

Relation between attitudes towards artificial intelligence and employee well-being in Serbia

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Abstract

The main aim of this paper is to investigate the relationship between attitude towards artificial intelligence (AI) and employee well-being in Serbia. Since previous studies showed that AI can have different effects not only on workplace behavior, but on other elements of employee life, we used employee well-being (EWB) as a construct that is composed of workplace, psychological, and life well-being. Regarding the methodology, we used a quantitative approach to investigate the proposed relation. The sample of the research contains 266 responses from employees in Serbia, who work in the service sector, mostly in IT, consulting, and banking industries, in privately owned companies. Also, most of the respondents are highly educated, from the northern part of the country, the Autonomous Province of Vojvodina. The questionnaires used in the research were adapted from the AI attitude scale with 4 questions, while the employee well-being scale was adapted from an 18-question scale. Additionally, we added several demographic questions to the final questionnaire. The Spearman's correlation and multiple regression model were used to investigate the effects of different control and independent variables on employee well-being.

Keywords: artificial intelligence, employee wellbeing, regression analysis, Serbia

1. Introduction

There is a growing body of knowledge on EWB and all the significance and benefits that this concept has in modern HRM (Wright, 2006; Wright & Huang, 2012; Mäkilangas et al., 2016; Guest, 2017; Han et al., 2025). However, well-being and other concepts are faced with a new reality of AI today. AI represents a significant innovation in the business world, although the concept itself is not new; what is new is its application. AI has permeated every aspect of business and private life in recent years (Daugherty & Wilson, 2024). Today, companies rely on AI and insights into various HRM practices, from staffing, rewards, training, performance management, to exit interviews (Malik et al., 2023, Gupta, 2024; Mendy et al., 2025) to make HRM function more strategically oriented and less transactional. According to Wamba-Taguimdje et al. (2020) AI has “ability to optimize existing processes and improve automation, information and transformation effects, but also to detect, predict and interact with humans... and to improve on performance at both the organizational (financial, marketing and administrative) and process levels” (p. 1893). While AI offers many advantages, there is also concern, especially regarding employees. This fear has two sides. One side is about the newness of AI, including how it will be used and the skills needed to operate it effectively. The other side of the fear is that AI will replace jobs, making certain roles obsolete and allowing AI to dominate business (Jin et al., 2024). Since there is limited research on this topic, the researchers in this paper explored the relationship between AI and employee well-being, examining whether attitudes toward AI influence how employees feel.

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The structure of the paper contains five sections. After the introduction, the second section presents the body of knowledge in employee well-being and the AI area. The third section explains the methodology, data, sample, and analytical approach, while the fifth section presents the results of correlation and multiple regression analysis. Finally, in the conclusion section, we provided the main conclusions, theoretical and practical implications, and a few limitations of the research and directions for future studies.

2. Theoretical background

The development of digital technologies and the spread of artificial intelligence (Artificial Intelligence, AI) are key determinants of the Fourth Industrial Revolution. AI is increasingly being integrated into business processes, from automating routine tasks to decision support and predictive analytics. Numerous reports emphasize that the application of AI has the potential to significantly improve productivity and efficiency (Brynjolfsson & McAfee, 2017). However, the question of how these changes affect the people who work with AI technologies is increasingly present.

Artificial intelligence is defined as “a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation” (Kaplan & Haenlein, 2019, p. 15). AI “describes a machine's capacity to carry out operations that ordinarily require human intellect, such as speech recognition, understanding of natural language, and decision-making” (Soori et al., 2023, p. 54). AI applications are changing businesses by making operations and decision-making better and giving workers more creative work to do instead of boring, repetitive, physical, and manual tasks (Zirar et al., 2023). The combination of AI with robotics and machine learning has become important in many areas, such as self-driving cars, chatbots, operational planning and scheduling, forecasting and capacity management, gaming, marketing, and pricing strategies. AI applications encompass aiding employees via online training programs, improving customer service operations, and enabling interventions in cognitive therapy (Zirar et al., 2023). These types of AI affect modern work, work demands, and resources, which in turn affects the health of employees.

Employee well-being is a complex idea that includes how employees feel mentally, emotionally, socially, and physically. It encompasses more than the absence of illness or stress; it includes job satisfaction, life balance, psychological resilience, and a sense of purpose in the workplace (Zheng et al., 2015). Because EWB affects things like engagement, productivity, and employee turnover, it's becoming more and more important to understand how AI affects EWB. Zheng et al. (2015) created a comprehensive model of employee well-being that includes three aspects: life, psychological, and work well-being. This model shows that EWB comes from more than just work; it also comes from other parts of life.

The Job Demands–Resources (JD-R) theoretical framework is especially beneficial for comprehending the impact of AI on employee well-being (Demerouti et al., 2001; Bakker & Demerouti, 2017). This model posits that employee well-being is contingent upon the equilibrium between work demands and resources (Adil & Baig, 2018). AI can serve as a resource (facilitating work, enhancing efficacy, generative AI) and simultaneously as an additional demand (heightening stress, inducing uncertainty), impacting employees' professional and personal domains (productivity, job satisfaction, work–family conflict (Chuang et al., 2025)).

According to a study by Valtonen et al. (2025), the introduction of AI does not directly affect the well-being of employees. Instead, it has indirect effects by making tasks easier and safer at work. This supports the idea that AI can help make the workplace better, lower the physical and mental stress on workers, and make them safer. Giuntella et al. (2025), utilizing longitudinal data from Germany, discovered that exposure to AI technologies did not result in a decline in employees' mental health. Conversely, a marginal positive impact on self-assessed health and health satisfaction was observed. These results indicate that AI can enhance well-being when its implementation is meticulously strategized and attuned to employee requirements. Arboh et al. (2024) demonstrated in a cohort of healthcare workers in Ghana that awareness of AI enhances informal learning and employee adaptability. In this instance, AI functions as a resource that aids in navigating intricate work environments, thereby enhancing employee well-being indirectly. This discovery aligns with the JD-R model, which posits that resources enhance resilience and satisfaction. A review by García-Madurga et al. (2024) underscores the capacity of AI to enhance employee wellness programs via personalization, early identification of psychosocial risks, and mental health support. The authors, however, caution against the significance of safeguarding privacy and ethical frameworks. According to the OECD AI surveys, 80% of workers said that AI had helped them do their jobs better, and 60% said it had made their jobs more enjoyable, better for their physical and mental health, and more helpful for making decisions (Lane et al., 2023).

Conversely, Jin et al. (2024) discovered that heightened employee awareness of Smart Technology, Artificial Intelligence, Robotics, and Algorithms (STAR) technologies adversely impacts affective well-being. The mechanism

involves heightened work-related stress and insecurity, which diminish employees' sense of control and safety. Psychological resilience has been demonstrated as a protective factor, indicating that individual differences influence employees' experiences with AI. Meng et al. (2025), in their research on employee collaboration and AI, discovered that engagement with AI can exacerbate feelings of loneliness and emotional fatigue. These effects indicate the potential risk of undermining interpersonal relationships and the psychological well-being of employees, particularly when AI is employed as a replacement for human interaction. Souлами et al. (2024), in a bibliometric analysis, ascertain that the influence of AI on employee well-being is dual-faceted. Some studies demonstrate a decrease in stress and an enhancement in job satisfaction, whereas others reveal an escalation in insecurity and workload. The authors stress that the result depends on the context in which it is carried out, how involved the employees are, and the culture of the organization.

A review of the literature indicates that the influence of AI on employee well-being is contingent upon various factors. In the context of an organization, the way that things are put into place and how employees are talked to are very important. When AI is framed as a supportive tool rather than a replacement for employees, the beneficial outcomes are more significant (Valtonen et al., 2025; Giuntella et al., 2025). When AI is viewed as a threat or an added burden, the likelihood of stress and diminished well-being escalates (Jin et al., 2024). At the individual level, factors such as psychological resilience, digital competencies, and attitudes towards technology influence perceptions of AI. Employees with favorable attitudes toward AI and a sense of competence are more inclined to view technology as a resource, whereas those exhibiting lower resistance regard AI as a stressor (Arboh et al., 2024).

Artificial intelligence is becoming a big part of modern workplaces, and how it affects the health and happiness of workers is one of the most important areas of study and practice. A review of the literature shows that AI can have both good and bad effects. For example, it can help with tasks, make things safer, and support health, but it can also cause stress, insecurity, and emotional exhaustion. The impact of AI is contingent upon the organizational context, the individual attributes of employees, and the method of implementation. In practice, this means that managers should be open and honest with their employees, give them training and help, and find a balance between new technologies and keeping the human side of work. For researchers, this creates opportunities for longitudinal and comparative studies that will investigate more comprehensively the mechanisms by which AI influences various aspects of employee well-being.

3. Methodology

The sample of this research contains data gathered from employed people in Serbia. The sample description is given in Table 1.

Table 1. Demographic structure of respondents

	N	Percentage
<i>Gender</i>		
Male	132	49.6
Female	134	50.4
<i>Age</i>		
18-25	27	10.2
26-35	80	30.1
36-45	99	37.2
46-55	37	13.9
55+	23	8.6
<i>Education</i>		
High School	31	11.7
Bachelor	103	38.7
Master	98	36.8
PhD	34	12.8
<i>Management position</i>		
No	184	69.2
Yes	82	30.8
<i>Monthly income</i>		
Up to 500 EUR	41	15.4
From 500 to 750 EUR	38	14.3
From 750 to 1000 EUR	31	11.7
From 1000 to 1500 EUR	65	24.4
From 1500 EUR	91	34.2

Source: Author's calculation

The research was conducted in 2025, from July to September, via an electronic questionnaire. We used LinkedIn Business Network to gather as many answers as possible. The minimum requirements for accessing the questionnaire are that the person is employed or doing business in Serbia, and that it has a minimum high school degree. After 2 months of data collection, we gathered 266 valid responses. We informed our respondent that the research is for academic purposes only,

that their personal data will not be shared with anyone else, and we explained the main purpose of this study. Also, by answering the questionnaire, they provide us with their consent.

As we can see, there were 50% of males and females in the sample, mostly in the Y generation, and more than 60% of respondents are in the age group from 26 to 45 years of age. Most of the respondents are highly educated persons, with BSc and MSc degrees (about 75%), while only 11.7% have a high school degree. About 30% of respondents are in managerial positions, while the rest of the sample are employed without managerial positions. Finally, most respondents earn more than 750 euros per month, 67% respondents.

We used a questionnaire developed for the purpose of investigating the effects of AI on employee well-being. The questionnaire had 3 sections. The first one contained demographic questions, the second one contained 18 questions about employee well-being (adapted from Zheng et al., 2015), while the third section contained 4 questions about general AI assessment (AIAS, AI assessment scale) (Grassini, 2023), and some other questions about the frequency of AI usage for personal and business life.

Data analysis encompassed a validity check of the constructs, data normalization, Spearman's correlation, and multiple hierarchical regression. We used the Cronbach alpha coefficient to test the validity of the scales. Results pointed out that in all cases the Cronbach alpha coefficients reached satisfactory values, above 0.7, for EWB, it was 0.933, and for AIAS, it was 0.905. Since the data showed non-normal distribution, we did z-scores for interval variables.

4. Results

Results are presented in the following tables and discussed later. We started with Spearman's correlation analysis.

Table 2. Correlation analysis

	1	2	3	4	5	6	7	8	9	10	11	12
Gender 1	1											
Age 2	-0.03	1										
Education 3	0.047	.207**	1									
Management 4	-0.04	.130*	0.095	1								
Work experience 5	-0.06	.866**	.197**	.225**	1							
Monthly income 6	-.23**	.247**	.290**	.440**	.354**	1						
AIUSAGEJOB 7	-.138*	-.277**	.228**	.137*	-.192**	.253**	1					
AIUSAGELIFE 8	-0.01	-.332**	-.121*	.128*	-.252**	0.011	.289**	1				
LEVELAIJOB 9	-0.11	-.123*	.181**	.130*	-0.025	.316**	.654**	.300**	1			
LEVEAISLIFE 10	-0.08	-.206**	-0.003	0.09	-0.119	.126*	.309**	.639**	.562**	1		
AIAS 11	-.140*	-.141*	.155*	0.106	-0.092	.157*	.354**	.346**	.622**	.672**	1	
EWB 12	-0.01	-.277**	0.048	.145*	-.248**	0.067	0.095	.344**	0.062	.257**	.249**	1

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

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

Source: Author's calculation

According to the results of Spearman's correlation analysis, presented in Table 2, employee well-being was negatively correlated with age ($r=-0.277$, $p < 0.01$), indicating that younger employees reported higher levels of well-being compared to their older counterparts. A similar negative relationship emerged with work tenure ($r=-0.248$, $p < 0.01$), suggesting that employees with longer tenure perceived lower levels of well-being. No significant association was found between EWB and gender, education, or monthly income. The small but positive correlation with management position implies that employees in managerial roles experienced slightly higher well-being ($r=0.145$, $p < 0.05$). With respect to AI-related constructs, EWB demonstrated a positive association with AI usage in life (AIUSAGELIFE) ($r=0.344$, $p < 0.01$), indicating that employees who integrate AI more frequently into their private lives tend to report enhanced well-being. In contrast, the relationship with AI usage at work (AIUSAGEJOB) was not significant. Furthermore, a positive correlation emerged between EWB and Level of AI use in life (LEVEAISLIFE) ($r=0.257$, $p < 0.01$), suggesting that greater intensity of AI use in everyday life is associated with higher well-being. However, the level of AI use at work (LEVELAIJOB) did not show a statistically significant link with EWB. Finally, EWB was positively correlated with the AI Attitudes Scale (AIAS) ($r=0.249$, $p < 0.01$). This result indicates that more favorable attitudes toward AI correspond to higher reported levels of employee well-being. It is important to mention that all correlation coefficients were weak or low moderate, according to Cohen (1988).

The authors ran a hierarchical regression analysis conducted in two steps. According to the data in Table 3, the R value of 0.346 indicates a moderate level of prediction (before adding AI variables). The coefficient of determination, R-squared, is 0.119, indicating that the model explains 11.9% of the variability in the dependent variable. The level of autocorrelation was also investigated. The variance inflation factors (VIF) and tolerance further pointed out that there was no multicollinearity in the model. In both models, VIFs were lower than the generally accepted threshold of 10 (Hair et al., 1995; Cohen et al., 2003). After adding AI variables, the R was increased, which means that AI variables explained the variance of the dependent variable, too. The R of the final model is 0.492, and the R-squared is 0.242. This means that the full model explained 24.2% of the variance of the Employee Well-Being. The change in R-squared was significant

($F(5,254)=8.206$, $p<0.01$). The introduction of the AI variables altered the coefficient of determination to a significant degree, for more than 12%.

Table 3. Coefficients of determination of the models

Model	R	R Square	Adjusted R Square	SE of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.346	.119	.099	.94922165	.119	5.852	6	259	.000
2	.492	.242	.209	.88937306	.122	8.206	5	254	.000

Source: Author's calculation

The F-ratio in the ANOVA table 4 demonstrated that the overall regression model is a good fit for the data. The independent variables in the final model (model 2) statistically predict the dependent variable $F(11,254) = 7.366$, $p<0.001$).

Table 4. ANOVA test of the model

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	31.635	6	5.273	5.852	.000b
	Residual	233.365	259	.901		
	Total	265.000	265			
2	Regression	64.090	11	5.826	7.366	.000c
	Residual	200.910	254	.791		
	Total	265.000	265			

Source: Author's calculation

Table 5 presents the coefficients of the regression model for the EWB as dependent variables. At first, the regression model showed that most of the controls did not have significant relations to the EWB, except for managerial position and work experience. According to the positive beta coefficient ($\beta=0.416$, $p<0.01$), employees in managerial positions are associated with a higher level of EWB compared to employees who are not in management positions. This means that a managerial position is a statistically significant predictor of EWB. Contrary to this, a negative beta coefficient ($\beta=-0.235$, $p<0.01$), shorter working experience is associated with a higher level of EWB. The length of working experience is a statistically significant predictor of EWB. This means that employees who have less working experience, usually younger employees, have higher employee well-being.

Table 5. Regression models

	Model 1			Model 2		
	B	Std. Error	t	B	Std. Error	t
(Constant)	-.136	.318	-.427	-.849**	.379	-2.243
Gender	.039	.120	.322	.066	.115	.578
Age	-.025	.099	-.250	.039	.099	.400
Education	.128	.073	1.761	.149*	.072	2.053
Management position	.416**	.141	2.953	.302*	.134	2.247
Work experience	-.235**	.085	-2.769	-.218**	.081	-2.699
Monthly income	.047	.051	.906	.066	.050	1.314
AI use for job				-.049	.189	-.261
AI use for life				.610**	.201	3.033
Level of AI use for job				-.286**	.091	-3.134
Level of AI use for life				.053	.095	.552
AIAS				.247**	.084	2.959

Source: Author's calculation

Following the inclusion of independent variables, AI variables, the results of model 2 showed that both position and work experience retained their significant effects on EWB, while the education gained statistical significance. According to the positive beta coefficient ($\beta=0.149$, $p<0.05$), a higher level of education of employees is a statistically significant predictor of EWB, when the other variables in the model are controlled (held fixed). This means that more educated employees are expressing higher EWB. According to the positive beta coefficient ($\beta=0.302$, $p<0.05$), employees in managerial positions are associated with a higher level of EWB compared to employees who are not in management positions. This means that a managerial position is a statistically significant predictor of EWB. A negative beta coefficient ($\beta=-0.218$, $p<0.01$), shorter working experience is associated with a higher level of EWB. The length of working experience is a statistically significant predictor of EWB. This means that employees who have less working experience, usually younger employees, have higher employee well-being. When AI variables, as independents, are in question, we can see from Table 5 that AI use for everyday life, the level of usage of AI for job purposes, and attitude towards AI have statistically significant predictive effects on EWB. According to the positive beta coefficient ($\beta=0.610$, $p<0.01$), use of AI for everyday life is associated with a higher level of EWB compared to. This means that the use of AI for life needs is a statistically significant predictor of EWB. Employees who use AI for life needs have a higher level of EWB compared to employees who do not use AI. However, a negative beta coefficient ($\beta=-0.286$, $p<0.01$) showed that less use of AI for job purposes leads to higher EWB. Employees who are using AI for job purposes more they show lower EWB. Finally, a positive and

statistically significant beta coefficient ($\beta=0.247$, $p<0.01$) shows that a positive attitude towards AI in general is associated with a higher level of EWB.

5. Discussion and conclusions

The relationship between the AI and employee well-being is still a black box. As a new normal, AI is making changes in our private and business lives, and we are still not sure where this will continue in the future. Because of this uncertainty, the team in this research tried to do some of the first research on the AI-EWB link, through a pilot study involving 266 responses in the Republic of Serbia. We found that AI assessment has a positive effect on overall employee well-being. This result is partially related to the results of Valtonen et al. (2025), who found that AI adoption does not impact employee well-being directly, but indirectly through work-related factors of task optimization and safety. They emphasized the need for strategic implementation of AI in the workplace to maximize well-being. Also, Giuntella et al. (2025) did not find a negative effect on well-being and health of employees in Germany. However, García-Madurga et al. (2024) considered that the excessive use of AI applications can increase stress on workers and create a climate of mistrust, and that AI systems should be developed in a way that is acceptable to end users and supportive of worker health and productivity. On the contrary, Jin et al. (2024) found that perceived awareness of smart technologies, robotics, algorithms, and AI is a negative predictor of affective well-being at work, i.e., the greater awareness of technological change, the greater work stress, which then reduces affective well-being. Therefore, Soulami et al. (2024) also emphasized the need for more of this kind of research and that companies should implement supportive strategies to mitigate the potential adverse effects of AI on employee well-being.

This research contributes to the literature on AI and EWB by connecting two areas that have so far been analyzed largely separately. The findings confirm that positive attitudes towards AI, as well as the use of AI in private life, can contribute to a higher level of employee well-being, while intensive use of AI in a business context can have negative consequences. These results reinforce the thesis of the Job Demands–Resources (JD-R) model, according to which AI can simultaneously act as a resource (facilitating tasks, optimizing processes) and as a demand (increasing stress and uncertainty) (Bakker & Demerouti, 2017; Chuang et al., 2025). This provides a theoretical framework for understanding the ambiguous impact of AI on the psychological and work aspects of employee well-being. The results also confirm previous research that points to the contextual conditioning of the impact of AI, while Valtonen et al. (2025) and Giuntella et al. (2025) emphasize indirect and positive effects, Jin et al. (2024) warn of an increase in stress and a decrease in affective well-being. In this way, the paper enriches the theoretical discussion on AI and EWB by emphasizing the need for an integrative approach in research.

Research findings have direct implications for managers and HR policy makers. The positive correlation between the use of AI in personal life and employee well-being suggests that organizations should encourage the development of digital skills and digital literacy of employees, so that technology is perceived as a resource, not a threat. This can be achieved through training programs, transparent communication about the goals of introducing AI and participatory approaches in the design of technological solutions (Arboh et al., 2024; García-Madurga et al., 2024). At the same time, managers must recognize that the excessive use of AI in business tasks can reduce the subjective sense of well-being, so it is crucial to ensure a balance between technological innovation and preserving the human aspect of work (Soulami et al., 2024). The results show that education and managerial positions have a positive effect on well-being, indicating that organizations should invest in competence development and employee empowerment through greater involvement in the technology decision-making process. In addition, managers should implement mental health protection strategies, including stress reduction programs and work-life balance, thereby mitigating the negative effects of intensive use of AI at work (Jin et al., 2024). Practically, this means that it is necessary to create flexible HR policies that will allow employees to use AI as a tool to increase productivity and satisfaction, but without compromising their psychological well-being. This opens up space for sustainable and ethically responsible use of AI.

The limitations of this paper are seen in relatively small sample, only 266 respondents, who are mostly highly educated. Employees with lower level of education should be also investigated, since many of them work on operational and transactional tasks that are faced with strong involvement of AI. We did not control our models for specific sector or industry, which will be very important, too. Also, we took EWB as an integrated construct, while there is a division on psychological, work, and life well-being. Analysing these three types of well-being may show more detailed results.

These limitations are actually our future directions, with inclusion of other variables that could lead to more comprehensive understanding of the EWB-AI link.

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