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<p>Pramonės 4.0 / 5.0 įrankių diegimo poveikis gyvenimo darbe kokybės rodikliams</p>	<p>The Impact of Industry 4.0 / 5.0 Tools Implementation on the Quality of Work Life Indicators</p>
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INTRODUCTION

Relevance of the topic. The global industrial landscape is rapidly changing due to the advancement of digital technologies, marking a shift from traditional manufacturing paradigms to automated, data-driven production systems. These changes are reflected in the concept of Industry 4.0, a revolution based on real-time automation, analysis of data and connectivity. While these technologies have made a significant contribution to improving productivity and production efficiency, their impact on the human factors of work, in particular quality of work life (QWL), remains complex, ambiguous and, in some cases, contradictory (Williams et al., 2020).

The ongoing digital transformation driven by Industry 4.0 and the emerging paradigm of Industry 5.0 is reshaping workplaces and rewriting human work experience. While Industry 4.0 emphasises efficiency through automation, connectivity and artificial intelligence, its direct impact on quality of work life (QWL) indicators such as job satisfaction, stress levels and skills development is questionable. Industry 5.0 offers a human-centred perspective that integrates collaborative robotics, augmentation technologies and digital twins to foster creativity, resilience and employee well-being (Kolade & Owoseni, 2022; Zafar et al., 2023).

This quantitative research investigates the relationship between the implementation of Industry 4.0 and 5.0 tools and worker perceptions of QWL. A structured survey collected data from 150 randomly selected employees in digitally changing organizations. Data analyses were performed using descriptive statistics, regression analysis, and structural equation modeling (SEM) to test the hypothesized relationships between technological adoption and QWL constructs.

The level of exploration of the topic and novelty of the thesis. To address these challenges, Industry 5.0 has emerged as a more human-centred evolution of industrial growth. Rather than focusing on efficiency alone, Industry 5.0 seeks to balance technological advancement with human values such as creativity, sustainability and well-being (European Commission, 2021; Nahavandi, 2019). Tools such as collaborative robots (cobots) “*Unlike traditional industrial robots, cobots are equipped with sophisticated sensors, software, and safety features that allow them to work safely and effectively alongside humans without the need for safety barriers or other protective measures*” (Zafar et al., 2023), digital twins “*The use of*

digital twins also facilitates communication and coordination between human and robot collaborators. The digital twin can provide a shared visual representation of the physical system, which can help to improve the understanding of the system and its behavior." (Zafar et al., 2023), augmentation technologies (AR, VR, MR), and human-centric AI comprise the core of this paradigm. These technologies not only support productivity but also aim to advance employee experience by improving safety, engagement, training, and flexibility.

The emergence of digital industrial paradigms has not been complete but has been the consequence of decades of changes in relationships between technology, work, and organization. Industry 4.0 or "Fourth Industrial Revolution," represents the culmination of long-term trends in automation and systems integration (Schwab, 2016). In contrast to previous changes that focused on mechanization or electrification, this revolution brings in smart, networked technologies that operate with minimal interference from people, deeply impacting not just production efficiency but also organizational culture and the role of people in it (Kolade & Owoseni, 2022).

However, as global economies adopt these digital frameworks at varying speeds and intensities, the transformation's social and psychological implications for workers have gained attention. Promises of efficiency are often at odds with growing fears of worker displacement, loss of autonomy, algorithmic oversight, and a growing need for constant adaptation (Williams et al., 2020). In many industries, digital transformation has not only changed work processes, but also the social fabric of the workplace, changing perceptions of what it means to be skilled, valuable or even 'employable' (Tamunomiebi & Oyibo, 2020).

Industry 5.0 is emerging in part as a response to these contradictions. Rather than simply superimposing new technologies on old systems, this new paradigm reflects a broader shift in priorities, from performance to people (Grybauskas et al., 2022). It highlights the need to embed ethical, social, and psychological dimensions into how innovation is designed and implemented. This includes ensuring that technological advancements foster creativity, human collaboration, well-being, and inclusivity—thus rebalancing the human-machine dynamic that Industry 4.0 disrupted (Nahavandi, 2019).

In this broader landscape, Quality of Work Life (QWL) is gaining recognition as both a diagnostic and strategic tool. It helps organizations evaluate not just performance outcomes, but also the lived experience of their employees in technologically evolving environments

(Williams et al., 2020; De Witte, 2005). By focusing on QWL, researchers and practitioners can better understand whether digital progress enhances or erodes essential aspects of working life such as mental health, skill relevance, and job satisfaction. The novelty of the thesis lies in its focus on the worker-centred outcomes of digital industrial transformation, specifically in comparing the automation-centred approach of Industry 4.0 with the human-centred approach of Industry 5.0. The thesis empirically assesses how specific technologies such as collaborative robots, artificial intelligence, digital twins and AR/VR affect stress, job security and skills development (or QWL) in a regional environment that has not been widely studied. Research has shown that technologies aligned with human needs can significantly improve these indicators of quality of work life, whereas poorly implemented systems can exacerbate stress, undermine autonomy, and lead to job dissatisfaction (Williams et al., 2020). Successful integration of Industry 5.0 technologies thus depends not only on technical infrastructure, but also on sound organisational design and inclusive digital governance.

The problem of the thesis. While the tools of Industry 4.0 and 5.0 are being rapidly adopted by companies, their impact on employee well-being and quality of work life remains poorly understood. There is a need to examine whether these technologies enhance or diminish important work-related outcomes such as job satisfaction, psychological distress and the ability to develop new skills. The problem addressed by this thesis is the lack of empirical insight into how digital transformation affects QWL indicators within the evolving industrial context.

The aim of the thesis is to evaluate the impact of Industry 4.0 and Industry 5.0 tools on Quality of Work Life (QWL) of employees.

The object of the thesis. This study seeks to explore how Industry 4.0 and 5.0 tools influence Quality of Work Life (QWL).

The methods deployed by the Master thesis. The study adopts a *quantitative* research approach. This strategy allows for the collection of standardized, measurable data that can be used to assess correlations and potential causal relationships between the adoption of Industry 4.0/5.0 technologies and QWL indicators. Quantitative methods are suitable for generalizing findings across a broader sample and for conducting inferential statistical analyses to test the proposed hypotheses.

The description of the structure of the thesis. The thesis is structured into three main chapters, each addressing a specific stage of the research process.

The first chapter, the literature review, introduces the conceptual and theoretical background of the study. It begins with an overview of the evolution of industrial revolutions, leading to the emergence of Industry 4.0 and Industry 5.0. The chapter then defines the concept of Quality of Work Life (QWL) and justifies its operationalisation through three indicators: stress, job security, and skills development. Subsequent sections provide an in-depth analysis of Industry 4.0 as a technology-driven paradigm and Industry 5.0 as a human-centric alternative, followed by a synthesis of recent empirical findings linking technological adoption to employee outcomes. The chapter concludes with the development of the conceptual model and hypotheses.

The second chapter presents the empirical methodology of the study. It outlines the research aim, objectives, and hypotheses, followed by the description of the quantitative research design. This chapter details the questionnaire structure, measurement instruments, sampling strategy, data collection procedures, and ethical considerations. It also describes the analytical techniques applied, including descriptive statistics, reliability testing, correlation analysis, regression analysis using SPSS, and Structural Equation Modeling (SEM) conducted with SmartPLS.

The third chapter contains the empirical analysis and results. It presents descriptive statistics of the sample, evaluates the reliability of measurement scales, and reports the outcomes of correlation and regression analyses. The chapter also interprets the SEM results, assessing the relationships between Industry 4.0/5.0 technologies and QWL indicators. The findings are discussed in relation to the proposed hypotheses and existing literature.

The thesis concludes with a section summarising the main findings, identifying research limitations, and suggesting directions for future studies.

1. THE ANALYSIS OF SCIENTIFIC LITERATURE

1.1 Quality of Work Life (QWL) Framework

As digital transformation accelerates under the paradigms of Industry 4.0 and 5.0, the concept of Quality of Work Life (QWL) has become increasingly central to discussions about the future of employment. QWL encompasses not only contractual or material conditions but also the psychological, social, and ethical dimensions that shape the everyday experience of work (Williams, Zhou, & Zou, 2020). In a rapidly changing technological environment, these elements collectively determine whether work is perceived as meaningful, sustainable, and supportive of employee well-being.

Multidimensional Model of QWL. Drawing on the framework proposed by Williams, Zhou, and Zou in *Mapping Good Work* (2020), QWL can be conceptualised through seven interconnected dimensions:

- terms of employment (job security, contract stability, guaranteed hours),
- pay and benefits,
- job design and the nature of work (autonomy, skill use, opportunities for progression, sense of purpose),
- social support and cohesion,
- voice and representation,
- work–life balance,
- health, safety, and psychosocial well-being.

These dimensions encourage a shift away from traditional wage-focused definitions of “good work” and instead emphasise the intrinsic and experiential qualities of labour (Williams et al., 2020). Their extensive UK-based research demonstrates that employees consistently value enjoyment of tasks, job security, and positive managerial relationships above purely financial considerations. Furthermore, the authors highlight the structural labour market changes brought about by digitalisation—specifically, the ongoing polarisation in which middle-income, routine jobs decline while high-autonomy, high-skill positions and low-wage

precarious roles expand. This “hollowing out” is strongly associated with automation and carries significant implications for QWL, particularly regarding equity and access to meaningful work (Williams et al., 2020).

QWL in the Age of Digital Sovereignty. Complementing this multi-dimensional perspective, Hartmann and Schajek in *The New Digital Work: Digital Sovereignty at the Workplace* (2023) introduce the concept of digital sovereignty as a crucial determinant of quality of work life in environments shaped by advanced technologies. Digital sovereignty refers to the degree to which employees and organisations maintain control over their digital work environment, including the technological tools, data flows, and algorithmic decision-making processes that influence everyday tasks and responsibilities (Hartmann & Schajek, 2023). This concept emphasises the importance of agency and transparency in contexts where digital systems increasingly mediate work.

Their analysis identifies a central pattern: when digital tools are implemented in ways that enhance autonomy, support skill development, and strengthen employees’ sense of self-efficacy, they tend to improve job satisfaction, work engagement, and overall well-being (Hartmann & Schajek, 2023). In contrast, digitalisation that introduces excessive surveillance, algorithmic control, or contributes to perceptions of job insecurity can have detrimental effects, including rising stress levels, employee resistance, and declining job satisfaction. In this sense, the same technologies that promise efficiency and optimisation may undermine the experiential quality of work if implemented without careful consideration of human factors.

Importantly, Hartmann and Schajek (2023) highlight that the impact of digitalisation is strongly shaped by regional, organisational, and governance contexts. When digital transformation is approached thoughtfully—with ethical data practices, clear communication, participatory implementation strategies, and adequate training opportunities—Industry 4.0 tools can enhance productivity while simultaneously preserving, or even strengthening, workers’ dignity and sense of control. However, in organisations where such safeguards are absent, digitalisation is more likely to result in work intensification, marginalisation of certain employee groups, and diminished autonomy. These contrasting outcomes underscore the importance of aligning technological change with human-centred principles to maintain or improve QWL in modern workplaces (Hartmann & Schajek, 2023).

From Automation to Collaboration: A growing body of literature converges on the argument that technological progress can meaningfully enhance Quality of Work Life only when it is guided by human-centric principles. This perspective reflects the broader transition from Industry 4.0—primarily oriented toward efficiency, automation, and optimisation—to Industry 5.0, which emphasises collaboration between humans and intelligent systems, creativity, adaptability, and organisational resilience (Hartmann & Schajek, 2023). Industry 5.0 thus reframes the role of technology: rather than replacing human capabilities, it seeks to augment them and ensure that technological innovation serves social and well-being objectives alongside economic ones.

Within this paradigm, workers are no longer conceptualised as passive recipients of technological change but as active agents whose experiences, needs, and values should shape the design, implementation, and governance of digital tools. This approach aligns with human-centred design traditions and reinforces the notion that the quality of technological integration must be evaluated not only through productivity indicators but also through its impact on employee autonomy, competence, and sense of meaningful engagement at work (Hartmann & Schajek, 2023).

Accordingly, technologies such as collaborative robots, immersive learning systems (e.g., AR/VR/MR), and predictive AI must be assessed through a dual lens: their potential to improve operational performance and their capacity to foster psychological safety, support skill development, and strengthen workers' agency. Industry 5.0 research suggests that when these tools are implemented in ways that reinforce employee empowerment and participation, they can significantly contribute to an improved QWL; however, if deployed without such considerations, their benefits may be limited or even counterproductive (Hartmann & Schajek, 2023).

1.2 Conceptualizing Quality of Work Life (QWL) as a Single Construct

Quality of Work Life (QWL) is a comprehensive construct that reflects employees' overall assessment of their work environment and the extent to which it meets their personal and professional needs. Traditionally, QWL is conceptualised as a multidimensional construct that includes such elements as job satisfaction, physical and psychological well-being, work-life balance, autonomy, security and opportunities for personal growth (Walton, 1975;

Sirgy et al., 2001). These dimensions collectively describe the conditions under which employees experience work as meaningful, satisfying, and sustainable.

Despite its multidimensional origins, a growing body of empirical research supports the treatment of QWL as a single, unified construct. Easton and Van Laar (2013) developed the Work-Related Quality of Life (WRQoL) scale, which synthesizes various QWL dimensions into one composite measure. The WRQoL scale includes indicators like general well-being, home-work interface, job and career satisfaction, working conditions, control at work, and stress at work—all of which contribute to a singular QWL score. Factor analytic studies confirm that these subdimensions load onto a higher-order QWL factor, suggesting that employees perceive their work life as a cohesive experience rather than a disjointed set of components.

Moreover, research in organisational psychology supports this holistic approach. Hackman and Oldham's model of workplace characteristics, while focusing on workplace design, also implies that key workplace attributes interact to shape overall motivation and job satisfaction. Similarly, Ryan and Deci's Self-Determination Theory positions autonomy, competence, and relatedness as interdependent drivers of well-being at work. These systems support the idea that employees form a complex perception of quality of work life that is influenced by overlapping and complementary factors.

Several studies using Structural Equation Modeling (SEM) have demonstrated that QWL, when treated as a higher-order latent variable, shows strong predictive power for key outcomes such as job satisfaction, organizational commitment, and employee performance (Sirgy et al., 2001). This modeling approach not only captures the complexity of the construct but also enables a parsimonious hypothesis structure—allowing researchers to examine QWL as a singular mediating or outcome variable without disaggregating it into multiple dependent variables.

The human-centred vision of Industry 5.0 is consistent with this holistic view of QWL. Emerging technologies such as collaborative robots, digital twins, augmented reality and human-centred AI aim not only to optimize specific working conditions, but also to improve the overall employee experience (Nahavandi, 2019; Zafar et al., 2023). Thus, a comprehensive measure of QWL allows researchers to better assess how the combined impact of technological, organisational and social change affects workers.

Adopting QWL as a single construct in this thesis is reasonable. This approach reflects the inherently integrated nature of employees' work experiences and corresponds with established psychometric frameworks that conceptualise QWL as a higher-order latent variable. Treating QWL as a unified construct also enables the application of more parsimonious and statistically efficient analytical models, reducing redundancy and preventing the artificial fragmentation of related dimensions. Most importantly, it allows the study to address the overarching research question in a holistic manner: how do Industry 4.0 and Industry 5.0 technologies shape employees' overall quality of work life?

Although Quality of Work Life (QWL) is widely acknowledged as a multidimensional construct (Walton, 1975; Sirgy et al., 2001), the present study operationalizes QWL through three core dimensions: stress levels, opportunities for skill development, and job security. This selection reflects both theoretical relevance and practical considerations of the research design. The decision to focus on these three dimensions is based on their centrality to the contemporary challenges posed by Industry 4.0 and Industry 5.0, as well as their established role in validated psychological scales.

Stress levels are a key determinant of QWL because digital transformation often introduces new forms of pressure, such as technological overload, continuous monitoring, and heightened performance expectations. The Perceived Stress Scale (Cohen, et al., 1983) has consistently been applied in organizational contexts to measure employees' psychological strain, and research shows that stress directly influences job satisfaction, mental well-being, and productivity. In the context of Industry 4.0/5.0, stress emerges as a crucial mediator of how employees experience digitalization in their daily work.

Skill development represents another indispensable dimension. The implementation of advanced industrial technologies requires employees to continually acquire and update digital competencies. Opportunities for training and learning therefore strongly affect both job satisfaction and perceptions of employability (Easton & Van Laar, 2013). Studies in the field of organizational psychology emphasize that perceived competence and opportunities for growth are among the strongest predictors of motivation and well-being at work (Ryan & Deci, 2000). Industry 5.0, with its emphasis on human-machine collaboration, further reinforces the importance of lifelong learning and reskilling, making skill development a central QWL component.

Job security, although sometimes seen as an external or organizational factor, is in fact directly tied to employees' lived experience of work. Perceptions of insecurity—whether related to redundancy, contract instability, or the perceived risk of automation—affect mental well-being, organizational commitment, and overall QWL (De Witte, 2005). To capture this dimension, the present study uses the Job Insecurity Scale (De Witte, Short Form), which is one of the most widely validated measures of employment-related uncertainty. Conceptually, job security aligns with established QWL frameworks, such as Walton's (1975) criteria and Sirgy et al.'s (2001) need-based model, both of which identify employment stability as an essential aspect of work quality. Empirical studies further demonstrate that perceived job insecurity is not only associated with negative outcomes such as stress and dissatisfaction, but also undermines skill acquisition and long-term career planning (De Witte, 2005).

The decision to restrict QWL to these three dimensions is justified on methodological grounds as well. A parsimonious construct allows for efficient measurement and analysis while maintaining conceptual validity. By focusing on stress, skill development, and job security, the model captures psychological, developmental, and existential aspects of QWL that are most directly influenced by digital transformation. This approach avoids redundancy and fragmentation while remaining grounded in established scales and theories.

1.3 Evolution of Industrial Revolutions

The evolution of industrial paradigms reflects how technological change reshapes organisational structures, workforce requirements, and the management of human labour. Rather than representing purely technological milestones, successive industrial revolutions have progressively altered how work is organised, how skills are deployed, and how employees experience their roles within production systems. Understanding this evolution is essential for contextualising contemporary challenges associated with Industry 4.0 and Industry 5.0, particularly those related to workforce adaptation and Quality of Work Life (QWL) (Calp & Bütüner, 2022). As industrial revolutions progressed, the balance between technological advancement and human involvement in production has repeatedly been renegotiated, making the historical sequence essential for contextualising the present transition toward human-centric digitalisation.

Early industrial paradigms established the foundations of modern work organisation. Industry 1.0 introduced mechanisation and factory-based labour, creating structured working hours,

task specialisation, and managerial control over production processes. Industry 2.0 further intensified these patterns through electrification and mass production, reinforcing hierarchical management structures and standardised job roles (Xu et al., 2021; Mathur et al., 2022). These stages institutionalised efficiency-driven models of labour organisation that continue to influence managerial thinking today.

Industry 3.0 marked a turning point in workforce management, as organisations became increasingly dependent on technical expertise, continuous training, and human–technology interaction. These shifts introduced early concerns regarding skills mismatches, reskilling costs, and employee adaptability—issues that remain highly relevant in contemporary digital transformation strategies (Xu et al., 2021)

In contrast to earlier industrial paradigms, Industry 4.0 represents not only a technological shift but a managerial challenge, as organisations must balance efficiency gains with workforce stability, employee autonomy, and long-term capability development (Xu et al., 2021; Mathur et al., 2022). The Fourth Industrial Revolution (Industry 4.0) was formally conceptualised in 2011 through a German government initiative aimed at strengthening manufacturing competitiveness in the global economy. Industry 4.0 represents a shift from isolated automated systems to highly interconnected and intelligent production environments characterised by cyber-physical systems (CPS), the Internet of Things (IoT), artificial intelligence (AI), cloud computing, and big data analytics (Mathur et al., 2022). Smart factories operate through continuous data exchange between machines, digital platforms, and human operators, enabling predictive maintenance, autonomous decision-making, and real-time optimisation of production processes.

While Industry 4.0 significantly enhances efficiency, customisation, and resource utilisation, it also introduces profound socio-technical challenges. Scholars increasingly highlight concerns about workforce displacement, algorithmic monitoring, and the potential intensification of work due to constant digital oversight (Xu et al., 2021; Mathur et al., 2022). The automation of routine tasks may reduce physical strain and improve accuracy, yet it simultaneously raises fears of job redundancy and skill obsolescence, creating uncertainty and stress for employees. These dynamics position Industry 4.0 as a critical point of tension in contemporary labour research, directly connecting technological capability with evolving perceptions of job security, autonomy, and overall Quality of Work Life.

The Fifth Industrial Revolution (Industry 5.0) has emerged in response to the socio-technical challenges associated with Industry 4.0, particularly concerns related to job displacement, loss of autonomy, and the intensification of digital monitoring. Unlike Industry 4.0, which is primarily oriented toward automation, data integration, and operational efficiency, Industry 5.0 places human welfare and societal value at the centre of industrial transformation. It emphasises collaborative interaction between humans and intelligent systems, where technology enhances rather than replaces human capabilities (Xu et al., 2021). This paradigm promotes the coexistence of advanced automation with uniquely human attributes such as creativity, critical thinking, and emotional intelligence.

Industry 5.0 also reflects a broader commitment to sustainability and social responsibility. Scholars argue that industrial innovation must move beyond economic performance to incorporate ecological resilience, ethical governance, and social cohesion (Calp & Bütüner, 2022). From this perspective, Industry 5.0 is not merely a technological evolution but a normative shift in how societies conceptualise the role of technology in work and production. Digital tools such as human-centric AI, personalised assistance systems, augmented and virtual reality environments, and digital twins are positioned as enablers of meaningful, safe, and empowering work experiences. Industry 5.0 aligns closely with contemporary discussions on Quality of Work Life (QWL). The paradigm underscores the need to ensure that technological deployment enhances autonomy, learning opportunities, and well-being—elements consistently identified in QWL frameworks as central to positive work experiences. By prioritising human dignity, resilience, and sustainable development, Industry 5.0 provides an alternative model to the automation-dominated trajectory of Industry 4.0, advocating for a balanced integration of technological efficiency with human-centric values.

Together, the five industrial revolutions illustrate a historical progression from mechanisation to automation and, ultimately, toward collaborative and sustainable innovation. While Industry 1.0 through Industry 4.0 primarily advanced productivity and operational efficiency, Industry 5.0 represents a paradigm shift aimed at reconciling technological advancement with human development and societal well-being.

1.4 INDUSTRY 4.0: TECHNOLOGY-DRIVEN EFFICIENCY

Industry 4.0 is rooted in the integration of cyber-physical systems, artificial intelligence (AI), big data analytics, and the Internet of Things (IoT) into industrial processes (Friesner, 2019).

This paradigm emphasizes automation, real-time data exchange, interconnected production systems, and algorithmic decision-making designed to maximise operational efficiency. Through advanced sensing technologies and autonomous control mechanisms, Industry 4.0 enables predictive maintenance, smart logistics, and self-optimising manufacturing environments, positioning digital intelligence at the centre of industrial activity (Friesner, 2019; Xu et al., 2021).

Despite the productivity gains associated with these technologies, research increasingly highlights the socio-technical tensions embedded within the Industry 4.0 model. Automated systems can reduce physical strain, minimise human error, and streamline repetitive tasks, yet they simultaneously reshape job structures and skill requirements in ways that may challenge workers' sense of stability and professional identity (Ghobakhloo, 2018). The rise of algorithmic management—where AI-guided processes allocate tasks, evaluate performance, or monitor workflows—further intensifies concerns about surveillance, reduced autonomy, and technological pressure (Hartmann & Shajek, 2023). These dynamics position Industry 4.0 as a complex paradigm in which efficiency-oriented technological design often overshadows considerations related to job satisfaction, psychological well-being, and broader Quality of Work Life indicators.

Scholars also draw attention to the risk of worker deskilling under extensive automation. As machines increasingly assume routine and even semi-skilled tasks, employees may experience diminished opportunities for meaningful task engagement, potentially leading to alienation and decreased motivation (Williams et al., 2020). Job displacement fears are likewise prevalent: widespread deployment of AI and robotics contributes to heightened perceptions of job insecurity, a phenomenon particularly pronounced in environments where transparent communication and upskilling initiatives are insufficient (De Witte, 2005; Xu et al., 2021). These concerns indicate that the implications of Industry 4.0 extend beyond technological adoption, touching the psychological and social dimensions of work central to contemporary QWL research.

The final report of the Industrie 4.0 Working Group in Germany (Kagermann, Wahlster, & Helbig, 2013) positioned Industry 4.0 as a strategic initiative designed to secure the long-term competitiveness of German manufacturing within a rapidly globalising economy. The report articulated four core design principles—interoperability, information transparency, technical

assistance, and decentralized decision-making—which together envisioned a highly autonomous yet human-supportive production environment. These principles underscored an aspiration not only to enhance productivity but also to strengthen human decision-making through improved access to information and intelligent assistance systems (Kagermann et al., 2013). However, subsequent empirical developments suggest that, in industrial practice, the application of these principles has tended to prioritise cost reduction, automation, and operational efficiency over the human-centric elements originally envisioned (Acatech, 2016).

Research examining the consequences of Industry 4.0 technologies for employees indicates a complex and often ambivalent picture. On one hand, automation and sensor-based monitoring can significantly reduce physical strain, eliminate repetitive manual tasks, and increase flexibility in production processes, contributing to improved occupational safety and workflow optimisation (Acatech, 2016; Xu et al., 2021). These benefits align with the argument that digital technologies, when implemented responsibly, can support ergonomic improvements and diminish the physical burden traditionally associated with industrial labour.

On the other hand, scholars increasingly highlight the potential adverse effects associated with Industry 4.0 systems. The replacement of routine tasks with automated processes may contribute to job alienation, as workers experience a reduction in task ownership and meaningful engagement (Williams et al., 2020). Furthermore, technologies such as real-time IoT monitoring, AI-based performance analytics, and digital tracking systems raise concerns about workplace surveillance, potentially leading to increased psychological pressure, diminished autonomy, and a sense of constant evaluation (Hartmann & Shajek, 2023). At the same time, the rapid pace of digitalisation heightens the risk of skill redundancy, particularly when organisations fail to provide adequate training and continuous learning opportunities to help employees adapt to more technologically sophisticated roles (Ghobakhloo, 2018).

Ethical considerations further complicate the Industry 4.0 landscape. IoT-enabled data flows and algorithmic oversight generate significant questions about privacy, informed consent, and control over work processes. Employees may feel uncertain about how their data is collected, interpreted, or used, creating tension between organisational efficiency goals and workers' expectations of autonomy and dignity in the workplace (Hartmann & Shajek, 2023). These

concerns illustrate that Industry 4.0's transformative potential carries both enabling and constraining implications for the Quality of Work Life, reinforcing the need for a more balanced approach to technological integration.

More recent analyses argue that Industry 4.0 should also be viewed as a transitional stage rather than a final industrial paradigm, particularly due to the human and organisational challenges associated with its implementation. Research highlights that the rapid adoption of digital technologies has created significant skill gaps, uneven workforce preparedness, and increasing pressure on employees to continuously adapt to new digital tools and processes (Turcan & Pojar, 2024). The authors demonstrate that while Industry 4.0 has accelerated automation and data-driven optimisation, it has simultaneously intensified demands for both advanced technical competencies—such as data analytics and AI literacy—and non-technical skills such as resilience, adaptability, and creativity. These evolving expectations introduce new sources of job-related stress and insecurity, especially for workers who lack access to adequate training or reskilling programmes (Turcan & Pojar, 2024).

Such challenges underscore the inherent tension between productivity-driven technological innovation and employee well-being, suggesting that purely efficiency-oriented models offer limited capacity to support sustainable workforce development. This recognition strengthens the argument that Industry 4.0 functions as a necessary but incomplete stage that must evolve toward more human-centric frameworks. Scholars increasingly contend that addressing skills gaps through proactive upskilling and creating organisational environments that prioritise human capabilities are essential prerequisites for transitioning to Industry 5.0 (Turcan & Pojar, 2024; Xu et al., 2021).

In summary, Industry 4.0 represents a profound technological shift characterised by automation, cyber-physical integration, and algorithmic decision-making. However, as Kagermann et al. (2013) emphasise, its implementation often overlooks the social and human implications of industrial transformation. These limitations provide the foundation for Industry 5.0, which seeks to rebalance innovation by integrating human-centric, sustainable, and resilient approaches into the next phase of industrial development.

1.5 INDUSTRY 5.0: HUMAN-CENTRIC INNOVATION

Industry 5.0 has emerged as a direct response to the structural limitations of Industry 4.0, particularly those linked to workforce displacement, skill obsolescence, and the psychological pressures associated with continuous automation. Unlike Industry 4.0, which prioritises operational efficiency and autonomous production, Industry 5.0 places human value creation at the centre of industrial development (European Commission, 2021). This paradigm emphasises the complementarity between human capabilities and advanced technologies, proposing a model in which digital tools enhance—rather than replace—human judgment, creativity, and agency (Xu et al., 2021). Through this shift, Industry 5.0 seeks to rebalance the socio-technical system by ensuring that technological progress remains aligned with human needs and long-term societal wellbeing (Ambhore, 2023).

A defining characteristic of Industry 5.0 is its emphasis on human–machine collaboration. Technologies such as digital twins, intelligent assistance systems, and augmentation platforms (including AR, VR, and MR) illustrate this transition toward symbiotic interaction, where technology serves as an extension of human capability rather than an autonomous substitute (Kolade & Owoseni, 2022). These tools aim to enhance decision-making, improve safety, and foster more personalised and adaptive forms of work. Human-centric robotics and AI-supported decision systems further operationalise this vision by enabling workers to engage in more meaningful, cognitively complex, and less physically demanding tasks.

The European Commission’s (2021) conceptualisation of Industry 5.0 extends beyond technological innovation to include sustainability and resilience as core pillars of industrial transformation. This framework positions Industry 5.0 as a model that integrates economic performance with environmental responsibility and social cohesion, thereby aligning industrial development with key United Nations Sustainable Development Goals (SDGs). By advocating for resource-efficient production, inclusive work environments, and long-term societal value, Industry 5.0 reframes the purpose of industrial progress: productivity is pursued not as an end in itself, but as a means to support human flourishing and sustainable futures (Ambhore,2023).

Research on the workforce transition from Industry 4.0 to Industry 5.0 highlights several emerging challenges that shape the modern industrial environment. As digital technologies become increasingly embedded in production and decision-making processes, employees are confronted with continuous upskilling requirements, shifting job boundaries, and heightened

uncertainty regarding their long-term roles within technologically evolving organisations (Xu et al., 2021; Kolade & Owoseni, 2022). These pressures may intensify stress or resistance, particularly when technological change is implemented without adequate preparation or communication. The literature emphasizes that such challenges can be mitigated through proactive strategies, including lifelong learning programmes, transparent and ethical governance of digital systems, and inclusive human resource practices that give employees a voice in digital transformation processes (Grybauskas, Stefanini, & Ghobakhloo, 2022). In the absence of these initiatives, digitalisation may exacerbate workplace exclusion, contribute to skill mismatches, and reinforce perceptions of technological advancement as a source of threat rather than an opportunity for professional and personal development.

From a theoretical perspective, the principles underlying Industry 5.0 align closely with foundational frameworks in organisational psychology. Job Characteristics Theory (Hackman & Oldham, 1976) underscores the role of autonomy, task identity, and feedback in shaping work motivation, satisfaction, and performance. Self-Determination Theory (Deci & Ryan, 1985) complements this view by identifying autonomy, competence, and relatedness as essential psychological needs that underpin well-being at work. Industry 5.0 technologies—such as digital assistance systems, immersive training tools, and human–machine collaborative platforms—are designed to support these needs by reducing repetitive or physically demanding tasks, expanding opportunities for skills enhancement, and enabling employees to engage in more meaningful, creative, and cognitively enriched work (Kolade & Owoseni, 2022; Grybauskas et al., 2022). Consequently, the human-centric ethos of Industry 5.0 provides a conceptual foundation for improving Quality of Work Life by fostering environments in which technological progress reinforces, rather than diminishes, human agency and well-being.

In practice, Industry 5.0 is understood not only as a technological paradigm but also as a broader socio-technical vision that seeks to embed ethical, environmental, and human-centric values within industrial systems. This perspective emphasizes that effective digital transformation requires more than the integration of advanced technologies; it necessitates organisational cultures that prioritise dignity, participation, and sustainable development (European Commission, 2021; Kolade & Owoseni, 2022). By explicitly aligning industrial progress with the United Nations Sustainable Development Goals, particularly those concerning decent work and innovation, Industry 5.0 reframes the role of employees as active

contributors in shaping technological innovation rather than passive recipients of imposed change (Grybauskas, Stefanini, & Ghobakhloo, 2022). This shift underscores the central premise of the Industry 5.0 framework: technological advancement must enhance human potential and societal well-being, thereby reinforcing the foundations of Quality of Work Life in the context of rapid digitalisation.

1.6 Linking Industry 4.0/5.0 Technologies and Quality of Work Life

The increasing integration of advanced technologies into the workplace—particularly those associated with Industry 4.0 and 5.0—has fundamentally reshaped the conditions under which employees perform their work. This transformation has introduced new opportunities for efficiency, innovation, and continuous skill development, while simultaneously creating challenges related to psychological well-being, role stability, and the need for rapid technological adaptation (Grybauskas & Cárdenas-Rubio, 2024; Zafar et al., 2024).

To capture these dynamics, this research proposes a conceptual model that links the adoption of digital tools to key Quality of Work Life (QWL) indicators. At the core of the model are four major technological dimensions: artificial intelligence, digital assistance systems (including digital twins and automated guidance tools), augmented and virtual reality technologies, and work process digitalisation (Zafar et al., 2024; Hartmann & Shajek, 2023). These tools have become embedded in everyday organisational processes, shaping how tasks are performed, how information is accessed, and how employees interact with digitally mediated environments (Grybauskas & Cárdenas-Rubio, 2024).

Consistent with the literature on human–technology interaction, the model identifies three principal QWL indicators likely to be directly influenced by these technologies: stress levels, job security, and skills development. These dimensions reflect well-established components of QWL frameworks and are frequently emphasised in research exploring the human implications of digital transformation (Williams, Zhou & Zou, 2020; De Witte, 2005).

Artificial intelligence provides a particularly clear illustration of these dual effects. On the one hand, AI systems can reduce repetitive workload, increase decision-making efficiency, and support routine operational demands, which may decrease perceived stress in structured settings. On the other hand, concerns related to algorithmic opacity, task displacement, and the perceived threat of automation may increase anxiety and undermine job stability.

Accordingly, this study hypothesises that increased AI use may be negatively associated with QWL through elevated stress and reduced job security (H1, H2), while simultaneously fostering skill development when AI functions in an augmentative rather than substitutive capacity (H3) (Grybauskas & Cárdenas-Rubio, 2024).

Digital assistance systems—including digital twins, automated operational support, and intelligent interfaces—represent another category of technologies with complex implications for QWL. These tools can enhance workplace ergonomics, improve safety, and strengthen employees' task performance by providing real-time guidance, thereby supporting the acquisition of new skills and potentially alleviating cognitive or physical strain (Hartmann & Shajek, 2023). On this basis, the model anticipates positive associations between digital assistance and both stress reduction and skills development (H4, H6). At the same time, digital assistance tools may modify job structures or require new competencies, thus contributing to increased perceptions of job insecurity during periods of technological adoption or reskilling (H5) (Grybauskas & Cárdenas-Rubio, 2024; Hartmann & Shajek, 2023).

Augmented and virtual reality (AR/VR) technologies are increasingly recognized as influential tools in employee learning and professional development. Prior research demonstrates that immersive training environments can enhance skill acquisition, improve confidence in task execution, and reduce learning-related anxiety by simulating complex work scenarios in a controlled environment (Hartmann & Shajek, 2023; Xu et al., 2021). At the same time, studies caution that insufficient instructional support during AR/VR use may introduce cognitive overload or diminish interpersonal aspects of collaborative learning, thereby influencing stress levels and overall well-being (Grybauskas & Cárdenas-Rubio, 2024). These mixed findings justify the formulation of hypotheses predicting that AR/VR may reduce stress by improving learning efficiency (H7), enhance perceived job security through competence building (H8), and positively affect skill development by expanding access to experiential learning opportunities (H9).

Process digitalization—encompassing the integration of IoT systems, blockchain technologies, cyber-physical systems, and interconnected smart factory infrastructures—further transforms the nature of work by enabling real-time data flow, operational transparency, and predictive decision support (Xu et al., 2021; Hartmann &

Shajek, 2023). While such systems can enhance efficiency and reduce uncertainty in workflow management, scholars also note that heightened visibility and continuous performance monitoring may contribute to increased feelings of surveillance, reduced autonomy, and elevated stress among employees (Williams et al., 2020; Grybauskas & Cárdenas-Rubio, 2024). In line with these dynamics, the present model hypothesizes that process digitalization may increase stress where monitoring is perceived as intrusive (H10), contribute positively to job security when systems stabilize operational forecasting (H11), and strengthen opportunities for skill development by exposing employees to digital processes and data-driven decision-making (H12).

Taken together, these variables illustrate how digital transformation can either buffer or intensify its effects on Quality of Work Life. Prior literature shows that adequate communication, training, and participatory implementation procedures significantly moderate employees' perceptions, shaping whether emerging technologies are experienced as enabling or threatening (Williams et al., 2020; Hartmann & Shajek, 2023). For instance, workers who receive continuous upskilling support are more likely to interpret AI and digital systems as complementary tools that enhance competence, whereas insufficient preparation may amplify fears of redundancy or create resistance to technological change. The conceptual framework developed in this thesis therefore integrates both direct relationships (e.g., AR/VR improving skill development) and indirect pathways (e.g., poor implementation increasing stress despite functional benefits), reflecting the multifaceted nature of digital transformation and its relevance to the human experience of work (Williams et al., 2020; Grybauskas & Cárdenas-Rubio, 2024).

2. THE EMPIRICAL RESEARCH METHODOLOGY

2.1 Research Purpose and Model Conceptual Framework

The study adopts a *quantitative* research approach. This strategy allows for the collection of standardized, measurable data that can be used to assess correlations and potential causal relationships between the adoption of Industry 4.0/5.0 technologies and QWL indicators. Quantitative methods are suitable for generalizing findings across a broader sample and for conducting inferential statistical analyses to test the proposed hypotheses.

The research model for this study is developed based on a synthesis of existing literature on Industry 4.0 and 5.0 technologies and their impact on human-centered outcomes in the workplace. The model proposes a structured framework for understanding the relationship between the implementation of digital industrial tools and key indicators of Quality of Work Life (QWL).

The study conceptualizes Quality of Work Life (QWL) as a single, multidimensional construct that integrates employees' perceived stress levels, job security, skill development opportunities, and job satisfaction. The independent variables are organized into four major technological domains that reflect ongoing trends in industrial digital transformation:

1. Automation and Artificial Intelligence (AI):

encompassing employees' use of AI-powered tools, automated systems integrated into daily work, and AI-driven decision-making or scheduling mechanisms (e.g., predictive automation and intelligent task allocation).

2. Digital Assistance:

referring to the use of digital assistants, digital twins, and other intelligent support technologies that guide work tasks, provide operational insights, or augment human decision-making.

3. Augmentation Technologies:

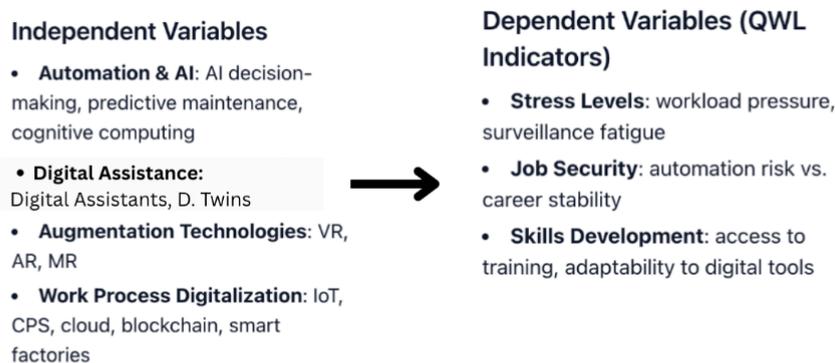
including virtual, augmented, and mixed reality tools designed to enhance training quality, improve situational awareness, and support task performance through immersive digital environments.

4. Work Process Digitalization:

covering Internet-of-Things (IoT) devices, cyber-physical systems (CPS), cloud-based digital platforms, blockchain-enabled systems, and other smart infrastructures that structure daily operations, collaboration, and information flow.

Figure 1

Theoretical model



Source: Compiled by the author based on the current research

2.2 Hypotheses

This study investigates how four technological domains of Industry 4.0 and Industry 5.0—artificial intelligence (AI), digital assistance, augmentation technologies, and work process digitalization—shape employees’ Quality of Work Life (QWL). QWL is conceptualized as a unified construct comprising three key dimensions: perceived stress, job security, and opportunities for skill development. Accordingly, twelve hypotheses are formulated to capture the expected influence of each technological domain on these dimensions.

Artificial Intelligence (AI)

Research consistently shows that AI-based automation affects worker well-being by reshaping task structure, influencing decision autonomy, and altering perceptions of replaceability (Ryan & Deci, 2000; De Witte, 2005; Williams et al., 2020). While AI may

reduce repetitive workload and support more efficient decision-making, it may also heighten anxiety when employees fear technological displacement or lack clarity about algorithmic processes (Grybauskas & Cárdenas-Rubio, 2024).

H1. AI has a positive effect on employees' stress levels.

H2. AI has a negative effect on employees' perceived job security.

H3. AI has a positive effect on employees' opportunities for skill development.

Digital Assistance

Digital assistance systems—such as digital twins, automated guidance tools, and intelligent interfaces—can facilitate task execution, improve ergonomics, and support learning, thereby reducing physical and cognitive strain. At the same time, these technologies may introduce new competency requirements or shift job responsibilities in ways that increase perceived insecurity (Grybauskas & Cárdenas-Rubio, 2024; Hartmann & Shajek, 2023).

H4. Digital assistance has a negative effect on employees' stress levels.

H5. Digital assistance has a negative effect on employees' perceived job security.

H6. Digital assistance has a positive effect on employees' opportunities for skill development.

Augmentation Technologies (VR, AR, MR)

Literature indicates that immersive technologies can improve training quality, enhance competence, and reduce uncertainty, yet may also introduce cognitive strain when insufficiently supported (Hartmann & Shajek, 2023; Xu et al., 2021; Grybauskas & Cárdenas-Rubio, 2024).

H7. Augmentation technologies have a negative effect on employees' stress levels.

H8. Augmentation technologies have a positive effect on employees' perceived job security.

H9. Augmentation technologies have a positive effect on employees' opportunities for skill development.

Work Process Digitalization (IoT, CPS, cloud systems, blockchain)

Research emphasizes that process digitalization increases transparency and workflow predictability, but may simultaneously heighten perceptions of monitoring and reduce

autonomy (Williams et al., 2020; Hartmann & Shajek, 2023; Grybauskas & Cárdenas-Rubio, 2024).

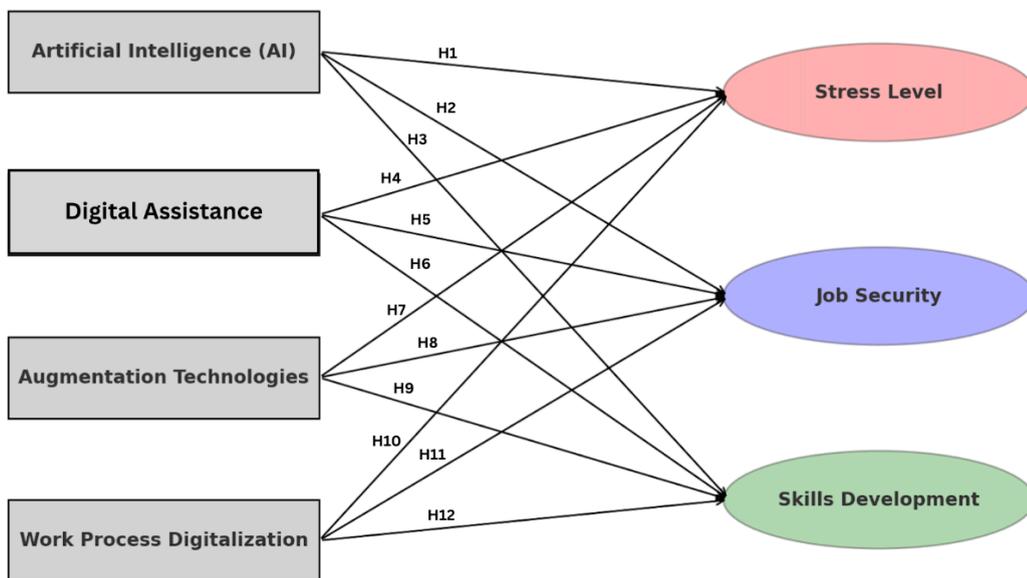
H10. Work process digitalization has a positive effect on employees' stress levels.

H11. Work process digitalization has a positive effect on employees' perceived job security.

H12. Work process digitalization has a positive effect on employees' opportunities for skill development.

Figure 2

Research Model



Source: Compiled by the author based on the current research

The research model posits that the four technological domains influence employees' Quality of Work Life (QWL) through stress, job security, and skill development. Artificial intelligence may enhance efficiency yet increase stress or job insecurity due to automation-related concerns. Digital assistance is expected to lower stress and strengthen job security and skill development by providing digital guidance and support. Augmentation technologies (VR/AR/MR) may reduce stress through improved situational awareness and immersive training while enhancing development opportunities. Work process digitalization

(IoT, CPS, cloud systems, blockchain) is anticipated to streamline work processes, reduce stress, and improve job stability and digital skills.

The model also assumes that the strength of these relationships may vary depending on contextual variables such as job role, industry sector, access to training, and organizational digital maturity. This hypothesis structure enables a systematic examination of how Industry 4.0 and 5.0 technologies jointly shape the human experience of work.

2.3 Data Collection Methods

The primary data for this research were collected through a structured questionnaire designed to capture employees' perceptions of digital transformation and its impact on Quality of Work Life (QWL). The instrument consists of three main sections.

The first section gathers demographic information, including gender, industry, job role, and tenure. These variables provide essential context for understanding differences in respondents' experiences across sectors and positions.

The second section, titled "Use of Industry 4.0 / 5.0 Tools," assesses the perceived use and integration of digital technologies in respondents' daily work.

This section was developed by the researcher based on a comprehensive review of the academic literature on Industry 4.0 and Industry 5.0 technologies, digital transformation, and human–technology interaction.

Items were formulated to represent four core technological domains frequently cited in the literature:

- Artificial Intelligence (AI) and automation systems, encompassing the use of AI-powered tools, automated decision-making mechanisms, and AI-driven scheduling systems integrated into employees' daily tasks.
- Digital assistance refers to intelligent digital tools such as digital assistants, digital twins, and other smart systems that provide operational guidance, task support, and enhanced human–machine interaction.

- Augmentation technologies, including virtual, augmented, and mixed reality solutions designed to enhance training, improve situational awareness, and support task execution through immersive digital environments.
- Work process digitalization, covering digitally connected infrastructures such as Internet-of-Things (IoT) devices, cyber-physical systems (CPS), cloud-based platforms, blockchain technologies, and smart workflow systems that shape and transform everyday work processes.

Each item reflects practical aspects of technology exposure and adoption within workplace settings, allowing for the measurement of employees' familiarity with and reliance on advanced industrial tools.

The third section evaluates Quality of Work Life (QWL) through validated psychological scales widely recognized in organizational research:

- Perceived Stress Scale (PSS) (Cohen et al., 1983) for stress levels;
- Job Insecurity Scale (De Witte, 2000) for perceived employment stability;
- Learning and Development Satisfaction (LDS) items, adapted from the Work-Related Quality of Life (WRQoL) framework (Easton & Van Laar, 2013), for skill development and learning opportunities.

All items use a five-point Likert scale, ranging from 1 (Strongly disagree) to 5 (Strongly agree). Reverse-coded items are adjusted prior to analysis to ensure consistency in interpretation.

The design of this questionnaire, combining literature-derived items with validated scales, ensures content validity, reliability, and comparability with previous empirical studies in digitalization and organizational behavior.

2.4 Sampling Strategy

The survey targeted a minimum of 150 respondents working in Lithuanian organisations that are actively adopting Industry 4.0 and Industry 5.0 technologies. The target sample size of 150 was determined based on methodological recommendations for quantitative modelling as well as empirical precedents in comparable studies.

In structural equation modelling—particularly PLS-SEM—the minimum required sample size is often preliminarily estimated using the “10-times rule,” which states that the number of observations should be at least ten times the maximum number of arrows pointing to any latent construct in the structural model (Hair et al., 2021). In this study, the most complex construct had three predictors, which would imply a minimum of approximately 30 respondents. Alternative guidelines recommend substantially larger sample sizes to ensure statistical stability, accuracy of path estimates, and generalisability. *“Some evidence exists that simple SEM models could be meaningfully tested even if sample size is quite small (Hoyle, 1999; Hoyle and Kenny, 1999; Marsh and Hau, 1999), but usually, N = 100–150 is considered the minimum sample size for conducting SEM (Tinsley and Tinsley, 1987; Anderson and Gerbing, 1988; Ding, Velicer, and Harlow, 1995; Tabachnick and Fidell, 2001). Some researchers consider an even larger sample size for SEM, for example, N = 200 (Hoogland and Boomsma 1998; Boomsma and Hoogland, 2001; Kline, 2005). Simulation studies show that with normally distributed indicator variables and no missing data, a reasonable sample size for a simple CFA model is about N = 150 (Muthén and Muthén, 2002). For multi-group modeling, the rule of thumb is 100 cases/observations per group (Kline, 2005)”* (Wang, J., & Wang, X., 2012). Therefore, the target of 150 respondents aligns with widely accepted methodological recommendations and is appropriate for the complexity of the conceptual model proposed in this study.

A non-probability purposive sampling approach was applied, focusing on employees directly involved in or affected by digital transformation processes in their organisations. The use of purposive sampling is common in Industry 4.0 and QWL research, where the goal is to capture respondents with relevant exposure to technological change.

Empirical precedents further support the adequacy of a 150-respondent sample size. Numerous Quality of Work Life (QWL) studies employ approximately 150 participants when analysing links between work conditions, job satisfaction, skills development, and employee outcomes. For example, Putra et al. (2021) examined QWL and job performance among 150 hotel employees in Indonesia, while Aghimien et al. (2024), using PLS-SEM to analyse robotics and automation in construction, highlight that sample sizes above 150 are both typical and sufficient for models of moderate complexity. These examples demonstrate that a sample of 150 respondents is methodologically consistent with current empirical practices

and provides an adequate foundation for statistical analysis including correlations, regression, and PLS-SEM.

Participants were recruited through company contacts, professional associations, and digital communication channels such as email and LinkedIn. The inclusion criteria required that respondents:

- Work full-time or part-time in Lithuania;
- Be employed in sectors exposed to Industry 4.0/5.0 implementation;
- Be familiar with or affected by digital tools in their daily tasks.

This approach ensured that participants had relevant experience with digital transformation, providing a reliable dataset for analyzing the human impact of industrial technologies. The targeted sample size allows for sufficient statistical power in correlation, regression, and Structural Equation Modeling (SEM) analyses.

Data Analysis Methods

The collected data were analyzed to identify patterns and relationships between the implementation of Industry 4.0/5.0 technologies and key QWL indicators. Both descriptive and inferential statistical techniques were applied.

- Descriptive statistics (means, standard deviations, and frequencies) were used to summarize demographic characteristics and overall response trends.
- Regression analysis was performed to test linear relationships between exposure to technological domains and QWL dimensions.
- Structural Equation Modeling (SEM) using SmartPLS was applied to test the full conceptual model and the twelve proposed hypotheses, allowing for the examination of both direct and indirect effects.

Software Tools

The quantitative data were analyzed using SPSS version 31.0.0.0 (117) for conducting descriptive statistics, reliability analysis (Cronbach's alpha), and preliminary regression tests.

In addition, SmartPLS 4.0 was used to perform the Partial Least Squares Structural Equation Modeling (PLS-SEM) procedures, including the assessment of the measurement model (indicator loadings, composite reliability, AVE, discriminant validity) and the structural model (path coefficients, R^2 , effect sizes, and bootstrapping for significance testing).

3. THE ANALYSIS OF EMPIRICAL RESULTS

3.1 Sample Characteristics and Descriptive Statistics

A total of 151 respondents participated in the survey. The sample included a diverse representation of employees working in Lithuania across different industries, job roles, and levels of experience.

Demographic Characteristics

Gender

The sample consisted of 45% women, ~44% men, with additional respondents identifying as non-binary (~3%) or choosing not to disclose (~8%). This distribution indicates good representation of different gender groups within Lithuanian workplaces.

Industry

Most respondents were employed in IT (36%), Finance (29%), and Logistics (17%), with smaller groups working in Manufacturing (15%), Hospitality (<2%), and other sectors. This reflects a digital-intensive sample, aligning well with the study's focus on Industry 4.0/5.0 technologies.

Job Role

The majority of participants were Operational Staff (67%), followed by Managers (26%) and Executives (6%). This distribution ensures insights from both frontline and decision-making levels.

Work Experience

Respondents varied in experience:

- 1–3 years: 40%
- 4–6 years: 37%
- 7+ years: 15%
- 0–1 year: 7%

This suggests the sample includes both early-career and experienced professionals.

These demographic patterns demonstrate that the sample is reasonably distributed across professional groups and suitable for examining perceptions of technological integration and Quality of Work Life (QWL).

3.2 Descriptive Statistics

Descriptive statistics were calculated to summarise the central tendencies and variability of key Quality of Work Life (QWL) indicators and levels of technology adoption across organisations. Table X presents the means and standard deviations for all composite constructs, while Figure X visualises the distribution patterns.

Quality of Work Life Indicators

Employees reported high levels of job satisfaction ($M = 3.91$, $SD = 0.66$) and strong perceptions of skill development opportunities ($M = 4.00$, $SD = 0.60$). Stress levels were moderate ($M = 2.35$, $SD = 0.67$), whereas job security scores were comparatively low ($M = 2.09$, $SD = 0.74$), suggesting potential concerns related to technological and organisational changes.

Technology Adoption

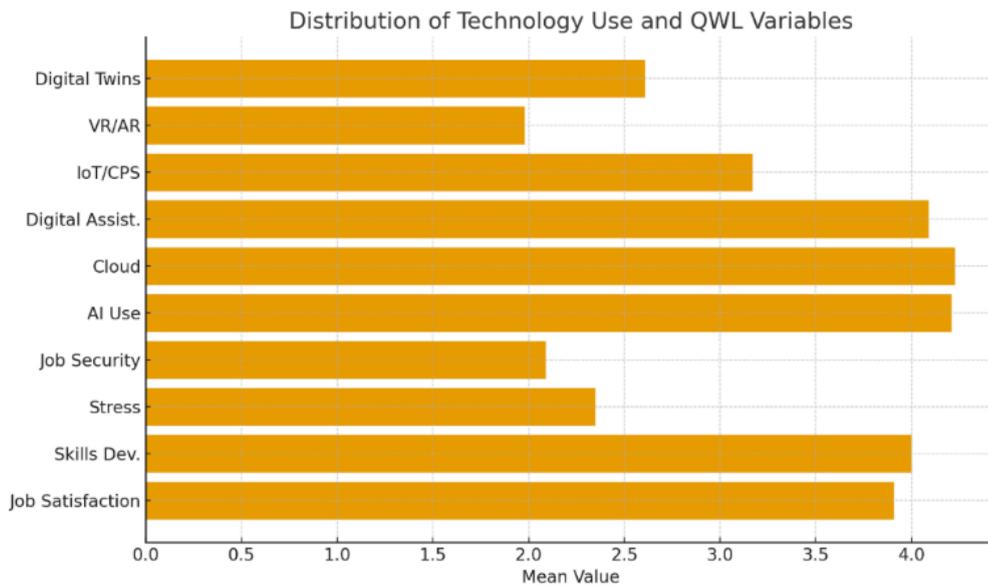
Industry 4.0 technologies demonstrated the highest rates of practical integration. Daily AI use ($M = 4.21$, $SD = 0.75$), digital assistants ($M = 4.09$, $SD = 0.77$), and cloud-based platforms ($M = 4.23$, $SD = 0.65$) were reported as widely implemented.

Intermediate digitalisation technologies such as IoT/CPS integration—cyber-physical and interconnected systems—showed moderate adoption ($M = 3.17$, $SD = 0.96$).

In contrast, Industry 5.0 technologies remain in their early adoption stage. Augmented/virtual reality tools ($M = 1.98$, $SD = 0.83$) and digital twins ($M = 2.61$, $SD = 0.97$) were used infrequently across sampled organisations.

Figure 3

Distribution of Technology Use and QWL Variables



Source: Compiled by the author based on the current research

Descriptive statistics indicate a digital landscape characterised by strong reliance on mature Industry 4.0 technologies, while more advanced Industry 5.0 solutions are still emerging in Lithuanian organisations.

3.3 Reliability Analysis

The internal consistency of the study’s multi-item scales was assessed using Cronbach’s alpha. Overall, the reliability analysis indicated that the majority of constructs met or exceeded commonly accepted thresholds.

The Perceived Stress Scale (PSS-4) demonstrated satisfactory reliability ($\alpha = .792$), suggesting that the four items consistently measure the underlying construct of perceived stress. No items showed a substantial improvement in reliability if deleted, therefore all were retained for subsequent analysis.

The Job Insecurity Scale (De Witte, short form) initially produced a low reliability coefficient ($\alpha = .458$). Inspection of item-total correlations revealed that the reverse-worded item (“I am sure that I will keep my job”) suppressed the internal consistency of the scale.

Reverse-worded items frequently introduce measurement artefacts in applied surveys, particularly when respondents vary in familiarity with Likert-style questionnaires. After removing this item, the reliability of the three-item scale improved markedly to $\alpha = .883$, indicating excellent internal consistency. The revised three-item job insecurity index was therefore used in all subsequent analyses.

The Skills Development Scale showed high reliability ($\alpha = .828$), demonstrating that the items coherently capture employees' perceptions of learning and development opportunities related to digital technologies. All items were retained, and a composite index was created by averaging the item scores.

Finally, the Job Satisfaction Scale (MSQ – Short Form) exhibited strong internal consistency ($\alpha = .873$). The four items demonstrated high inter-item correlations, supporting their use as a unified measure of job satisfaction. The scale was therefore retained in full and operationalized as a composite satisfaction index.

3.4 Correlation Analysis

Industry 4.0/5.0 Technologies and Stress Levels

Across all technological variables, correlations with the stress index are weak and statistically non-significant. Coefficients generally fall within the range of $r = -.137$ to $.030$, indicating the absence of meaningful linear relationships. AI use shows a very weak negative association with stress ($r = -.122$, $p > .05$). IoT, cloud systems, digital twins, VR, and digital assistants all show similarly negligible associations (all $p > .05$). These findings suggest that the mere presence or use of Industry 4.0/5.0 tools does *not* significantly predict employees' perceived stress levels. This reflects the idea that stress at work is influenced more by broader organizational, interpersonal, and managerial factors than by technological exposure alone. The absence of significant correlations contrasts with concerns in the literature regarding digital over-load or techno-stress, implying that in this sample, employees do not experience advanced technologies as stressful.

Industry 4.0/5.0 Technologies and Job Security

The analysis reveals a consistent pattern of negative correlations between Industry 4.0/5.0 tools and job security, suggesting that higher technological exposure is associated with stronger perceptions of job insecurity. AI use is moderately negatively correlated with job security ($r = -.307, p < .001$). Digital assistants also show a significant negative correlation ($r = -.195, p < .05$). Cloud-based processes demonstrate a negative association ($r = -.207, p < .05$). Digital twins and AI scheduling show small and statistically non-significant relationships ($r = .137, r = -.023, p > .05$). This pattern supports longstanding arguments in the literature that employees may perceive digital technologies as potential substitutes for human labor, heightening fears about future job loss. Even when technological tools facilitate work processes or skill acquisition, they may simultaneously generate uncertainty regarding long-term employment stability. These negative relationships, although modest in magnitude, are meaningful in the context of digital transformation. They highlight the need for transparent communication, retraining initiatives, and participatory implementation strategies to mitigate the insecurity associated with automation and AI-driven systems.

Industry 4.0/5.0 Technologies and Skills Development

The strongest cross-construct correlations appear between technological variables and the skills development index. Several Industry 4.0/5.0 tools are significantly and positively associated with employees' perceptions of skill growth. AI use ($r = .557, p < .001$) — the strongest positive correlation in the dataset. AI scheduling systems ($r = .234, p < .01$). Digital assistants ($r = .184, p < .05$). Cloud-based tools ($r = .458, p < .001$). IoT tools ($r = .136, n.s.,$ but directionally positive). These results indicate that increased interaction with advanced technologies is associated with greater opportunities for learning, digital skill acquisition, and professional growth. This finding aligns closely with the Industry 5.0 paradigm, which positions human-centric technology adoption as a driver of continuous learning and capability enhancement. This suggests that employees perceive emerging tools not only as work facilitators but also as avenues for personal development. The moderate effect sizes indicate a substantive relationship, reinforcing the importance of digital literacy initiatives and structured training programs during technological transitions.

Industry 4.0/5.0 Technologies and Job Satisfaction

Several Industry 4.0/5.0 tools also exhibit positive correlations with job satisfaction: AI use demonstrates a moderate positive correlation ($r = .412, p < .001$), AI scheduling also

correlates positively ($r = .227, p < .01$), Cloud-based tools show a moderate positive association ($r = .365, p < .001$), Digital assistants show a weak positive association ($r = .066, n.s.$). These findings suggest that, when implemented effectively, digital tools may enhance employees' satisfaction by improving efficiency, autonomy, and access to work-related resources. The associations are consistent with the literature linking technological support tools to enriched job roles and enhanced work experiences

Figure 4

Pearson Correlation Matrix for Industry 4.0/5.0 Tools and Quality of Work Life Indicators

		Correlations										
		sat_index	skills_index	JobSec_index	stress_index	ai_use(num)	ai_scheduling(num)	digitaltwins_n	digital_assist_n	vr_use_n	iot_use_n	cloud_changes_n
sat_index	Pearson Correlation	1	.762**	-.619**	-.512**	.412**	.227**	.056	.066	.132	.117	.365**
	Sig. (2-tailed)		<.001	<.001	<.001	<.001	.005	.496	.424	.107	.154	<.001
	N	151	151	151	151	151	151	150	151	150	151	151
skills_index	Pearson Correlation	.762**	1	-.543**	-.332**	.557**	.234**	.004	.184*	.104	.136	.458**
	Sig. (2-tailed)	<.001		<.001	<.001	<.001	.004	.961	.024	.204	.095	<.001
	N	151	151	151	151	151	151	150	151	150	151	151
JobSec_index	Pearson Correlation	-.619**	-.543**	1	.487**	-.307**	-.023	.137	-.195*	-.015	.012	-.207*
	Sig. (2-tailed)	<.001	<.001		<.001	<.001	.784	.095	.016	.853	.880	.011
	N	151	151	151	151	151	151	150	151	150	151	151
stress_index	Pearson Correlation	-.512**	-.332**	.487**	1	-.122	.030	-.003	-.090	.025	-.137	-.005
	Sig. (2-tailed)	<.001	<.001	<.001		.136	.713	.970	.272	.764	.093	.949
	N	151	151	151	151	151	151	150	151	150	151	151
ai_use(num)	Pearson Correlation	.412**	.557**	-.307**	-.122	1	.277**	-.155	.405**	.114	.006	.436**
	Sig. (2-tailed)	<.001	<.001	<.001	.136		<.001	.059	<.001	.166	.940	<.001
	N	151	151	151	151	151	151	150	151	150	151	151
ai_scheduling(num)	Pearson Correlation	.227**	.234**	-.023	.030	.277**	1	.269**	-.038	.188*	.056	.100
	Sig. (2-tailed)	.005	.004	.784	.713	<.001		<.001	.645	.021	.497	.222
	N	151	151	151	151	151	151	150	151	150	151	151
digitaltwins_n	Pearson Correlation	.056	.004	.137	-.003	-.155	.269**	1	-.270**	.279**	.447**	-.045
	Sig. (2-tailed)	.496	.961	.095	.970	.059	<.001		<.001	<.001	<.001	.583
	N	150	150	150	150	150	150	150	150	149	150	150
digital_assist_n	Pearson Correlation	.066	.184*	-.195*	-.090	.405**	-.038	-.270**	1	.170*	.114	.305**
	Sig. (2-tailed)	.424	.024	.016	.272	<.001	.645	<.001		.037	.163	<.001
	N	151	151	151	151	151	151	150	151	150	151	151
vr_use_n	Pearson Correlation	.132	.104	-.015	.025	.114	.188*	.279**	.170*	1	.266**	.145
	Sig. (2-tailed)	.107	.204	.853	.764	.166	.021	<.001	.037		<.001	.076
	N	150	150	150	150	150	150	149	150	150	150	150
iot_use_n	Pearson Correlation	.117	.136	.012	-.137	.006	.056	.447**	.114	.266**	1	.258**
	Sig. (2-tailed)	.154	.095	.880	.093	.940	.497	<.001	.163	<.001		.001
	N	151	151	151	151	151	151	150	151	150	151	151
cloud_changes_n	Pearson Correlation	.365**	.458**	-.207*	-.005	.436**	.100	-.045	.305**	.145	.258**	1
	Sig. (2-tailed)	<.001	<.001	.011	.949	<.001	.222	.583	<.001	.076	.001	
	N	151	151	151	151	151	151	150	151	150	151	151

** . Correlation is significant at the 0.01 level (2-tailed).

* . Correlation is significant at the 0.05 level (2-tailed).

Source: Compiled by the author based on the current research

Correlation structure indicates tendencies: Stress levels are not significantly associated with Industry 4.0/5.0 tools, suggesting technology alone is not a primary stressor. Job security decreases as exposure to digital technologies increases, reflecting employees' concerns about automation and AI displacement. Skills development and job satisfaction increase with technological use, highlighting the developmental benefits of digital transformation.

3.5 Regression Analysis

3.5.1 Regression Analysis for Job Satisfaction

Model 1, which included only technological variables, explained 22.8% of the variance in job satisfaction ($R^2 = .228$, $p < .001$).

Model 2, which additionally incorporated demographic variables, explained 34.5% of the variance ($R^2 = .345$, $p < .001$), indicating that demographic factors strengthen the explanatory power of the model.

Significant predictors

Four variables demonstrated statistically significant positive effects on job satisfaction:

1. Use of AI in daily work ($\beta = .348$, $p < .001$):

Employees who frequently use AI tools score higher on job satisfaction.

2. Use of cloud / digital collaboration platforms ($\beta = .246$, $p = .004$):

Cloud-based systems improve efficiency and communication, contributing to higher satisfaction.

3. Job role level ($\beta = .270$, $p = .002$):

Higher-level positions (manager / executive) are associated with higher job satisfaction compared to operational staff.

4. Work experience ($\beta = .100$, $p = .045$):

Employees with longer tenure report slightly higher job satisfaction.

Non-significant predictors

- Industry type, gender, digital twins, IoT, VR/AR, AI-driven scheduling, and digital assistants did not show significant effects ($p > .05$).
- This indicates that not all advanced technologies directly influence satisfaction, and some are still too new or not widely used to create measurable impact.

Multicollinearity was low (all VIF < 2), confirming that predictors do not distort the model. The regression results support the hypothesis that certain Industry 4.0/5.0 technologies—particularly AI and cloud platforms—positively contribute to job satisfaction, together with role level and work experience.

Model 1 demonstrated a moderate explanatory power ($R^2 = .228$), indicating that technological factors alone account for a meaningful but not dominant portion of job satisfaction variance. Model 2 increased the explained variance to a stronger level ($R^2 = .345$), suggesting that the inclusion of demographic characteristics substantially improves the model's predictive ability. Overall, the job satisfaction models may be classified as moderate-to-strong.

3.5.2 Regression Analysis for Job Security

The linear regression analysis was conducted to examine the extent to which Industry 4.0 and 5.0 technologies predict employees' perceived job security.

In Model 1 (**ANNEX 1**), which included only the technological predictors (AI use, AI-driven scheduling, digital assistants, digital twins, VR/AR, IoT, and cloud platforms), the model was statistically significant ($F(7,141)=2.667$, $p=.013$) and explained 11.7% of the variance in job security (Adjusted $R^2 = .073$). Among the predictors, only the use of AI in daily work had a significant negative effect on job security ($\beta = -0.238$, $p = .017$), indicating that employees who work more intensively with AI report a stronger fear of job loss.

Model 2 (**ANNEX 2**) expanded the analysis by including demographic controls (gender, industry, role, experience). This enhanced the explanatory power of the model to 20.8% (Adjusted $R^2 = .143$), with the model remaining highly significant ($F(11,134)=3.194$, $p < .001$).

Two predictors remained statistically significant:

1. AI use ($\beta = -0.219$, $p = .030$) – confirming that higher exposure to AI is associated with lower job security.
2. Job role ($\beta = -0.238$, $p = .013$) – employees in higher-level or managerial roles reported lower job security than operational staff.

No other technologies nor demographic characteristics showed significant influence.

The job security regression showed a weak model fit in Model 1 (Adjusted $R^2 = .073$), meaning technological variables alone provide limited explanatory value. Model 2 improved the explanatory power to a modest level (Adjusted $R^2 = .143$), but the model remains relatively weak, indicating that job security is influenced by factors largely outside the measured technological and demographic variables.

3.5.3 Regression Analysis for Stress

The regression analysis was conducted to examine whether the adoption of Industry 4.0 and 5.0 technologies predicts employees' perceived stress levels.

Model 1 (ANNEX 3) included only technological variables (AI use, AI-driven scheduling, digital assistants, digital twins, VR/AR, IoT, and cloud platforms). The model was not statistically significant ($F(7,141)=1.117$, $p = .356$), explaining only 0.5% of the variance (Adjusted $R^2 = .005$). None of the technologies showed a significant effect on stress levels, suggesting that employees do not experience increased stress directly due to technological tools.

Model 2 (ANNEX 4) introduced demographic controls (gender, industry, job role, and work experience). The model became significant ($F(11,134)=2.052$, $p = .028$) and explained 7.4% of the variance in stress (Adjusted $R^2 = .074$). Among all predictors, gender emerged as a significant factor ($\beta = .172$, $p = .042$), indicating that women reported higher stress levels than men. Job role was marginally significant ($\beta = -.193$, $p = .051$), suggesting that employees in managerial positions tend to experience higher stress than operational staff.

The stress regression demonstrated a very weak model in both steps. Model 1 was non-significant and explained almost none of the variance (Adjusted $R^2 = .005$). Model 2 became statistically significant but remained weak (Adjusted $R^2 = .074$), suggesting demographic variables contribute slightly, while technologies play no meaningful predictive role. This implies that stress among employees is shaped more by organizational or personal factors than by technological adoption itself. Both models are classified as weak.

3.5.4 Regression Analysis for Skills Development

A linear regression analysis was conducted to evaluate how the adoption of Industry 4.0 and 5.0 technologies predicts employees' perceived skills development. Model 1 (ANNEX 5), which included only technological variables, was statistically significant ($F(7,141)=12.474$, $p<.001$) and explained 35.2% of the variance in skills development (Adjusted $R^2 = .352$).

Among the predictors, two technologies showed strong and significant positive effects: AI use ($\beta = .461$, $p < .001$) and cloud-based digital platforms ($\beta = .263$, $p < .001$). This indicates that employees who frequently work with AI systems or cloud solutions report substantially higher levels of digital skill growth. Other technologies, such as VR/AR, digital twins, IoT, and digital assistants, did not show significant effects.

Model 2 (ANNEX 6) expanded the analysis by including demographic characteristics (gender, industry, job role, and work experience). The model remained highly significant ($F(11,134)=7.365$, $p<.001$), explaining 32.6% of the variance (Adjusted $R^2 = .326$), but the inclusion of demographic variables did not substantially increase the explanatory power. AI use ($\beta = .431$, $p < .001$) and cloud platforms ($\beta = .245$, $p = .003$) continued to be the only significant predictors.

The skills development regression showed a strong model fit in Model 1 (Adjusted $R^2 = .352$), indicating that technological variables—especially AI and cloud platforms—explain a substantial portion of skills development. Model 2 remained similarly strong (Adjusted $R^2 = .326$), confirming that skill development is primarily driven by technology exposure rather than demographics. Thus, this is the strongest model among the four QWL outcomes.

3.6 Measurement Model Evaluation (PLS-SEM)

The evaluation of the measurement model was conducted prior to assessing the structural relationships to ensure that the latent constructs were measured reliably and validly. In SmartPLS, this analysis included the examination of indicator reliability, internal consistency reliability, and convergent validity.

Indicator Reliability

Indicator reliability was assessed by examining the standardized outer loadings of the reflective indicators. As recommended in the literature (Hair et al., 2021), loadings above 0.70 are considered satisfactory, although values between 0.60–0.70 may be accepted in

exploratory research.

Across all constructs—AI Integration, Job Security, Skills, Satisfaction, and Stress—the majority of loadings exceeded the 0.70 threshold, indicating strong item contributions to their corresponding latent variables.

Figure 5

Outer loadings

	Outer loadings
ai_use_n <- Ai_integration	0.873
cloud_changes_n <- Ai_integration	0.776
digital_assist_n <- Ai_integration	0.608
jobsec1_n <- JobSecurity	0.918
jobsec2_n <- JobSecurity	0.907
jobsec4_n <- JobSecurity	0.882
sat1_n <- Satisfaction	0.903
sat2_n <- Satisfaction	0.835
sat3_n <- Satisfaction	0.811
sat4_n <- Satisfaction	0.866
skill1_n <- Skills	0.851
skill2_n <- Skills	0.829
skill3_n <- Skills	0.798
skill4_n <- Skills	0.795
stress1_n <- Stress	0.744
stress2_r <- Stress	0.771
stress3_r <- Stress	0.829
stress4_n <- Stress	0.790

Source: Compiled by the author based on the current research

A small number of indicators demonstrated slightly lower loadings; however, they were retained due to theoretical justification and because their removal would not substantially improve construct reliability.

Internal Consistency Reliability (CR, rho_A, Alpha)

Internal consistency reliability was assessed using Cronbach's Alpha, rho_A, and Composite Reliability (CR). All constructs exceeded the recommended threshold of 0.70 for each reliability coefficient, indicating that the items consistently measure the underlying construct.

Figure 6

Internal Consistency Reliability

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Ai_integrati on	0.650	0.729	0.801	0.578
JobSecurity	0.886	0.891	0.929	0.814
Satisfaction	0.877	0.889	0.915	0.730
Skills	0.835	0.838	0.890	0.670
Stress	0.793	0.808	0.864	0.615

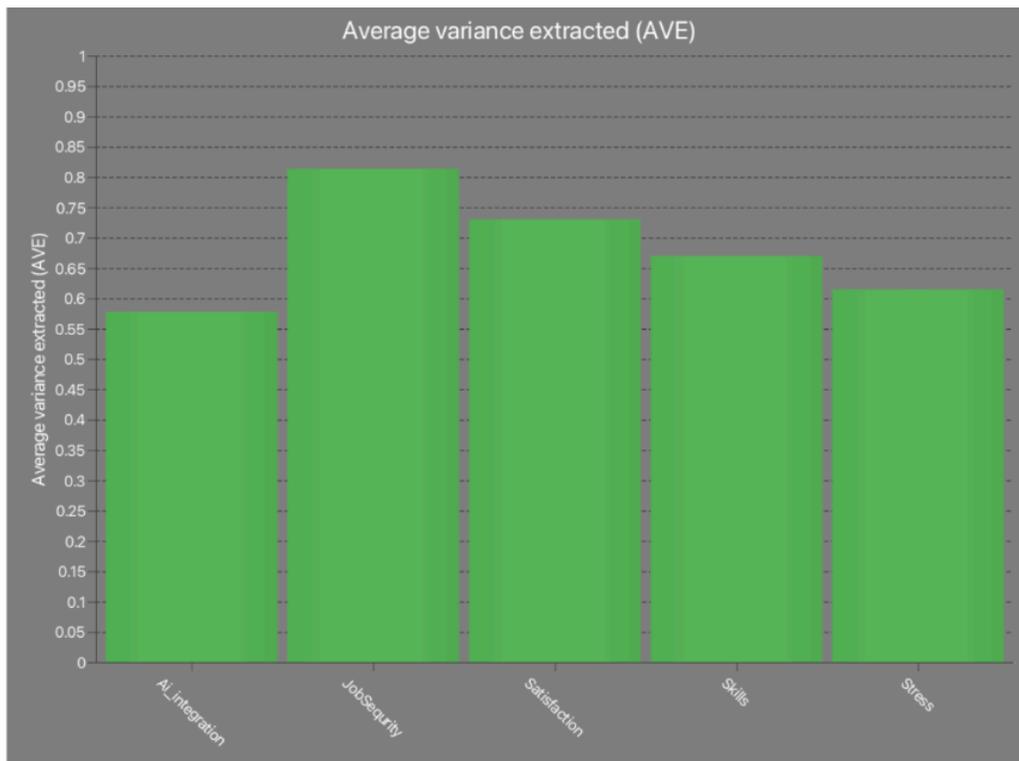
Source: Compiled by the author based on the current research

Convergent Validity (AVE)

Convergent validity was evaluated using the Average Variance Extracted (AVE). All constructs achieved AVE values above the recommended minimum of 0.50, confirming that each latent variable explains more than half of the variance in its indicators.

Figure 7

Average variance extracted (AVE)



Source: Compiled by the author based on the current research

Together, these results confirm that the measurement model demonstrates adequate reliability and convergent validity, supporting the appropriateness of the reflective constructs for subsequent structural analysis.

3.7 Structural Model Evaluation

Following the establishment of measurement quality, the structural model was evaluated. This included assessing collinearity, examining model explanatory power (R^2), and interpreting the path coefficients between constructs.

3.7.1 Coefficient of Determination (R^2)

The model's explanatory power varied across the four endogenous constructs. R^2 values indicate how much variance in each outcome variable is explained by its predictors.

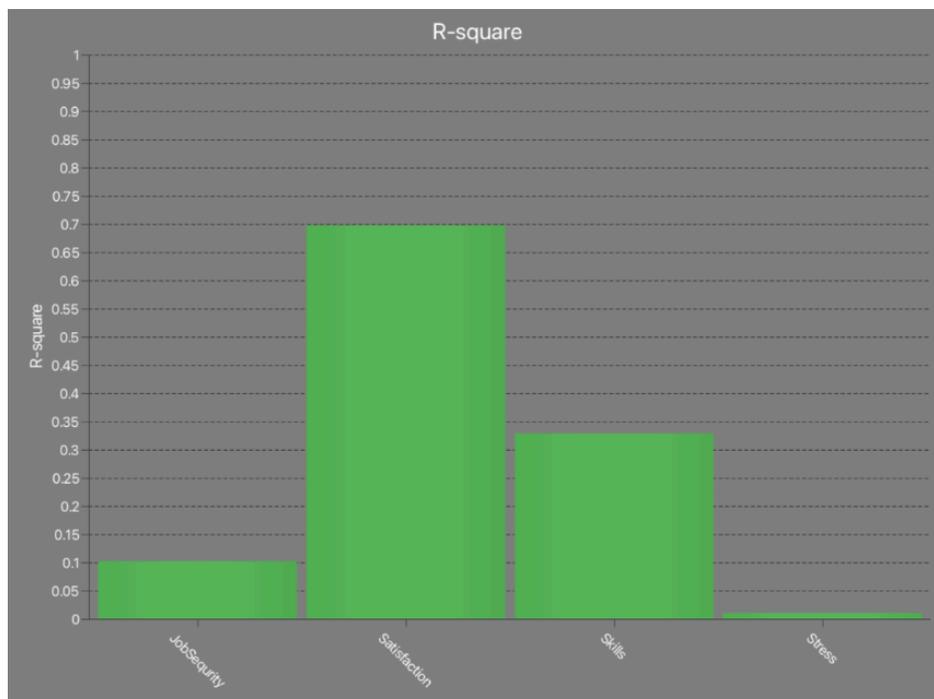
- Job Security: $R^2 = 0.102$
 → Indicates weak explanatory power, suggesting that AI Integration accounts for a

modest proportion of variance in perceived job security.

- Skills: $R^2 = 0.329$
→ Indicates moderate explanatory power, demonstrating that digital technologies substantially influence employees' opportunities for skill development.
- Satisfaction: $R^2 = 0.698$
→ Indicates substantial explanatory power, meaning that Skills, Job Security, and Stress collectively explain nearly 70% of job satisfaction.
- Stress: $R^2 = 0.010$
→ Indicates very weak explanatory power; AI Integration explains only a minimal portion of differences in stress.

Figure 8

Coefficient of Determination (R^2)



Source: Compiled by the author based on the current research

3.7.2 Path Coefficients

Path coefficients were analyzed to determine the strength and direction of hypothesized relationships. Bootstrapping (5,000 samples) was used to assess statistical significance.

Key results:

- AI Integration → Skills: $\beta = 0.573$
A strong positive effect, indicating that technology adoption significantly enhances employees' digital skill development.
- AI Integration → Job Security: $\beta = -0.320$
A moderate negative effect, suggesting increased technology use is associated with reduced feelings of job security.
- AI Integration → Stress: $\beta = -0.101$
A weak negative effect, indicating only minor stress reduction attributable to technology use.
- Skills → Satisfaction: $\beta = 0.584$
A strong positive effect; skill development emerges as the strongest predictor of job satisfaction.
- Job Security → Satisfaction: $\beta = -0.193$
A weak negative effect; lower job security slightly reduces satisfaction.
- Stress → Satisfaction: $\beta = -0.238$
A moderate negative effect; higher stress meaningfully reduces satisfaction.

Figure 9

Path coefficients

	Path coefficients
Ai_integration -> JobSecurity	-0.320
Ai_integration -> Skills	0.573
Ai_integration -> Stress	-0.101
Job Security -> Satisfaction	-0.193
Skills -> Satisfaction	0.584
Stress -> Satisfaction	-0.238

Source: Compiled by the author based on the current research

3.7.3 Hypothesis Testing Summary

H1. AI has a positive effect on employees' stress levels.

The association between AI use and stress was weak and statistically non-significant across all analyses. SEM also demonstrated a very small negative path coefficient ($\beta = -0.101$).

H1 is not supported.

H2. AI has a negative effect on employees' perceived job security.

Correlation analysis showed a moderate, significant negative relationship ($r = -.307$, $p < .001$). Regression models confirmed this effect, and SEM supported the negative impact ($\beta = -0.320$).

H2 is supported.

H3. AI has a positive effect on employees' opportunities for skill development.

AI use displayed the strongest positive correlation with skills development ($r = .557$, $p < .001$). Both regression models and the structural model confirmed this relationship ($\beta = 0.573$).

H3 is supported.

H4. Digital assistance has a negative effect on employees' stress levels.

No significant correlations or regression effects were identified, and results showed no predictive capability for stress.

H4 is not supported.

H5. Digital assistance has a negative effect on employees' perceived job security.

Although a weak negative correlation was observed ($r = -.195$, $p < .05$), this effect did not remain significant in regression models or SEM.

H5 is not supported.

H6. Digital assistance has a positive effect on employees' opportunities for skill development.

A weak positive correlation was found ($r = .184$, $p < .05$), but the effect was not statistically significant in regression models.

H6 is not supported.

H7. Augmentation technologies have a negative effect on employees' stress levels.

No significant effects or correlations were detected.

H7 is not supported.

H8. Augmentation technologies have a positive effect on employees' perceived job security.

No significant associations or predictive effects were observed.

H8 is not supported.

H9. Augmentation technologies have a positive effect on employees' opportunities for skill development.

Despite theoretical expectations, empirical results did not show significant relationships.

H9 is not supported.

H10. Work process digitalisation has a positive effect on employees' stress levels.

No significant correlation or regression results were observed for digitalisation and stress.

H10 is not supported.

H11. Work process digitalisation has a positive effect on employees’ perceived job security.

This hypothesis was not supported; correlations were negative and regression results were non-significant.

H11 is not supported.

H12. Work process digitalisation has a positive effect on employees’ opportunities for skill development.

This hypothesis is supported specifically for cloud-based digital tools. Cloud systems showed a moderate positive correlation ($r = .458, p < .001$) and significant regression coefficients ($\beta \approx .245-.263$).

H12 is supported.

Table 1

Summary of Hypothesis Testing Results

Hypothesis	Statement	Result
H1	AI has a positive effect on employees’ stress levels	Not supported
H2	AI has a negative effect on employees’ perceived job security	Supported
H3	AI has a positive effect on employees’ opportunities for skill development	Supported
H4	Digital assistance has a negative effect on employees’ stress levels	Not supported
H5	Digital assistance has a positive effect on employees’ perceived job security	Not supported
H6	Digital assistance has a positive effect on employees’ opportunities for skill development	Not supported
H7	Augmentation technologies have a negative effect on employees’ stress levels	Not supported
H8	Augmentation technologies have a positive effect on employees’ perceived job security	Not supported
H9	Augmentation technologies have a positive effect on employees’ opportunities for skill development	Not supported
H10	Work process digitalization has a positive effect on employees’ stress levels	Not supported
H11	Work process digitalization has a positive effect on employees’ perceived job security	Not supported
H12	Work process digitalization has a positive effect on employees’ opportunities for skill development	Supported

Source: Compiled by the author based on the current research

Integrated Interpretation

Across all analyses, several consistent patterns emerge regarding the relationship between Industry 4.0/5.0 technologies and Quality of Work Life (QWL):

1. Technologies differ substantially in their impact on QWL.
AI and cloud-based digitalisation emerge as the strongest and most consistent predictors of QWL indicators.
 - AI demonstrates a *positive association with skills development* and a *negative association with job security*.
 - Cloud platforms significantly *enhance opportunities for skill development*, but are also *linked to lower perceived job security*.
By contrast, digital assistance tools and augmentation technologies (AR/VR) show *weak or non-significant* effects across all QWL dimensions.
2. Stress levels are not significantly influenced by the use of digital technologies.
Across correlation results, regression models, and PLS-SEM estimates, none of the technological variables significantly predict stress. Instead, stress appears to be influenced more by demographic and contextual factors (e.g., gender, job role) rather than technology use.
3. Skills development is the central positive mechanism within QWL.
Skills development demonstrates the strongest and most consistent positive associations within the QWL construct. It functions as a key pathway through which digital technologies—particularly AI and cloud systems—contribute to more favourable employee experiences. This finding underscores the role of continuous learning and competence-building as essential components of well-being in digitally transforming workplaces.

3.7.4 Conclusion of Structural Model Analysis

The structural model provides clear evidence of how different categories of digital technologies shape key components of Quality of Work Life (QWL). The analysis demonstrates that AI and cloud-based systems exert the strongest influence, primarily by enhancing employees' opportunities for skills development—an outcome that emerges as the most robust positive contributor within the QWL framework. At the same time, AI shows a significant negative relationship with job security, reinforcing concerns documented in the literature regarding automation-related uncertainty.

In contrast, stress is only weakly related to the technological variables in the model and does not appear to be significantly shaped by digitalisation. This suggests that stress in the workplace is driven more by individual or organisational factors than by technology adoption itself.

The structural model underscores the dual nature of digital transformation: on one side, digital tools—especially AI and cloud technologies—enable substantial opportunities for competence building and professional growth; on the other, they heighten employee concerns about job stability. These findings reflect the broader tension characterising Industry 4.0 and Industry 5.0 environments, where technological advancement simultaneously expands capability and uncertainty in the modern workplace.

CONCLUSIONS

The aim of the Master's thesis was to evaluate the impact of Industry 4.0 and Industry 5.0 tools on Quality of Work Life (QWL) of employees, with particular attention to stress levels, job security, and skills development. Based on the empirical analysis, the following conclusions can be drawn:

1. The literature review demonstrates that Industry 4.0 is primarily driven by efficiency, automation, and data integration, often prioritising productivity over human-centric considerations. While these technologies improve operational performance, they simultaneously introduce risks related to job insecurity, deskilling, and reduced autonomy. These tensions highlight the limitations of a purely technology-driven approach to industrial transformation.
2. Industry 5.0 emerges in the literature as a response to the socio-technical challenges of Industry 4.0, emphasising human–machine collaboration, sustainability, and employee well-being. Theoretical frameworks such as Job Characteristics Theory and Self-Determination Theory support the premise that human-centric technologies can enhance motivation, competence, and autonomy. This paradigm provides a conceptual foundation for examining digital transformation through the lens of Quality of Work Life.
3. The empirical findings of this study confirm that the impact of Industry 4.0 and 5.0 technologies on Quality of Work Life is heterogeneous rather than uniform. Different technological domains influence QWL indicators in distinct ways, indicating that digitalisation should not be treated as a single homogeneous phenomenon. This conclusion directly supports the study's objective to assess differentiated technological effects on employee experience.
4. Skills development is identified as the QWL dimension most positively affected by digital transformation. The use of artificial intelligence and cloud-based platforms shows strong and statistically significant positive effects on employees' perceived learning and competence development. This finding supports the Industry 5.0 assumption that technology can enhance human capabilities when used in an augmentative manner.

5. Job security emerges as the most negatively affected Quality of Work Life indicator. Increased exposure to artificial intelligence and digitally automated processes is consistently associated with stronger perceptions of job insecurity. These results confirm that even when technologies support skill development, they simultaneously generate concerns related to automation, redundancy, and long-term employability.

6. Contrary to common assumptions in the literature on techno-stress, the study finds no significant relationship between Industry 4.0/5.0 technologies and employees' perceived stress levels. Stress appears to be influenced more by demographic and organisational factors than by the use of digital tools themselves. This challenges prevailing narratives that directly associate digitalisation with increased psychological strain.

7. Advanced Industry 5.0 technologies, such as augmented and virtual reality and digital twins, currently show limited measurable effects on Quality of Work Life. This is largely attributable to their low adoption levels and early-stage implementation within Lithuanian organisations. As a result, their potential benefits for employee experience may not yet be fully realised.

The findings confirm the dual nature of digital transformation: it simultaneously enables employee development and generates feelings of insecurity. The study concludes that technological progress alone does not guarantee improvements in Quality of Work Life; instead, outcomes depend on how technologies are implemented, communicated, and supported within organisations. This conclusion directly addresses the central research aim of evaluating the impact of Industry 4.0 and 5.0 tools on QWL.

Theoretical Contributions

The research clarifies how different categories of Industry 4.0/5.0 technologies produce distinct patterns of influence on QWL. The findings show that technologies do not operate as a homogeneous block: AI, digital assistance, augmentation tools, and process digitalisation each affect stress, job security, and skills development in unique ways. This differentiation contributes to ongoing theoretical debates by highlighting that digitalisation must be analysed at the level of specific tools rather than broad paradigms.

The results provide empirical grounding for treating QWL as an integrated construct shaped by interdependent psychological and organisational factors. The strong links between skills

development and job satisfaction reinforce holistic models of QWL, supporting approaches that conceptualise employee experience as a unified system rather than a collection of isolated indicators.

The study contributes nuance to theories of techno-stress and digital strain. Contrary to assumptions that digitalisation inherently increases stress, the findings show no significant association between technological use and employees' stress levels. This suggests that stress mechanisms may lie outside technological deployment—likely in organisational culture, managerial practices, or workload norms—prompting refinement of existing techno-stress models.

The research adds empirical insight from Lithuania, a context rarely examined in Industry 4.0/5.0 or QWL scholarship. By analysing digitalisation effects in a small, rapidly modernising economy, the study extends theoretical discussions beyond the typically studied industrial regions and demonstrates how local labour-market structures shape the employee experience of digital transformation.

RESEARCH LIMITATIONS

This study is subject to several limitations that need to be acknowledged. The geographical scope is restricted to Lithuania. While this provides valuable insights into a specific national context, the findings cannot be uncritically generalized to other countries with different institutional environments or policy frameworks. However, it should also be noted that many of the organizations implementing Industry 4.0 and 5.0 technologies in Lithuania are part of multinational networks. Prior research suggests that digital transformation in industrial settings often follows standardized practices across international subsidiaries, especially in sectors such as manufacturing, logistics, and IT (Ghobakhloo, 2018; Kagermann et al., 2013). Consequently, while the Lithuanian context has its particularities, the technological and organizational dynamics identified here may be broadly representative of workplaces in other regions undergoing similar transitions.

The conceptualization of Quality of Work Life (QWL) in this study focuses on stress levels, opportunities for skill development, and job security. While these are central aspects, the construct of QWL is multidimensional, and other factors such as work–life balance, social

support, and employee voice were not incorporated. This narrower operationalization may therefore only partially capture the complexity of QWL.

The cross-sectional design of the study captures employee perceptions at a single point in time. This precludes analysis of how Quality of Work Life may evolve in response to long-term technological adoption or organizational change.

Finally, the rapid pace of technological innovation in the context of Industry 4.0 and 5.0 presents an additional limitation. The findings of this research reflect the current state of technological implementation but may lose relevance as new tools and practices emerge.

Future studies could address several areas to advance understanding of digital transformation and QWL: Longitudinal designs should be used to analyse changes in QWL over time as organisations deepen their digital maturity; Research should be expanded to include other countries and industries, allowing comparative analysis across contexts; Additional QWL dimensions—such as autonomy, supervisory support, work–life balance, and organisational justice—should be incorporated to enrich the construct; Mediating mechanisms, such as perceived organisational support, trust, and digital competence, should be examined to understand how technology influences QWL indirectly; Moderating factors, including age, gender, job position, and organisational culture, should be explored to identify which groups are more vulnerable to negative outcomes or more able to benefit from digitalisation.

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The Impact of Industry 4.0 / 5.0 Tools Implementation on the Quality of Work Life Indicators

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Master Thesis

Business Process Management Master Programme

Faculty of Economics and Business Administration, Vilnius University

Supervisor Prof. Dr. Serafinas, Vilnius, 2026

SUMMARY

75 pages, 1 table, 9 figures, 34 sources.

The main purpose of this Master thesis is to examine how Industry 4.0 and Industry 5.0 technologies influence employees' perceived Quality of Work Life (QWL), with a specific focus on stress levels, job security, and opportunities for skills development.

The thesis is structured into three main parts: a literature analysis, an empirical research section, and conclusions with recommendations. The literature review traces the evolution from Industry 1.0 to Industry 5.0 and outlines the main technological domains shaping contemporary industrial transformation. Industry 4.0 encompasses automation, artificial intelligence, cyber-physical systems, and the Internet of Things, whereas Industry 5.0 introduces a human-centric approach aimed at promoting human-machine collaboration through tools such as cobots, digital twins, and augmented reality. The chapter also examines Quality of Work Life as a multidimensional concept and justifies its operationalisation in this study through three core indicators: stress, job security, and skills development.

The empirical research investigates how employees' exposure to Industry 4.0/5.0 tools relates to perceived QWL outcomes. A quantitative survey was conducted, yielding 150 valid responses from employees working in digitally transforming organisational settings. The questionnaire integrated validated scales for stress and job insecurity, as well as adapted items for skills development and technological usage. Data were analysed using SPSS and SmartPLS. SPSS was applied for descriptive statistics, reliability testing, Pearson correlations, and regression analysis, while SmartPLS was used for Structural Equation Modeling (SEM) to validate the proposed research model and examine latent relationships between constructs.

The results indicate that technological adoption has the strongest positive association with employees' skills development, suggesting that exposure to advanced digital tools enhances competence and learning. Digitalisation shows a negative relationship with job security, implying that technological change may reinforce concerns regarding job displacement. No significant relationship was found between the use of technologies and stress levels, suggesting that technology exposure does not inherently increase psychological strain. Regression and SEM results also confirm that skills development is a key predictor of job satisfaction within the broader QWL construct.

Pramonės 4.0 / 5.0 įrankių diegimo poveikis gyvenimo darbe kokybės rodikliams

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Magistro baigiamasis darbas

Verslo procesų valdymas

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Darbo vadovas Prof. Dr. Dalius Serafinas, Vilnius, 2026

SANTRAUKA

75 puslapiai, 1 lentelė, 9 paveikslų, 34 šaltiniai.

Šio magistro baigiamojo darbo tikslas – išnagrinėti, kaip Industry 4.0 ir Industry 5.0 technologijos veikia darbuotojų suvokiamą darbo gyvenimo kokybę (QWL), ypač vertinant streso lygius, darbo saugumo jausmą ir galimybes tobulinti skaitmeninius įgūdžius.

Darbas susideda iš trijų pagrindinių dalių: literatūros analizės, empirinio tyrimo ir tyrimo rezultatų apibendrinimo su rekomendacijomis. Literatūros analizėje aptariama pramonės raida nuo pirmosios iki penktosios pramonės revoliucijos ir išskiriamos pagrindinės šiuolaikines pramonės transformacijas lemiančios technologijos. Industry 4.0 apima automatizaciją, dirbtinį intelektą, kibernetines-fizines sistemas ir daiktų internetą, o Industry 5.0 remiasi žmogaus ir technologijų sąveika, bendradarbiaujančiais robotais, skaitmeniniais dvyniais ir išplėstinės realybės sprendimais. Taip pat analizuojama darbo gyvenimo kokybės samprata ir pagrindžiama jos operacionalizacija trimis rodikliais: stresu, darbo saugumu ir įgūdžių tobulėjimu.

Empirinis tyrimas vykdytas siekiant nustatyti, kaip darbuotojų sąlytis su Industry 4.0/5.0 technologijomis susijęs su QWL rodikliais. Taikyta kiekybinė apklausos metodika; gauti 150 galiojančių atsakymų iš darbuotojų, dirbančių skaitmeninės transformacijos procesuose dalyvaujančiose organizacijose. Klausimynas sudarytas naudojant patvirtintas psichologines skales streso ir darbo nesaugumo matavimui bei adaptuotus teiginius įgūdžių tobulėjimo ir technologijų naudojimo vertinimui. Duomenys analizuoti naudojant SPSS ir SmartPLS programas. SPSS taikyta aprašomajai statistikai, patikimumo analizei, koreliacijų ir regresijų skaičiavimui, o SmartPLS – Struktūrinių lygčių modeliui (SEM) sudaryti ir tyrimo modelio ryšiams patvirtinti.

Tyrimo rezultatai parodė, kad technologijų naudojimas labiausiai susijęs su teigiamais įgūdžių tobulėjimo pokyčiais, t. y. darbuotojai, dažniau naudojantys skaitmeninius įrankius, jaučia didesnį kompetencijų augimą. Tuo tarpu skaitmenizacija turi neigiamą ryšį su darbo saugumu, kas rodo, kad technologinė pažanga gali stiprinti darbuotojų nerimą dėl potencialios darbo vietos praradimo. Reikšmingo ryšio tarp technologijų naudojimo ir streso nenustatyta. Regresijos ir SEM analizės patvirtino, kad įgūdžių tobulėjimas yra stipriausias darbo pasitenkinimo ir bendros QWL konstrukto dalies prediktorius.

ANNEXES

ANNEX 1

Regression results for Job Security included only the technological predictors. SPSS

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.342 ^a	.117	.073	.70355

a. Predictors: (Constant), cloud_changes_n, digitaltwins_n, ai_scheduling(num), vr_use_n, digital_assist_n, iot_use_n, ai_use(num)

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	9.241	7	1.320	2.667	.013 ^b
	Residual	69.792	141	.495		
	Total	79.034	148			

a. Dependent Variable: JobSec_index

b. Predictors: (Constant), cloud_changes_n, digitaltwins_n, ai_scheduling(num), vr_use_n, digital_assist_n, iot_use_n, ai_use(num)

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.541	.512		6.918	<.001
	ai_use(num)	-.230	.096	-.238	-2.405	.017
	ai_scheduling(num)	.021	.059	.032	.358	.721
	digital_assist_n	-.086	.091	-.091	-.951	.343
	digitaltwins_n	.027	.077	.036	.353	.725
	vr_use_n	.028	.077	.032	.366	.715
	iot_use_n	.029	.074	.039	.399	.690
	cloud_changes_n	-.101	.104	-.090	-.965	.336

a. Dependent Variable: JobSec_index

ANNEX 2

Regression results for Job Security including demographic controls. SPSS

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.456 ^a	.208	.143	.67640

a. Predictors: (Constant), experience(num), ai_scheduling(num), cloud_changes_n, gender(num), industry(num), vr_use_n, digital_assist_n, iot_use_n, role(num), ai_use(num), digitaltwins_n

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	16.072	11	1.461	3.194	<.001 ^b
	Residual	61.308	134	.458		
	Total	77.380	145			

a. Dependent Variable: JobSec_index

b. Predictors: (Constant), experience(num), ai_scheduling(num), cloud_changes_n, gender(num), industry(num), vr_use_n, digital_assist_n, iot_use_n, role(num), ai_use(num), digitaltwins_n

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.482	.670		5.193	<.001
	ai_use(num)	-.216	.098	-.219	-2.191	.030
	ai_scheduling(num)	.013	.060	.019	.214	.831
	digital_assist_n	-.055	.094	-.055	-.584	.560
	digitaltwins_n	.038	.080	.051	.480	.632
	vr_use_n	-.014	.079	-.016	-.181	.857
	iot_use_n	.115	.076	.151	1.507	.134
	cloud_changes_n	-.144	.104	-.124	-1.386	.168
	gender(num)	.105	.072	.117	1.450	.149
	industry(num)	.063	.061	.095	1.018	.310
	role(num)	-.259	.102	-.238	-2.531	.013
	experience(num)	-.048	.086	-.053	-.555	.580

a. Dependent Variable: JobSec_index

ANNEX 3

Regression results for Stress included only technological variables. SPSS

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.229 ^a	.053	.005	.66626

a. Predictors: (Constant), cloud_changes_n, digitaltwins_n, ai_scheduling(num), vr_use_n, digital_assist_n, iot_use_n, ai_use(num)

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3.470	7	.496	1.117	.356 ^b
	Residual	62.589	141	.444		
	Total	66.060	148			

a. Dependent Variable: stress_index

b. Predictors: (Constant), cloud_changes_n, digitaltwins_n, ai_scheduling(num), vr_use_n, digital_assist_n, iot_use_n, ai_use(num)

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients		Sig.
		B	Std. Error	Beta	t	
1	(Constant)	2.814	.485		5.807	<.001
	ai_use(num)	-.153	.091	-.173	-1.687	.094
	ai_scheduling(num)	.039	.056	.063	.689	.492
	digital_assist_n	-.051	.086	-.059	-.596	.552
	digitaltwins_n	-.002	.073	-.003	-.024	.981
	vr_use_n	.066	.072	.082	.906	.366
	iot_use_n	-.118	.070	-.169	-1.688	.094
	cloud_changes_n	.121	.099	.118	1.228	.222

a. Dependent Variable: stress_index

ANNEX 4

Regression results for Stress introduced demographic controls. SPSS

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.380 ^a	.144	.074	.64706

a. Predictors: (Constant), gender(num), digitaltwins_n, cloud_changes_n, experience(num), ai_scheduling(num), digital_assist_n, industry(num), vr_use_n, role(num), ai_use(num), iot_use_n

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	9.451	11	.859	2.052	.028 ^b
	Residual	56.104	134	.419		
	Total	65.555	145			

a. Dependent Variable: stress_index

b. Predictors: (Constant), gender(num), digitaltwins_n, cloud_changes_n, experience(num), ai_scheduling(num), digital_assist_n, industry(num), vr_use_n, role(num), ai_use(num), iot_use_n

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.887	.641		4.502	<.001
	ai_use(num)	-.140	.094	-.154	-1.485	.140
	ai_scheduling(num)	.046	.057	.075	.807	.421
	digital_assist_n	-.048	.090	-.052	-.532	.596
	digitaltwins_n	-.023	.076	-.034	-.308	.759
	vr_use_n	.046	.075	.058	.616	.539
	iot_use_n	-.063	.073	-.091	-.871	.386
	cloud_changes_n	.103	.099	.097	1.040	.300
	experience(num)	-.054	.082	-.065	-.650	.517
	role(num)	-.193	.098	-.193	-1.971	.051
	industry(num)	-.007	.059	-.012	-.125	.901
	gender(num)	.142	.069	.172	2.054	.042

a. Dependent Variable: stress_index

ANNEX 5

Regression results for Skills Development included only technological variables. SPSS

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.618 ^a	.382	.352	.48460

a. Predictors: (Constant), cloud_changes_n, digitaltwins_n, ai_scheduling(num), vr_use_n, digital_assist_n, iot_use_n, ai_use(num)

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	20.506	7	2.929	12.474	<.001 ^b
	Residual	33.112	141	.235		
	Total	53.618	148			

a. Dependent Variable: skills_index

b. Predictors: (Constant), cloud_changes_n, digitaltwins_n, ai_scheduling(num), vr_use_n, digital_assist_n, iot_use_n, ai_use(num)

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.428	.353		4.051	<.001
	ai_use(num)	.367	.066	.461	5.559	<.001
	ai_scheduling(num)	.035	.041	.064	.859	.392
	digital_assist_n	-.057	.062	-.073	-.912	.363
	digitaltwins_n	.017	.053	.027	.310	.757
	vr_use_n	-.008	.053	-.010	-.143	.887
	iot_use_n	.032	.051	.051	.628	.531
	cloud_changes_n	.243	.072	.263	3.383	<.001

a. Dependent Variable: skills_index

ANNEX 6

Regression results for Skills Development included only technological variables. SPSS

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.614 ^a	.377	.326	.48303

a. Predictors: (Constant), gender(num), digitaltwins_n, cloud_changes_n, experience(num), ai_scheduling(num), digital_assist_n, industry(num), vr_use_n, role(num), ai_use(num), iot_use_n

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	18.902	11	1.718	7.365	<.001 ^b
	Residual	31.264	134	.233		
	Total	50.166	145			

a. Dependent Variable: skills_index

b. Predictors: (Constant), gender(num), digitaltwins_n, cloud_changes_n, experience(num), ai_scheduling(num), digital_assist_n, industry(num), vr_use_n, role(num), ai_use(num), iot_use_n

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.998	.479		4.172	<.001
	ai_use(num)	.342	.070	.431	4.872	<.001
	ai_scheduling(num)	.041	.043	.076	.964	.337
	digital_assist_n	-.104	.067	-.131	-1.557	.122
	digitaltwins_n	-.008	.057	-.013	-.138	.891
	vr_use_n	.022	.056	.031	.384	.702
	iot_use_n	-.005	.054	-.008	-.091	.928
	cloud_changes_n	.228	.074	.245	3.075	.003
	experience(num)	-.004	.061	-.006	-.073	.942
	role(num)	.099	.073	.113	1.358	.177
	industry(num)	-.084	.044	-.159	-1.924	.056
	gender(num)	-.001	.051	-.002	-.026	.979

a. Dependent Variable: skills_index

ANNEX 7

Questionnaire

Industry 4.0 and 5.0 Technologies and Quality of Work Life

You are invited to participate in a research study conducted as part of a Master’s Thesis. This study explores how Industry 4.0 and Industry 5.0 technologies influence employees’ Quality of Work Life (QWL). Participation is voluntary and anonymous. It will take a maximum of 5 minutes to complete. No personal identifiers will be collected, and all responses will be used solely for academic purposes. By continuing, you consent to participate in this study.

General Information

1. Gender:

- Male

- Female
- Prefer not to say
- Non-binary

2. What industry do you work in?

- Manufacturing
- IT
- Logistics
- Finance
- Other (please specify): _____

3. What is your current job role?

- Operational staff
- Manager
- Executive
- Other: _____

4. How long have you worked in your current organization?

- Less than 1 year
 - 1–3 years
 - 4–6 years
 - 7+ years
-

Use of Industry 4.0 / 5.0 Tools

1. I use artificial intelligence (AI) or automated systems in my daily work.

- Strongly agree

- Agree
- Neither agree not disagree
- Disagree
- Strongly disagree

2. My work tasks are influenced or scheduled by AI-driven systems.

- Strongly agree
- Agree
- Neither agree not disagree
- Disagree
- Strongly disagree

3. I interact with digital assistants at my job.

- Strongly agree
- Agree
- Neither agree not disagree
- Disagree
- Strongly disagree

4. I receive support or guidance from digital systems (e.g., digital twins or smart machines).

- Strongly agree
- Agree
- Neither agree not disagree
- Disagree
- Strongly disagree

5. Augmented or virtual reality (AR/VR) tools are used in my work or training.

- Strongly agree
- Agree
- Neither agree not disagree
- Disagree
- Strongly disagree

6. Internet-connected systems (e.g., IoT, CPS, smart factories) are a regular part of my work environment.

- Strongly agree
- Agree
- Neither agree not disagree
- Disagree
- Strongly disagree

7. The use of digital platforms (e.g., cloud computing, blockchain, workflow systems) has changed how I collaborate with colleagues.

- Strongly agree
- Agree
- Neither agree not disagree
- Disagree
- Strongly disagree

QWL:

Stress Levels

Perceived Stress Scale (PSS-4)

(Source: Cohen, Komarck & Mermelstein, 1983)

In the last month...

8. I felt that I was unable to control the important things in my life.
- Strongly agree
 - Agree
 - Neither agree not disagree
 - Disagree
 - Strongly disagree
9. I felt confident about my ability to handle personal problems. *(Reverse-scored)*
- Strongly agree
 - Agree
 - Neither agree not disagree
 - Disagree
 - Strongly disagree
10. I felt that things were going my way. *(Reverse-scored)*
- Strongly agree
 - Agree
 - Neither agree not disagree
 - Disagree
 - Strongly disagree
11. I felt difficulties were piling up so high that I could not overcome them.
- Strongly agree
 - Agree
 - Neither agree not disagree

- Disagree
- Strongly disagree

Job Security

Job Insecurity Scale (De Witte, Short Form)

12. I feel insecure about the future of my job.

- Strongly agree
- Agree
- Neither agree not disagree
- Disagree
- Strongly disagree

13. I think I might lose my job in the near future.

- Strongly agree
- Agree
- Neither agree not disagree
- Disagree
- Strongly disagree

14. I am sure that I will keep my job. (*Reverse-scored*)

- Strongly agree
- Agree
- Neither agree not disagree
- Disagree
- Strongly disagree

15. I worry about the possibility of getting laid off.

- Strongly agree
- Agree
- Neither agree not disagree
- Disagree
- Strongly disagree

Skills Development

Adapted from Learning and Development Satisfaction Scale (LDS)

16. My organization provides opportunities to learn new digital skills.

- Strongly agree
- Agree
- Neither agree not disagree
- Disagree
- Strongly disagree

17. I have developed new skills due to the implementation of new technologies.

- Strongly agree
- Agree
- Neither agree not disagree
- Disagree
- Strongly disagree

18. I feel that learning to use Industry 4.0/5.0 tools has improved my job performance.

- Strongly agree
- Agree
- Neither agree not disagree

- Disagree
- Strongly disagree

19. I am encouraged to participate in training and professional development activities.

- Strongly agree
- Agree
- Neither agree not disagree
- Disagree
- Strongly disagree

Job Satisfaction

Minnesota Satisfaction Questionnaire (MSQ – Short Form)

20. I am satisfied with the kind of work I do.

- Strongly agree
- Agree
- Neither agree not disagree
- Disagree
- Strongly disagree

21. I feel a sense of accomplishment in my job.

- Strongly agree
- Agree
- Neither agree not disagree
- Disagree
- Strongly disagree

22. I am satisfied with the degree of independence in my work.

- Strongly agree
- Agree
- Neither agree not disagree
- Disagree
- Strongly disagree

23. I am satisfied with the opportunities for advancement in my organization.

- Strongly agree
- Agree
- Neither agree not disagree
- Disagree
- Strongly disagree

Open-Ended Questions (*Optional but useful*)

24. What do you see as the main benefits of new technologies in your workplace?

25. What concerns or challenges have you faced related to digital tools or automation?