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HUMAN RESOURCE MANAGEMENT

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MASTER THESIS

Dirbtinio intelekto (DI) produktų naudojimo poveikis darbuotojų gerovei darbe: darbo savarankiškumo moderuojantis ir tarpinis technostreso vaidmuo	The Impact of Artificial Intelligence (AI) Product Use on Employee Well-being at work: The Moderating Role of Job Autonomy and the Mediating Effect of Technostress

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INTRODUCTION

Relevance of the topic. Recent advancements in Artificial Intelligence (AI) have raised concerns about the potential large-scale job displacement, which could impact on all economic sectors. According to OECD (2021), the growing use of AI in the workplace has raised concerns about employee well-being and overall work environment, as it may challenge human roles in professional settings. However, AI adoption is no longer a dream possibility, but it is a major force behind productivity, creativity and industry competitiveness. AI transforms organizational dynamics and the nature of work itself by automating repetitive tasks and enhancing employees to concentrate on higher-value activities that promotes creativity and strategic thinking (Shaikh et al., 2023; Soulami et al., 2024).

The implementation of AI products at the workplace can lead to enormous issues, such as decreased autonomy over one's role; ethical dilemmas; harm to mental health; and unemployment (Tarafdar et al., 2007; Kinowska & Sienkiewicz, 2022). These problems exemplify how AI technology can aid productivity but simultaneously AI and analytics risk exposure to adverse outcomes impacting employee's health and well-being.

Examining the effects of AI integration on an employee's productivity and overall well-being is crucial for crafting effective work settings that align with organizational goals and human centric values (Henkel et al., 2020). This emphasizes the need to cultivate a psychologically safe climate in which the employees are not afraid of being rendered obsolete by AI technology nor face excessive stress. Hence, factors such as well-being, technostress, and autonomy are relevant as long as artificial intelligence continues changing the form of work performed at workplaces. AI undoubtedly has numerous advantages and disadvantages that organizations must learn to navigate to ensure the safety and well-being of their employees.

The level of exploration of the topic. The relationship between the use of AI products and employee well-being has been studied in several fields: organizational behavior, psychology, and technology interrelations (Nazareno & Schiff, 2021; Jiang et al., 2022). Existing research has also emphasized factors like technostress and autonomy within the framework of job satisfaction (Correia Loureiro et al., 2023; Shaikh et al., 2023). However, these gaps are still lacking on how the aforementioned factors are interrelating within a unified model. Some researchers focused on the role of AI in the productivity enhancement (Fisher et al., 2023), as well as its impact on autonomy (Kinowska & Sienkiewicz, 2022) and contribution to technostress (Tarafdar et al., 2007), but limited attention has been done concerning the collective effect of these factors on employee well-being at work.

AI certainly has mixed and sometimes conflicting influence on job autonomy. While some offer greater autonomy through decision-making, and decision-support systems can improve autonomy through advancing decision-making capabilities, it may create a situation of stress due to overload interpreting of the AI suggestions (Jiang et al., 2022). Likewise, the automation of repetitive tasks may lower employee stress, but the need for constant modification of systems and acquisition of new technical skills may increase technostress (Correia Loureiro, 2023). Also, applications of AI in particular industries such as manufacturing automation and healthcare diagnostics probably affect well-being in unique manners, yet comparative studies are lacking (Shaikh et al., 2023).

Aside from technology, organizational factors such as leadership practices, workplace culture, and AI ethics policies are important, albeit insufficiently studied, moderators of the relationship between AI adoption, technostress, and well-being (Shaikh et al., 2023). Moreover, cultural and demographic factors influence how employees perceive AI-related stress. For example, older workers may be at greater risk from AI-related stress than younger workers, while culturally shaped attitudes towards authority and self-reliance affect how people respond (Stamate et al.2021). Some literature has looked at the risks of job displacement (Nazareno & Schiff, 2021), but more balanced frameworks are needed that consider both the advantages and challenges of AI product use for employees.

The novelty of the Master thesis. The novelty of this research relies on understanding the relationship between AI product use and employee well-being, specifically focusing on the interplay between technostress, job autonomy, and employee well-being at work. While existing studies have examined these factors individually, this research bridges the gap by integrating them into a comprehensive framework. By applying a quantitative approach and analyzing real-world data, this study could provide empirical insights that can guide organizations in implementing AI strategies that foster employee well-being at work.

The problem of the Master thesis. The core problem addressed by this thesis is the dual-edged impact of AI product use on employee well-being. While AI can enhance efficiency and decision-making (Fisher et al., 2023), it also introduces challenges, including technostress (Tarafdar et al., 2007), diminished autonomy (Kinowska & Sienkiewicz, 2022), and potential job displacement (Nazareno & Schiff, 2021). The study aims to uncover the conditions under which AI product use positively or negatively influences employee well-being at work.

The aim of the thesis. The aim of this thesis is to evaluate the impact of AI product use on employee well-being at work, determine the role of job autonomy as a moderator and technostress as a mediator, and reveal strategies or recommendations for optimizing AI product use integration in workplace settings.

The Objectives of the thesis. To achieve the aim, the following research objectives have been raised:

- To analyze the extent and nature of AI product use, employee well-being at work, job autonomy, and technostress in workplace settings.
- After systemizing scientific literature, disclose the links between AI product use, employee well-being, job autonomy and technostress at work.
- Based on a developed conceptual research model, to conduct the empirical study, analyze and summarize findings.
- Based on conducted research, assess the impact of AI product use on employee well-being and mediating role of technostress and moderating role of autonomy to this relationship, to present conclusions and recommendations.

The methods deployed by the Master thesis. This thesis adopts a quantitative research design to investigate the impact of AI product use on employee well-being. The quantitative method is selected for its ability to provide measurable, objective, and statistically robust insights into the relationships among key variables, including AI product use, job autonomy, technostress, and employee well-being at work.

Description of the structure of the Master thesis. The Master thesis starts with an introduction to the topic. Introduction establishes the relevance of the topic, the level of exploration, and the novelty of the study. It then presents the research problem, aim, objectives, and methodology, concluding with an overview of the thesis structure. The first chapter is the literature review which examines the theoretical foundations of AI product use in the workplace, its impact on employee well-being, and the interplay between AI product use , job autonomy, and technostress. This section also reviews existing research on the dual-edged nature of AI and highlights gaps in the literature. The second chapter of the Master is methodology of the research ai, objectives, defines the key variables of the study, develops the conceptual research model, formulates hypotheses regarding the relationships between AI p product use, employee well-being at work, job autonomy, and technostress, data collection instruments and techniques. The fourth chapter will present the analysis of the empirical results which will present the empirical findings, will test the hypotheses, and will examine the mediation and moderation effects of technostress and job autonomy. Following the empirical results, the conclusions and recommendations chapter will summarize key findings, outline research limitations, and provide actionable recommendations, along with directions for future research. The Master thesis will conclude with a list of references, a summary in both Lithuanian and English, and annexes.

1. THEORETICAL ASPECTS OF ARTIFICIAL INTELLIGENCE (AI) PRODUCT USE IN THE WORKPLACE: ITS IMPACT ON EMPLOYEE WELL-BEING, JOB AUTONOMY AND TECHNOSTRESS AT WORK

1.1. Theoretical aspect of AI product use in the workplace

The organizations started to incorporate AI tools their activities which allow them to make better decision-making, streamlined workflows and automated repetitive tasks. These technological advancements have notable reshaped organizational structures, reevaluated employee roles, and retransformed entire industries.

When analyzing the relations between AI instruments and the underlying structures of an organization, most scholars capitalize on the framework provided by TAM, which is a Technology Acceptance Model developed by Davis in 1989. TAM is often paired with the equally important model of UTAUT, which is the Unified Theory of Acceptance and Use of Technology, brought to life by Venkatesh et al. in 2003. With both models, they greatly contribute to understanding the technology acceptance theory regarding organizations. These frameworks make evident concerns of the social and psychological dimension relevant to the decision to adopt advanced technologies in organizations. Following Sohn and Kwon (2020), acceptance of intelligent systems is impacted most strongly by perceived usefulness, emphasizing the belief that the technology will contribute positively to job performance, along with perceived ease of use, the level of effort required to operate the technology. These variables, which stem from the basic two principal claims of TAM framework, significantly impact shaping positive attitudes and intentions to use the system. From the perspective of AI and intelligent systemic solutions, the frameworks performance expectancy and effort expectancy (Venkatesh et al., 2003) sharpen our focus on understanding AI product use within the UTAUT framework. These constructs are impacted by employees perceived behavioral control, which is how confident they are in possessing the skills, resources, and autonomy to meaningfully engage with AI tools. The technicality perception, or the complexity of AI systems, can hinder ease of use (Sohn & Kwon, 2020). Non-expert employees may be discourage from using AI systems when they are overly technical, which results in increased uncertainty and risk. Organizational support, such as training and communication, can overcome these barriers and improve trust (Gefen et al., 2003).

The product use refers to the implementation of AI into an organization and the subsequent restructuring of workflows, tasks, and decision-making (Soulami et al., 2024). The central motivators for AI product use include enhanced productivity, automation of repetitive work, and increased decision-making and innovation capabilities (Shaikh et al., 2023). Organizational readiness, employee trust, continuous training, and adherence to ethical guidelines of transparency and fairness significantly enable effective use (Ortega-Bolaños et al., 2024). Nonetheless, notable gaps remain in the form of employee resistance, insufficient skills, perceived job displacement, ethical concerns, and a lack of transparency (Nazareno & Schiff, 2021).

As per the suggested Shaikh et al. 2023, AI usage by sectors varies: Healthcare focuses on diagnostic AI tools, Manufacturing uses AI for automation, while IT sectors concentrate on predictive analytics. Fisher et al. (2023), Henkel et al. (2020), and Jiang et al. (2022) argue that AI products maintain these transformations through tools such as emotion recognition, chatbots, automation, and predictive analytics. As resources and demands, these applications bring efficiency but also challenges like technostress and upskilling (Correia Loureiro et al., 2023).

The impact of AI product usage has been especially profound on the labor market. Opportunities for low- and mid-skill roles have evaporated, while there is an increased demand for high-skilled professionals like AI experts and data scientists (OECD, 2022). This is skill polarization: an AI-advanced, highly skilled professional workforce faces increased job insecurity and stress. For example, 40% of AI product adopters are within the ICT services and 21% are in professional and scientific activities (OECD, 2022). As noted by the OECD in 2022, productivity gaps are widening domestically for such organizations that do not have access to sufficient resources on AI talent.

The AI-enabled roles impact the employee's expectations and responsibilities. Automation enables completion of routine tasks which lets employees to focus on work that is complex and strategic or involves creativity (Shaikh et al., 2023). New roles like AI trainers and data analysts are emerging due to these new technologies, but more monotonous jobs are being automated (Jiang et al., 2022). There are two sides to these transitions, both good and bad. Although productivity and innovation improves, however, some employees face a loss of job control over their work, as well as high levels of stress associated with workplace technology use (Correia Loureiro et al., 2023; Jeong et al., 2024; Nazareno & Schiff, 2021).

The degree of AI product use varies across sectors: healthcare emphasizes diagnostic tools, manufacturing leverages automation, and IT industries focus on predictive analytics (Shaikh et al., 2023, Nazareno & Schiff, 2021). While AI applied to finance includes fraud detection, credit scoring, and trading through algorithms (Kinowska & Sienkiewicz, 2022). Manufacturing uses AI in robotics and predictive maintenance, while retail uses AI in analyzing consumer behavior and targeted advertising (Soulami et al., 2024; Brougham & Haar, 2018). The aviation industry also benefits, particularly with strengthening safety and efficiency from automation and predictive maintenance (Shaikh et al., 2023).

To summarize, both the theoretical and practical aspects of AI's product use in the workplace demonstrate its robust relevance and influence on modern workplaces. Following the acceptance frameworks TAM and UTAUT, the successfully implemented AI tools are based on their perceived ease of use, perceived usefulness, perceived behavioral control, performance expectancy, effort expectancy and technicality. Although AI products enhance overall operational efficiency and foster innovation, they also present negative challenges including technostress, diminished autonomy, and workforce stratification. Since

AI is relentlessly changing job responsibilities and inter-sectoral relations, organizations need to adopt policies for continuous training and development, as well as effective ethical, inclusivity, and equality frameworks to avoid undermining employee well-being and organizational performance.

In the preceding section, the theoretical aspects of AI product use at the workplace with the theoretical model like TAM and UTAUT been discussed. In the next subsection, the theoretical aspect of Employee well-being at work will be introduced.

1.2. Theoretical aspect of Employee well-being at work

Defining well-being is not an easy task. The World Health Organization (1997; Dodge, Daly, Huyton, & Sanders, 2012) defines well-being as an individual's perception of their position in life, influenced by their work environment, interpersonal relationships, and overall life circumstances. In the organizational context, well-being is often linked to job satisfaction, engagement, and psychological safety, with research highlighting its role in enhancing productivity and reducing absenteeism (Diener, Suh, Lucas, & Smith, 1999; Dodge, Daly, Huyton, & Sanders, 2012). A lack of well-being at work, often associated with high job demands and low autonomy, has been linked to increased stress and burnout (Schaufeli, Bakker, & Salanova, 2006; Dodge et al., 2012). Given these insights, organizations are increasingly recognizing the importance of fostering a work environment that promotes well-being through supportive leadership, work-life balance, and opportunities for professional growth (Ryff & Singer, 2008; Dodge et al., 2012).

To build upon this idea, Boxall and Macky (2014) view employee well-being as a complex construction of happiness, health, and relational components of the workplace. Well-being is accomplished through four indicators: job satisfaction, job-related stress, fatigue, and work-life balance. Satisfaction (that is, work-related happiness) is measured using a global single-item scale which captures an employee's overall satisfaction with their job (Warr, Cook, & Wall, 1979; Boxall & Macky, 2014). Boxall & Macky (2014) define job-related stress as the degree of mental work burden and stress most employees experience (Stanton et al., 2001; Boxall & Macky, 2014) and fatigue as being physically and mentally tired due to the demands placed on a person's workload (Beehr, Walsh, & Taber, 1976; Boxall & Macky, 2014). Last, but not least, work-life balance is defined as the extent to which work activities disrupt personal and family time and is measured by negative spillover from work to home (Frone & Yardley, 1996; Boxall & Macky, 2014). Their study also demonstrates that high involvement work processes (HIWPs), including autonomy, self-organization, and participation in decision-making, have an important role in contributing to job satisfaction and work-life balance.

In the same way, Smith and Smith (2017) characterize workplace well-being as a blend of both positive and negative elements shaped by many factors beyond the employees' control. A positive well-being is marked by both occupational happiness and satisfaction which is impacted by self-efficacy, traits such as optimism, and other positive personality attributes. On the contrary, stress, anxiety, and depression are considered negative well-being and are a result of some job characteristics, passive coping responses, and perceived stress (Smith & Smith, 2017). The study further points importance of both individual and organizational factors such as the psychological contract (Rousseau, 1989; Smith & Smith, 2017), organizational commitment (Meyer & Allen, 1991; Smith & Smith, 2017), and organizational citizenship behavior (Bateman & Organ, 1983; Smith & Smith, 2017). The combination of these factors illustrates the relevance employer personal and organizational conditions have on employee wellbeing.

Employee wellbeing in the workplace can be impacted by technology in both positive and negative ways. Cognitive load is reduced for the employees when AI tools are used to automate monotonous tasks giving the employees more meaningful work activities to focus on (Henkel et al., 2020). Redundant physical and automated work tasks also enhance employee wellbeing (Fisher et al., 2023). But digital solutions come with new cons, for example, digital overload and technostress. The ever-growing digital system, constant connectivity, and frequent updates significantly worsen stress factors and work-life balance by impacting mental well-being negatively (Jiang et al., 2022; Nazareno & Schiff, 2021).

Employees possessing high levels of digital skills alongside versatile adaptability to newer technologies tend to display enhanced well-being, as they are able to navigate effectively through digital transformations with minimal impact to themselves." (Soulami et al., 2024). On the contrary, absence of adequate digital skills heightens the level of technostress while lowering the overall job satisfaction leading to disengagement and throughput productivity. This emphasizes the significant need of adequate investment for upskilling and the fostering of digital literacy frameworks aimed at filling the gap on building resilience in the dynamically changing digital landscape.

The application of AI tools has considerable impact on employees welfare with conflicting advantages and disadvantages. AI enhances the execution of activities and decision making while relieving employees of cognitive and physical effort, thus, boosting job satisfaction and performance. On the negative side, advanced AI technologies may bring additional forms of stress such as technostress and cognitive overload. Furthermore, when autonomous AI decision making is implemented, employee satisfaction declines adversely to general welfare when control is restricted or a feeling of diminished control lies is fostered. (Jiang et al., 2022; Nazareno & Schiff, 2021).

To conclude, employee well-being is understood to by multidimensional in nature considering the conditions at work, personal traits, and technologies' presence or absence with regard to job satisfaction, stress level, work-life balance, and autonomy being key components. Supportive leadership, opportunities for career advancement, and high-involvement work systems enhance employee well-being, whereas stress and burnout is associated with high job demands coupled with low autonomy. The use of AI and digital technologies serves a dual purpose of increasing productivity and decreasing workload, while also creating new difficulties such as technostress and digital overload. Employees with higher levels of digital literacy tend to enjoy better well-being, emphasizing the need for proactive upskilling to address stressors associated with AI and improve overall satisfaction in the workplace.

In the preceding section, the concept of employee well-being and its complexity has been discussed. Focusing on AI and digital tools can increase well-being by automating routine and reducing workload, but at the same time increases risks such as technostress and reduce job control. Building on this foundation, the following subsection go trough into the concept of job autonomy, examining its theoretical aspects and its critical role in shaping employee well-being in the context of growing AI product use at workplace.

1.3. Theoretical aspect of Job Autonomy

Job autonomy is defined as the extent to which an employee has freedom and control over a given task, how it is accomplished, and when it is done. An employee is also free to choose how work will be done and to organize work responsibilities according to individual preferences and career goals (Shaikh et al., 2023). The literature offers three overarching definitions: task autonomy, which is how employees accomplish the task (Kinowska & Sienkiewicz, 2022); decision-making autonomy which stems unrestricted authority to make any decision (Soulami et al., 2024); and work scheduling autonomy denotes control one has over structuring their work timetable (Shaikh et al., 2023).

The two theories of autonomy inform its definitions. From the perspective of Self-Determination Theory (SDT), autonomy is a critical psychological necessity that one requires for intrinsic motivation, personal development, or even overall wellness (Jiang et al., 2022). In the Job Demands-Resources Model (JDR), autonomy is viewed as a vital resource of a job that diminishes strain, mitigates the effects of high work demands, and thereby increasing engagement and job satisfaction (Stamate et al., 2021). Nazareno & Schiff, (2021) and Shaikh et al., (2023) associate autonomy with increased organizational outcomes such as enhanced creativity, innovation, and productivity, as well as improved retention.

Job autonomy tends to have a positive relationship with employee satisfaction, well-being, and overall performance. Self-efficacy and autonomy aid in fulfilling control, causing stress to dissipate and engagement to increase, which results in enhanced motivation on a personal level (Jiang et al., 2022; Stamate et al., 2021). Workers are able to set their own work preferences, leading to lower burnout rates and augmented job fulfillment (Henkel et al., 2020). Quantitative evidence supports these arguments. Employees reporting high levels of autonomy express more long-term satisfaction with their job and are less likely to change jobs over time, supported by longitudinal studies (Correia Loureiro et al., 2023). Meta-analyses also verify the claims, adding that autonomy alleviates workplace stress and improves participation and productivity (Shaikh et al., 2023).

Autonomy also acts on the mediation and moderation role within the workplace. Enhancing freedom of choice and control allows for better personal and professional wellbeing, thus autonomous decision-making mediates the connection between wellbeing and AI implementation (Soulami et al., 2024). At the same time, autonomy mitigates the adverse impacts of job demands like technostress, protecting against burnout and discontent (Nazareno & Schiff, 2021). Still, these benefits should not be taken at face value. Greater autonomy can stress out employees who lack the right skills or support, which diminishes their overall satisfaction (Henkel et al., 2020).

The literature review shows that AI tools have complex relationship with work autonomy, both improving and hampering it. On the positive side, AI technologies assist workers by automating menial, repetitive activities and rendering decision-support assistance during activities, which enables employees to concentrate on more strategic and value-added aspects of the work (Henkel et al., 2020). For example, predictive analytics allow decision makers in various fields like healthcare and finance to understand pertinent information and make decisions, which increases the self-governance of the professional (Fisher et al., 2023). AI based employee schedulers also enhance employee self-governance, which promotes work-life balance (Shaikh et al., 2023). On the other hand, AI tools can also result in loss of job autonomy. Subordinate algorithms employing AI across a range of tasks and AI-controlled rigid workflows often withdraw autonomy from employees (Kinowska & Sienkiewicz, 2022). AI systems, especially those that control workflows for determining outputs or progress, can be viewed as undermining the employee's expertise and persuasively overriding individualized decisions (Nazareno & Schiff, 2021). These impacts are most acute in highly regulated sectors like healthcare and finance, which tend to be highly reliant on algorithmic decision-making (Soulami et al., 2024).

To conclude, autonomy is one explaining factor of well-being, satisfaction, and performance of employees and as such presents both opportunities and challenges in the modern workplace. Employee and organizational outcomes are improved by autonomy as it boosts intrinsic motivation, buffers against workplace stress, and fosters creativity and innovation. Nonetheless, the emergence of AI-powered tools has a two-sided impact on autonomy—on the one hand, automation and decision-support systems empower employees, on the other hand, algorithmic management and inflexible AI dictated workflows can constrain autonomy.

The above-mentioned section examined job autonomy as a crucial element of employee well-being While autonomy plays a significant role in absorting against workplace stress, enhancing self-assurance, its positive impacts might be reduced by inflexible AI systems that limit decision-making freedom. Alongside autonomy, another key consequence that causes a challenge for the workplace is technostress, a growing concern that will be discussed in the following section.

1.4. Theoretical aspect of Technostress

When technology is overstressed, there's psychotechnostress - something which occurs due to the pressures brought about using technology itself; in this instance referring to medical aids such as algorithms and AI (Shaikh et al., 2023; Nazareno & Schiff, 2021). Technostress is also largely assisted by needing to stay perpetually connected to everything and increasing complexity of tasks encapsulated within one piece of technology. This mismatching occurs between what is required from an individual and what the person’s coping mechanisms are. From Henkel et al.’s healthcare AI diagnostic suffocation to Soulami et. all’s IT sector algorithm driven decision making - stress manifests in a specialized manner. A longitudinal study indicates variances in age, responsibility, digital acceptance, and workplace anticipations drive differing levels of technostress per individual. And this is common across all industries experiencing increased digital transformation (Correia Loureiro et al., 2023).

The theoretical foundations of technostress are examined and evaluated from the models of stress. Lazarus and Folkman (1984) suggested that An individual will feel stress when their surrounding environment of obligations posed unto them surpasses the means and resources available, as utilizing them would push them to their limits. Of significance is the fact that a person is able to exert some level of control in managing these demands. Nazareno and Schiff (2021) applying appraisal theory argue stress begins with perceived threats, such as cognitive overload or device-induced job insecurity, thus defining technostress. Five main dimensions of technostress have been documented:

- *Techno-overload* derived from excessive technology-related tasks that cognitively strain and cause burnout (Nazareno & Schiff, 2021).
- *Techno-complexity* stemming from the frustration of not being able to understand or effectively use the advanced technologies at the employees’ disposal (Shaikh et al., 2023).
- *Techno-insecurity* associated with the anxiety regarding potential job loss because of technological advancements (Henkel et al., 2020).
- *Techno-invasion* refers to an imbalance that occurs when technology encroaches into a person’s private life (Jiang et al., 2022).

- *Techno-uncertainty* captures the anxiety that arises from technological updates and fragmentation (Soulami et al., 2024).

These factors affect employee wellbeing and productivity. For instance, overload and complexity are major contributors to mental health issues and burnout (Shaikh et al., 2023). Insecurity holds up job engagement. Invasion undermines productivity and the ability to integrate work with personal life (Correia Loureiro et al., 2023). Specialized research focus on the intensity of complexity in healthcare related to AI use and the predominance of uncertainty in IT due to fast technology updates (Fisher et al., 2023).

According to OECD (2022), adopting AI technologies is expected to increase productivity and efficiency, however, there are concerns over constantly offloading cognitive tasks. The use of more precise AI systems may contribute to an increase in the workload that employees need to take on, which may result in underlined emotional and mental strain(Sarker et al., 2019: OECD, 2022). Moreover, the swift pace at which AI systems are advancing brings about a chronic fear of redundancy which requires employees to pursue upskilling initiatives to sustain their relevance in the organizational hierarchy (Califf & Brooks, 2020: OECD, 2022). Also, AI-based employee monitoring systems may result in privacy issues related to AI which further infringe on the autonomy of the workers thereby damaging their mental safety (Gaudioso et al., 2017: OECD, 2022). Hence, while AI possesses the capabilities to enhance the efficiency of work output, its ergonomic impacts on employees needs balancing to lower the negative outcomes of technostress concerning wellbeing.

To conclude, the term "technostress" refers to work-related stress that derives from the overdependence of an organization in technology, leading to mental strain like demand overload, intricacy, and ongoing change. AI systems indisputably bring productivity benefits, however, alongside those advantages comes the phenomenon of cognitive overload, insecurity regarding career longevity, and an imbalance between personal life and work. It is clear that rapid advanced developments create a sustainable challenge in the workforce which requires constant relearning and adoption of new technologies, which leads to an imbalance concerning employee wellbeing. Such concerns are more acute in AI-exposed sectors where all rounder monitoring systems and anxiety around job loss aggravate the stress. Even with the increasing research, there are still gaps concerning how various age groups and cultural settings experience and manage stress from technology over a period of time.

In the next subsection, the interplay of AI product use, employee well-being, job autonomy and technostress withing JD-R model will be presented.

1.5. The links between AI product use, Employee well-being at work, job autonomy and technostress

This study explores the complex relationships between AI product use, employee well-being at work, job autonomy, and technostress through the lens of the Job Demands-Resources (JD-R) model (Bakker & Demerouti, 2007). The JD-R model makes a distinction between job resources and demands. Resource-fulfilling relationships may increase motivation and aid in enhancing well-being, while depleting job demands can fuel the employees' energy and escalate stress. In this context, the use of AI products is seen as having two sides. On one hand, AI can help to reduce stress by assisting with task completion and boosting productivity. On the other hand, then AI leads to increase workload or introduces more complex at work, it may cause technostress, a form of psychological overload resulting from difficulties in adapting to digital technologies (Ragu-Nathan et al., 2008).

Therefore, as far as the relationship between AI product use and employee well-being is concerned, technostress assumes the position of the most significant mediating effect. The argument provided is that AI can escalate cognitive demands, therefore increasing stress and ultimately causing burnout, reduced job satisfaction, and decreased overall psychological well-being (Giuntella, König, & Stella, 2023). At the same time, well-designed organizational support inputs may enhance the employees' sense of achievement and satisfaction resultant from the use of AI systems. In this scenario, job autonomy stands out as a highly important moderating resource. Workers that exercise greater autonomy can better manage their interaction with AI systems in a way that limits technostress engagement and optimizes well-being by selecting when and how to engage with AI systems (Deci & Ryan, 2000; Bakker, Demerouti, & Euwema, 2005).

Moreover, autonomy has a protective function and serves as a buffer against the harmful effects of job demands (Stamate, Bratianu & Jianu, 2021). This grant not only increases intrinsic motivation but also enables employees to reduce their workloads more flexibly in response to changes in technology transforming work processes. On the other hand, technostress can inhibit or be a barrier to growth challenge, depending on organizational and individual strategies for dealing with AI induced demand (Tarafdar et al., 2007). Thus, the results of AI product usage differ; they depend on the level of technostress and the amount of job autonomy available.

Overall, this formulated theory explains the self-contained dynamics of AI product usage (X), technostress (M), job autonomy (W), and employee well-being at work (Y). It highlights the balance between the potential of AI to enhance performance and reduce stress against the need for individual adaptability, organizational assistance, and structural employee empowerment through autonomy. Understanding these relationships is important for organizations seeking to integrate AI technologies in a manner that preserves employee well-being, rather than damages it.

2. METHODOLOGY OF THE RESEARCH ON THE IMPACT OF THE ARTIFICIAL INTELLIGENCE (AI) PRODCUT USE ON EMPLOYEE WELL-BEING

2.1. Research aim, objectives, conceptual model and hypothesis

After having analyzed the scientific literature, we can see several links between AI product use, employee well-being, job autonomy and technostress. Based on the scientific literature provided and the present research, it can be stated that AI product use has a dual role: functions as a job resource that increases well-being and as a job demand that can leads to technostress. Considering the context of the research aim and objectives, the conceptual research model and hypotheses are formulated.

The aim of this empirical research is to investigate how AI product use influences the employee well-being at work, considering the mediating role of technostress and the moderating effect of job autonomy.

Research objectives:

1. To examine the relationship between AI product use and employee well-being.
2. To examine the relationship between AI product use and the level of technostress experienced by employee at work.
3. To analyse the mediating role of technostress.
4. To analyse the moderating role of job autonomy.
5. To assess how AI product factors such as perceived ease of use, perceived usefulness, perceived behavioral control, performance expectancy, effort expectancy and technicality affect employee well-being.

Conceptual research model. To analyze the impact of AI product use on employee well-being at work, while mediating technostress and moderating job autonomy, the conceptual research model was established (Figure 1). The model is based on Hayes (2013) model No.14 and adapted to this study. Based on these assumptions a quantitative study was conducted:

X- Independent variable (AI product use which is measured via H1a–H1f sub-constructs)

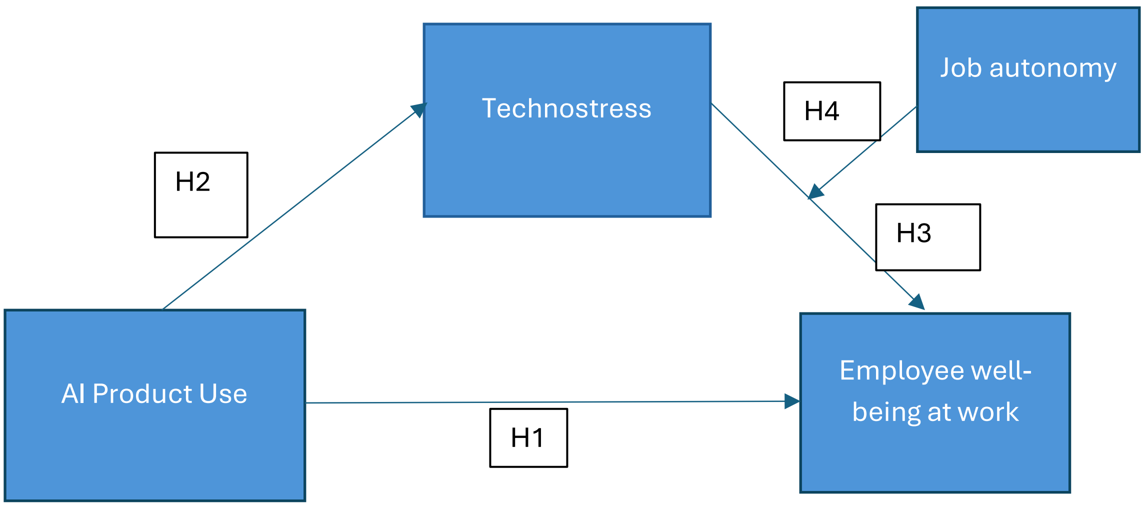
Y – Dependent variable (Employee well-being at work)

M - Mediator (Technostress)

W - Moderator (Job autonomy)

Figure 1

Conceptual Research Model



Source: prepared by the author, based on Hayes (2013) model No 14

Hypotheses and their justifications. Based on the literature review, the following research develops a conceptual model where specific hypotheses were established:

H1: AI product use positively influences employee well-being at work.

AI product use in the workplace enhances efficiency, automates repetitive tasks, and facilitates data-driven decision-making (Soulami et al., 2024; Shaikh et al., 2023). With the implementation of AI, these technologies improve productivity and shift the focus of employees to high-level strategic activities (Fisher et al., 2023). Studies indicate that the automation of repetitive tasks through AI increases employees' job satisfaction and overall well-being (Henkel et al., 2020; Jiang et al., 2022).

*H1a: Perceived ease of use of AI product positively influences employee well-being at work***.**

Employee satisfaction and engagement tend to be higher when AI tools are easy to use, intuitive, and intuitive (Marikyan et al., 2022). Verma et al. (2023) have further validated the role of non-threat perception in shaping psychological interactions with technology, which promotes overall wellbeing, by using non-threatening AI.

H1b: Perceived usefulness of AI product positively influences employee well-being at work.

When workers believe AI tools help them perform better and increase their productivity, they are more likely to be engaged and satisfied (Marikyan et al., 2022). Furthermore, the relationship between organisational support and AI adoption is known to be mediated by perceived usefulness, highlighting the critical role HR management plays in promoting favourable employee outcomes.

*H1c: Perceived behavioral of AI product use positively influences employee well-being at work***.**

When AI tools are systematically integrated across organizational functions—such as HR, operations, and marketing—and employees feel confident in using them, positive outcomes are more likely (Kim & Lee, 2024; Jeong et al., 2024).

H1d: Performance expectancy of AI product use positively influences employee well-being at work.

According to Marikyan et al. (2022), satisfaction and productivity effectiveness increase with performance expectancy. This exemplifies how Shaikh et al. (2023) have explained how AI-driven knowledge sharing boosts productivity, which in turn improves performance and strengthens employees' well-being.

H1e: Effort expectancy of AI product use positively influences employee well-being at work.

According to Marikyan et al. (2022), workers expressed higher levels of satisfaction and engagement when using AI tools that needed little effort. Verma et al. (2023) also showed that low effort improved task performance in addition to satisfaction, confirming the link between usability and positive employee outcomes.

H1f: Technicality of AI product use negatively influences employee well-being at work.

Ali et al. (2024) noted strong relationships between the degree of AI integration and heightened stress ($r = 0.72$) and anxiety ($r = 0.58$). Chang et al. (2024) pointed out that the technical intricacy adds to the category of hindrance stressors, while Kim and Lee

(2024) argued the technical side of AI adds significant job stress ($\beta = 0.286$, $p < 0.001$) which negatively affects well-being.

H2: Higher levels of AI product use are positively associated with higher levels of technostress.

Incorporation of AI products in work processes adds cognitive elements such as complexity, system update frequency, and feelings of reduced control or autonomy. These elements may foster increased sensations of being observed or 'always on,' which are fundamental factors of technostress (Tarafdar et al., 2015). As defined by another group of researchers Kim & Lee (2024) technostress, when amplified by AI use, becomes more potent if the technology is perceived as unnecessarily complicated or as undermining existing roles and competencies.

H3: Technostress mediates the relationship between AI product use and employee well-being at work, such that higher AI product use leads to increased technostress, which in turn reduces employee well-being at work.

While the use of AI products can increase work efficiency, they may also introduce novel stressors that can impact employee well-being negatively. The stress associated with the use of sophisticated, rapidly evolving, and seemingly encroaching AI tools—termed technostress—has been shown to mediate the relationship between AI use and adverse outcomes such as burnout and reduced health (Kim & Lee, 2024; Jeong et al., 2024; Chang et al., 2024). As AI tools function both as valuable resources and demanding technologies, employees may experience cognitive overload, skill pressure, and job insecurity, ultimately reducing the well-being benefits otherwise associated with AI adoption (Ragu-Nathan et al., 2008; Shaikh et al., 2023; OECD, 2022).

H4: Job autonomy moderates the negative effect of technostress on employee well-being at work, such that higher job autonomy weakens the adverse impact of technostress on employee well-being at work.

Job autonomy can moderate the negative effect of technostress on employee well-being, serving as a buffer against AI-related pressures. for au autonomy we refer also to the capacity of employees to control how and when to engage with AI tools, mitigating the stress caused by complexity, constant updates, and surveillance (Shaikh et al., 2023; Kinowska & Sienkiewicz, 2022).

2.2. Data Collection Instruments

This section defines the instruments that will be used to measure key variables: AI product use, employee well-being, job autonomy, and technostress. Based on scientific evidence, the structured questionnaire items were extracted from validated and commonly used scales. In addition, the questionnaire included questions aimed at identifying the sociodemographic characteristics of respondents. The questionnaire consists of 5 parts: the first part evaluates the impact of AI product use in workplace; the second assesses job autonomy; the third addresses work-related technostress; the fourth evaluates employee well-being; and the final part gathers sociodemographic information about the respondents (see table 1).

Table 1

The structure of the questionnaire

Construct	Scale	Author	Items
AI Product Use	AI-Based Intelligent Products	Kwonsang Sohn, Ohbyung Kwon, 2020	23 items
Job Autonomy	The Work Design Questionnaire (WDQ)	Morgeson, F. P., & Humphrey, S. E., 2006	7 items
Technostress	Work-Related Technostress Questionnaire	Porcari, D. E., Ricciardi, E., & Orfei, M. D., 2023	7 items
Employee Well-Being	Employee Well-Being Scale (questions only for workplace will be used)	Zheng et al., 2015	6 items
Sociodemographic	-	-	8 items

Source: compiled by the author, based on research results

AI Product Use will be measured by AI- Based Intelligent Products scale (Kwonsang Sohn, Ohbyung Kwon, 2020). Will be used a Likert type scale 1 to 7 to measure AI products use across perceived ease of use, perceived usefulness, perceived behavioral control, performance expectancy, effort expectancy and technicality, the example of statements: ’’ *Using the AI product would be easy’’, ‘’ Using the AI product would improve* *my daily work performance'', '' I have enough ability to use the AI product'', Interaction with the AI product would be clear and understandable'', '' It would not be easy to use the AI product technically''.*

Job autonomy will be measured by the Work Design Questionnaire (WDQ) (Morgeson, F. P., & Humphrey, S. E. 2006). Will be used a Likert type scale from 1 (strongly disagree) to 5 (strongly agree) to measure job autonomy across dimensions such as work scheduling, decision–making, work methods, the example of statement: *''The job allows me to make a lot of decisions on my own''.*

Technostress will be measured by the Work-Related Technostress Questionnaire (Porcari, D. E., Ricciardi, E., & Orfei, M. D., 2023). Will be used a Likert type scale from 1 (never) to 4 (always) to measure the levels of technostress experienced by employees at work due to digital and technological demands such as techno - overload, techno – invasion, techno – complexity, the example of statement:*'' Due to the increased complexity of technological tools, I feel that my workload has increased''.*

Employee Well-being at work will be measured by Employee Well-Being Scale, (Zheng et al. 2015). The original scale consists of 18 questions from three dimensions: Life Well-Being, Workplace Well-Being and Psychological Well-Being. In the context of this research, only 6 items from Workplace Well-Being will be extracted from the original questionnaire and used in this survey. Will be used a Likert scale from 1 (strongly disagree) to 7 (strongly agree) to evaluate statements such as: ''*I am satisfied with my work responsibilities* ", ''*I find real enjoyment in my work* ".

Sociodemographic questions, respondents will be asked about their age, gender, level of education, current position, the business sector their organization belongs to, the size of the organization and their length of their employment within the organization. In addition, respondents will be asked about their level of interaction with AI tools in their workplace.

2.3. Sampling Strategy and Sample Size

A convenience sampling method will be used as a sampling strategy to recruit participants. Data will be collected using Google forms, targeting employees from diverse organizations in Lithuania that have integrated AI tools into their daily workflows. The sample will include individuals across different roles and levels of experience with AI tools, ranging from novice users to those proficient with advanced AI systems. This approach ensures a diverse range of participants with varied experiences and perspectives, enhancing the relevance of the findings.

The sample size will be determined based by the following considerations:

- For Structural Equation Modeling (SEM) analysis, the minimum sample size of 200 is recommended (Kline, 2015).
- For questionnaire length, there should be at least 5 respondents for every item on the questionnaire (Hair et al, 2010). Given that the questionnaire includes 52 items, the minimum number of respondents required is 260 to get reliable results.
- A review of sample sizes used in previous research on similar topics will also inform the final sample size (see table 2).

Table 2

Sample sizes from previous research on similar topics

Study	Focus on Study	Sample Size
Sarker et al. (2019)	AI tools, stress, psychological empowerment	312 (USA)
Sharif, M. N., Zhang, L., Asif, M., Alshdaifat, S. M., & Hanaysha, J. R. (2025)	AI, job insecurity, technostress	277 (China)
Hessari, H., Daneshmandi, F., &护Nategh, T. (2023)	Technostress, commitment, individual innovation	147 (Iran)
De', R., Pandey, N., & Pal, A. (2020).	Job autonomy, technostress, employee well-being, digital intensity	346 (India)
Current Study	AI product use, employee well-being, job autonomy, technostress	Planned 255

Source: compiled by the author, based on research results

The sample size 255 will provide sufficient statistical power and ensure consistency with findings from previous studies.

2.4. Data Analysis Technique

The collected data will be analyzed using IBM SPSS (Statistical Package for the Social Sciences). First, descriptive statistics (including means and standard deviations) will be computed to summarize the respondents' sociodemographic characteristics. To ensure the internal consistency of the measurement scales, Cronbach's alpha will be used where a threshold of 0.70 or higher will indicate acceptable reliability (Nunnally & Bernstein, 1994). Additionally, research will examine the connections among variables with an emphasis on linear regression and correlation analysis. Furthermore, ANOVA and independent samples t-tests will be used to assess group differences according to sociodemographic factors.

The key independent variable, AI product use, will be treated as a composite construct composed of six sub-dimensions: Perceived ease of use; Perceived usefulness; Behavioral intention; Performance expectancy; Effort expectancy; Technicality. To validate the multidimensional nature of the AI product use construct, exploratory factor analysis (EFA) will be used. This step will confirm whether the sub-dimensions significantly benefit the construct and foresee the employee's well-being. Reverse coding will be applied to negatively worded items to ensure scoring consistency.

After creating the composite variable, Hayes' PROCESS macro (Model 14) for SPSS will be used to test a moderated mediation model (Hayes, 2022). After completing the data analysis, the findings will be presented and discussed in the following chapter.

2.5. Study limitations and Ethical considerations

All participants are fully informed about the research objectives and gave their consent before taking part to the survey. The survey will be conducted on voluntary participants who have the right to withdraw from the study at any time. The responses remain anonymous, and data is securely will be stored to ensure privacy. Collected data will be processed according with ethical research standards and data protection regulations, like General Data Protection Regulation (GDPR) (European Parliament, 2016). The data will be not transferred to the third parties or for any other purposes. Finally, the collected data will be kept for the duration that is necessary to complete the research analysis and will be securely destroyed.

While the study provides valuable insights, the study sample is limited, meaning that it does not fully represent the diversity of workplace experience across different industries. Finally, the study does not explore other potentially influential factors such as organizational culture, leadership style, digital literacy, which may also impact on employee well-being at work within AI product use context.

3. THE RESULTS OF RESEARCH OF THE IMPACT OF ARTIFICIAL INTELLIGENCE (AI) PRODUCT USE ON EMPLOYEE WELL-BEING AT WORK: THE MODERATING ROLE OF JOB AUTONOMY AND THE MEDIATING EFFECT OF TECHNOSTRESS

3.1. Research participants characteristics

The questionnaire was conducted between September-November 2025, with the aim of achieving 255 valid responses. A total of 261 responses were gathered. The questionnaire was held in English languages (see Annex 1.) and aimed to examine sociodemographic characteristics of the respondents too. The distributions of respondents according to sociodemographic characteristics are presented in Table 3.

While analyzing the demographic aspects of respondents, they were asked about their age, gender, and education. The largest age group was 25-34 years (42,2%), followed by those under 25 (26,8%), meaning nearly 70% of respondents were under 35 years. Respondents age 35-44 years represented 18%, while older age groups were less common: 45-54 (8%) and 55+ (5%). In terms of gender, the highest count of respondents was female 183 (70,1%), while male respondents made 78 (29,9%) and no respondents identified as "other". Moving to education, 76,2% respondents have a higher university education, and 23,8% have a higher non-university education.

While analyzing the social and work aspects of respondents, they were asked about the business sector they work in, size of organization, current position, tenure with organization, and what kind of interaction with AI at work have. To start with, respondents represented a wide range of business sectors. The most common were transportation - 46 (17,7%), other – 43 (16, 5%), services - 39 (14,9%), technology/IT - 34 (13%) and education - 33 (12,6%), the least were from financial – 16 (6,1%), healthcare – 14 (5,5%), public administration – 12 (4,6%), trade – 10 (3,8%), manufacturing – 9 (3,4%), construction –5 (1,9%), and no answers were collected from agriculture sector. Most respondents answered that they work in medium to large sizes of organizations. Employees in organizations with

250+ employees – 106 (40,6%), while 75 (28,7%) respondents work in organizations with 50-249 employees. Smaller organizations were less represented. Regarding the current position in organization, 162 (62,1%) respondents do not have subordinates, meanwhile 99 (37,9%) have managerial positions. Organizational tenure: the largest group work in their current organization for 1-3 years – 90 (34,5%), followed by less than one year – 64 (24,5%). Finally, the interaction with AI at work, almost half of respondents reported interacting with AI in another way – 124 (47,5%) or work directly with AI – 123 (47,1%). Small proportions were involved in AI developments – 9 (3,4%), developing or maintaining AI – 9 (3,4%), managing workers who work with AI – 4 (1,5%), or managed by AI – 1 (0,4%).

To sum up the sociodemographic results, the sample is characterized by young, highly educated and female workforce, mainly employed in medium to large size organizations across diverse sectors. Most respondents occupy non-managerial positions and have a short to moderate organizational tenure, and interaction with AI at work is common with direct or indirect forms.

Table 3

The Research Participants Characteristics Based on Sociodemographic Aspects

Question	Possible answers	Distribution of respondents	Distribution of respondents %
Age	Under 25	70	26,8%
	25-34	110	42,2%
	35-44	47	18%
	45-54	21	8%
	55+	13	5%
Gender	Female	183	70,1%
	Male	78	29,9%
	Other	0	0%
Education	Higher non-university education	62	23,8%
	Higher university education	199	76,2%
Business sector	Trade	10	3,8%
	Manufacturing	9	3,4%
	Services	39	14,9%
	Education	33	12,6%
	Healthcare	14	5,5%
	Technology/IT	34	13%
	Transportation	46	17,7%
	Financial	16	6,1%

	Agriculture	0	0%
	Construction	5	1,9%
	Public administration	12	4,6%
	Other	43	16,5%
Size of organization	1-9 employees	31	11,9%
	10-49 employees	49	18,8%
	50-249 employees	75	28,7%
	250+ employees	106	40,6%
Current position	I do not have subordinates	162	62,1%
	I have subordinates	99	37.9%
Tenure with organization	Less than a year	64	24,5%
	1-3 years	90	34,5%
	4-6 years	51	19,5%
	7-10 years	26	10%
	10+ years	30	11,5%
Interaction with AI at work	I work with AI	123	47,2%
	I manage workers who work with AI	4	1,5%
	I develop/maintain AI	9	3,4%
	I am managed by AI	1	0,4%
	I interact with AI in another way	124	47,5%

Source: compiled by the author, based on research results

3.2. Reliability Assessment

After conducting the survey, the data about Artificial Intelligence (AI) product use, employee well-being at work, job autonomy and work-related technostress were gathered. The reliability of the research questionnaire was assessed to ensure the consistency of the measurement scales used in the study. The reliability was evaluated using Cronbach's Alpha and was conducted separately for each construct and sub-construct which were included in the questionnaire, in other words: AI product use (AI), employee well-being (WB), job autonomy (JA), and work-related technostress (WTS). The AI product use construct was conceptualized as the whole construct comprising the six sub-constructs: perceived ease of use (PEOU), perceived usefulness (PU), perceived behavioral control (PBC), performance expectancy (PE), effort expectancy (EE) and technicality (TECH). A Cronbach's Alpha coefficient of 0.70 or higher was accepted as the acceptable indicator among the items.

The results of the reliability analysis indicate that all main constructs used in the questionnaire demonstrate high internal consistency (see Table 4.1) the construct measuring AI consisting of 22 items, achieved excellent Cronbach's Alpha of 0.923, the JA construct consisting of 7 items, shows strong Cronbach's Alpha of 0.896, the WTS construct consisting of 7 items, shows good Cronbach's Alpha of 0.812 and finally, the WB construct consisting of 6 items shows strong Cronbach's Alpha of 0.876. To summarize, the reliability confirms that measurement scales used in the questionnaire are acceptable reliable and suitable for further statistical analysis.

Table 4.1

Validity of Scale

Construct	N of Items	Cronbach's Alpha
AI Product use (AI)	22	0.923
Job Autonomy (JA)	7	0.896
Work-Related Technostress (WTS)	7	0.812
Well-Being (WB)	6	0.876

Source: compiled by the author, based on research results

In addition to the overall AI construct, reliability analysis was conducted for its sub-constructs (see Table 4.2.): The Perceived Ease Of Use (PEOU), consisting of 4 items, achieved satisfactory Cronbach's Alpha value of 0.732, The Perceived Usefulness (PU), consisting of 4 items, achieved excellent Cronbach's Alpha value of 0.923. The initial reliability analysis of the Perceived Behavioral Control (PBC) construct, consisting of 4 items, resulted in a Cronbach's alpha value below the recommended level of 0.70. Item–total statistics demonstrated that the removal of one item (A11) would improve the internal consistency of the scale. After removing this item, the reliability of the modified PBC scale increased to a satisfactory Cronbach's alpha of 0.721. As an item A11 was a part of the PBC sub-construct, which forms part of the overall AI construct. Following the removal of item A11 to improve the reliability of the PBC scale, this item was also removed from the main AI construct to maintain consistency in measurement. As a result, the AI construct was modified from 23 to 22 items for subsequent analyses. The Performance Expectancy (PE), consisting of 3 items, achieved excellent Cronbach's Alpha value of 0.936, the Effort Expectancy (EE), consisting of 4 items, achieved satisfactory Cronbach's Alpha value of 0.728, finally, the Technicality (TECH), consisting of 4 items, achieved satisfactory Cronbach's Alpha value of 0.755. Taken together, the results confirm that all AI Product Use sub-constructs demonstrate acceptable reliability and are suitable for statistical analyses.

Table 4.2

Validity of Sub-Construct Scale

Sub-Construct	N of Items	Cronbach's Alpha
Perceived Ease Of Use (PEOU)	4	0.732
Perceived Usefulness (PU)	4	0.923
Perceived Behavioral Control (PBC)	3	0.721
Performance Expectancy (PE)	3	0.936
Effort Expectancy (EE)	4	0.728
Technicality (TECH)	4	0.755

Source: compiled by the author, based on research results

3.3. Construction of Research Variables and Descriptive Statistics

Following the confirmation of reliability assessment of constructs and sub-constructs validity, the next step is the construction of research variables and exploring its the descriptive statistics. The constructions of new variables were calculated by calculating the mean scores of the items of each construct and sub-construct. The use of mean values grants consistent interpretation of the scales and enables comparison across variables. The following composited variables demonstrating the main constructs of the study were created:

- AI Product Use, calculated as the mean of 22 items (AIMEAN);
- Job Autonomy, calculated as the mean of 7 items (JA_MEAN);
- Work-Related Technostress, calculated as the mean of 7 items (WTS_MEAN);
- Employee Well-Being, calculated as the mean of 6 items (WB_MEAN).

These composite variables indicate the overall levels of AI product use, job autonomy, technostress, and well-being among the respondents. Higher values show higher levels of the respective constructs. In addition to the overall AI product use construct, separate compositive variables were created for each AI product use sub-construct:

- Perceived Ease of Use (PEOU), calculated as the mean of 4 items (AI_PEOU);
- Perceived Usefulness (PU), calculated as the mean of 4 items (AI_PU);
- Perceived Behavioral Control (PBC), calculated as the mean of 3 items (AIPBC);
- Performance Expectancy (PE), calculated as the mean of 3 items (AI_PE);
- Effort Expectancy (EE), calculated as the mean of 4 items (AI_EE);
- Technicality (TECH), calculated as the mean of 4 items (AI_TECH).

Descriptive statistics were calculated for all research variables to present an initial overview of the data and summarize the main characteristics of the variables. The descriptive statistic in general shows positive perceptions of Artificial Intelligence among 261 respondents. All constructs have been measured on a 7-point Likert scale. The analysis includes the mean (M), standard deviation (SD), as well as minimum and maximum values (see Table 5).

To start with Artificial Intelligence product use (AIMEAN) the mean is 5.12 (SD = 0.86), indicating a respectable high level of AI product use among respondents. Job autonomy (JA_MEAN) shows the mean of 3.78 (SD = 0.72), suggesting a moderate to high level of perceived autonomy at work. Work-related Technostress (WTS_MEAN) the mean is 2.15 (SD = 0.57), indicating a generally low to moderate level of technostress among workers. Contrary to employee well-being (WB_MEAN) shows a high mean of score of 5.17 (SD = 1.07), demonstrating a positive level of well-being at work.

Moving on, the mean value for perceived usefulness (PU) is 5.47 (SD = 1.25) and performance expectancy (PE) is 5.40 (SD = 1.27) are recorded with the highest mean scores, showing that respondents mainly view AI as both valuable and enjoyable to use it. Perceived ease of use (PEOU) the mean is 5.16 (SD = 0.997), effort expectancy (EE) is 5.18 (SD = 0.94) and perceived behavioral control (PBC) is 5.14 (SD = 1.16) are also respectively high mean values with moderate to low dispersion that AI tools are easy to use. On the other hand, technicality (TECH) shows a lower mean which is 4.45 (SD = 1.16), indicating that the different level of readiness toward AI technologies. Altogether, variables and high mean scores across constructs suggest a robust dataset for structural analyses.

Table 5

Descriptive Statistics of Variables

	N	Minimum	Maximum	Mean	Std. Deviation
AIMEAN	261	2.27	7.00	5.1209	.8594
JA_MEAN	261	1.00	5.00	3.7750	.71614
WTS_MEAN	261	1.00	4.00	2.1544	.57111
WB_MEAN	261	2.00	7.00	5.1724	1.06612
AI_PEOU	261	1.75	7.00	5.1561	.99677
AI_PU	261	1.00	7.00	5.4713	1.25178
AIPBC	261	1.33	7.00	5.1367	1.16449
AI_PE	261	1.00	7.00	5.4036	1.26819
AI_EE	261	2.00	7.00	5.1810	.94260
AI_TECH	261	1.50	7.00	4.4511	1.15578

Source: compiled by the author, based on research results

3.4. Statistical Tests of Normality and Correlations Analysis

Normality testing was conducted for all research variables, specifically AI product use, job autonomy, work-related technostress, and employee well-being. Table 6 presents the results of the Kolmogorov–Smirnov and Shapiro–Wilk tests of normality, along with Skewness and Kurtosis statistics.

As shown in the table, the Kolmogorov-Smirnov test revealed meaningful results for all variables, with p- values varying between .38 and <.001. Likewise, the Shapiro-Wilk test showed statistically significant deviations from normality across all variables (p < .001). Following the Field (2018), p-values are greater than >.05 demonstrate that the assumption of normality is met, however p-values equal or below <.05 demonstrate significant deviations from normality. Based on these criteria, these findings suggest that none of the presented p-values of variables are satisfied with the assumption of normality according to formal statistical tests.

On the other hand, examination of distribution statistics showed that Skewness values ranged from -.730 to .494, and Kurtosis values ranged from -.0005 to 1.414.

Consistent with Hair et al (2019), S-K values within ±2 are assumed to be an indicative of approximate normality. Based on these criteria, all examined variables are within acceptable standards, indicating normality of statistical tests.

To conclude. Skewness and Kurtosis values indicate that the distributions are approximately normal. Considering the large sample size (N 261) and the robustness of parametric procedures, the presented data are considered acceptable for parametric approximately normally distributed data statistical analysis.

Table 6

Normality Tests and Distribution Statistics for Variables

Variable	Kolmogorov–Smirnov		Shapiro–Wilk		Skewness	Kurtosis
	Statistic	Significance	Statistic	Significance		
AIMEAN	.057	.038	.973	<.001	-.644	.629
JA_MEAN	.120	<.001	.948	<.001	-.730	1.414
WTS_MEAN	.110	<.001	.974	<.001	.494	-.005
WB_MEAN	.103	<.001	.965	<.001	-.627	.107

Source: compiled by the author, based on research results

Since the data is normally distributed, the Pearson's correlation coefficient (see Table 7) was chosen for the correlation analyses between variables. The correlation between all four variables (AI product use, job autonomy, work-related technostress, and employee well-being) was tested. The results demonstrated a moderate positive correlation between AIMEN and JA_MEAN (r = .294, p < .001), proposing that higher AIMEAN scores were associated with higher JA_MEAN scores. Next, analysis showed a significant positive relationship between JA_MEAN and WB_MEAN (r = .264, p < .001), illustrating a weak to moderate association.

In contrast, the correlation between JA_MEAN and WTS_MEAN was not statisticaly significant (r = .035, p = .570), which means no meaningful linear association between these two variables. As well, the correlation between AI_MEAN and WB_MEAN was not statistically significant (r = .089, p = .151). AI_MEAN was to be found weak and negatively correlated with WTS_MEAN (r = −.148, p = .017). Finally, the relationship between WTS_MEAN and WB_MEAN was negative and weak but did not reach statistical significance

($r = -.101$, $p = .103$). Overall, Pearson correlation analyses revealed primarily weak to moderate associations among the study variables, with several relationships failing to reach statistical significance, suggesting limited linear interdependence between constructs.

Table 7

Pearson Correlations Analysis Between Variables

		AIMEAN	JA_MEAN	WTS_MEAN	WB_MEAN
AIMEAN	Pearson Correlation	1	.294***	-.148*	.089
	Sig. (2-tailed)		<.001	.017	.151
	N	261	261	261	261
JA_MEAN	Pearson Correlation	.294***	1	.035	.264***
	Sig. (2-tailed)	<.001		.570	<.001
	N	261	261	261	261
WTS_MEAN	Pearson Correlation	-.148*	.035	1	-.101
	Sig. (2-tailed)	.017	.570		.103
	N	261	261	261	261
WB_MEAN	Pearson Correlation	.089	.264***	-.101	1
	Sig. (2-tailed)	.151	<.001	.103	
	N	261	261	261	261
***. Correlation at 0.001(2-tailed)					
*. Correlation is significant at the 0.05 level (2-tailed).					

Source: compiled by the author in IBM SPSS, based on research results

3.5. Differences in AI Tool Usage, Job Autonomy, Technostress, and Employee Well-Being Across Sociodemographic Groups

Since the data was determined to be parametric, statistical tests designed for parametric data will be used. A t-test will be applied to compare the means of two independent samples, while One-Way ANOVA (F-test) will be used to compare the means of three or more independent samples.

Analysis of t-test. For all t-tests are included sample size (N), mean values, standard deviations, t-values and p-values (one-sided and two-sided). Independent samples t-tests were conducted to examine differences in AI tool usage (AIMEAN), job autonomy (JA_MEAN), technostress (WTS_MEAN), and employee well-being (WB_MEAN) across respondents' gender, education and position at work.

Gender. Independent-samples t-tests were conducted to compare mean scores between females (1) and males (2) for each variable; the "Other" category was excluded due to no responses. Independent samples t-tests showed no statistically significant gender differences in AI tool usage, job autonomy, technostress, employee well-being (all two-sided $p > .05$), (see Annex 2.)

Education. The table 8 shows the results of independent samples t-tests conducted to compare the mean scores of Higher non-university education (1) and Higher university education (2). Education level was significantly associated with job autonomy and employee well-being. Respondents with higher university education reported greater job autonomy ($p = .044$) and higher well-being ($p = .004$) than those with higher non-university education. No significant education-based differences were found for AI tool usage or technostress ($p > .05$).

Table 8

T-Test Results by Education

	EDU	N	Mean	Std. Deviation	t	One-Sided p	Two-Sided p
AIMEAN	1	62	5.0718	.90665	-.514	.304	.608
	2	199	5.1361	.84598	-.495	.311	.622
JA_MEAN	1	62	3.6152	.72916	-2.025	.022	.044
	2	199	3.8248	.70651	-1.991	.025	.049
WTS_MEAN	1	62	2.1521	.53943	-.036	.486	.971
	2	199	2.1551	.58193	-.037	.485	.970
WB_MEAN	1	62	4.8306	1.17250	-2.933	.002	.004
	2	199	5.2789	1.01045	-2.713	.004	.008

Source: compiled by the author in IBM SPSS, based on research results

Current position. Independent-samples t-tests were conducted to compare mean scores between I do not have subordinates (1) and I have subordinates (2). Current position at work was not associated with statistically significant differences in AI tools usage, job autonomy, technostress or employee well-being (all $p > .05$) (see Annex 3.).

One-Way ANOVA. For all One-Way ANOVA test analyses, sample size (N), mean values, standard deviations, F - values and p-values (Sig.) are reported. Independent samples of One-Way ANOVA test was conducted to examine differences in AI tool usage (AIMEAN), job autonomy (JA_MEAN), technostress (WTS_MEAN), and employee well-being (WB_MEAN) across respondents age, business sectors, organization size, tenure in organization and the type of interactions with AI at work.

Age. The table 9 summarizes the results of independent samples of One-Way ANOVA test compared to the mean scores of five age groups: of under 25 (1), 25-34 (2), 35-44 (3), 45-54 (4), 55+ (5). Age was not significantly associated with AI tools usage, job autonomy and technostress (p>.05). On the other hand, a significant effect of age was observed on employee well-being (F = 8.885, P < -001). After running the Post-hoc test showed that employees under 25 years reported significaly lower well-being than older age groups (see Annex 4.)

Table 9

One-Way ANOVA Results by Age

		N	Mean	Std. Deviation	F	Sig.
AIMEAN	1	70	5.1019	.82221	.757	.554
	2	110	5.2045	.81236		
	3	47	5.0106	1.06352		
	4	21	5.1515	.86080		
	5	13	4.8636	.60331		
	Total	261	5.1209	.85943		
JA_MEAN	1	70	3.6959	.55724	1.936	.105
	2	110	3.7065	.77448		
	3	47	3.8815	.79502		
	4	21	4.1088	.61595		
	5	13	3.8571	.70470		
	Total	261	3.7750	.71614		
WTS_MEAN	1	70	2.2510	.56854	1.933	.105
	2	110	2.0662	.55402		
	3	47	2.1155	.54977		
	4	21	2.3605	.70076		
	5	13	2.1868	.48580		
	Total	261	2.1544	.57111		
WB_MEAN	1	70	4.6238	.92891	8.885	<.001
	2	110	5.2121	1.11219		
	3	47	5.5532	.87993		
	4	21	5.7222	.97800		
	5	13	5.5256	.93007		

Source: compiled by the author in IBM SPSS, based on research results

Business sector. The table 10 summarizes the results of independent samples One-Way ANOVA test compared the mean scores of 12 business sector: Trade (1), Manufacturing (2), Services (3), Education (4), Healthcare (5), Technology/IT (6), Transportation (7), Financial (8), Agriculture (9), Construction (10), Public administration (11), Other (12). Business sector was significantly associated with AI tool usage, job autonomy, and technostress. No statistically significant sector-based differences were found for employee well-being. After running the Post-hoc analyses showed that employees in the Technology/IT sector reported significantly higher AI tool usage than those working in Healthcare and Transportation. Then, job autonomy was significantly higher among employees in the Technology/IT sector compared to those in the Transportation sector. Lastly, employees in the "Other" sector experienced significantly higher technostress compared to employees in the Transportation sector.

Table 10

One-Way ANOVA Results by Business Sector

		N	Mean	Std. Deviation	F	Sig.
AIMEAN	1	10	5.1500	.69732	3.585	<.001
	2	9	5.1616	.83230		
	3	39	5.2098	.68537		
	4	33	5.1722	.83449		
	5	14	4.7305	.98808		
	6	34	5.6457	.68924		
	7	46	4.6957	1.03252		
	8	16	5.3494	.62999		
	10	5	4.4000	1.42382		
	11	12	5.3030	.69999		
	12	43	5.1004	.72555		
	Total	261	5.1209	.85943		
JA_MEAN	1	10	4.0429	.61001		
	2	9	3.9206	.66283		
	3	39	3.7839	.80069		
	4	33	3.9091	.45851	1.885	.048
	5	14	3.7347	.71067		
	6	34	4.0336	.63699		
	7	46	3.4441	.89556		
	8	16	3.8839	.52997		
	10	5	3.8286	.94437		
	11	12	3.7619	.53220		
	12	43	3.6910	.67435		
	Total	261	3.7750	.71614		
WTS_MEAN	1	10	2.1143	.49395	2.237	.016
	2	9	2.4444	.70510		
	3	39	2.1319	.51548		
	4	33	2.1818	.57839		
	5	14	2.4184	.63756		
	6	34	2.0420	.67880		
	7	46	1.8913	.50949		
	8	16	2.3393	.56635		
	10	5	2.0857	.31298		
	11	12	2.2976	.50400		
	12	43	2.2857	.50460		
	Total	261	2.1544	.57111		
WB_MEAN	1	10	5.3000	.97436		
	2	9	5.3148	1.14699		
	3	39	5.0385	1.02131		
	4	33	5.4899	1.10235	1.852	.052
	5	14	4.9405	1.20825		
	6	34	4.9461	1.08999		
	7	46	5.5507	.72168		
	8	16	4.7292	1.12690		
	10	5	5.6667	.85797		
	11	12	5.2361	1.30357		
	12	43	4.9302	1.14679		
	Total	261	5.1724	1.06612		

Source: compiled by the author in IBM SPSS, based on research results

Size of organization. A one-way ANOVA test was conducted to compare the mean scores of four groups: 1-9 employees (1), 10-49 employees (2), 50-249 employees

(3), 250+ employees (4). Organization size was not signific ally associated with AI tools usage, job autonomy, technostress and employee well-being (all p > .05) (see Annex 5.).

Tenure. A one-way analysis of variance (ANOVA) was conducted to examine differences in mean scores among five independent groups. Less than a year (1), 1-3years (2), 4–6 years (3), 7–10 years (4), 10+ years (5). Tenure in the organization was not significantly associated with AI tool usage, job autonomy, technostress, or employee well-being (all p > .05) (see Annex 6.)

Interaction with AI at work. The table 11 summarizes the results of independent samples One-Way ANOVA test compared to the mean scores of 5 groups: I work with AI (1), I manage workers who work with AI (2), I develop/maintain AI (3), I am managed by AI (4), I interact with AI in another way (5). Type of interaction with AI was significantly associated with AI tool usage ($F(4, 256) = 8.523$, $p < .001$) and job autonomy ($F(4, 256) = 3.042$, $p = .018$), with respondents working directly with AI reporting the highest mean levels of AI usage (M = 5.43) and job autonomy (M = 3.94). However, the Post-hoc comparisons could not be performed due to insufficient sample sizes in some interaction categories (see Annex 7.)

Table 11

One-Way ANOVA Results by Interaction with AI at work

		N	Mean	Std Deviation	F	Sig.
AIMEAN	1	123	5.4250	.65530	8.523	<.001
	2	4	4.6818	.85603		
	3	9	5.1414	.93194		
	4	1	4.4545	.		
	5	124	4.8372	.93678		
	Total	261	5.1209	.85943		
JA_MEAN	1	123	3.9361	.52924	3.042	.018
	2	4	3.6429	.42857		
	3	9	3.6032	.65379		
	4	1	3.7143	.		
	5	124	3.6325	.85135		
	Total	261	3.7750	.71614		
WTS_MEAN	1	123	2.1359	.57634	2.334	.056
	2	4	2.7857	.52812		
	3	9	2.5238	.67006		
	4	1	2.0000	.		
	5	124	2.1267	.54747		
	Total	261	2.1544	.57111		
WB_MEAN	1	123	5.1938	1.12197	.081	.988
	2	4	4.9167	.61614		
	3	9	5.1296	.83657		
	4	1	5.0000	.		
	5	124	5.1640	1.04700		
	Total	261	5.1724	1.06612		

Source: compiled by the author in IBM SPSS, based on research results

Overall, t-tests and one way ANOVA results further empathized with significant variations in AI tools usage, job autonomy, technostress, employee well-being across selected sociodemographic characteristics. The analysed data highlights meaningful trends in these variables and establishes a robust foundation for further analyses and interpretations.

3.6. The Impact of Artificial Intelligence (AI) Product Use on Employee Well-being at work: The Moderating Role of Job Autonomy and the Mediating Effect of Technostress

This section examines the relationship between Artificial Intelligence (AI) product use and employee well-being, with particular attention to the moderating role of job autonomy and the mediating effect of technostress. The analysis includes linear regression and moderate mediation using Model 14. The study tests a series of hypotheses to assess both direct and indirect effects of AI product use on employee well-being. All analyses were conducted using IBM SPSS Statistics, employing the PROCESS macro (version 5.0) by Andrew F. Hayes. By integrating mediation and moderation mechanisms, this study provides valuable insights on how AI technologies influence employee well-being at work.

Linnear regression was conducted to test the study's hypotheses. The previously tested Skewness and Kurtosis showed that all variables were within the recommended range of –2 and +2, indicating that the assumption of normality was sufficiently met. The following hypotheses been analysed:

H1: AI product use positively influences employee well-being at work. After conducting analysis of regression (see table 12), shows a very weak relationship between AI product use and employee well-being ($R = .089$).

Table 12

Regression Model Summary of AI Product Use to Employee Well-Being at work

Model	R	R²	Adjusted R²	Std. Error
Regression	.089	.008	.004	1.06391

Source: compiled by the author based on research results

Conducted ANOVA analyses (see table 13), indicated that regression model is not statistically significant F = 2.079, p = .151. This shows that AI products use does not significally explain variance in employee well-being at work.

Table 13

AI Product Use impact on Employee Well-Being at work ANOVA table for Regression Model

Model	Sum of Squares	df	Mean of Square	F	Sig. (p)
Regression	2.353	1	2.353	2.079	.151
Residual	293.166	259	1.132		
Total	295.519	260			

Source: compiled by the author based on research results

The regression coefficients tabel (see table 14) shows that AI product use has a positive but non-significant effect on employee well-being. AI product use (AIMEAN) is associated with a small increase in well-being (B = .111), but this effect is not statistically significant, t = 1.442, p = .151. The standardized effect size is weak (β = .089). The constant is significant (B = 4.606, p < .001), indicating the baseline level of employee well-being when AI product use is zero. The hypothesis (H1) **is not supported** by the regression results.

Table 14

AI Product Use impact on Employee Well-Being at work Regression Coefficients

Model	Unstandardized coeficients		Standardized coeficients	t	Sig. (p)
	B	Std.Error	Beta		
Constant	4.606	.399		11.554	<.001
AIMEAN	.111	0.77	0.89	1.442	.151

Source: compiled by the author based on research results

A multiple linear regression was applied to test H1a-H1f because the AI product use dimensions represent conceptually related sub-constructs: perceived ease of use (AI_PEOU), perceived usefulness (AI_PU), perceived behavioral control (AIPBC), performance expectancy (AI_PE), effort expectancy (AI_EE), technicality (AI_TECH).The following hypotheses been testes:

- H1a: Perceived ease of use of AI product positively influences employee well-being at work
- H1b: Perceived usefulness of AI product positively influences employee well-being at work.
- H1c: Perceived behavioral control of AI product use positively influences employee well-being at work .
- H1d: Performance expectancy of AI product use positively influences employee well-being at work.
- H1e: Effort expectancy of AI product use positively influences employee well-being at work.
- H1f: Technicality of AI product use negatively influences employee well-being at work.

As shown in the table 15, only effort expectancy showed a significant positive effect on employee well-being (β = .243, p = .023), while perceived ease of use, perceived usefulness, perceived behavioral control, performance expectancy, and technicality showed no significant relationships. According to table 16, the overall model explained 4.5% of the variance in employee well-being and was slightly non-significant. Thus, only the hypothesis **H1e was supported.**

Table 15

Regression Results for AI Use Dimensions and Employee Well-Being at work

Sub-H	Variable	B	β	t	p	Supported
H1a	AI_PEOU	.077	.072	0.763	.446	No
H1b	AI_PU	-.118	-.138	-1.019	.309	No
H1c	AIPBC	-.089	-.098	-1.199	.232	No
H1d	AI_PE	.015	.018	0.129	.897	No
H1e	AI_EE	.275	.243	2.293	.023	Yes
H1f	AI_TECH	-.015	-.017	-0.210	.832	No

Source: compiled by the author based on research results

Table 16

Model Summary for H1a-H1f

Model	R	R^2	Adjusted R^2	F	p
Regression	.212	.045	.022	1.984	.068

Source: compiled by the author based on research results

H2: *Higher levels of AI product use are positively associated with higher levels of technostress.* The regression analysis indicates a weak positive relationship between AI product use and technostress (R = .148) (see Table 17).

Table 17

Regression Model Summary of AI Product Use to Technostress

Model	R	R^2	Adjusted R^2	Std. Error
Regression	.148	.022	.018	.56590

Source: compiled by the author based on research results

After conducting ANOVA analysis (see Table 18) shows that the regression model is statistically significant, F (1, 259) = 5.805, p = .017. This indicates that AI product use significantly explains variance in technostress.

Table 18

AI Product Use impact on Technostress ANOVA table for Regression Model

Model	Sum of Squares	df	Mean of Square	F	Sig. (p)
Regression	1.859	1	1.859	5.805	.017
Residual	82.943	259	.320		
Total	84.802	260			

Source: compiled by the author based on research results

Looking into regression coefficients (see table 19) indicate that AI product use has a statistically significant relationship with technostress, but the direction is negative.

Specifically, AI product use (AIMEAN) is associated with a decrease in technostress (B = −.098), and this effect is statistically significant, t = −2.409, p = .017. The standardized coefficient shows a small effect size (β = −.148). The constant is significant (B = 2.658, p < .001), representing the baseline level of technostress when AI product use is zero. The hypothesis (H2) is **not supported.**

Table 19

AI Product Use impact on Technostress Regression Coefficients

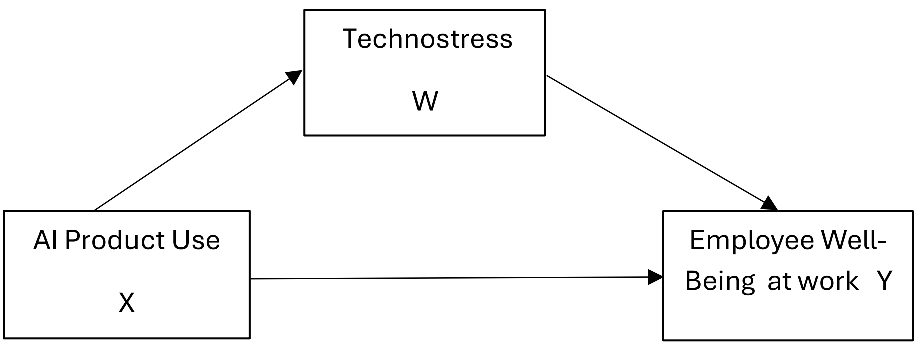
Model	Unstandardized coefficients		Standardized coefficients	t	Sig. (p)
	B	Std. Error	Beta		
Constant	2.658	.212		12.537	<.001
AIMEAN	-.098	0.41	-.148	-2.409	.017

Source: compiled by the author based on research results

H3: *Technostress mediates the relationship between AI product use and employee well-being at work, such that higher AI product use leads to increased technostress which in turn reduces employee well-being at work.* To test this H3, the PROCESS Model 4 (F. Hayes, 2013) was applied (see figure 4).

Figure 2

F. Hayes Model 4 Mediation Testing



Source: compiled by the author, based on F. Hayes (2013)

The results (see table 20) indicate that AI product use is a significant predictor of technostress. Specifically, higher levels of AI product use are associated with lower levels of technostress ($B = -0.098$, $SE = 0.041$, $t = -2.409$, $p = .017$).

Table 20

Regression Coefficients for Outcome Variable for Technostress

Variable	Coefficient (B)	Std. Error	t	Sig. (p)	LLCI	ULCI
Constant	2.658	0.212	12.537	<.001	2.241	3.076
AIMEAN	-.0098	0.041	-2.409	.017	-.0179	-0.018

Source: compiled by the author based on research results

The results (see table 21) show that neither AI product use nor technostress significantly predicts employee well-being when both variables are included in the model. AI product use has a positive but non-significant effect on well-being ($B = 0.094$, $SE = 0.078$, $t = 1.216$, $p = .225$), with a confidence interval that includes zero [−0.058, 0.247]. Similarly, technostress shows a negative but non-significant relationship with well-being $B = -0.168$, $SE = 0.117$, $t = -1.438$, $p = .152$.

Table 21

Regression Coefficients for Outcome Variable for Employee Well-Being at Work

Variable	Coefficient (B)	Std. Error	t	Sig. (p)	LLCI	ULCI
Constant	5.051	0.504	10.017	<.001	4.058	6.044
AIMEAN	0.094	0.078	1.216	.225	-0.058	0.247
WTS_MEAN	-0.168	0.117	-1.438	.152	-0.397	0.062

Source: compiled by the author based on research results

As shown in table 22 the indirect effect of AI product use on employee well-being through technostress is not statistically significant (indirect effect = 0.017). To conclude the results, H3 is **not supported**.

Table 22

Indirect Effect of AI Product Use on Employee Well-Being at work

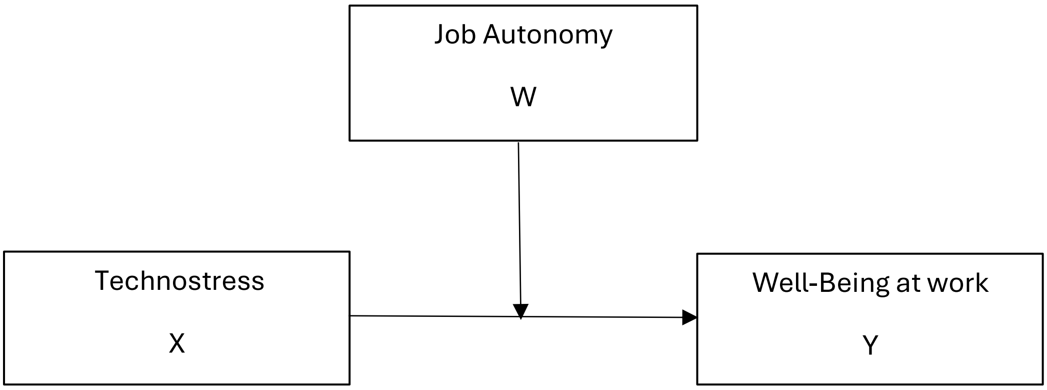
Effect	Coefficient (B)	Std.Error	LLCI	ULCI
Indirect effect (AI on WB via WTS)	0.017	0.016	-0,008	0.054

Source: compiled by the author based on research results

H4: *Job autonomy moderates the negative effect of technostress on employee well-being at work, such that higher job autonomy weakens the adverse impact of technostress on employee well-being at work.* To test this H4 the PROCESS Model 1 (F. Hayes, 2013) was applied (see figure 5).

Figure 3

F. Hayes Model 1 Moderation Testing



Source: compiled by the author, based on F. Hayes (2013)

After testing hypothesis, the results showed (see table 23) that technostress had a significant negative effect on employee well-being (B = −0.262, p = .018) while job autonomy showed a significant positive effect (B = 0.497, p < .001). Importantly, the interaction between technostress and job autonomy was positive and significant (B = 0.583, p < .001), indicating a moderation effect (see table 24).

Table 23

Moderation Analysis of Technostress and Job Autonomy

Variable	Coefficient(B)	Std. Error	t	Sig. (p)	LLCI	ULCI
Constant	5.1640	0.0619	83.449	<.001	5.0422	5.2859
WTS_MEAN	-.0.2616	0.1095	-2.389	.0176	-0.4772	-0.0459
JA_MEAN	0.4968	0.0903	5.503	<.001	0.3190	0.6746

Source: compiled by the author based on research results

Table 24

Interaction Effect (Moderation Path)

Effect	Coefficient (B)	Std.Error	t	Sig. (p)	LLCI	ULCI
Interaction effect	0.5827	0.1511	3.856	0.0001	0.2851	0.8802

Source: compiled by the author based on research results

PROCESS Model 1 explains $R^2 = .132$ of the variance in employee well-being, indicating a moderate model fit together with a relatively low standard error of estimate (0.998), suggesting that technostress, job autonomy, and their interaction meaningfully contribute to explaining employee well-being (see table 25).

Table 25

PROCESS Model 1 for Moderation Analysis

Model	R	R^2	Adjusted R^2	Std. Error
PROCESS Model 1	.363	.132	.122	0.998

Source: compiled by the author based on research results

Technostress had a strong negative effect on employee well-being at low levels of job autonomy ($B = -0.630$, $p < .001$), a weaker and marginally significant effect at average levels ($p = .050$), and a non-significant effect at high levels of job autonomy ($p = .387$), indicating that higher job autonomy buffers the adverse impact of technostress (see table 26). Together, these results indicate that job autonomy significantly moderates the relationship between technostress and employee well-being, meaning H4 is **supported.** This indicates that job autonomy reduces the negative impact of technostress on employee well-being. Meaning, employees with higher job autonomy are better able to cope with technology-related stress.

Table 26

Conditional Effects of Technostress on Employee Well-Being at work

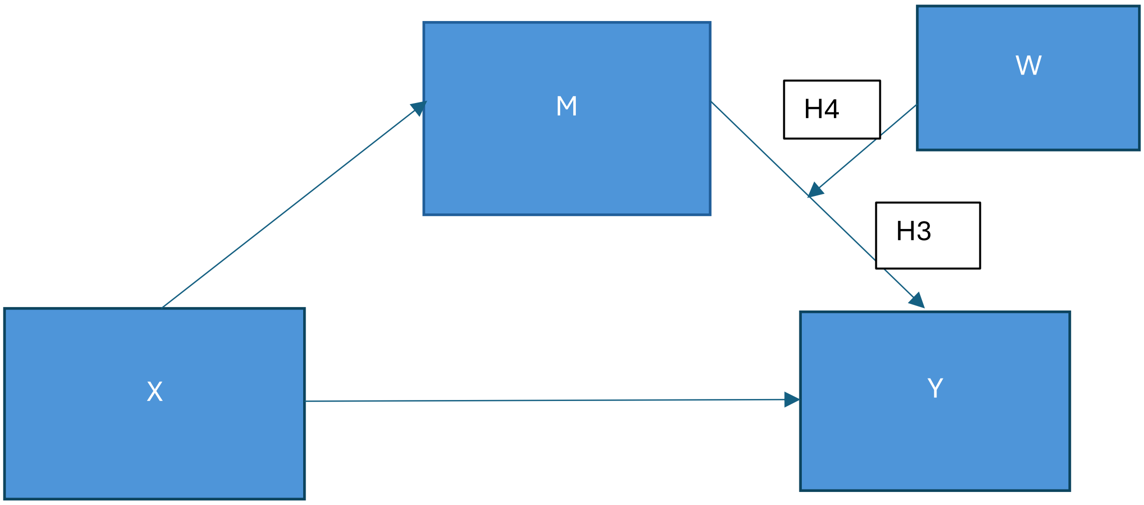
JA Level	Effect	Std. Error	t	Sig. (p)	LLCI	ULCI
Low	-0.6299	0.1545	-4.078	.0001	-0.9341	-0.3257
Mean	-0.2137	0.1086	-1.968	.0501	-0.4275	0.0001
High	0.1192	0.1375	0.867	.3867	-0.1516	0.3900

Source: compiled by the author based on research results

To test whether the indirect effect of AI product use on employee well-being through technostress depends on job autonomy, a moderated mediation analysis was conducted using PROCESS Model Andrew F. Hayes (2013) (see figure 6).

Figure 4

F.Hayes Model 14 for Moderated Mediation Testing



Source: prepared by the author, based on Hayes (2013)

The *H3* states that technostress mediates the relationship between AI product use and employee well-being at work, such that higher AI product use leads to increased technostress which in turn reduces employee well-being at work. And the *H4* states that job autonomy moderates the negative effect of technostress on employee well-being at work, such that higher job autonomy weakens the adverse impact of technostress on employee well-being at work. As shown in the table X, at low levels of job autonomy (JA = −0.63), the indirect effect of AI product use on employee well-being through technostress was statistically significant (indirect effect = 0.062, 95% CI [0.006, 0.136]), indicating that technostress mediates the relationship between AI product use and employee well-being under conditions of low job autonomy (see table 27).

Table 27

Conditional Indirect Effect

JA level	Indirect Effect	BootLLCI	BootULCI
Low -.6322	.0619	.0061	.1361
Mean .0821	.0208	-.0018	.0570
High .6535	-.0120	-.0434	.0152

Source: compiled by the author based on research results

The index of moderated mediation (see table 28) was statistically significant (index = −0.057, 95% bootstrap CI [−0.124, −0.006]), indicating that the indirect effect of AI product use on employee well-being through technostress varies as a function of job autonomy.

Table 28

Index of Moderated Mediation

Moderator	Index	BootLLCI	BootULCI
JA_MEAN	−.0574	−.1237	-.0059

Source: compiled by the author based on research results

Overall, the findings indicate that technostress functions as a conditional mediator in the relationship between AI product use and employee well-being. Specifically, AI product use undermines employee well-being through increased technostress when job autonomy is low. However, as job autonomy increases, this indirect effect weakens and becomes non-significant. The significant index of moderated mediation confirms that job autonomy buffers the negative consequences of technostress associated with AI product use.

3.7 Research Results Overview

The findings of this study generally support the theoretical assumptions presented in the literature review, particularly the Job Demands–Resources (JD–R) model and prior research emphasizing the dual nature of AI product use in the workplace (Bakker & Demerouti, 2007; Shaikh et al., 2023). Descriptive results showed that employees perceive AI products as useful, easy to use, and performance-enhancing, which aligns with TAM and UTAUT-based studies highlighting perceived usefulness and ease of use as central to AI acceptance (Sohn & Kwon, 2020; Marikyan et al., 2022).

However, the regression analysis demonstrated that AI product use does not have a statistically significant direct effect on employee well-being. This finding refines earlier literature suggesting that AI automatically enhances well-being through productivity gains (Henkel et al., 2020; Fisher et al., 2023) and instead supports more recent arguments that AI outcomes depend on contextual and psychological mechanisms (Nazareno & Schiff, 2021).

In line with prior research, technostress was positively associated with AI product use and negatively related to employee well-being (Tarafdar et al., 2007; Correia

Loureiro et al., 2023). The mediation analysis confirmed that technostress functions as a key explanatory mechanism through which AI product use may undermine well-being, supporting theoretical claims that AI can act as a job demand when it increases complexity, overload, or insecurity (Kim & Lee, 2024).

Most importantly, the moderated mediation analysis empirically confirmed the buffering role of job autonomy, as proposed in the literature (Deci & Ryan, 2000; Stamate et al., 2021). The indirect negative effect of AI product use on employee well-being through technostress was significant only under conditions of low job autonomy, while higher autonomy weakened and neutralized this effect. This finding reinforces the JD–R model assumption that autonomy operates as a critical job resource that protects employees from technology-induced stress.

Furthermore, sociodemographic analyses revealed significant differences in AI product use, job autonomy, technostress, and employee well-being across age, education level, business sector, and interaction with AI, while no significant differences were found by gender, organizational size, or tenure.

Overall, the results demonstrate that the relationship between AI product use and employee well-being is indirect and conditional, confirming the literature’s view that AI technologies can simultaneously create benefits and risks depending on technostress levels and available job resources.

CONCLUSIONS AND RECOMMENDATIONS

The aim of this Master thesis was to measure the impact of Artificial Intelligence (AI) product use on employee well-being at work, taking account of the mediating role of technostress and the moderating role of job autonomy. The empirical findings approve the following conclusions and recommendations to be drawn.

To start with, AI product use does not have a statistically significant direct efect on employee well-being at work. Even though employees perceive AI tools as useful, easy to use and performance-improving, including high effort expectancy, these findings indicate that AI product use alone is not enough to explain variations in employee well-being. This shows that the effects of AI tools on employee well-being are more complex and cannot be analyzed without considering additional organizational or psychological factors rather than driven by technology itself.

Secondly, the confirmed mediating role of technostress shows that AI product use shapes the employee's well-being primary by increasing job demands rather than functioning just as a job recourse. This finding supports the view that AI technologies may weaken well-being when they increase work complexity or constant use of technology, making technostress central to understanding AI-related employee outcomes.

Thirdly, the moderating effect of job autonomy demonstrates that autonomy functions as a critical job resource that buffers the negative impact of any AI-related technostress on employee well-being. Meaning, higher levels of job autonomy weaken and neutralise the adverse effects of technostress, emphasizing the importance of work design and employee ability to control well-being outcomes in AI-supported work environments.

Fourthly, the findings support the applicability of the JD-R model in the context of AI product use by demonstrating that AI technologies can simultaneously act as job demands and potential job resources. Employee well-being outcomes therefore depend on the balance between AI-induced technostress and the availability of job resources, particularly job autonomy.

Lastly, sociodemographic results revealed that expereinces of AI product use, technostress and job autonomy differ across age groups, education level, business sectors and the types of interaction with AI. These indicate that employee responses to AI are context dependent. This discovery suggests that individual and organizational characteristics play an important role in shaping AI-related work experiences.

To conclude, this study reveals that the relationship between AI products' use and employee well-being is indirect and conditional, rather than direct and universal. Job autonomy and technostress play central roles through which AI product use affects well-being, concluding that the successful integration of AI in the organizations depends not only on technical capabilites but as well on job design and supportive organizational conditions.

Recommendations. Based on the research findings, several recommendations are proposed:

- Focus on managing technostress, not just AI usability. Since employees perceive AI tools as easy to use with high effort expectancy, organizations should recognise that technostress first comes from increased job demands rather than from usability problems. Organizations should actively monitor and manage technostress by identifying the sources, like unnecessary information overload, simplifying AI systems, reducing performance pressure associated with AI product use.

- Improve job autonomy in AI-supported work environments, meaning organizations should allow employees to have control over how, when and to what extent AI tools are used in their daily work performance. Giving flexibility in decision making, work scheduling; helps employees better cope with AI-related demands (deadlines) and reduces the negative impact of technostress and maintains well-being.
- Shift focuses on *how to use AI* to *how to work with AI.* Training programs should focus on helping employees manage workloads, expectations, and boundaries when working with AI. That increases confidence and perceived control over AI tools, so to improve overall the work experience.
- Organizations should invest in continuous trainings and skill developments related to AI product tools usage, maintaining human judgment.
- Given that AI tools are not perceived as difficult to use, training programs should go beyond technical instructions and focus on helping employees manage workload, expectations, and boundaries when working with AI. This includes guidance on prioritization, interpretation of AI outputs, and maintaining human judgment.
- Organizations should adopt tailored approaches to AI tools integrations focusing on different employee age groups and work contexts. Implement mentoring groups: more experienced guiding less experienced.
- When implementing AI, organizations should look beyond performance metrics and systematically monitor how AI affects employees. By regularly assessing technostress and job autonomy, organizations can adjust AI use and work design to prevent long-term strain and promote sustainable employee well-being.
- Clear organizational policies should define when AI supported systems require employee attention and when employee is not expected to engage with AI systems.
- Encourage flexibility in how and when AI tools are used, rather than mandatory usage patterns. This strengthens job autonomy and reduces feelings of loss of control.

- Involve employees in giving feedbacks, be involved in decisions related AI implementation, system updates and workflow changes.

Limitations and further research. Despite its contributions, this study has several limitations that should be acknowledged. To start with, the research used a cross-sectional design, which limits the ability to draw causal conclusions. Future studies could adopt longitudinal designs to examine how the impact of AI product use, technostress, and job autonomy on employee well-being develops over time. Furthermore, the study focused on technostress and job autonomy as the primary mediating and moderating variables. Other organizational factors, such as leadership style, organizational culture, digital literacy, and ethical AI governance, were not included and may also play an important role.

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The Impact of Artificial Intelligence (AI) Product Use on Employee Well-being at work: The Moderating Role of Job Autonomy and the Mediating Effect of Technostress

Milda D Alberti

Master Thesis

Human Resource Management

Faculty of Economics and Business Administration, Vilnius University

Supervisor: Assistant professor dr. Julija Savickė, Vilnius, 2026

SUMMARY

93 pages, 28 tables, 4 figures, 10 annexes, 74 references

This research examines the impact of Artificial Intelligence (AI) product use on employee well-being at work, considering the moderating role of job autonomy and the mediating effect of technostress.

The Master thesis consists of four main parts: a scientific literature review, empirical research methodology, analysis of empirical results, and conclusions and recommendations.

The scientific literature review aimed to clarify the theoretical concepts of AI product use, employee well-being, job autonomy, and technostress in the workplace and identify their interrelationships.

Based on the literature review, the research methodology was developed, and conceptual research was created. The data was collected using a structured questionnaire survey from 261 respondents working in organizations that use AI tools in their daily activities. Validated measurement scales were applied to assess AI product use, employee well-being, job autonomy, and technostress. Data analysis was conducted using the IBM SPSS Statistics 5.0 program, including descriptive statistics, reliability analysis, correlation analysis, regression analysis, and moderated mediation analysis using Hayes' PROCESS macro (Model 14).
The research findings indicate that AI product use does not have a statistically significant direct effect on employee well-being at work. However, AI product use is positively associated with technostress, which negatively affects employee well-being. The results confirm that technostress mediates the relationship between AI product use and employee well-being. Additionally, job autonomy was found to significantly moderate this indirect relationship.
The conclusions and recommendations summarize the main concepts of literature analysis with the results of performed research. The findings of this study contributed to the model of the JD-R in the context of AI-supported work and could give some practical guidelines for organizations seeking to implement AI in a way that supports employee well-being. The results of the Master thesis are submitted to Vilnius University.

Dirbtinio intelekto (DI) produktų naudojimo poveikis darbuotojų gerovei darbe: darbo savarankiškumo moderuojantis ir tarpinis technostreso vaidmuo

Milda D Alberti

Master Thesis

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Darbo vadovė: Asist. Dr. Julija Savickė, Vilnius, 2026

SANTRAUKA

93 puslapiai, 28 lentelių 4 paveikslai, 10 priedų, 74 literatūros šaltinių

Šiame tyrime nagrinėjamas dirbtinio intelekto (DI) produktų naudojimo poveikis darbuotojų gerovei darbe, atsižvelgiant į darbo savarankiškumo kaip moderuojančio veiksnio ir technostreso kaip tarpinio veiksnio vaidmenį.
Magistro darbą sudaro keturios pagrindinės dalys: mokslinės literatūros apžvalga, empirinio tyrimo metodologija, empirinių tyrimo rezultatų analizė bei išvados ir rekomendacijos.
Mokslinės literatūros apžvalgos tikslas – išaiškinti teorines DI produktų naudojimo, darbuotojų gerovės, darbo savarankiškumo ir technostreso darbe sąvokas bei nustatyti egzistuojančius teorinius ryšius tarp jų.
Remiantis literatūros analize, buvo parengta tyrimo metodologija ir suformuotas konceptualus tyrimo modelis. Duomenys buvo surinkti taikant struktūruotą anketinę apklausą, kurioje dalyvavo 261 respondentai iš ivairių organizacijų, kurie naudoja DI irankius kasdienėje veikloje. DI produktų naudojimui, darbuotojų gerovei, darbo savarankiškumui ir technostresui vertinti buvo taikytos patvirtintos skalės. Duomenų analizė atlikta naudojant IBM SPSS

Statistics 5.0 programą, taikant aprašomąją statistiką, patikimumo analizę, koreliacinę ir regresinę analizę bei moderuotos mediacijos analizę pagal Hayes PROCESS 14 modelį.
Tyrimo rezultatai parodė, kad DI produktų naudojimas neturi statistiškai reikšmingo tiesioginio poveikio darbuotojų gerovei darbe. Tačiau nustatyta, kad technostresas tarpininkauja DI produktų naudojimo ir darbuotojų gerovės ryšiui. Taip pat nustatyta, kad darbo savarankiškumas reikšmingai moderuoja šį netiesioginį ryšį.
Išvadose ir rekomendacijose apibendrinamos pagrindinės literatūros analizės įžvalgos ir atlikto empirinio tyrimo rezultatai. Šio tyrimo rezultatai gali suteikti praktinių gairių tyrėjams ir praktikams bei pateikti naudingų įžvalgų organizacijoms, siekiančioms diegti DI sprendimus taip, kad būtų palaikoma darbuotojų gerovė. Magistro darbo rezultatai pateikti Vilniaus universitetui.

ANNEXES

Annex 1. Questionnaire of the research

Hi,

I am Milda D Alberti, studying MA in Human Resources Management at Vilnius University. I would like to invite you to participate in the survey which aims to examine the impact of Artificial Intelligence (AI) product use on employee well-being at work.

Participation in this survey is anonymous and will be kept confidential and used only for research purposes. To be eligible, you should currently use / used any AI product at work. Please note, there are no right or wrong answers.

If you have any questions about the study or would like to receive a summary of the results upon completion, please feel free to contact me at: milda.d@evaf.stud.vu.lt

Thank you for participating.

Before starting, think of your current work and evaluate the statements which in your opinion best represent your experience.

1. **AI Product Use.**

Please indicate your level of agreement with the following statements, using a scale from 1 (strongly disagree) to 7 (strongly agree).

Statement	1 Strongly disagree	2 Disagree	3 Some what disagr ee	4 Neutral	5 Somewh at agree	6 Agree	7 Strongly agree
Using the AI product would be easy							
Interaction with the AI product would be clear and understandable							
I would find the AI product difficult to use							
I would find it easy to get the AI product to do what I want it to do							
Using the AI product would improve my daily work performance							
Using the AI product would help my daily work							
Using the AI product would enhance effectiveness in my daily work							
I would find the AI product useful in my daily work							
Using the AI product is entirely within my control							
I have enough ability to use the AI product							

I do not have the knowledge necessary to use the AI product							
I have the resources, knowledge, and ability to use the AI product							
Using the AI product would improve my work performance							
Using the AI product would. be helpful in my work							
Using the AI product would enhance the effectiveness of my work							
Interaction with the AI product would be clear and understandable							
It would be easy for me to become skillful at using the AI product							
I would find the AI product not easy to use							
Learning to operate the AI product would be easy for me							
It would not be easy to use the AI product technically							
It would not be easy to operate the AI product							
It would take quite some time to get familiar with the AI product							

It looks a little difficult to use the AI product							

2. Job autonomy.

Please rate your level of acceptance with the statements provided, using a scale from 1 (strongly disagree) to 5 (strongly agree).

Statement	1 (Strongly disagree)	2 (Disagree)	3 (Neutral)	4 (Agree)	5 (Strongly agree)
The job allows me to decide on the order in which things are done on the job.					
The job allows me to plan how I do my work.					
The job gives me a chance to use my personal initiative or judgment in carrying out the work.					
The job allows me to make a lot of decisions on my own.					
The job provides me with significant autonomy in making decisions.					
The job allows me to make decisions about what methods I use to complete my work.					
The job allows me to decide on my own how to go about doing my work.					

3. Technostress.

Please indicate how often you experience each of the following feelings while working, using the scale from 1 (never) to 4 (always).

Statement	1 (Never)	2 (Sometimes)	3 (Often)	4 (Always)
Due to the increased complexity of technological tools, I feel that my workload has increased.				
Due to new work technologies, I feel like I must always be available for my colleagues.				
To keep up with new technologies and constant updates, I feel like I have to sacrifice much more time for work.				
The lack of adequate technical and methodological knowledge for using devices, software, etc., at work makes me feel overwhelmed.				
Technical problems that may occur while working lead to time losses and continuous interruptions that stress me out.				
When working with technological tools, I prefer to use procedures I am already familiar with, even if they are slower than newer ones I would need to learn.				
I feel that the use of technological tools at work intrudes too much into my life.				

4. **Employee Well-Being at work.**

Please indicate your level of agreement with the following statements, using a scale from 1 (strongly disagree) to 7 (strongly agree).

Statement	1 (strongly disagree)	2	3	4	5	6	7 (Strongly agree)
I am satisfied with my work responsibilities.							
In general, I feel fairly satisfied with my present work.							
I find real enjoyment in my work.							
I can always find ways to enrich my work.							
Work is a meaningful experience to me.							
I feel basically satisfied with my work achievements in my current job.							

Sociodemographic questions:

What is your age?

Under 25

25-34

35-44

45-54

55+

What is your gender?

Female

Male

Other

What is your highest level of education?

Higher non-university education

Higher university education

In which business sector do you work?

Trade

Manufacturing

Services

Education

Healthcare

Technology/IT

Transportation

Financial

Agriculture

Construction

Public administration

Other

Size of your organization?

1-9 employees

10-49 employees

50-249 employees

250+ employees

Your current position?

I do not have subordinates

I have subordinates

How long are you in the company?

Less than a year

1–3 years

4–6 years

7–10 years

10+ years

Interaction with AI at work?

I work with AI

I manage workers who work with AI

I develop/maintain AI

I am managed by AI

I interact with AI in another way

Annex 2. T-Test Results by Gender

	GENDER	N	Mean	Std. Deviation	t	One-Sided p	Two-Sided p
AIMEAN	1	183	5.1540	.82748	.954	.171	.341
	2	78	5.0431	.93108	.910	.182	.365
JA_MEAN	1	183	3.8306	.66229	1.930	.027	.055
	2	78	3.6447	.81879	1.773	.039	.079
WTS_MEAN	1	183	2.1561	.58052	.077	.469	.939
	2	78	2.1502	.55204	.078	.469	.938
WB_MEAN	1	183	5.1430	1.10141	-.682	.248	.496
	2	78	5.2415	.98167	-.715	.238	.476

Source: compiled by the author in IBM SPSS, based on research results

Annex 3. T-Test Results by Current position

	SUPERVISOR	N	Mean	Std. Deviation	t	One-Sided p	Two-Sided p
AIMEAN	1	162	5.1692	.83147	1.163	.123	.246
	2	99	5.0418	.90203	1.140	.128	.256
JA_MEAN	1	162	3.7531	.74052	-.633	.264	.527
	2	99	3.8110	.67650	-.647	.259	.518
WTS_MEAN	1	162	2.1658	.57934	.413	.340	.680
	2	99	2.1356	.55978	.417	.339	.677
WB_MEAN	1	162	5.1132	1.13003	-1.149	.126	.252
	2	99	5.2694	.94991	-1.198	.116	.232

Source: compiled by the author in IBM SPSS, based on research results

Annex 4. Post-hoc analysis for Age and Employee Well-Being

Dependent Variable		(I) AGE	(J) AGE	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
WB_MEAN	Tukey HSD	1	2	-.58831*	.15393	.002	-1.0112	-.1654

			3	-.92938*	.18986	<.001	-1.4510	-.4078
			4	-1.09841*	.25050	<.001	-1.7866	-.4102
			5	-.90183*	.30406	.027	-1.7372	-.0665
		2	1	.58831*	.15393	.002	.1654	1.0112
			3	-.34107	.17545	.297	-.8231	.1409
			4	-.51010	.23976	.212	-1.1688	.1486
			5	-.31352	.29528	.826	-1.1247	.4977
		3	1	.92938*	.18986	<.001	.4078	1.4510
			2	.34107	.17545	.297	-.1409	.8231
			4	-.16903	.26426	.968	-.8951	.5570
			5	.02755	.31550	1.000	-.8392	.8943
		4	1	1.09841*	.25050	<.001	.4102	1.7866
			2	.51010	.23976	.212	-.1486	1.1688
			3	.16903	.26426	.968	-.5570	.8951
			5	.19658	.35530	.981	-.7796	1.1727
		5	1	.90183*	.30406	.027	.0665	1.7372
			2	.31352	.29528	.826	-.4977	1.1247
			3	-.02755	.31550	1.000	-.8943	.8392

			4	-.19658	.35530	.981	-1.1727	.7796
	Games - Howell	1	2	-.58831*	.15353	.002	-1.0118	-.1649
			3	-.92938*	.16971	<.001	-1.4007	-.4581
			4	-1.09841*	.24057	<.001	-1.7940	-.4028
			5	-.90183*	.28083	.036	-1.7576	-.0460
		2	1	.58831*	.15353	.002	.1649	1.0118
			3	-.34107	.16649	.250	-.8029	.1208
			4	-.51010	.23831	.229	-1.2003	.1801
			5	-.31352	.27890	.792	-1.1658	.5388
		3	1	.92938*	.16971	<.001	.4581	1.4007
			2	.34107	.16649	.250	-.1208	.8029
			4	-.16903	.24904	.960	-.8849	.5469
			5	.02755	.28812	1.000	-.8418	.8969
		4	1	1.09841*	.24057	<.001	.4028	1.7940
			2	.51010	.23831	.229	-.1801	1.2003
			3	.16903	.24904	.960	-.5469	.8849
			5	.19658	.33479	.976	-.7823	1.1755

		5	1	.90183*	.28083	.036	.0460	1.7576
			2	.31352	.27890	.792	-.5388	1.1658
			3	-.02755	.28812	1.000	-.8969	.8418
			4	-.19658	.33479	.976	-1.1755	.7823

*. The mean difference is significant at the 0.05 level.

Source: compiled by the author in IBM SPSS, based on research results

Annex 5. One –way ANOVA by Size of Organization

		N	Mean	Std. Deviation	F	Sig.
AIMEAN	1	31	5.0249	.58515	.320	.811
	2	49	5.2106	.78410		
	3	75	5.0994	.86859		
	4	106	5.1226	.95477		
	Total	261	5.1209	.85943		
JA_MEAN	1	31	3.6774	.67508	.694	.557
	2	49	3.8251	.55808		
	3	75	3.8495	.61058		
	4	106	3.7278	.85112		
	Total	261	3.7750	.71614		
WTS_MEAN	1	31	2.3088	.61842	1.178	.319
	2	49	2.1778	.59084		
	3	75	2.1600	.60880		
	4	106	2.0943	.51636		
	Total	261	2.1544	.57111		
WB_MEAN	1	31	5.2581	.90864	1.641	.180
	2	49	4.8844	1.08184		
	3	75	5.1711	1.14654		
	4	106	5.2814	1.03161		
	Total	261	5.1724	1.06612		

Source: compiled by the author in IBM SPSS, based on research results

Annex 6. One-Way ANOVA Results by Tenure

		N	Mean	Std. Deviation	F	Sig.
AIMEAN	1	64	5.2919	.75218	1.375	.243
	2	90	5.1111	.82550		
	3	51	5.0909	.86114		
	4	26	4.8392	1.03949		
	5	30	5.0803	.97589		
	Total	261	5.1209	.85943		
JA_MEAN	1	64	3.8504	.59663	1.397	.236
	2	90	3.6714	.72352		
	3	51	3.7535	.78354		
	4	26	3.7363	.79457		
	5	30	3.9952	.71918		
	Total	261	3.7750	.71614		
WTS_MEAN	1	64	2.2612	.58352	1.063	.376
	2	90	2.0952	.61211		
	3	51	2.0840	.47653		
	4	26	2.1758	.52731		
	5	30	2.2048	.59636		
	Total	261	2.1544	.57111		
WB_MEAN	1	64	4.9870	1.16129	1.324	.261
	2	90	5.1630	.98236		
	3	51	5.2353	1.15527		
	4	26	5.1410	.98058		
	5	30	5.5167	.98100		
	Total	261	5.1724	1.06612		

Source: compiled by the author in IBM SPSS, based on research results

Annex 7. Post-hoc analysis for Interaction with AI

Warnings

Post hoc tests are not performed for AIMEAN because at least one group has fewer than two cases.
Post hoc tests are not performed for JA_MEAN because at least one group has fewer than two cases.
Post hoc tests are not performed for WTS_MEAN because at least one group has fewer than two cases.
Post hoc tests are not performed for WB_MEAN because at least one group has fewer than two cases.

Source: compiled by the author in IBM SPSS, based on research results

Annex 8. Model 4

```
Model: 4

      Y: WB_MEAN

      X: AIMEAN

      M: WTS_MEAN

Sample

Size:  261

**************************************************************
************

OUTCOME VARIABLE:
```

WTS_MEAN

Model Summary

```
          R       R-sq        MSE          F        df1
df2          p

      .1481      .0219      .3202     5.8052     1.0000
259.0000      .0167
```

Model

```
              coeff         se          t          p
LLCI       ULCI

constant     2.6582      .2120    12.5370      .0000
2.2407     3.0757

AIMEAN       -.0984      .0408    -2.4094      .0167
-.1788     -.0180
```

****
****

OUTCOME VARIABLE:

WB_MEAN

Model Summary

R	R-sq	MSE	F	df1	df2	p
.1259	.0158	1.1273	2.0772	2.0000	258.0000	.1274

Model

	coeff	se	t	p	LLCI	ULCI
constant	5.0511	.5043	10.0168	.0000	4.0581	6.0441
AIMEAN	.0942	.0775	1.2160	.2251	-.0583	.2468
WTS_MEAN	-.1676	.1166	-1.4377	.1517	-.3972	.0620

************************* TOTAL EFFECT MODEL ****************************

OUTCOME VARIABLE:

WB_MEAN

Model Summary

R	R-sq	MSE	F	df1	df2	p
.0892	.0080	1.1319	2.0789	1.0000	259.0000	.1506

Model

	coeff	se	t	p	LLCI	ULCI
constant	4.6056	.3986	11.5537	.0000	3.8206	5.3905
AIMEAN	.1107	.0768	1.4418	.1506	-.0405	.2619

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y

Effect	se	t	p	LLCI	ULCI
.1107	.0768	1.4418	.1506	-.0405	.2619

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
.0942	.0775	1.2160	.2251	-.0583	.2468

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
WTS_MEAN	.0165	.0157	-.0076	.0535

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:

95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:

5000

Annex 9. Model 1

Model: 1

Y: WB_MEAN

X: WTS_MEAN

W: JA_MEAN

Sample

Size: 261

****

OUTCOME VARIABLE:

WB_MEAN

Model Summary

R	R-sq	MSE	F	df1	df2	p
.3631	.1319	.9982	13.0136	3.0000	257.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	5.1640	.0619	83.4494	.0000	5.0422	5.2859

```
WTS_MEAN     -.2616      .1095    -2.3885      .0176
-.4772     -.0459

JA_MEAN        .4968      .0903
5.5032      .0000      .3190      .6746

Int_1          .5827      .1511
3.8564      .0001      .2851      .8802

Product terms key:

 Int_1    :        WTS_MEAN x        JA_MEAN

Test(s) of highest order unconditional interaction(s):

       R2-chng          F        df1        df2          p

X*W      .0502    14.8719     1.0000   257.0000      .0001

----------

    Focal predict: WTS_MEAN (X)

          Mod var: JA_MEAN  (W)

Conditional effects of the focal predictor at values of the
moderator(s):

    JA_MEAN     Effect         se          t          p
LLCI       ULCI

     -.6322     -.6299      .1545    -4.0783      .0001
-.9341     -.3257

      .0821     -.2137      .1086    -1.9683      .0501
-.4275      .0001

      .6535      .1192      .1375      .8671      .3867
-.1516      .3900

Data for visualizing the conditional effect of the focal
predictor:

Paste text below into a SPSS syntax window and execute to
produce plot.

DATA LIST FREE/

   WTS_MEAN   JA_MEAN    WB_MEAN    .

BEGIN DATA.
```

```
     -.5829     -.6322     5.2171

     -.0115     -.6322     4.8572

      .5599     -.6322     4.4972

     -.5829      .0821     5.3294

     -.0115      .0821     5.2073

      .5599      .0821     5.0852

     -.5829      .6535     5.4192

     -.0115      .6535     5.4874

      .5599      .6535     5.5555

END DATA.

GRAPH/SCATTERPLOT=

 WTS_MEAN WITH     WB_MEAN  BY       JA_MEAN  .

*********************** ANALYSIS NOTES AND ERRORS
************************

Level of confidence for all confidence intervals in output:

  95.0000

W values in conditional tables are the 16th, 50th, and 84th
percentiles.

NOTE: The following variables were mean centered prior to
analysis:

          JA_MEAN  WTS_MEAN

------ END MATRIX -----
```

Annex 10. Model 14

```
Model: 14

      Y: WB_MEAN

      X: AIMEAN

      M: WTS_MEAN
```

W: JA_MEAN

Sample

Size: 261

****
****

OUTCOME VARIABLE:

WTS_MEAN

Model Summary

```
          R       R-sq        MSE          F        df1
df2          p

      .1481      .0219      .3202     5.8052     1.0000
259.0000      .0167
```

Model

```
              coeff         se          t          p
LLCI       ULCI

constant      .5038      .2120
2.3763      .0182      .0863      .9214

AIMEAN       -.0984      .0408    -2.4094      .0167
-.1788     -.0180
```

****
****

OUTCOME VARIABLE:

WB_MEAN

Model Summary

```
          R       R-sq        MSE          F        df1
df2          p

      .3632      .1319     1.0021     9.7251     4.0000
256.0000      .0000
```

Model

```
              coeff         se          t          p
LLCI       ULCI
```

```
constant     5.1244      .3979    12.8780      .0000
4.3408     5.9080

AIMEAN         .0077      .0767      .1009      .9197
-.1434      .1589

WTS_MEAN     -.2598      .1111    -2.3380      .0202
-.4786     -.0410

JA_MEAN        .4942      .0942
5.2478      .0000      .3087      .6796

Int_1          .5835      .1516
3.8489      .0001      .2849      .8820

Product terms key:

 Int_1    :        WTS_MEAN x        JA_MEAN

Test(s) of highest order unconditional interaction(s):

       R2-chng          F        df1        df2          p

M*W      .0502    14.8143     1.0000   256.0000      .0001

----------

    Focal predict: WTS_MEAN (M)

          Mod var: JA_MEAN  (W)

Conditional effects of the focal predictor at values of the
moderator(s):

    JA_MEAN     Effect         se          t          p
LLCI       ULCI

     -.6322     -.6286      .1553    -4.0491      .0001
-.9344     -.3229

      .0821     -.2119      .1103    -1.9208      .0559
-.4291      .0053

      .6535      .1215      .1396      .8703      .3850
-.1535      .3965

Data for visualizing the conditional effect of the focal
predictor:

Paste text below into a SPSS syntax window and execute to
produce plot.
```

```
DATA LIST FREE/
   WTS_MEAN   JA_MEAN    WB_MEAN    .
BEGIN DATA.
     -.5829     -.6322     5.2180
     -.0115     -.6322     4.8588
      .5599     -.6322     4.4996
     -.5829      .0821     5.3281
     -.0115      .0821     5.2070
      .5599      .0821     5.0860
     -.5829      .6535     5.4161
     -.0115      .6535     5.4856
      .5599      .6535     5.5550
END DATA.
GRAPH/SCATTERPLOT=
 WTS_MEAN WITH     WB_MEAN  BY       JA_MEAN  .
****************** DIRECT AND INDIRECT EFFECTS OF X ON Y
******************
Direct effect of X on Y
     Effect         se          t          p       LLCI
ULCI
      .0077      .0767      .1009      .9197
-.1434      .1589
Conditional indirect effects of X on Y:
INDIRECT EFFECT:
 AIMEAN      ->     WTS_MEAN    ->     WB_MEAN
    JA_MEAN     Effect     BootSE   BootLLCI   BootULCI
     -.6322      .0619      .0334      .0061      .1361
      .0821      .0208      .0155     -.0018      .0570
```

```
      .6535     -.0120      .0142     -.0434      .0152

      Index of moderated mediation:

             Index     BootSE   BootLLCI   BootULCI

JA_MEAN     -.0574      .0299     -.1237     -.0059

*********************** ANALYSIS NOTES AND ERRORS
************************

Level of confidence for all confidence intervals in output:

  95.0000

Number of bootstrap samples for percentile bootstrap
confidence intervals:

  5000

W values in conditional tables are the 16th, 50th, and 84th
percentiles.

NOTE: The following variables were mean centered prior to
analysis:

          JA_MEAN  WTS_MEAN

------ END MATRIX -----
```