration must be followed by execution (Gill and VanBoskirk, 2016; Heini and Heikki, 2015) which is monitored throughout the DT. Finally, experience gained during the roll-out phase influences strategy renewal (Karippur and Balaramachandran, 2022; Tortorella et al., 2023).

IV.2.2.3. Organisational resources and structure

Once the direction is defined by the strategy, it is assumed that firms possess the necessary financial resources (Ghobakhloo and Iranmanesh, 2021). In this setting, knowledge accumulation and structural adjustments are further prerequisites of the exploitation of technological knowledge and capabilities (Alshehab et al., 2022; Heini and Heikki, 2015). Individuals supporting DT in terms of technological expertise should come from the most capable organisational units (Akçay Kasapoglu, 2018). Their presence, together with the assignment of formal roles and the provision of training (and new recruitments), ensures that the necessary digital skills are pervading the organisation (Alshehab et al., 2022; Ivan et al., 2019; Karippur and Balaramachandran, 2022).

IV.2.2.4. Culture

A firm cultivating DT reconciles top-down (e.g. supportive management attitude) and bottom-up (e.g. employee involvement and idea generation) directions of cultural development (Karippur and Balaramachandran, 2022). Key actions such as internal and external communication of the digital vision (Karippur and Balaramachandran, 2022; Gill and VanBoskirk, 2016), education and trainings at all levels (Akçay Kasapoglu, 2018; Tay and Low, 2017), managing beliefs related to risk-taking and willingness to take responsibility (Akçay Kasapoglu, 2018) support cultural shift (He et al., 2023).

One concludes that these pillars of DT are interdependent, e.g. lack of financial resources constrains digital skill development and hence slow down the digital journey; digital strategy influences effective exploration of new technological solutions etc. Therefore, our research relies on a comprehensive assessment of DT (Szukits, 2022).

IV.2.3. Operational performance

Manufacturing and competitive strategies play a pivotal role in determining how well a company operates and competes in the market (Amoako-Gyampah & Acquaah, 2008).

To achieve strategic goals, OP is a critical aspect of a firm's overall performance with outcomes including cost, reliability, flexibility and services, speed, dependability and quality (Slack et al., 2010). The positive impact of digital technologies on various OP measures has been widely documented (López-Gómez et al., 2018). To grasp a comprehensive assessment of OP implications, we adapted the OP dimension of the firm competitiveness index (Chikán et al., 2022).

IV.2.4. The relationship between leadership styles, digital transformation and operational performance

A limited number of studies investigate the relationship between (leadership) LSs, DT and performance (improvements) (Table 1). These works indicate several vague spots that limit the drawing of practical and specific conclusions.

In relation to DT, some authors adopt a technology-oriented operationalisation (Dubey et al., 2020; He et al., 2023; Imran et al., 2021), whereas others emphasise a comprehensive approach (Berman et al., 2020; Tortorella et al., 2023). Regarding performance implications, authors favour financial indicators (Berman et al., 2020; Dubey et al., 2020; He et al., 2023) and less attention is devoted to traditional OP indicators (Tortorella et al., 2023). Finally, studies describe leadership by different pools of attributes, traits and behaviours. As consistent conceptualisation of leadership is concerned, only entrepreneurial leadership (Dubey et al., 2020; Wu et al., 2021) and the polarised structure of task- and relationship-oriented LSs (Tortorella et al., 2023) appear.

Different assumptions permeate the interplay of concepts. Leadership is either identified as a direct driver of DT and performance (Dubey et al., 2020; Imran et al., 2021; Wu et al., 2021) or as an internal factor inseparable from DT (He et al., 2023; Imran et al., 2021) or as a moderator (Tortorella et al., 2023). Therefore, the role of DT differs also considerably: it is a context (Berman et al., 2020), a mediator (Dubey et al., 2020) or a moderator of mediated influence (Wu et al., 2021).

Studies represent a wide variety of methodological approaches. Relationships are examined by single and multiple cases (Imran et al., 2021; Tay and Low, 2017), single country and international survey-based research (Dubey et al., 2020; He et al., 2023; Tortorella et al., 2023). Narratives reflect the opinions of different managerial levels and even incorporate employee perceptions. Only two studies focused on a larger sample of manufacturing companies (Dubey et al., 2020; Tortorella et al., 2023). Furthermore, some works fall into the category of anecdotal evidence (Berman et al., 2020).

Our review revealed different interpretations of concepts and pointed out their different roles in the interplay. However, conclusions do converge: leadership plays a crucial role as it could enhance both DT and performance. Although, the positive performance implication narrative dominates both in financial (Dubey et al., 2020; Wu et al., 2021; Berman et al., 2020) or operational measures, a recent study claims that relationship-orientation could have a negative moderating influence (Tortorella et al., 2023).

Table 11: Summary of papers on leadership traits and behaviour, digital transformation, and performance outcomes

Authors	**Sample**	**Country**	**Study objective**	**Leadership styles, leadership attributes, behaviours, skills**		**Digital transformation**		**Performance outcomes**	**Research method(s)**	**Results**
				Description	**Role in the interplay**	**Description**	**Role in the interplay**			
(Berman et al., 2020)	1500 managers (incl. 750 Chief Digital Officers (CDOs))	23 countries	Examines the tasks, skills and behaviour of CDOs and how it contributes to financial performance	CDOs think and act strategically, contributes digital strategy, nurture culture, manage budget; cooperate and monitor; approach digitalisation as an evolutionary process	Influences performance directly	The organisation has launched or is planning to launch a highly strategic, enterprise-wide, cross-functional digital transformation program	Context	Financial performance: Return on Investment (ROI)	Mixed method: surveys and regressions and in-depth interviews	The presence of a CDO does appear to indicate a positive impact on an organisation's ROI of their digital investment; CDOs' background in business (strategy) is correlated to improved financial performance
(Dubey et al., 2020)	256 manufacturing firms	India	Develop and test a model that describes the role of EO on the adoption of BDA powered by AI and OP	Entrepreneurial orientation (EO): innovativeness, pro-activeness, risk taking	Influences DT and performance directly	Technologies (big data analytics (BDA) powered by artificial intelligence (AI)	Mediates the link between DT and performance	Financial performance: revenue growth, market share, ROI, cash flow, NPD, ROC employed, profit-to-revenue ratio	Cross-sectional survey, PLS SEM analysis	Leadership contributes to higher level of digitalisation and improves OP
(He et al., 2023)	474 employees from service firms	United States	Explores the relationship between DT, organisational resilience (OR) and consequences on organisation and employees and performance	Transformation management intensity (TMI): transformative and shared vision of DT, participation, culture change, digital skills development, coordinated initiatives, clear roles, unified KPI for digital initiatives, IT contribution	Interacts with DT; no direct influence on performance	Digital intensity: digital technologies and channels, automated processes, system integration, analytics, support customers, processes, and performance	Interacts with TMI, no direct influence on performance	Financial performance: profitability, ROI, sales growth	Structural equation modelling (SEM)	TMI and DI have indirect influence on financial performance via individual contribution and systematic control
(Imran et al., 2021)	4 global industrial companies	European Nordic countries	Explores enablers and performance outcomes of digital transformation	Leadership areas: 1) awareness, collaboration, driving digital change and culture,	Interacts with DT, influences performance directly	Technical system (implementation of digital technologies)	Interacts with leadership, no direct influence on	Agility, customer centricity, collaboration	Multiple case study, in-depth interviews	Leadership, organisational structure and culture are the key enablers of DT. These

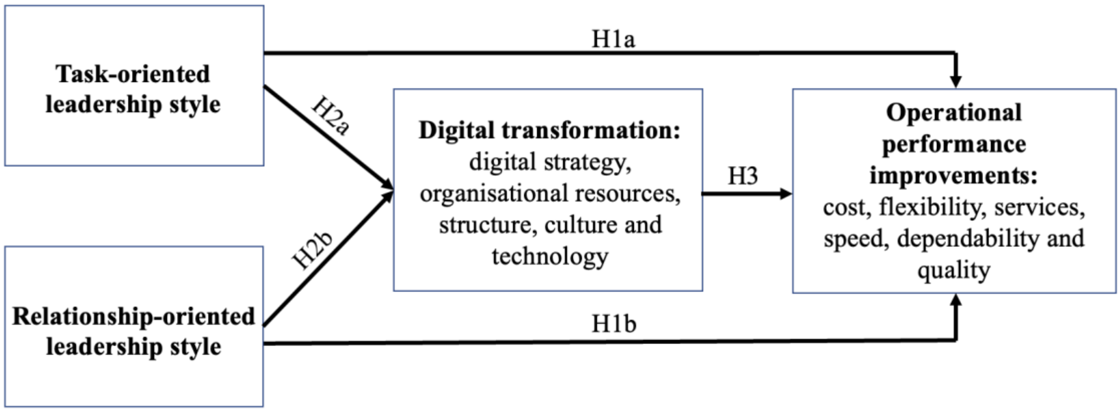
				leading by example, mentoring/ coaching-style leadership, transparency, value-driven; 2) adaptability, the right attitude, communication skills, data-driven decision-making, empowerment, failing fast, experimentation, open-mindedness, risk-taking, trust, surface-level technical knowledge and vision			performance			enablers lead to increased performance outcomes.
(Tortorella et al., 2023)	189 manufacturing firms	India and Brasil	Examine the moderating role of LSs on the relationship between I4.0 maturity and OP	Task-oriented, relations-oriented and change-oriented LSs	Moderates the link between DT and performance	Strategy, employee and culture, technology	Influences performance directly	OP: productivity, quality, delivery, inventory, safety	Multivariate data techniques	Task-oriented LS positively moderates the relationship between digitalisation and OP. The moderating effects of relations-oriented and change-oriented LSs were negative.
(Wu et al., 2021)	73 CEOs + 377 middle managers	China	Explores the relationships among entrepreneurial leadership, ambidextrous learning and organisational performance in DT	Entrepreneurial leadership: innovativeness, support, ability to flexibly change the environment and credibility	influences learning and no direct influence on performance	A firm-level organisational change that signifies the disruptive implications of digital technology for businesses	Moderates the mediator role of learning between leadership and performance; no direct influence on performance	Organisational performance: financial performance: growth of sales revenue, profitability, operational cost efficiency, growth of market share	Questionnaire analysed with hierarchical linear regression	Digital context moderates the mediation effect of ambidextrous learning between entrepreneurial leadership and organisational performance

Source: Authors' work, 2024

IV.3. Conceptual research model and hypothesis

Our work aims to solve the shortcomings of the current literature. First, we distinguish LSs on a conceptual basis, approach DT in a comprehensive manner and focus on textbook-wise OP measures most probably influenced by DT in manufacturing firms. Second, we target the top decision-maker of manufacturing firms and assume that his/her perception has the greatest influence on the effective deployment of DT. Our research model is presented in Figure 16.

Figure 16: The research model



Source: Authors' work, 2024

The following sections elaborate on the three main hypotheses of our research.

IV.3.1. Leadership styles and operational performance improvements

Task-oriented leadership contributes to OP improvements through clear goals, close monitoring, efficient resource allocation, promoting clarity, efficiency, accountability, continuous enhancement of processes and resource management (Fiedler, 1978; Hersey et al., 1979). Empirical evidence on DT underscores that traits related to task-oriented LS such as clear top-down communication and the ability to flexible change bring cost savings and higher quality (Tay and Low, 2017; Wu et al., 2021) and pave the way to productivity, delivery and safety (Tortorella et al., 2023).

Traits resonating with relationship-oriented LS such as people orientation, adaptability, proactiveness and long-term orientation typically support quality orientation and cost- effective operations (Imran et al., 2021) during DT. A similar pool of behaviour such as an emphasis on support, information sharing and relationship management also facilitate DT, which in turn leads to cost saving, better quality and faster information delivery (Tay and Low, 2017). Finally, innovativeness and risk-taking attitudes are associated with improved performance outcomes (Dubey et al., 2020; Berman et al., 2020).

It is postulated that managers with both task-oriented and relations-oriented LSs may facilitate a positive impact on OP improvements.

H1a: Task-oriented LS positively influences the improvement of OP.

H1b: Relationship-oriented LS positively influences the improvement of OP.

IV.3.2. Leadership styles and digital transformation

Task-oriented leaders believe in top-down communication, goal setting and clear instructions, efficient monitoring processes and personnel efficiency (Fiedler, 1971; Mikkelson et al., 2019). These factors can shape both development and execution of DT. For example, He et al. (2023) highlight that clear vision and top-down governance positively affect DT. Regarding the process level, timely information sharing, reporting (Tay and Low, 2017) and data-driven approach facilitate DT (Imran et al., 2021). Finally, task completion monitoring contributes to the desired outcome of the transformation (Kretschmer and Khashabi, 2020).

Relationship-oriented style can also have a positive influence on DT, albeit through a different modus operandi. These leaders are more employee-focused, provide emotional support and motivation, prioritise cooperation and put more emphasis on cultural alignment (Ardi et al., 2020; Fiedler, 1971; Mikkelson et al., 2019). Several papers conclude that to engage in a successful DT, leaders should disseminate awareness of DT topics (He et al., 2023) and nurture cultural change (Berman et al., 2020). Focus on employees can be seen when leaders promote empowerment and mentoring/coaching (Imran et al., 2021). In addition, they favour pro-activeness (Dubey et al., 2020) and credibility (Wu et al., 2021) instead of interventions (Tay & Low, 2017) during DT. To reach the desired goals of DT, they lead digital change by example (Imran et al., 2021) and value coordination of initiatives (Berman et al., 2020; He et al., 2023)

Based on these arguments, we assume that the influence of LSs on DT is positive:

H2a: Task-oriented LS contributes positively to DT.

H2b: Relationship-oriented LS contribute positively to DT.

IV.3.3. Digital transformation and operational performance improvements

Manufacturing firms embark on their digital journey with the expectation of improvements in all dimensions of the triple bottom line (Felsberger et al., 2020). Studies examining different "layers" (e.g. projects, applications, firm level) of digitalisation in a manufacturing context yielded similar results. Quality improvement and better inventory management are the primary means of improving perceived cost efficiency (López-Gómez et al., 2018). DT significantly enhances OP by enabling greater efficiency, flexibility and integration (Akçay Kasapoglu, 2018; Imran et al., 2021). By adopting advanced technologies and innovative processes enables companies to achieve cost savings, improved quality and faster information delivery (Tay and Low, 2017). Firms'

DT can improve firms' operating flexibility enabling quicker response (Tian et al., 2022). To summarise, DT can have a profound positive impact on OP.

H3: The DT positively influences improvements in OP.

IV.4. Research methodology

IV.4.1. The survey and the sample

Our research draws upon the survey data of the Competitiveness Research Center at Corvinus University of Budapest. The sampling frame was derived from the Hungarian Statistical Office's enterprise database, which contained 4,295 domestic firms. The sample was stratified according to size (50–99, 100–249 and > 250 employees), industries and regional dimensions. Data collection was completed in July 2019. Altogether, 2,062 firms were approached, and 234 companies completed the questionnaires. The financial data of sample companies was obtained from Bisnode, a financial service firm. After data cleaning, the final sample comprised 209 companies, 113 of them represented the manufacturing sector.

The survey programme utilises five distinct questionnaires. A general questionnaire, completed by the CEO, encompasses the primary characteristics of the company, institutional context and items of performance measures organised into a firm competitiveness index (FCI) (Chikán et al., 2022). The CEO questionnaire addresses topics pertaining to strategy, organisational structure and human resources. It was also completed by the CEO. Three questionnaires are linked to functional areas namely production (production manager), trade/marketing (sales/marketing manager) and finance (financial manager). The dependent and independent variables were in different questionnaires, thus ensuring a level of methodological and psychological separation (Craighead et al., 2011).

Our research sample comprises 94 manufacturing firms of the 113 due to missing data at the construct level. A 50% threshold limit was set for missing data in each construct. In the final sample (N = 94), there were 16 large (>250 employees) and 78 middle-sized firms (50–249 employees). The size and industry categories of the final sample accurately represent the national economy (Szukits, 2022). The nonresponse bias (Armstrong and Overton, 1977) was tested by comparing the variable means of the first and the last registered thirty responses via a t-test. At the 1% significance level, no differences were confirmed.

IV.4.2. Research techniques

To explore the data, we employed partial least squares structural equation modelling (PLS- SEM) analysis (Hair et al., 2017). Within the SEM family of methods PLS aims to maximise explained variance and is one of the most widely used methods (Hair et al., 2019). PLS-SEM does not require a normal distribution of manifest variables and can be used with relatively small samples (Hair et al., 2019; Henseler et al., 2009). The sample size of 94 companies and a significance level of 5% permit the model to have 5–10 inner or outer model links pointing at any latent variable, depending on effect sizes (Cohen, 1992) which limit we did not exceed. Additionally, the post hoc power analysis (Faul et al., 2008) indicates that, given our N = 94 sample size at a 5% statistical significance level the power of the analysis is 0.919, which is acceptable.

The PLS-SEM algorithm initially estimates the latent variables as linear combinations of the manifest variables. Subsequently, the structural equations describing the relationships between the latent variables are estimated (Hair et al., 2022). Our model comprises eight latent variables measured in a reflective manner, based on 29 manifest variables (Table 2). While some researchers suggest that a latent variable should be calculated based on a minimum of three variables (Sarstedt et al., 2020), others conclude that even one or two indicators are sufficient (Hayduk and Littvay, 2012). In our model three of the latent variables are expressed via two manifest variables, while the other five latent constructs are based on three to seven indicators. The PLS algorithm is iterative, estimating the parameters of the model by repeating a fixed number of times up to a target value. The SmartPLS 4 software (Ringle et al., 2022) was used to run the model with 1,000 iterations (Hair et al., 2019).

IV.4.3. Measures

In our confirmatory analysis we differentiated task-oriented and relationship-oriented LSs which is a common distinction in management (Northouse, 2021) and even in OM (van Dun et al., 2017). DT framework (Szukits, 2022) is derived from the works of Kane et al. (2017), Gill and VanBoskirk (2016) and a research report (IWI-HSG and Crosswalk AG, 2015). Finally, we assessed performance improvements based on the firm competitiveness index' (Chikán et al., 2022) OP dimension. Table 12 summarises our main concepts and the corresponding manifest variables.

IV.5. Data analysis and results

IV.5.1. The measurement model

We assessed reliability and validity with several tests. As shown in Table 12, factor loadings are all above 0.5 and most above 0.7. Cronbach's α and Composite Reliability (CR) coefficients were employed to assess the reliability of the model and for all latent variables they are above or close to the minimum value of 0.7. The AVE values, employed as an indicator of convergent validity, are all above the minimum threshold of 0.5.

Table 12: Descriptive statistics, factor loadings and tests

Measurement of main concepts	Latent variable	Manifest variable	Mean	Factor loadings	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Digital transformation To what extent does the following statement apply to your company? 1 – not at all 3 – medium 5 – fully	**Digital strategy**	The management of our organisation has clearly defined the digital business strategy of the organisation.	3.936	0.935	0.875	0.884	0.941	0.888
		Corporate management understands the digital challenges and opportunities facing the company.	3.404	0.950				
	Digital organisation and technology	We have allocated adequate financial resources to plan and implement the digital business transformation.	3.553	0.894	0.965	0.965	0.971	0.825
		Our organisation has the technological knowledge and skills for the DT.	3.532	0.893				
		In our organisation, we can come up with and embrace digitisation by bottom-up ideas.	3.543	0.924				
		We can quickly adjust our digital solutions to meet business challenges.	3.404	0.900				
		We are willing to take risks compared to our current practice by introducing innovative digital solutions.	3.628	0.928				
		We monitor cutting-edge digital solutions in our industry.	3.585	0.897				
		We are consciously testing new digital technologies to investigate their applicability.	3.415	0.921				
LS How important do you think the following patterns of behaviour and thinking are for an ideal leader? 1 – not at all 3 – medium 5 – very typical	**Relationship-oriented LS**	Leader communicates goals clearly and convincingly, jointly discusses tasks and entrusts implementation to colleagues, who can turn to him/her, if they feel the need.	4.223	0.696	0.825	0.829	0.877	0.589
		Key performance indicators (KPI) are only part of the leadership toolkit, it is necessary that leaders and employees feel that the goals are their own.	3.851	0.762				
		The task of the leader is to make the goals personal, to set an example and to mobilize the organisation in the direction of their implementation.	4.106	0.758				
		The leader's duties include emotional and professional support and development of the colleagues.	3.947	0.796				

		Building trust is an important leadership task because it is the way to achieve innovative solutions	4.011	0.818				
	Task-oriented LS	Key performance indicators (KPIs) convey the agreed goals to leaders and subordinates.	3.372	0.727	0.743	0.752	0.855	0.664
		The leader's tasks are largely aimed at ensuring that his/her colleagues perform their tasks as best as possible.	3.915	0.831				
		Because of the great responsibility in the work organisation, trust is based on control and follow-up.	3.830	0.878				
OP Our performance, compared to our competitors, between 2016 and 2018 in the selected dimension was 1 – much worse 3 – about the same 5 – much better	**Cost improvement**	Cost effectiveness	3.617	0.887	0.694	0.698	0.867	0.765
		Competitive prices	3.606	0.862				
	Quality and delivery	Product/service quality	3.851	0.847	0.802	0.846	0.865	0.618
		Quality of manufacturing activity	3.766	0.831				
		Quality of materials	3.596	0.762				
		Delivery time/service time	3.755	0.695				
	Flexible servicing	Flexibility of the logistics system	3.819	0.601	0.779	0.809	0.848	0.587
		Product/ service assortment	3.809	0.764				
		Quality of production/customer service	3.936	0.827				
		Organisation of distribution channels	3.745	0.849				

Notes: All items are measured on a 1-5 Likert scale and represent the perception of the CEO.

Source: Authors' work, 2024

The Fornell and Larcker (1981) criterion that AVE values should exceed the covariance between the latent variables is met considering most constructs. Although the AVE value for task-oriented LS (0.664) is very close to the covariance between the two LSs (0.666), the cross-loading values concerning these two latent constructs provide compelling evidence for discriminant validity. Furthermore, confirming healthy discriminant validity, all HTMT (Heterotrait-monotrait ratio) values are under the cut-off of 0.9. In conclusion, the outer structural model is sound from a reliability and validity perspective.

Confirmatory analyses indicate that the two LSs proposed are relevant. Regarding DT, we distinguish between two constructs. The "digital strategy" construct covers environment analysis and elaboration of formal digital strategy. The other digital construct combines organisational, cultural and technological elements, named as "digital organisation and technology".

In the case of performance improvements, our results confirm the validity of three operations-related constructs: "cost improvement", "quality and delivery" and "flexible servicing".

Building upon the aforementioned constructs, sub-hypotheses were developed (Table 13). As for H1 (LSs → OP), we compiled three sub-hypotheses for each performance construct in relation to each LS. Regarding H2 (LSs → DT), our four sub-hypotheses assume links between two LSs and two DT constructs. In H3 (DT → OP), we examine six sub-hypotheses on the links between the two DT and three OP constructs.

Table 13: Sub-hypotheses elaboration

Core concepts and their link	Main hypotheses	Sub-hypotheses
LSs → OP	*H1a: Task-oriented LS positively influences the improvement of OP.*	H1aa: *Task-oriented LS positively influences the improvement of cost improvement.*
		H1ab: *Task-oriented LS positively influences the improvement of flexible servicing.*
		H1ac: *Task-oriented LS positively influences the improvement of quality and delivery.*
	H1b: Relationship-oriented LS positively influences the improvement of OP.	H1ba: *Relationship-oriented LS positively influences the improvement of cost improvement.*
		H1bb: *Relationship-oriented LS positively influences the improvement of flexible servicing.*
		H1bc: *Relationship-oriented LS positively influences the improvement of quality and delivery.*
LSs → DT	*H2a: Task-oriented LS contributes positively to DT.*	H2aa: *Task-oriented LS contributes positively to digital strategy.*
		H2ab: *Task-oriented LS contributes positively to digital organisation and technology.*
	H2b: Relationship-oriented LS contributes positively to DT.	H2ba: *Relationship-oriented LS contributes positively to digital strategy.*
		H2bb: *Relationship-oriented LS contributes positively to digital organisation and technology.*
DT → OP	*H3: The digital transformation positively influences improvements in OP.*	H3a: *The digital strategy positively influences the improvement of cost improvement.*
		H3b: *The digital strategy positively influences the improvement of flexible servicing.*
		H3c: *The digital strategy positively influences the improvement of quality and delivery.*
		H3d: *The digital organisation and technology positively influences the improvement of cost improvement.*
		H3e: *The digital organisation and technology positively influences the improvement of flexible servicing.*
		H3f: *The digital organisation and technology positively influences the improvement of quality and delivery.*
DT	H4: *The digital strategy positively influences digital organisation and technology.*	-

Source: Authors' work, 2024

Finally, the explorative analysis of DT led to the conclusion that digital strategy is a prerequisite for the execution of initiatives (H4) (Hess *et al.*, 2016).

IV.5.2. The structural model

The R^2 values (Table 14) of the dependent variables – reflecting the predictive accuracy of the model – vary between 0.098 and 0.656, meaning that 9.8% – 65.6% of the variance of these constructs can be explained by the model. The explanatory power concerning the focal dependent constructs are considered significant in this research field and among the circumstances of the model.

Table 14: Explanatory power of the model (R^2)

	R^2	**R^2 adjusted**
Cost improvement	0.255	0.222
Digital strategy	0.381	0.367
Digital organisation and technology	0.656	0.645
Flexible servicing	0.203	0.168
Quality and delivery	0.098	0.058

Source: Authors' work, 2024

Bootstrapping has been employed to assess the path coefficients (see Figure 17 and Table 15).

Regarding other model fit measures, SRMR is below the generally accepted upper limit of 0.1 (and equal to the more conservative one, see also (Hu & Bentler, 1998) with a value of 0.080, while the d-G measure demonstrates good model fit, as the upper bound of the 95% confidence interval = 1.342 is larger than the original value of the d_G = 1.193 (Dijkstra & Henseler, 2015).

IV.5.3. Research question and hypothesis evaluation

Regarding H1, task-oriented LS does not have a direct effect on OP improvements (H1aa, H1ab and H1ac are not supported). However, relationship-oriented LS exerts weak yet statistically significant ($p < 0.05$) negative influence on OP constructs like quality and delivery and cost improvement ($f^2 = 0.079$ and 0.107 respectively) (H1ba, H1bb and H1bc are not supported). In conclusion, LSs do not exert a direct positive influence on OP (H1a and H1b are not supported).

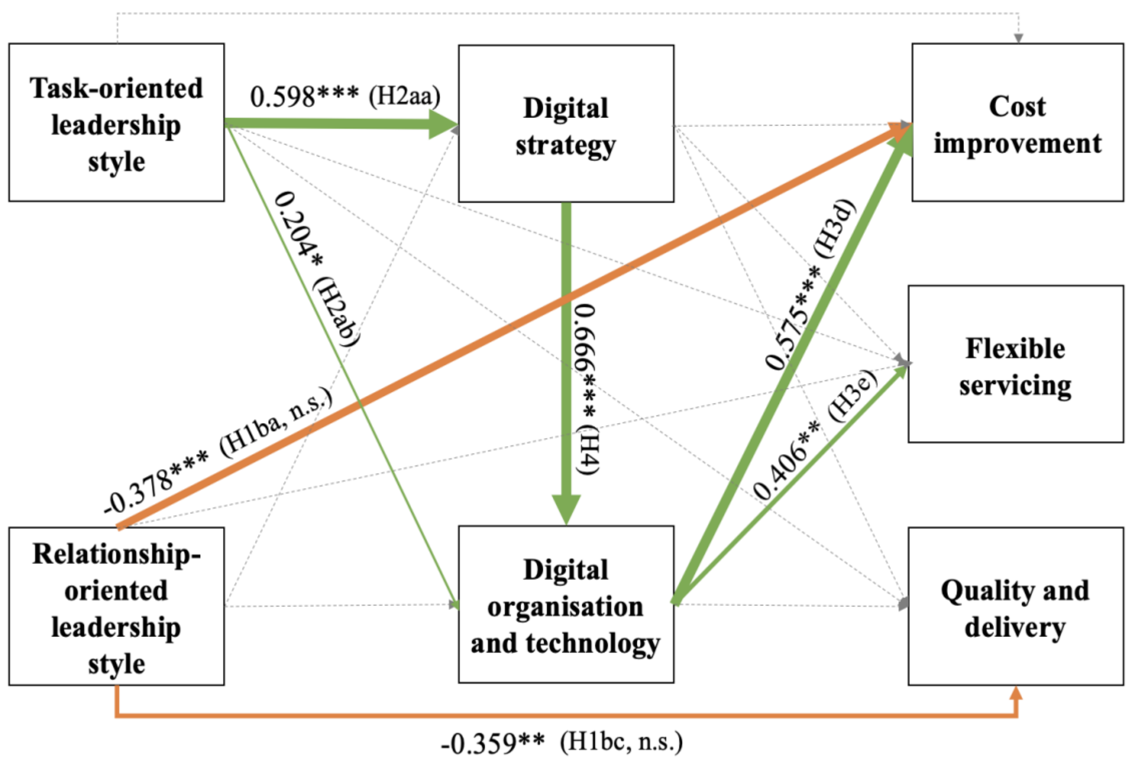
As for H2, task-oriented LS has a significant direct impact on digital strategy with a medium-level positive effect ($\beta = 0.598$, $p = 0.000$, $f^2 = 0.321$) (H2aa is supported). Furthermore, it exerts a direct positive influence on digital organisation and technology ($\beta = 204$, $p = 0.061$, $f^2 = 0.051$). This p-value (0.061) with our sample size indicates that

H2ab may also be supported. Relationship-oriented LS exerts no significant influence on DT (H2ba and H2ab are not supported). The study highlights the pivotal role of task-oriented LS in DT (H2a is supported) and finds no evidence for the influence of relationship-oriented LS in DT (H2b is not supported).

Looking at H3 while digital strategy does not directly influence any of the three OP improvement constructs (H3a, H3b and H3c are not supported), digital organisation and technology have a significant positive effect on cost improvement ($\beta = 0.575$, $p = 0.000$, $f^2 = 0.153$, H3d is supported) and flexible servicing ($\beta = 0.406$, $p = 0.038$, $f^2 = 0.071$, H3e is supported). However, quality and delivery construct is unaffected (H3f is not supported). Altogether, digital organisation and technology are the only construct of DT with a direct positive effect on OP.

While testing H4, digital strategy exerts a strong positive effect on digital organisation and technology ($\beta = 0.666$, $p = 0.000$, f2 = 0.798, H4 is supported). It indicates that digital strategy can also exert an indirect influence on certain OP measures through its positive impact on digital organisation and technology.

Figure 17: Research model and PLS path coefficients



Note(s): Path coefficients displayed above the arrows; significant path and related sub-hypothesis is supported (*p < 0.1; **p < 0.05; ***p < 0.01) (green path); n.s. – significant path, but sub-hypothesis is not supported (orange path); dashed grey arrows: non-significant paths

Source: Authors' work, 2024

Table 15: Structural model (direct effects) and hypotheses testing

Hypotheses and sub-hypotheses		**Supported (Y)/ not supported (N)**	**Direct effects**	**Path coefficient**	**Bootstrapping sample mean**	**Bootstrapping standard deviation**	**T statistics**	**p values**	**Result**
H1a: Task-oriented LS positively influences the improvement of OP.	H1aa	N	Task-oriented LS -> Cost improvement	0.044	0.047	0.153	0.287	0.774	not supported
	H1ab	N	Task-oriented LS -> Flexible servicing	0.110	0.111	0.144	0.764	0.445	
	H1ac	N	Task-oriented LS -> Quality and delivery	0.111	0.123	0.186	0.599	0.549	
H1b: Relationship-oriented LS positively influences the improvement of OP.	H1ba	N	Relationship-oriented LS -> Cost improvement	-0.378	-0.382	0.117	3.236	0.001	not supported (Relationship-oriented LS has a negative influence)
	H1bb	N	Relationship-oriented LS -> Flexible servicing	-0.185	-0.189	0.146	1.270	0.205	
	H1bc	N	Relationship-oriented LS -> Quality and delivery	-0.359	-0.367	0.143	2.506	0.012	
H2a: Task-oriented LS contributes positively to DT.	H2aa	Y	Task-oriented LS -> Digital strategy	0.598	0.591	0.117	5.113	0.000	supported
	H2ab	Y	Task-oriented LS -> digital transformation organisation and technology	0.204	0.204	0.109	1.873	0.061	
H2b: Relationship-oriented LS contributes positively to DT.	H2ba	N	Relationship-oriented LS -> Digital strategy	0.029	0.046	0.121	0.240	0.810	not supported
	H2bb	N	Relationship-oriented LS -> digital transformation organisation and technology	0.004	0.004	0.084	0.051	0.959	
H3: The digital transformation positively influences improvements in OP.	H3a	N	Digital strategy -> Cost improvement	-0.079	-0.081	0.162	0.488	0.626	not supported
	H3b	N	Digital strategy -> Flexible servicing	0.042	0.049	0.200	0.211	0.833	
	H3c	N	Digital strategy -> Quality and delivery	-0.139	-0.146	0.250	0.559	0.577	
	H3d	Y	DT organisation and technology ->	0.575	0.588	0.152	3.789	0.000	partially supported

			Cost improvement						
	H3e	Y	DT organisation and technology -> Flexible servicing	0.406	0.415	0.195	2.082	0.038	
	H3f	N	DT organisation and technology -> Quality and delivery	0.265	0.264	0.235	1.128	0.260	
H4: The digital strategy positively influences digital organisation and technology.	H4	Y	Digital strategy -> Digital organisation and technology	0.666	0.668	0.077	8.700	0.000	supported

Source: Authors' work, 2024

The results indicate that while a direct positive effect from LSs to OP improvements is undetectable, task-oriented LS indirectly influences OP improvements via DT. The chain of significant positive effects ($p < 0.05$) appears to originate from task-oriented LS through digital strategy (medium effect $f^2 = 0.321$) to digital organisation and technology (strong effect $f^2 = 0.798$) and finally to OP (cost improvement $f^2 = 0.153$, flexible servicing $f^2 = 0.071$, medium and weak effect). The quality and delivery constructs are not influenced by task-oriented style or by DT. This indirect mechanism of action is not observable concerning the relationship-oriented LS.

IV.6. Discussion

Our research uncovered novel insights on the interplay of LSs, DT and OP improvements. Regarding DT, similarly to Tortorella et al. (2023) and Berman et al. (2020), we confirm that DT is an organisation-wide phenomenon. Although we presented only two main pillars of DT, namely digital strategy and digital organisation and technology, the latter encompasses decisions related to organisation, resources, culture and technology. Our finding implies that digital strategy is a vital and distinct pillar of DT (Matt et al., 2015). As middle-sized firms dominate our final sample, our findings also underline the critical importance of a strategic approach to digitalisation in this size category (Ghobakhloo and Iranmanesh, 2021).

Our study explored the direct influence of leadership on DT. We concluded that task- oriented LS is the sole driver of DT. This is primarily due to its positive influence on digital strategy, but it also has a weak positive impact on organisational and technological aspects. Our work contradicts studies suggesting positive impacts of relationship-oriented traits and behaviours of leaders on DT (Berman et al., 2020; He et al., 2023). The results highlight the importance of goal setting (He et al., 2023), efficient processes (Tay and Low, 2017) and monitoring (Kretschmer and Khashabi, 2020).

Regarding the performance implications of LSs, a leadership paradox is revealed as the two LSs exert different influences on OP improvements. The positive and indirect effects of task- oriented LS via DT on OP improvements are complemented by the negative and direct influence of relationship-oriented LS on OP improvements. So, our work challenges the very positive performance implication narratives of leadership during DT (Berman et al., 2020; Dubey et al., 2020). Our findings are closer to Tortorella et al.'s (2023) results who also emphasised the positive influence of task-orientation and negative effect of relationship- orientation. The main difference is that we proved the direct negative influence of relationship- orientation on performance and found that it has no impact on DT.

Focusing solely on OP improvements, our model revealed a tricky situation in which managers are locked in. In some dimensions, LSs and DT are conflicting.

The tension between the two LSs is most striking in the cost improvement construct, which is of key importance in the region (Chanal et al., 2020). On one hand, the positive influence of DT on cost improvement is supported indirectly by task-oriented LS. DT can reduce labour costs and increase efficiency, leading to significant cost savings and can also provide insight into operational inefficiencies. Task-oriented leadership indirectly supports these improvements by ensuring that processes are optimised, resources are managed efficiently and performance is continuously monitored. On the other hand, relationship-oriented leaders are detached from the strong focus on task completion and cost efficiency. They prioritise building strong interpersonal relationships and team cohesion. While this is beneficial for team morale and collaboration, it has consequences on performance. To some extent, this difference might be linked to the manufacturing context. It is pervaded by strict standards and rules that could favour a task-oriented approach.

Regarding flexible services, our findings underline the positive direct influence of DT and the positive indirect of task-oriented LS. While DT provides the tools for data-driven decision- making, task-oriented leadership ensures that these tools are used effectively to continuously improve processes and adapt services by maintaining a balance between flexibility and operational discipline.

Contrary to the literature (Szász et al., 2021), quality and delivery are not (positively) affected by DT. Moreover, relationship-oriented LS has a negative influence on it. DT involves integrating advanced technologies into business processes, which can be complex and time- consuming. If not managed well, the initial stages of DT can disrupt existing processes, causing delays and affecting quality. In addition, relationship-oriented leaders might allocate resources based on team dynamics rather than on the basis of DT efforts. This can lead to sub- optimal use of resources, affecting both quality and delivery.

Many considerations bridge the revealed contradictions.

For example, different phases of the digital journey might require different approaches from leaders. Our findings could resonate with the challenges of the early phases of DT. At this stage, the primary driver is task-orientated LS that effectively sets directions and goals and monitors them. However, in the long-term managers can achieve more favourable results with relationship-oriented LS traits such as people-orientation or mentoring. Consequently, our findings could signal a limitation for the long-term success of DT because the transition from one LS (task) to another LS (relations) is unlikely at the individual level.

One must also consider the influence of organisational and contextual factors. Januszek et al. (2024) presented different perceptions of an OM paradigm (i.e. lean) between top (e.g. guiding through vision) and middle management (e.g. applying standards and defining tasks) of a large firm. The characteristic of our sample of having many medium-sized companies and the internal focus of DT strengthen the viability of effective task-oriented LS. Additionally, the results may reflect the Hungarian socio-cultural context. Earlier evidence suggests that micromanagement contributes to successful lean deployment in Hungary (Gelei et al., 2015), which indicates that less human-centred managerial behaviour is an enduring contextual characteristic there.

Finally, our findings deviate from previous experience of OM paradigms. For example, works on TQM emphasised skills linked to relationship-oriented LS (Beer, 2003). Later, lean transitions were related to both task-oriented and relationship-oriented traits (Gelei et al., 2015; van Dun et al., 2017). We only underscore the positive influence of task-orientated LS. One might speculate that this evolution from relationship-oriented to task-oriented LS could be associated with the immense nature of the paradigm.

IV.7. Conclusion

Our research design is based on the experience of OM: leadership is the primary initiator of effective deployment of any OM paradigm, among them digitalisation. We explored the interplay among LSs, DT and OP improvements.

Our findings identified two pillars of DT. Digital strategy, as one of the pillars, guides a comprehensive "execution" pillar of digital organisation and technology. Our investigation indicates that "one-fits-all" LS is effective for the deployment of DT. Namely, task-oriented LS is the only potential driver of DT and OP improvements. Furthermore, we urge that managers must consider unique interdependences. The revealed leadership paradox implies a potential offset effect between relationship-oriented LS and task-oriented LS. A striking tension is evident in the cost improvement dimension of OP improvements.

Our study has limitations that offer avenues for future research.

We exclusively focused on measures of OP improvements. However, both LSs and DT could influence other layers of performance (He et al., 2023). To depict a more comprehensive performance implication, future studies could analyse a broader set of indicators including individual- or team-level indicators or financial measures.

The research model was conceptualised on the assumption that LSs are "sticky" in the short run. It is also possible that, on the long run, DT could influence LSs or lead to appointments of new managers with new traits. Further studies, employing alternative methodologies, may also elucidate the direction of causal relations.

The cross-sectional analysis relies on data collected before COVID-19. The pandemic may have provided a significant impetus for numerous companies to adjust managerial attitudes to a more human-centric approach.

Our work relied on confirmatory analysis of extremely different LSs (i.e. task vs relation). Successful deployment of DT might require a mix of traits and ambidextrous behaviours of leaders.

Finally, one should compile an international survey to reveal how the embeddedness of leadership and organisational culture into national culture impacts the examined relations.

Altogether, we speculate that since behavioural and cultural traits alter slowly, our findings could guide efforts of firms engaged with DT in similar socio-cultural context.

CHAPTER V – Conclusion and discussion

My dissertation's key strength is its holistic view and multidisciplinarity. I examined generational differences, attitudes towards digitalisation, digital skills, leadership styles and their interactions in light of companies' operational performance of Hungarian manufacturing SMEs.

After the introduction of the research of my dissertation and the topics, I presented my research papers in Chapters II, III, and IV. In Chapter V, I present a summary of the principal conclusions and discussion arising from the three papers that form the basis of my dissertation. The researches were interconnected through the overarching themes of digital transformation, leadership styles, and the evolving views of young employees, particularly economists, on AI and robotics.

In the *first research paper*, I presented the topic of the connection between artificial intelligence (AI), robotics, and human resources (HR) from the perspective of younger generations (Zhong et al., 2017). This study explored the key pillars of Industry 4.0, namely artificial intelligence and robotisation, which guided the direction of my research (Lemaignan et al., 2017; Dvorsky, 2017). Following an overview of the theoretical and technological background, I proceeded to present the country-specific analysis of AI and robotisation that I had conducted. This analysis demonstrated that, although both Hungary and the United States were developed countries, there were significant differences in their research and development funding allocation. The United States invested considerably more in research based on AI than Hungary did. It was noteworthy that Hungary made significant advancements in its support of AI over the past year (OECD, 2019). However, it should be noted that different approaches might have yielded disparate outcomes.

Subsequently, an analysis was provided of the characteristics of Generations Y and Z (Zemke et al., 2000) and their behaviour in the labour market (Bencsik et al., 2016; Elmore, 2014), representing the other fundamental element of this study. It became evident that younger generations, shaped by the digital age, were integrated into the modern labour market in this way, making them ideal subjects for studying their opinion on the effects of AI and robotics on human resources (Törőcsik et al., 2014). In this context, the research questions were formulated with the objective of understanding how the Hungarian and American business communities perceived the relationship between digital tools and human resources. A more detailed hypothesis studied the opinion of the younger generations of economists in Hungary and the USA (the current and future workforce) regarding the motivation, confidence and interest of the younger generation, the impact of AI on HR, and the areas affected. A defining trait of today's youth was their high level of education. However, they tended to focus only on areas that genuinely interested them, and the current environment also presented uncertainties for them. In the context of the contemporary labour market, which was undergoing rapid transformation, examining the attitudes and opinions of those entering the workforce was paramount (Zhong et al., 2017; Bencsik & Machova, 2016). This was particularly relevant given the significant differences between younger and older generations. Considering this, the following research question was posed: What were the views of this cohort on artificial intelligence and the impact of robotisation on the workplace and society as a whole?

The primary research was conducted through an online, anonymous questionnaire targeting economists in the United States and Hungary from Generation Z and Y. The results were different than the literature (Törőcsik et al., 2014). In the short term, the opinions of American and Hungarian economists were found to be largely concordant and diverse motivations among the participants. The respondents expressed optimism regarding the impact of AI on economic, labour market, and social issues. Additionally, they demonstrated high confidence in their abilities, which employers should endeavour to support. It was perceived that the sectors most likely to be impacted in the near future were telecommunications and transport. In the longer term, the areas of health and space were identified as the most concerning. A significant proportion of respondents, particularly those of younger age groups, indicated that opportunities for learning and professional growth served as key motivators in their work. Nevertheless, despite the aforementioned considerations, the implications of AI had yet to fully capture the respondents' attention, although they did find it intriguing. Both groups of young people concurred that soft and hard skills would be significant in the era of AI, affording them a competitive advantage. My long-term observation was that these young economists did not foresee the disappearance of jobs but rather their evolution, with robots assuming a more significant role in tasks and becoming increasingly human-like.

It was, therefore, imperative for companies to retain their workforce, with a particular emphasis on providing training and education, as indicated by the respondents. Education also served as a valuable tool for modern youth, who tended to pursue it as a personal endeavour. Although the respondents demonstrated a limited understanding of the subject matter, they exhibited the potential to achieve notable outcomes if they were to expand their knowledge base. Furthermore, these individuals represented the future leaders and decision-makers who must comprehend these changes and their underlying rationale.

The findings of the study indicated that the general perception of AI and robotics among young economists is predominantly positive. Despite the uncertainties that the future might hold, it was evident that the majority of respondents, irrespective of age or geographical location, espoused an optimistic outlook on these subjects. This was arguably one of the most significant findings and a key takeaway for leaders.

My research indicated that this was one of the most critical issues of our time, given the vast amounts of data generated daily. However, there was no consistent strategy for companies to ensure profitability, nor was there a consensus on the types of training or retraining those economic entities should offer, whether by employers or the state. The subject matter was sufficiently interdisciplinary and relevant to justify further study. While the present study focused on the impact of AI on HR, there were numerous other areas where additional research could have been conducted (Lemaignan et al., 2017). Furthermore, the accelerated rate of technological advancement required continuous observation and investigation into the optimal leadership structure.

The initial paper presented a series of pivotal inquiries that served to establish the fundamental premises for subsequent deliberations. These included the role of top management in facilitating digital transformation and the potential consequences thereof. The second paper built on this foundation by exploring the concerns about Hungary's digital transformation, focusing on small and medium-sized enterprises. This marked the point at which the connection to leadership began to emerge, giving rise to questions concerning the ways in which management could effectively harness positive attitudes towards AI. This chapter emphasised the significance of strategic leadership in navigating digital change and optimising the opportunities it offers, thereby establishing the foundation for an investigation of leadership styles.

In the *second research* paper, I presented the importance of understanding the relationship between the proper leadership styles and digital transformation in manufacturing companies.

This study examined the digital transformation and its potential for enhanced effectiveness and success. It also investigated the impact of leadership styles (relationship- and task-oriented styles) on the transformation process. While international studies elucidated the role of leadership in digital transformation and its implications for successful implementation (Ruel et al., 2021), there was a paucity of domestic studies on this topic. Nevertheless, assuming that all leadership styles were equally effective in influencing digital transformation would be erroneous. Top management had the opportunity to select the most appropriate style (Alshehab et al., 2022). This was because, in a different environment (such as Hungary and the USA), a different leadership style would be appropriately applied in a different business model (Lovelance et al., 2019; Weber et al., 2022).

In order to ensure that companies applied the most appropriate leadership style during digital transformation, it was necessary to discuss which style was most effective. At that moment, digitalisation was not at an advanced stage in Hungary (Szalavetz, 2020), so it was essential to be prepared for this to maintain competitiveness. A model was built to understand the connection between two leadership styles and digital transformation pillars.

The concept of digital transformation was founded upon four principal pillars. Much literature highlighted the utmost importance of a well-defined digital strategy, the proper organisational structure, resources, corporate culture that supported digitalisation within the manufacturing companies and, the existing technologies that could be the base of digital transportation, and the approach to try new technologies (Galbraith & Kates, 2010; Heini & Heikki, 2015; Gill & VanBoskirk, 2016; Ivan et al., 2019; Móricz & Drótos, 2019; Tavoletti et al., 2021; Alshehab et al., 2022; Karippur & Balaramachandran, 2022). However, my research indicated that these four pillars could be grouped into two principal categories in SMEs: digital strategy and activities related to digital transformation.

Regarding digital transformation, there was less consistency in the alignment between the findings of the literature review and those of my own research. Several studies highlighted the importance of having a well-defined strategy in place during the process of digital transformation. This view was expressed by Matt (2015), Ghobakhloo (2018), Teece (2016), Demeter (2003), Amoako-Gyampah & Acquaah (2008) and Brunetti et al. (2020). However, the empirical evidence did not consistently support this view (Avella et al., 2001). As Swink & Harvey (1998) previously observed, their new framework did not prioritise strategy significantly.

Those task-oriented leaders tended to prioritise three key areas: the tasks to be completed, the methods by which these tasks should be carried out and the optimal timing for their completion. Such individuals were inclined to engage in excessive monitoring and control, which could be perceived as micromanagement (Katz et al., 1950; Fiedler, 1951; Tortorella et al., 2019). It was corroborated by evidence of enhanced group efficacy, productivity, and positivity among employees in groups led by task-oriented leaders (Tabernero et al., 2023; Mikkelson et al., 2019). However, other studies indicated that employees under relationship-oriented leaders exhibited enhanced cohesion and superior performance (Mikkelson et al., 2019; MacKenzie et al., 2001; Jung & Avolio, 2017). Those who adopted a relationship-oriented approach to leadership tended to prioritise the well-being of their subordinates and the quality of the relationships between them. It was the responsibility of the leader to assign tasks to the actors rather than the other way around. Such individuals were typically more knowledgeable about their colleagues and their work tasks (Yukl, 2012; Tortorella et al., 2018; Rüzgar, 2018).

The findings on leadership styles demonstrated a consistency between the literature review results and the quantitative model. It was crucial to differentiate between the strategic plan and the tangible actions undertaken to facilitate digital transformation. Teece (2016) emphasised the pivotal function of leadership style in influencing strategic orientation, a perspective mirrored in the model. The sources concurred that a combination of task- and relationship-oriented leadership styles was the optimal method for facilitating digital transformation. Furthermore, the task-oriented leadership style was identified as exerting a more pronounced influence on the digital processes, in general, and primarily at the early stages of digital transformation (Henkel et al., 2019).

A synthesis of the model and the results to date indicated that the majority of the variables within the model exerted a significant impact. The findings demonstrated that leadership styles were pivotal in propelling digital transformation. Among the leadership styles examined, the style with more task-oriented attributes with attention to performance and employees was demonstrated to exert a more pronounced influence on digital transformation, particularly on the strategic pillar. However, it was important to consider the long-term relationship attributes within the process.

The *third research paper* was directly connected to the second one, as it explored the ways in which different leadership styles – particularly task-oriented and relationship-oriented - could influence the success of digital transformation. Furthermore, the paper reiterated the concerns previously raised regarding the role of top management in ensuring effective digital change. This chapter offered a critical examination of how digital transformation mediated the relationship between leadership and performance outcomes. Furthermore, it linked to the perspectives of younger individuals and leadership adaptability, as discussed in earlier chapters.

It was established that leadership style was a significant factor in the implementation of digital transformation and the subsequent operational performance of firms.

The initial and most significant conclusion was the phenomenon of the complexity inherent to digital transformation. The concept of digital transformation was approached as a complex socio-technical system that extends beyond the technology domain. A literature review revealed that digital transformation could be grouped into four principal categories. The findings of this study demonstrated the existence of a distinctive configuration of digital transformation. In Hungarian manufacturing firms, two pillars of digital transformation were identified: strategy and activities. Evidently, strategy played a pivotal role in driving the transformation tasks within these firms. Local manufacturing companies had experience with technology, but this was mainly limited to introductory tools such as MS Office programs, mailing systems, cloud storage, and software programs. This indicated that the companies were at the outset of their digital transformation process when the questionnaire was completed. The timing of the survey suggested that the analysis presented herein represents the initial phase of investigation into the digital transformation process of the firms in question rather than an examination of the advanced stages of this process.

The paradigm of leadership. The findings of the study highlighted the pivotal role of leadership in managing SMEs' digital transformation. Despite the international literature indicating that the two leadership styles would have a similar positive effect on digital transformation (Tortorella et al., 2019), our findings did not align with this expectation. The task-oriented leadership style was demonstrated to be of particular significance in the context of digital transformation, particularly in the domain of strategic planning. The significance of task orientation was corroborated by prior research (Tortorella et al., 2023). Conversely, the evidence did not bear out the anticipated effects of relationship orientation on digital transformation. This might be because task orientation was the key at the implementation phase (Henkel et al., 2019), and based on domestic research, digital transformation was still in its infancy (Demeter et al., 2021). Furthermore, influenced by their cultural context, Hungarian leaders adhered to the efficacy of task-oriented strategies. These strategies offered a defined vision and delineated tasks instrumental in facilitating digital transformation and its successful implementation. An additional reason might be attributed to the disparate external and internal foci.

It was contended that the causal relationship we examined accurately reflected the reality of the evolving transformation, given that leadership styles and cultural traits tended to be relatively enduring. It seemed reasonable to posit that, over time, digital transformation might have influenced styles and traits, leading to a convergence with the characteristics associated with this new digital era (Fouad, 2019). Further research could elucidate whether managers alter their approach or whether new managers with the requisite styles were appointed.

Implications for operational performance were pivotal. The findings of the third study emphasised the significance of the role of leadership and the impact of digital transformation on operational management innovation in manufacturing firms. The model generally affected the operational performance indicators, although the specific effects were not uniform.

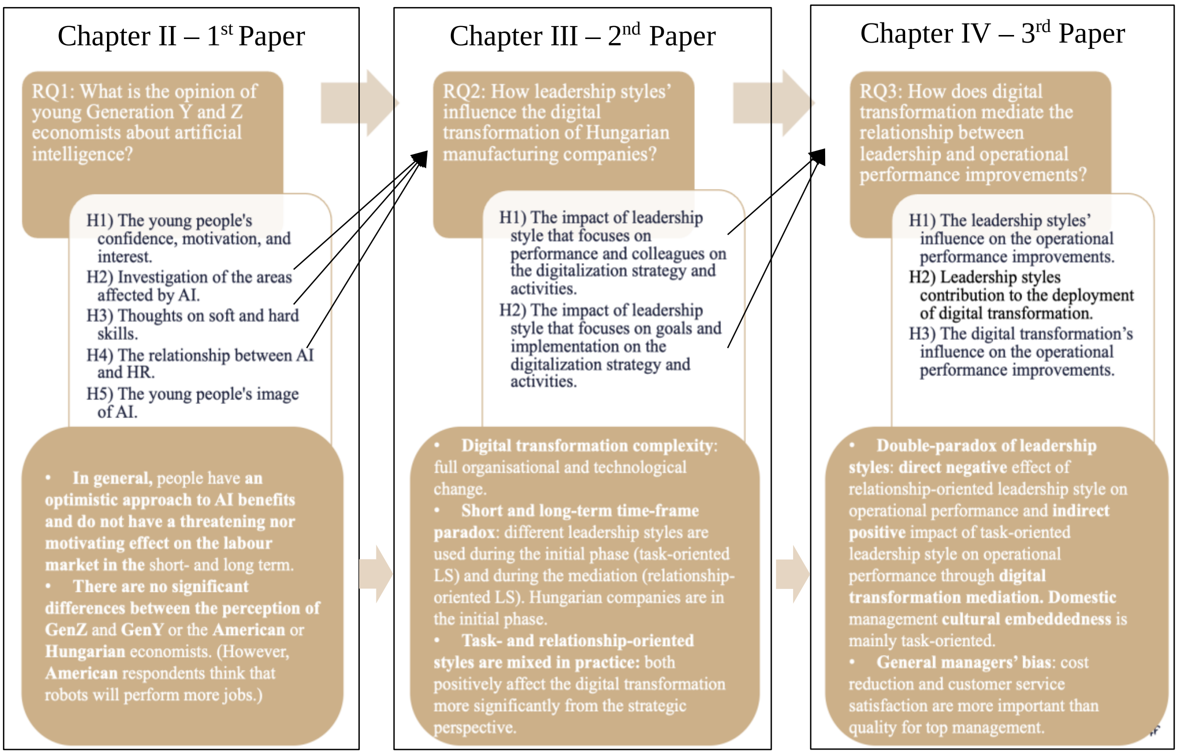
The influence of digital transformation extended well beyond operational measures. The concept of digital transformation was primarily associated with financial measures, such as improved return on sales and return on investments (Dubey et al., 2020; He et al., 2023). Additionally, studies emphasised the pivotal role of cost reduction in the Central and Eastern European region (Chahal et al., 2020; Demeter, 2003) and globally (Berman et al., 2020; Dubey et al., 2020). Conversely, enhancements in quality and greater flexibility in services and delivery were equally crucial in the context of manufacturing. The results of our study did not align precisely with the direct positive outcomes on operational performance improvements that the literature suggests. Digital transformation activities had a direct positive impact on operational performance indicators such as cost efficiency and flexible services, a conclusion that was also supported by the literature. However, the results indicate that digital transformation did not affect quality and delivery, contrary to most international literature on the subject. A digital transformation strategy guided the implementation of digital transformation activities. However, the influence of this strategy on performance outcomes was not direct, representing a previously unanticipated connection. The absence of a direct positive impact of strategy might be attributed to a reactive (leadership) approach in contrast to a more proactive stance.

Some international literature indicated that both leadership orientations positively impacted operational performance. However, the current understanding of this phenomenon is limited. The findings of this study revealed a *leadership paradox*. This finding underscored the notion that relationship orientation influenced pathways distinct from digital transformation-associated pathways. However, it also revealed a direct and adverse impact on operational performance. The relationship orientation did not yield the anticipated results concerning its impact on operational performance. This was contrary to the literature, as evidenced by the studies of Akçay Kasapoğlu (2018) and Dubey et al. (2020), which suggested that quality should have been positively affected. The results demonstrated the disparate effects of the two styles on the firm's performance. In addition to the positive and indirect impact of the task-oriented style, there was a negative and direct effect of the relationship-oriented style. This led us to inquire about the utility of relations from a performance perspective.

Several studies in the field of leadership focused on the soft aspects of individuals, teams, and organisations (Mikkelson et al., 2019; Tabernero et al., 2009). It might be the case that the effects should not be sought at this level of operational performance. It was evident that merely focusing on task-oriented approaches to management would not suffice in ensuring the optimal functioning of the human aspect of the organisation. Concurrently, task orientation was paramount during the implementation phase (Henkel et al., 2019). In accordance with domestic research, digital transformation was still in its infancy (Demeter et al., 2021); thus, the findings aligned with those of international studies. Conversely, Hungarian leaders believed task orientation was more conducive to productivity than relationship orientation in manufacturing leadership.

In conclusion, the dissertation demonstrates a cohesive narrative, beginning with the evolving perspectives of young economists regarding the interrelationship between AI, robotics, and HR. It also highlighted these factors' pivotal role in formulating leadership and digital transformation strategies within Hungarian manufacturing SMEs. Integrating these elements enables companies to address key workforce insights, select leadership styles that foster innovation, and guide digital transformation efforts with greater efficacy. These factors combined a comprehensive strategy that ultimately resulted in enhanced operational performance. The chapters were structured to allow the reader to gain a deeper understanding of the subject matter by building on the preceding chapters. The overarching theme that united the various elements was that of leadership styles, which were seen to significantly impact employees' views, the process of digital transformation, and the overall operational performance improvement of a manufacturing organisation.

Figure 18: Research questions and answers



Source: Author's work, 2025

The employment of a dual approach, integrating both top-down and bottom-up methodologies, facilitated a comprehensive understanding of the multifaceted nature of digital and human interactions. The bottom-up approach played a pivotal role in fostering an environment conducive to creativity, thereby enabling digitalisation to permeate various levels of an organisation. Concurrently, the top-down approach provided an overarching digital strategy, thereby ensuring a seamless transformation process with a strong leadership attitude. The synchronised analysis of both approaches enabled the identification of success factors and the identification of potential system deficiencies. The success of this process could be measured in terms of leadership style, implementation, process success and operational performance. Practical applications for leaders included the ability to identify the attitudes of their subordinates and apply personalised digital strategies to both younger and older generations.

In future research, it might be beneficial to consider incorporating a cross-functional analysis by engaging with a diverse range of professionals beyond economists, including engineers, doctors, pharmacists, technology experts, sociologists, business leaders, and policymakers, with a view to gaining a more comprehensive understanding of digital, economic, and societal trends. Additionally, it may be beneficial to consider conducting interviews with older generations of the workforce, such as Baby Boomers or Generation X, as this could offer valuable historical perspectives, experiential insights, and generational comparisons with current data that could enrich contemporary analysis. By integrating viewpoints from multiple disciplines and age groups, future studies may be able to develop more holistic and practical recommendations that reflect the complexities of real-world decision-making. It can provide valuable perspectives on technological adaptation, workforce transitions, and the long-term impact of digitalisation, ensuring that digital transformation strategies are both inclusive and sustainable. The role of leadership in integrating AI and robotics into society has been pivotal. The future will be characterised by the effective and ethical management of technological advancements, with the objective being to ensure that these systems complement human work and creativity rather than replace it.

Reference list

Akçay Kasapoğlu, Ö. (2018). Leadership and Organisation for the Companies in the Process of Industry 4.0 Transformation, *International Journal of Organisational Leadership, 7*(3), 300-308, https://doi.org/10.33844/ijol.2018.60217

Alkaraan, F., Albitar, K., Hussainey, K., & Venkatesh, V. (2022). Corporate transformation toward Industry 4.0 and financial performance: The influence of environmental, social and governance (ESG), *Technological Forecasting and Social Change*, *175*, https://doi.org/10.1016/j.techfore.2021.121423

AlNuaimi, B. K., Singh, S. K., & Harney, B. (2021). Unpacking the role of innovation capability: Exploring the impact of leadership style on green procurement via a natural resource-based perspective, *Journal of Business Research, 134,* 78-88. https://doi.org/10.1016/j.jbusres.2021.05.026

Al-Okaily, M., Younis, H., & Al-Okaily. A. (2024). The impact of management practices and industry 4.0 technologies on supply chain sustainability: A systematic review, *Heliyon*, *10*(17)

Alshehab, A., Alfozan, T., Gaderrab, H. F., Alahmad, M. A., & Alkandari, A. (2022). Identifying significant elements of the digital transformation of organizations in Kuwait, *Indonesian Journal of Electrical Engineering and Computer Science, 26*(1), 318-325. https://doi.org/10.11591/ijeecs.v26.i1.pp318-325

Amoako-Gyampah, K., & Acquaah, M. (2008). Manufacturing strategy, competitive strategy and firm performance: An empirical study in a developing economy environment, *International Journal of Production Economics*, *111*(2), 575-592, https://doi.org/10.1016/j.ijpe.2007.02.030

Annosi, M. C., Balzano, M., Ciacci, A., Marzi G., & Terlouw, J. (2024). Managing Generational Tensions Toward Digital Transformation: A Microfoundational Perspective, *IEEE Transactions on Engineering Management*, *71*, 13802-13813, https://doi.org/10.1109/TEM.2023.3285735

Ardi, D. S. P., Bernarto, I., Sudibjo, N., Yulianeu, A., A.Nanda, H., & A.Nanda, K. (2020). The Relationship Between Digital Transformational Leadership Styles and Knowledge-Based Empowering Interaction for Increasing Organisational

Innovativeness, *International Journal of Innovation, Creativity and Change*, *11*(3), 259-277.

Armstrong, J., & Overton, T. (1977). Estimating nonresponse bias in mail surveys, *Journal of Marketing Research*, *14*(3), 396-402, https://doi.org/10.2307/3150783

Avella, L., Fernández, E., & Vázquez, C. J. (2001). Analysis of manufacturing strategy as an explanatory factor of competitiveness in the large Spanish industrial firm, *International Journal of Production Economics*, *72*(2), 139–157. https://doi.org/10.1016/S0925-5273(00)00099-2

Balahurovska, I. (2023). The Role of Leadership in Industry 4.0, *System Safety: Human – Technical Facility – Environment*, *5*(1), 66-74. https://doi.org/10.2478/czoto-2023-0008

Bass, B. M. (1990). From transactional to transformational leadership: Learning to share the vision. *Organizational Dynamics*, *18*(3), 19-31.

Beer, M. (2003). Why Total Quality Management Programs Do Not Persist: The Role of Management Quality and Implications for Leading a TQM Transformation, *Decision Sciences*, *34*(4), 623-642, https://doi.org/10.1111/j.1540-5414.2003.02640.x

Behrendt, P., Matz, S., & Göritz, A. S. (2017). An integrative model of leadership behavior. *The Leadership Quarterly*, *28*(1), 229–244. https://doi.org/10.1016/j.leaqua.2016.08.002

Bencsik, A., Horváth-Csikós, G., & Juhász, T. (2016). Y and Z Generations at Workplaces *Journal of Competitiveness*, *8*(3), 90–106. https://doi.org/10.7441/joc.2016.03.06

Bencsik, A., & Machova, R. (2016). *Knowledge Sharing Problems from the Viewpoint of Intergeneration Management.* ICMLG2016 – 4th International Conference on Management, Leadership and Governance.

Berman, S., Heller Baird, C., Eagan, K., & Marshall, A. (2020). What makes a Chief Digital Officer successful?, *Strategy and Leadership*, *48*(2), 32-38, https://doi.org/10.1108/SL-12-2019-0180

Bouwman, H., Nikou, S., & Reuver, M. de. (2019). Digitalization, business models, and SMEs: How do business model innovation practices improve performance of digitalizing SMEs?, *Telecommunications Policy*, *43*(9). https://doi.org/10.1016/j.telpol.2019.101828

Büchi, G., Cugno, M., & Castagnoli, R. (2020). Smart factory performance and Industry 4.0, *Technological Forecasting and Social Change*, *150*(119790), 1-10, https://doi.org/10.1016/j.techfore.2019.119790

Brunetti, F., Matt, D. T., Bonfanti, A., De Longhi, A., Pedrini, G., & Orzes, G. (2020). Digital transformation challenges: strategies emerging from a multi-stakeholder approach, *The TQM Journal*, *32*(4), 697-724. https://doi.org/10.1108/TQM-12-2019-0309

Bunjak, A., Bruch, H., & Černe, M. (2022). Context is key: The joint roles of transformational and shared leadership and management innovation in predicting employee IT innovation adoption, *International Journal of Information Management*, *66*. https://doi.org/10.1016/j.ijinfomgt.2022.102516

Burns, J. M. (1978). *Leadership,* Harper and Row, New York, NY.

Buzurovic, I., Debeljkovic, D. L., Misic, V., & Simeunovic, G. (2014). Stability of the Robotic System with Time Delay in Open Kinematic Chain Configuration, *Acta Polytechnica Hungarica* ,*11*(8), 45–64.

Chahal, H., Gupta, M., Bhan, N., & Cheng, T. C. E. (2020). Operations management research grounded in the resource-based view: a meta-analysis, *International Journal of Produc-tion Economics journal*, *230*(1). https://doi.org/10.1016/j.ijpe.2020.107805

Chardonnens, S. (2025). Adapting educational practices for Generation Z: integrating metacognitive strategies and artificial intelligence, *Frontiers in Education, 10*, 1-14. https://doi.org/10.3389/feduc.2025.1504726

Chen, Y. P., Velu, C., & McFarlane, D. (2024). The Effect of Robot Adoption on Profit Margins, *IEEE Transactions on Engineering Management, 71*, 8951-8963. https://doi.org/10.1109/TEM.2023.3260734

Chikán, A., Czakó, E., Losonci, D., & Kiss-Dobronyi, B. (2019). *A 4. ipari forradalom küszöbén. Gyorsjelentés a 2019. évi kérdőíves felmérés eredményeiről.* Versenyképesség Kutató Központ, Budapest. http://unipub.lib.uni-corvinus.hu/4328/

Chikán, A., Czakó, E., Kiss-Dobronyi, B., & Losonci, D. (2022). Firm competitiveness: A general model and a manufacturing application, *International Journal of Production Economics, 243*(108316), 1-13. https://doi.org/10.1016/j.ijpe.2021.108316

Chu, L. F., & Kurup, V. (2025). The Promise of Artificial Intelligence and Machine Learning in Geriatric Anesthesiology Education: An Idea Whose Time Has Come, *Current Anesthesiology Reports 15*(15), 1-10. https://doi.org/10.1007/s40140-024-00660-x

Cortellazzo, L., Bruni, E., & Zampieri, R, (2019). The Role of Leadership in a Digitalized World: A Review, *Frontiers in Psychology, 10*(1938). https://doi.org/10.3389/fpsyg.2019.01938

Cohen, J. (1992). A power primer, *Psychological Bulletin, 112*(1), 155-159. https://doi.org/10.1037/0033-2909.112.1.155

Craighead, C., Ketchen, D., Dunn, K., & Hult, G. (2011). Addressing common method variance: guidelines for survey research on information technology, operations and supply chain management, *IEEE transactions on engineering management*, *58*(3), 578-588. https://doi.org/10.1109/TEM.2011.2136437

Csiki, O., Demeter, K., & Losonci, D. (2023). How to improve firm performance? – The role of production capabilities and routines, *International Journal of Operations and Production Management*, *43*(12), 1-26. https://doi.org/10.1108/IJOPM-03-2022-0221

Culot, G., Nassimbeni, G., Orzes, G., & Sartor, M. (2020). Behind the definition of Industry 4.0: Analysis and open questions, *International Journal of Production Economics*, *226*(4-5). https://doi.org/10.1016/j.ijpe.2020.107617

Deloitte. (2014). *Industry 4.0 – Challenges and solutions for the digital transformation and use of technologies*. Available: https://www2.deloitte.com/content/dam/Deloitte/ch/Documents/manufacturing/ch-en-manufacturing-industry-4-0-24102014.pdf (Download: 2022. 02. 06)

Deloitte. (2018). *2018 Deloitte Millennial Survey*. Available: https://www2.deloitte.com/content/dam/Deloitte/hu/Images/inline_images/hu-millenial-survey-18-infographic.jpg (Download: 2022. 02. 06.)

Del Vecchio, P., Secundo, G., & Garzoni, A. (2024). Digital transformation and resilience in family business: an exploratory study of generational dynamics, *European Journal of Innovation Management*, https://doi.org/10.1108/EJIM-02-2024-0137

Demeter, K. (2003). Manufacturing strategy and competitiveness. *International Journal of Pro-duction Economics, Proceedings of the Eleventh International Symposium on Inventories*, *81*(82), 205-213. https://doi.org/10.1016/S0925-5273(02)00353-5

Demeter, K., Losonci, D., & Nagy, J. (2021). Road to digital manufacturing – a longitudinal case-based analysis, *Journal of Manufacturing Technology Management*, *32*(3), 820-839. https://doi.org/10.1108/JMTM-06-2019-0226

Demeter, K. (2020). A negyedik ipari forradalom gazdasági és menedzsmenthatásai, *Vezetéstudomány / Budapest Management Review*, *51*(6), 2-4. https://doi.org/10.14267/VEZTUD.2020.06.01

Demeter, K., & Losonci, D. (2020). Business and Technological Perspectives of Industry 4.0 – A Framework for Thinking with Case Illustration, *Vezetéstudomány / Budapest Management Review*, *51*(5), 2-14. https://doi.org/10.14267/VEZTUD.2020.05.01

Demeter, K., Losonci, D. Marciniak, R., Nagy, J., Móricz, P., Matyusz, Zs., Baksa, M., Freud, A., Jámbor, Zs., Pistrui B., & Diófási-Kovács, O. (2020a). Industry 4.0 through the Lenses of Technology, Strategy and Organisation: A Compilation of Case Study Evidence, *Vezetéstudomány / Budapest Management Review*, *51*(11), 14-25. https://doi.org/10.14267/VEZTUD.2020.11.02

Demeter, K., Losonci, D., Szász, L., & Rácz, B-G. (2020b). Magyarországi gyártóegységek Ipar 4.0 gyakorlatának elemzése – technológia, stratégia, szervezet, *Vezetéstudomány / Budapest Management Review*, *51*(3), 2-14. https://doi.org/10.14267/VEZTUD.2020.04.01

Digitális Jóléti Program. (2020). *Mesterséges Intelligencia Koalíció*. Available: https://digitalisjoletprogram.hu/hu/tartalom/mesterseges-intelligencia-koalicio (Download: 2022. 02. 06.)

Dijkstra, T., & Henseler, J. (2015). Consistent and Asymptotically Normal PLS Estimators for Linear Structural Equations, *Computational Statistics and Data Analysis, 81*(1), 10-23. https://doi.org/10.1016/j.csda.2014.07.008.

Dióssy, K. (2024). Y és Z generációs fiatal közgazdászok vélekedése a mesterséges intelligenciáról, *Köz-Gazdaság – Review of Economic Theory and Policy*, *19*(1), 114-131. https://doi.org/10.14267/RETP2024.01.08

Dióssy, K., Losonci, D. I., & Városiné Demeter, K. (2023). Vezetési stílusok hatása a digitális transzformációra, *Vezetéstudomány / Budapest Management Review*, *54*(10), 2–14. https://doi.org/10.14267/VEZTUD.2023.10.01

Dióssy, K., Losonci, D. I., Aranyossy, M., & Városiné Demeter, K. (2025). The role of leadership in digital transformation – a paradox way to improve operational performance, *Journal of Manufacturing Technology Management*, *36*(9), 88-113. https://doi.org/10.1108/JMTM-07-2024-0386

Dirican, C. (2015). The Impacts of Robotics, Artificial Intelligence On Business and Economics, *Procedia - Social and Behavioral Sciences*, *195*, 564–573. https://doi.org/10.1016/j.sbspro.2015.06.134

Dubey, R., Gunasekaran, A., Childe, S., Bryde, D., Giannakis, M., Foropon, C., Roubaud, D., & Hazen, B. (2020). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations, *International Journal of Production Economics, 226*. https://doi.org/10.1016/j.ijpe.2019.107599

Dunavölgyi, M. (2022). *Leadership kutatás digitális transzformáció idején. Műhelytanulmány (working paper).* Budapesti Corvinus Egyetem Vezetéstudományi Intézet, Budapest.

Dvorsky, G. (2017). Robots Are Already Replacing Human Workers At An Alarming Rate. Available: https://www.gizmodo.com.au/2017/03/robots-are-already-replacing-human-workers-at-an-alarming-rate/ (Download: 2019. 04. 05.)

Eirich, R., Schäfer, B., & Ringlstetter, M. (2019). An organizationaI design framework for digital innovation: Critical review of Galbraith's STAR Model. In *ISPIM Conference Proceedings*, 1-27. The International Society for Professional Innovation Management (ISPIM).

Eller, R., Alford, P., Kallmünzer, A., & Peters, M. (2020). Antecedents, consequences, and challenges of small and medium-sized enterprise digitalization, *Journal of Business Research, 112*, 119–127. https://doi.org/10.1016/j.jbusres.2020.03.004

Elmore, T. (2014). How Generation Z Differs from Generation Y. In Bencsik, A., Horváth-Csikós, G., & Juhász, T. (2016). Y and Z Generations at Workplaces, *Journal of Competitiveness, 8*(3), 90-106.

Endrődi-Kovács, V., & Stukovszky, T. (2022). The adoption of industry 4.0 and digitalisation of Hungarian SMEs, *Society and Economy*, *44*(1), 138-158. https://doi.org/10.1556/204.2021.00024

Erboz, G., Hüseyinoğlu, I. Ö., & Szegedi, Z. (2022). The partial mediating role of supply chain integration between Industry 4.0 and supply chain performance, *Supply Chain Management*, *27*(4), 538-559. https://doi.org/10.1108/SCM-09-2020-0485

Farina, M., Yu, X., & Lavazza, A. (2025). Ethical Considerations and Policy Interventions Concerning the Impact of Generative AI Tools in the Economy and in Society, *AI and Ethics*, *5*, 737–745. https://doi.org/10.1007/s43681-023-00405-2

Faul, F., Erdfelder, E., Lang, A., & Buchner, A. (2008). G*Power 3: a flexible statistical power analysis program for the social, behavioral and biomedical sciences, *Behavioral Research Methods*, *39*(2), 175-191. https://doi.org/10.3758/BF03193146

Felsberger, A., Qaiser, F. H., Choudhary, A., & Reiner, G. (2020). The impact of Industry 4.0 on the reconciliation of dynamic capabilities: Evidence from the European manufacturing industries, *Production Planning and Control*, *33*(2-3), 277-300. https://doi.org/10.1080/09537287.2020.1810765

Fiedler, F. E. (1971). Validation and extension of the contingency model of leadership effectiveness: A review of empirical findings, *Psychological bulletin*, *76*(2), 128–148. https://doi.org/10.1037/h0031454

Fiedler, F. E. (1978). The Contingency Model and the Dynamics of the Leadership Process, *Advances in Experimental Social Psychology*, *11*, 59-112. https://doi.org/10.1016/S0065-2601(08)60005-2

Flores, E., Xu, X., & Lu, Y. (2020). Human Capital 4.0: a workforce competence typology for Industry 4.0, *Journal of Manufacturing Technology Management*, *31*(4), 687-703. https://doi.org/10.1108/JMTM-08-2019-0309

Fouad, A. B. K. (2019). Digital Transformation and Leadership Style: A Multiple Case Study, *ISM Journal*, *3*(1), 24-33. 2150-1076

Fornell, C., & Larcker, D. (1981). Evaluating structural equation models with unobservable variables and measurement error, *Journal of Marketing Research*, *18*(1), 39-50. https://doi.org/10.1177/002224378101800104

Frank, A. G., Dalenogare, L. S. & Ayala, N. F. (2019). Industry 4.0 technologies: Implementation patterns in manufacturing companies, *International Journal of Production Economics*, *210*, 15-26. https://doi.org/10.1016/j.ijpe.2019.01.004

Frank, A.G., Thürer, M., Godinho Filho, M., & Marodin, G.A. (2024). Beyond Industry 4.0 – integrating Lean, digital technologies and people, *International Journal of Operations & Production Management*, *44*(6), 1109-1126. https://doi.org/10.1108/IJOPM-01-2024-0069

Frey, C., & Osborne, M. (2013). *The Future of Employment: How Susceptible Are Jobs to Computerisation?,* Oxford Martin, *114*. https://doi.org/10.1016/j.techfore.2016.08.019

Füstös, L., & Tárnok, O. (2017). *Strukturális egyenletek modellje - Másodgenerációs statisztikai módszerek.* Társadalmi Elemzések Alkalmazott Műhelye.

Gabrielova, K., & Buchko, A. A. (2021). Here comes Generation Z: Millennials as managers, *Business Horizons*, *64*(4), 489-499, https://doi.org/10.1016/j.bushor.2021.02.013

Galbraith, J. R. (2002). Organizing to Deliver Solutions. *CEO Publications*, *423*, 1-18. Center for Effective Organizations Marshall School of Business University of Southern California.

Galbraith, J. R., & Kates, A. (2010). *Designing Your Organization: Using the STAR Model to Solve 5 Critical Design Challenges*. John Wiley & Sons.

Gandolfi, F., & Stone, S. (2018). Leadership, Leadership Styles, and Servant Leadership, *Journal of Management Research*, *18*(4), 261-26.

Gelei, A., Losonci, D., & Matyusz, Z. (2015). Lean production and leadership attributes – the case of Hungarian production managers, *Journal of Manufacturing Technology Management*, *26*(4), 477-500. https://doi.org/10.1108/JMTM-05-2013-0059

Gerbert, P., Lorenz, M., Rüßmann, M., Waldner, M., Justus, J., Engel, P., & Harnisch, M. (2015): *Industry 4.0: The Future of Productivity and Growth in Manufacturing Industries*. BCG Perspectives. Available: https://www.bcgperspectives.com/content/articles/engineered_products_project_business_industry_40_future_productivity_growth_manufacturing_industries/#chapter1 (Download: 2022. 02. 06.)

Ghobakhloo, M. (2018). The future of manufacturing industry: a strategic roadmap toward Industry 4.0, *Journal of Manufacturing Technology Management*. https://doi.org/10.1108/JMTM-02-2018-0057

Ghobakhloo, M., & Iranmanesh, M. (2021). Digital transformation success under Industry 4.0: a strategic guideline for manufacturing SMEs, *Journal of Manufacturing Technology Management*, 1533-1556. https://doi.org/10.1108/JMTM-11-2020-0455

Gill, M., & VanBoskirk, S. (2016). *The Digital Maturity Model 4.0 Benchmarks: Digital Business Transformation Playbook,* Forrester.

González-Mohíno, M., Donate, M. J., Muñoz-Fernández, G. A., & Javier Cabeza-Ramírez, L. (2024). Robotic Digitalization and Business Success: The Central Role of Trust and Leadership in Operational Efficiency - A Hybrid Approach Using PLS-SEM and fsQCA, *IEEE Access*, *12*, 192113-192126. https://doi.org/10.1109/ACCESS.2024.3509623

Guzmán, V., Muschard, B., Gerolamo, M., Kohl, H., & Rozenfeld, H. (2020). Characteristics and Skills of Leadership in the Context of Industry 4.0, *Procedia Manufacturing*, *43*, 543-550. https://doi.org/10.1016/j.promfg.2020.02.167

Habidin, N. F., Muhammad Yusri, Y., Mohd Zahirwan Halim, Z. A., & Abd Munir, M. N. (2016). Penang waqaf management: A Galbraith approaches, *International Journal of Academic Research in Business and Social Sciences*, *6*(10), 392-401. http://dx.doi.org/10.6007/IJARBSS/v6-i10/2417

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). *Multivariate Data Analysis.* Prentice Hall, Upper Saddle River, NJ.

Hair, J. F., Hult, G. T., Ringle, C. M., & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, Sage Publications, Washington DC.

Hair, J. F., Hult, G. T., Ringle, C. M., & Sarstedt, M. (2022). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM) (3 ed)*, Sage Publications, Thousand Oaks, CA.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM, *European Business Review*, 31(1), 2-24, https://doi.org/10.1108/EBR-11-2018-020

Hanafizadeh, P., & Ravasan, A. Z. (2011). A McKinsey 7S model-based framework for ERP readiness assessment, *International Journal of Enterprise Information Systems*, *7*(4), 23-63. http://dx.doi.org/10.4018/jeis.2011100103

Hater, J. J., & Bass, B. M. (1998). Superiors' evaluations and subordinate perceptions of transformation and transactional leadership, *Journal of Applied Psychology*, *73*, 695-702.

Hayduk, L., & Littvay, L. (2012). Should researchers use single indicators, best indicators, or multiple indicators in structural equation models?, *BMC Medical Research Methodology*, *12*159), 1-17. https://doi.org/10.1186/1471-2288-12-159

He, Z., Huang, H., Choi, H., & Bilgihan, A. (2023). Building organisational resilience with digital transformation, *Journal of Service Management*, *34*(1), 147-171. https://doi.org/10.1108/JOSM-06-2021-0216

Heini, M. T., & Heikki, K. (2015). The usage of digital marketing channels in SMEs. *Journal of Small Business and Enterprise Development*, *22*(4), 633-651. https://doi.org/10.1108/JSBED-05-2013-0073

Henkel, T. G., Marion, J. W., & Bourdeau, D. T. (2019). Project Manager Leadership Behavior: Task-Oriented Versus Relationship-Oriented, *Journal of Leadership Education*, *18*(2). https://doi.org/10.12806/V18/I2/R8

Henseler, J., Ringle, C., & Sinkovics, R. (2009). The Use of Partial Least Squares Path Modeling in International Marketing, *Advances in International Marketing*, *20*(4), 277-319. https://doi.org/10.1108/S1474-7979(2009)0000020014

Hersey, P., & Blanchard, K. H. (1977). Management of organizational behavior: Utilizing human resources, *Academy of Management Journal.*

Hersey, P., Blanchard, K., & Johnson, D. (2001). *Management of organizational behavior*. 8th ed., Prentice-Hall, Englewood Cliffs, NJ.

Hersey, P., Blanchard, K., & Natemeyer, W. (1979). Situational Leadership, Perception and the Impact of Power, *Group and Organisation Studies*, *4*, 418-428, https://doi.org/10.1177%2F105960117900400404

Hess, T., Matt, C., Benlian, A., & Wiesböck, F. (2016). Options for Formulating a Digital Transformation Strategy, *MIS Quarterly Executive*, 15(2), 123-139.

Hortoványi, L., Szabó, Zs. R., Nagy, S. Gy., & Stukovszky, T. (2020). A digitális transzformáció munkahelyekre gyakorolt hatásai – Felkészültek-e a hazai vállalatok a benne rejlő nagy lehetőségre (vagy a veszélyekre)? *Külgazdaság*, *64*, 73–96. https://doi.org/10.47630/KULG.2020.64.3-4.73

Howe, N., & Strauss, W. (1992). *Generations: The history of America's future*, 1584 to 2069. Harper Collins.

Hu, L., & Bentler, P. (1998). Fit Indices in Covariance Structure Modeling: Sensitivity to Underparameterized Model Misspecification, *Psychological Methods*, *3*(4), 424-453. https://doi.org/10.1037/1082-989X.3.4.424

Imran, F., Shahzad, K., Butt, A., & Kantola, J. (2021). Digital Transformation of Industrial Organisations: Toward an Integrated Framework, *Journal of Change Management*, *21*(4), 451-479. https://doi.org/10.1080/14697017.2021.1929406

Inversini, A. (2025). Human centered digital transformation in travel: a horizon 2050 paper, *Tourism Review*, *80*(1), 326-337. https://doi.org/10.1108/TR-12-2023-0886

Isensee, C., Teuteberg, F., Griese, K.-M., & Topi, C. (2020). The relationship between organizational culture, sustainability, and digitalization in SMEs: A systematic review, *Journal of Cleaner Production*, *275*. https://doi.org/10.1016/j.jclepro.2020.122944

Ivan, L., Vuk, V. B., & Spremic, M. (2019). Mastering the Digital Transformation Process, *Business Practices and Lessons Learned Technology Innovation Management Review*, *9*(2), 36-50.

IWI-HSG & Crosswalk AG (2015). *Digital Maturity and Transformation Study 2015-2016 Questionnaire*. Available: https://aback.iwi.unisg.ch/fileadmin/projects/aback/web/images/swiss%20digital%20transformation%20initiative/questionnaire_english.pdf (Download: 2023. 05. 20.)

Jones E. O. (2024). Indigenous knowledge management practices in subsistence farming: A comprehensive evaluation, *Sustainable Technology and Entrepreneurship, 3*(2), https://doi.org/10.1016/j.stae.2023.100058

Januszek, S., Netland, T.H., & Furlan, A. (2024). The role of managerial perceptions and behaviors across hierarchical levels during lean implementation, *International Journal of Operations and Production Management*, *44*(1), 54-74, https://doi.org/10.1108/IJOPM-07-2022-0417

Jones I., & Avolio, B. J. (2017). Effects of Leadership Style and Followers' Cultural Orientation on Performance in Group and Individual Task Conditions, *Academy of Management Journal*, *42*(2), 208-218. https://doi.org/10.5465/257093

Kane, G. C., Palmer, D., Phillips, A., Kiron, D., & Buckley, N. (2017). *Achieving Digital Maturity (14 ed),* MIT Sloan Management Review and Deloitte University Press, Cambridge, MA.

Karippur, N. K., & Balaramachandran, P. R. (2022). Antecedents of Effective Digital Leadership of Enterprises in Asia Pacific. *Australasian Journal of Information Systems*, *26*, 1-35. https://doi.org/10.3127/ajis.v26i0.2525

Katz, D., Macoby, N., & Morse, N. (1950). *Productivity, supervision and morale in an office situation*, Institute for Social Research, Ann Arbor, MI.

Keller, T., & Weibler, J. (2014). Behind managers' ambidexterity-Studying personal traits, leadership and environmental conditions, *Schmalenbach Business Review*, *66*(3), 309–333.

Keszey, T., & Zsukk, J. (2017). Az új technológiák fogyasztói elfogadása. A magyar és nemzetközi szakirodalom áttekintése és kritikai értékelése, *Vezetéstudomány / Budapest Management Review*, *48(*10) 38-47. https://doi.org/10.14267/VEZTUD.2017.10.05

Kim, M.- K., & Jee, K.- Y. (2007). Factors influencing strategie use of information technology and its impact on business performance of SMEs, *ETRI Journal, 29*(4), 497-506. https://doi.org/10.4218/etrij.07.0106.0303

Koebe, P. (2025). How digital technologies and AI contribute to achieving the health-related SDGs, *International Journal of Information Management Data Insights*, *5*(1). https://doi.org/10.1016/j.jjimei.2024.100298

Központi Statisztikai Hivatal (2021). *Ipar.* Available*:* https://www.ksh.hu/ipar (Download: 2022. 03. 30.)

Kretschmer, T., & Khashabi, P. (2020). Digital Transformation and Organisation Design: An Integrated Approach, *California Management Review, 62*(4), https://doi.org/10.1177/0008125620940296

Krishnan, S. (2024). *Leadership in the Age of Artificial Intelligence (AI),* 43-51. https://doi.org/10.70301/CONF.SBS-JABR.2024.1/1.3

Kwiotkowska, A., Gajdzik, B., Wolniak, R., Vveinhardt, J., & Gębczyńska, M. (2021). Leadership Competencies in Making Industry 4.0 Effective: The Case of Polish Heat and Power Industry. *Energies, 14*(14), 1-21. https://doi.org/10.3390/en14144338

Lemaignan, S., Warnier, M., Sisbot, E. A., Clodic, A., & Alami, R. (2017):. Artificial cognition for social human–robot interaction: An implementation, *Artificial Intelligence*, *247*, 45–69. https://doi.org/10.1016/j.artint.2016.07.002

Liao, Y., Deschamps, F., Loures, E., & Ramos, L. (2017). Past, present and future of industry 4.0: a systematic literature review and research agenda proposal, *International Journal of Production Research*, *55*(12), 3609-3629. https://doi.org/10.1080/00207543.2017.1308576

Liu, H. (2020). Research on Library Data Management Reform: Discussion on McKinsey 7S System Thinking Model. 2020 6th IEEE International Conference on Information Management, ICIM 2020, 295–298. https://doi.org/10.1109/ICIM49319.2020.244714

López-Gómez, C., McFarlane, D., O'Sullivan, E., & Velu, C. (2018). *The practical impact of digital manufacturing: results from recent international experience. Interim Report. Policy Links, Institute for Manufacturing (IfM)*, University of

Cambridge, Cambridge, United Kingdom. Available: https://www.ifm.eng.cam.ac.uk/uploads/Content_Images/IfM_IUK_Interim_revised.PDF (Download: 2022. 09.15.).

Lovelace, J. B., Neely, B. H., Allen, J. B., & Hunter, S. T. (2019). Charismatic, ideological, and pragmatic (CIP) model of leadership: a critical review and agenda for future research, *Review. The Leadership Quarterly*, *30*(1), 96-110.

MacKenzie, S. B., Podsakoff, P. M., & Rich, G. A. (2001). Transformational and transactional leadership and salesperson performance, *Journal of the Academy of Marketing Science*, 29(2), 115–134. https://doi.org/10.1177/03079459994506

Matt, C., Hess, T., & Benlian, A. (2015). Digital transformation strategies. *Business & In-formation Systems Engineering*, *57*(5), 339–343. https://doi.org/10.1007/s12599-015-0401-5

McKinsey.com (2008). *Enduring Ideas: The 7-S Framework. Available:* McKinsey Quarterly. https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/enduring-ideas-the-7-s-framework (Download: 2022. 03. 23.)

Menezes, K. A., & Malhotra, P. (2022). Learning preferences and attitude towards change acceptance of diverse generational workforce in digital era, *International Journal of Business and Globalisation*, *32*(2-3), 223-237. https://doi.org/10.1504/IJBG.2022.127361

Meretei, B. (2017). Generációs különbségek a munkahelyen – szakirodalmi áttekintés. *Vezetéstudomány / Budapest Management Review*, *48*(10) 10–18. https://doi.org/10.14267/VEZTUD.2017.10.02

Mikkelson, A. C., Sloan, D., & Hesse, C. (2019). Relational Communication Messages and Leadership Styles in Supervisor/Employee Relationships, *International Journal of Business Communication*, *56*(4), 586–604. https://doi.org/10.1177/2329488416687267

Móricz, P. (2022). A magyarországi vállalatok digitális képessége a pandémia előtt. *Vezetéstudomány / Budapest Management Review*, *53*(3), 2-18. https://doi.org/10.14267/VEZTUD.2022.03.01

Móricz, P., & Drótos, G. (2019). *Az információmenedzsmenttől a digitalizációig – Tendenciák az információmenedzsment és digitalizáció vállalati* *versenyképességben játszott szerepének vizsgálatában (Műhelytanulmány)*. Budapest: Budapesti Corvinus Egyetem, Versenyképesség Kutató Központ. Budapest.

Müller, S. D., Konzag, H., Nielsen, J. A., & Sandholt, H. B. (2024). Digital transformation leadership competencies: A contingency approach, *International Journal of Information Management*, *75*. https://doi.org/10.1016/j.ijinfomgt.2023.102734

Nagy, J., Oláh, J., Erdei, E., Máté, D., & Popp, J. (2018). The Role and Impact of Industry 4.0 and the Internet of Things on the Business Strategy of the Value Chain—The Case of Hungary, *Sustainability, 10(*10), 3491.

Nagy, M. (2018), Ipar 4.0: mindent átformál. Available: https://piacesprofit.hu/kkv_cegblog/ipar-4-0-az-uj-szabvany/ (Download: 2019. 05. 30.)

Nahavandi, A. (2002). The art and science of leadership, 3rd ed., Upper Saddle River, NJ, Prentice Hall.

Nakayama, R. S., de Mesquita Spínola, M., & Silva, J. R. (2020). Towards I4.0: A comprehensive analysis of evolution from I3.0, *Computers & Industrial Engineering*, *144*, 106453. https://doi.org/10.1016/j.cie.2020.106453

Nonaka, I., Takeuchi, H., & Umemoto, K. (1996). A theory of organizational knowledge creation, *International Journal of Technology Management*, *11*(7-8), 833–845.

Northouse, P. G. (2021). *Leadership: Theory and Practice*, Sage Publications.

Obermayer, N., Csizmadia, T., Hargitai, D. M., & Kigyós, T. A. (2021). Az Ipar 4.0 implementációval kapcsolatos vezetői motivációk és akadályozó tényezők elemzése hazai vállalatvezetők véleménye alapján, *Vezetéstudomány / Budapest Management Review*, *52*(2), 60–72. https://doi.org/10.14267/VEZTUD.2021.02.06

OECD. (2019). Artificial Intelligence in Society. Available: https://www.oecd-ilibrary.org/science-and-technology/artificial-intelligence-in-society_eedfee77-en (Download: 2022. 02. 06.)

Oyekunle, D., & Boohene, D. (2024). Digital Transformation Potential: The role of Artificial Intelligence in Business. *International Journal of Professional Business Review*, *9*(3), 1-17. https://doi.org/10.26668/businessreview/2024.v9i3.4499

Padeli, W., Mustafa W. A., Pangil, F., Abd Kadir, K., & Dwita, V. (2025). Knowledge Management and the Fourth Industrial Revolution (4IR): A Recent Systematic Review, *Journal of Advanced Research in Applied Sciences and Engineering Technology, 51*(2), 18-33. https://doi.org/10.37934/araset.51.2.1833

Pal, P. K., Hens, A., Behera, N., & Lahiri, S. K. (2025). Digital twins: Transforming the chemical process industry - A review, *Canadian Journal of Chemical Engineering, 1*. https://doi.org/10.1002/cjce.25611

Pfeffer, J. (1987). Bringing the environment back in: the social context of business strategy, *The Business Strategist Series*, 119-135.

Porfírio, J. A., Carrilho, T., Felício, J. A., & Jardim, J. (2021). Leadership characteristics and digital transformation. *Journal of Business Research, 124*, 610-619. https://doi.org/10.1016/j.jbusres.2020.10.058

Puhovichova, D., & Jankelova, N. (2021). Leadership in Conditions of Industry 4.0. *SHS Web of Conferences. 115*. https://doi.or/10.1051/shsconf/202111503013

PWC. (2019). *900 ezer magyar munkahelyet érint a mesterséges intelligencia a következő 15 év alatt.* Available: https://www.pwc.com/hu/hu/sajtoszoba/2019/ai_munkaeropiac.html (Download: 2022. 02. 06.)

Reeves Huapaya, E. S., Lazo Chucos, G., Parillo Sosa, E., & Iparraguirre Meza, M. (2025). Disruptive technologies in the university curriculum: use of artificial intelligence, *International Journal of Evaluation and Research in Education (IJERE), 14*(1), 671-681. http://doi.org/10.11591/ijere.v14i1.30450

Ringle, C. M., Wende, S., & Becker, J.-M. (2022). *SmartPLS 4. Oststeinbek: SmartPLS*, Available: https://www.smartpls.com (Download: 2022. 02. 10.)

Rousseau, D. M. (1995). *Psychological contracts in organizations: Understanding written and unwritten agreements,* Sage Publications, London.

Ruel, H., Rowlands, H., & Njoku, E. (2021). Digital business strategizing: the role of leadership and organizational learning, *Competitiveness Review: An International Business Journal, 31*(1), 145-161. http://doi.org/10.1108/CR-11-2019-0109

Rüzgar, N. (2018). The Effect of Leaders' Adoption of Task-Oriented or Relationship-Oriented Leadership Style on Leader-Member Exchange (LMX), In the

Organizations That Are Active In Service Sector: A Research on Tourism Agencies, *Journal of Business Administration Research*, *7*(1), 50-60. https://doi.org/10.5430/jbar.v7n1p50

Saghafi, F. (2016). Impact of Personal and Environmental Factors on the Effectiveness in Aca-demic E-Learning Systems; A Case Study: E-Learning System of The University of Sis-tan and Baluchestan, *Interdisciplinary Journal of Virtual Learning in Medical Sciences*, *7*(2) 1-13. https://doi.org/10.5812/ijvlms.12155

Sarstedt, M., Ringle, C., & Hair, J. (2020). Partial Least Squares Structural Equation Modeling, Homburg, C., Klarmann M. and Vomberg, A. (Ed.s), *Handbook of Market Research*, Springer Cham, Switzerland, 1-47, https://doi.org/10.1007/978-3-319-05542-8

Schneider, H. (2024). Managing the Generational Divide in Digitally Transformed Workforces, *Digital Transformation and Administration Innovation*, *1*(2), 17-23.

Semeraro, F., Griffiths, A., & Cangelosi, A. (2023). Human–robot collaboration and machine learning: A systematic review of recent research, *Robotics and Computer-Integrated Manufacturing*, *79*, 102432. https://doi.org/10.1016/j.rcim.2022.102432

Slack, N., Chambers, S., & Johnston, R. (2010). *Operations management*, Pearson education, Essex.

Smith, A. M., & Green, M. (2018). Artificial Intelligence and the Role of Leadership, *Journal of Leadership Studies*, *12*(4). https://doi.org/10.1002/jls.21605

Soori, M., Dastres, R., Arezoo, B., Karimi, F., & Jough, G. (2024). Intelligent robotic systems in Industry 4.0: A review, *Journal of Advanced Manufacturing Science and Technology*, *4*(3), 2024007. https://doi.org/10.51393/j.jamst.2024007

Sufian, A. T., Abdullah, B. M., & Miller, O. J. (2025). Smart Manufacturing Application in Precision Manufacturing. *Applied Sciences*, *15*(2), 915. https://doi.org/10.3390/app15020915

Swink, M., & Hegarty, W. H. (1998). Core manufacturing capabilities and their links to product differentiation, *International Journal of Operations & Production Management*, *18*(4), 374–396. https://doi.org/10.1108/01443579810199748

Szalavetz, A. (2020). *Ki profitál a digitális átalakulásból?,* Közgazdaság- és Regionális Tudományi Kutatóközpont Világgazdasági Intézet - Műhelytanulmányok 139. 1–45.

Szász, L., Demeter, K., Rácz, B. G., & Losonci, D. (2021). Industry 4.0: a review and analysis of contingency and performance effects, *Journal of Manufacturing Technology Management*, 32(3), 667-694, https://doi.org/10.1108/JMTM-10-2019-0371

Szerb, L., Komlósi, É., & Páger, B. (2020). Új technológiai cégek az Ipar 4.0 küszöbén – a magyar digitális vállalkozói ökoszisztéma szakértői értékelése, *Vezetéstudomány / Budapest Management Review*, *51*(6), 81–96. https://doi.org/10.14267/VEZTUD.2020.06.08

Szukits, Á. (2022). The illusion of data-driven decision making – The mediating effect of digital orientation and controllers' added value in explaining organisational implications of advanced analytics. *Journal of Management Control, 33,* 403-446. https://doi.org/10.1007/s00187-022-00343-w

Tabernero, C., Chambel, M. J., Curral, L., & Arana, J. M. (2009). The Role of Task-Oriented Versus Relationship-Oriented Leadership on Normative Contract and Group Performance, *Social Behavior and Personality: an international journal*, *37*(10), 1391-1404. https://doi.org/10.2224/sbp.2009.37.10.1391

Tari, A. (2010). *Y generáció.* Budapest, Jaffa Kiadó.

Tari, A. (2011). *Z generáció*. Tericum Kiadó Kft.

Tavoletti, E., Kazemargi, N., Cerruti, C., Grieco, C., & Appolloni, A. (2021). Business model innovation and digital transformation in global management consulting firms, *European Journal of Innovation Management*. https://doi.org/10.1108/EJIM-11-2020-0443

Tay, H. L., & Low, S. (2017). Digitalization of learning resources in a HEI – a lean management perspective, *International Journal of Productivity and Performance Management*, 66(5), 680-694. https://doi.org/10.1108/IJPPM-09-2016-0193

Teece, D. J. (2016). Dynamic capabilities and entrepreneurial management in large organizations: Toward a theory of the (entrepreneurial) firm, European Economic Review, *86*, 202–216. http://dx.doi.org/10.1016/j.euroecorev.2015.11.006

Teece, D., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management, *Strategic Management Journal,* 18(7), 509-533, https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

Tegmark, M., & Werner, A. C. (2018). La inteligencia artificial nos hará profesionalmente irrelevantes?, *Gestion*. Available: https://gestion.pe/blog/anunciasluegoexistes/2018/05/la-inteligencia-artificial-nos-hara-profesionalmente-irrelevantes.html (Download: 2022. 02. 06.)

Tian, G., Li, B., & Cheng, Y. (2022). Does digital transformation matter for corporate risk-taking?, *Finance Research Letters*, 49, https://doi.org/10.1016/j.frl.2022.103107

Tilson, D., Lyytinen, K., & Sørensen, C., (2010). Digital infrastructures: the missing IS research agenda. *Information Systems Research, 21*(4), 748–759. https://doi.org/10.1287/isre.1100.0318

Törőcsik, M., Szűcs, K., & Kehl D. (2014). How Generations Think: Research on Generation Z, *Acta Universitatis Sapientiae, Communicatio, 1*(2014), 23–45.

Tortorella, G., Prashar, A., Antony, J., Cawley, A., Vassolo, R., & Sony, M. (2023). Role of leadership in the digitalisation of manufacturing organisations, *Journal of Manufacturing Technology Management,* 34(2), 315-336, https://doi.org/10.1108/JMTM-09-2022-0312

Tortorella, G.L., Fettermann, D., Frank, A., & Marodin, G. (2018). Lean manufacturing implementation: leadership styles and contextual variables, *International Journal of Operations & Production Management, 38*(5), 1205-1227. https://doi.org/10.1108/IJOPM-08-2016-0453

Tortorella, G.L., & Fogliatto, F. (2017). Implementation of lean manufacturing and situational leadership styles: An empirical study, *Leadership & Organisation Development Journal, 38*(7), 946-968.

Tortorella, G., van Dun, D. H., & Gundes de Almeida, A. (2019). Leadership behaviors during lean healthcare implementation: a review and longitudinal study, *Journal of manufacturing technology management, 31*(1), 193-215. https://doi.org/10.1108/JMTM-02-2019-0070 van Dun, D. H., Hicks, J. N., & Wilderom, C. P. (2017). Values and behaviors of effective lean managers: Mixed-methods exploratory research, *European Management Journal*, *35*(2), 174-186. https://doi.org/10.1016/j.emj.2016.05.001

Weber, E., Büttgen, M., & Bartsch, S. (2022). How to take employees on the digital transformation journey: An experimental study on complementary leadership behaviors in managing organisational change, *Journal of Business Research*, *143*, 225-238. https://doi.org/10.1016/j.jbusres.2022.01.036

Westerman, G., Tannou, M., Bonnet, D., Ferraris, P., & McAfee, A. (2012). The Digital Advantage: How Digital Leaders Outperform their Peers in Every Industry. MIT Center for Digital Business and Capgemini Consulting.

White, R., & Lippitt, R. (1960). *Autocracy and democracy: an experimental inquiry,* Harper and Brothers, New York, NY.

Wimmer, Á., & Csesznák, A. (2021). *A hazai vállalatok versenyképességi jellemzői a negyedik ipari forradalom idején,* Versenyképesség könyvsorozat. Alinea Kiadó – BCE Versenyképesség Kutató Központ, Budapest. http://doi.org/10.14267/978-615-5669-49-1

Wong, K. K. K. (2013). Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS, *Marketing Bulletin*, *24*(1), 1-32.

Wu, T., Chen, B., Shao, Y., & Lu, H. (2021). Enable digital transformation: entrepreneurial leadership, ambidextrous learning and organisational performance, *Technology Analysis and Strategic Management,* *33*(12), 1-15, https://doi.org/10.1080/09537325.2021.1876220

Xu, S., Stienmetz, J., & Ashton, M. (2020). How will service robots redefine leadership in hotel management? A Delphi approach, *International Journal of Contemporary Hospitality Management, 32*(6), 2217-2237. https://doi.org/10.1108/IJCHM-05-2019-0505

Xue, J., Li, G., & Ivanov, D. (2025). Digital transformation in the blockchain era: Balancing efficiency and resilience in operations management, *International Journal of Production Economics, 282*. https://doi.org/10.1016/j.ijpe.2025.109525

Yılmaz, B., Kısaçtutan, E. D., & Karatepe, S. G. (2024). Digital natives of the labor market: Generation Z as future leaders and their perspectives on leadership, *Frontiers in Psychology, 15*. https://doi.org/10.3389/fpsyg.2024.1378982

Yukl, G., Gordon, A., & Taber, T. (2002). A hierarchical taxonomy of leadership behavior: integrating a half- century of behavior research, *Journal of Leadership and Organisational Studies*, *9*, 15-32. http://doi.org/10.1177/107179190200900102

Yukl, G. (2012). Effective Leadership Behavior: What We Know and What Questions Need More Attention, *Academy of Management Perspectives*, *26*, 66-85. https://doi.org/10.5465/amp.2012.0088

Zahra, S. A., & George, G. (2002). Absorptive Capacity: A Review, Reconceptualization and Extension, *Academy of Management Review*, 27(2), 185–203, https://doi.org/10.2307/4134351

Zairi, M. (1994). Leadership in TQM Implementation: Some Case Examples, *The TQM Magazine*, *6*(6), 9-16. https://doi.org/10.1108/09544789410073586

Zemke, R., Raines, C., & Filipczak, B. (2000). Generations at Work: Managing the Clash of Veterans, Boomers, Xers, and Nexters in Your Workplace. *New York: American Management Association*.

Zhong, R. Y., Xu, X., Klotz, E., & Newman, S. T. (2017). Intelligent Manufacturing in the Context of Industry 4.0: A Review, *Engineering*, *3*(5), 616-630. Available: https://www.sciencedirect.com/science/article/pii/S2095809917307130 (Download: 2019. 05. 31.)