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EXPLORING BUSINESS STUDENTS' PERCEPTIONS OF ARTIFICIAL INTELLIGENCE'S IMPACT ON THE LABOR MARKET: A PILOT STUDY

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Abstract. Artificial intelligence (AI) and its impact on a large array of economic and social facets has recently become one of the most debated topics both in academic and civic environment. Existing literature varies from topics touching on the AI ethics to the future of the labor market. Current research highlights significant divergences and a lack of consensus on the future implications of AI, leading to a heterogeneous perception among the general public. In this context, our research explores the intersection between AI and its profound impact on the labor market, focusing on business students' perceptions of AI impact on skills, productivity and employment dynamics. The study examines how personal AI competencies, risk perception, and anticipated economic effects of AI technologies shape labor market expectations using structural equations modelling. Seven hypotheses were tested which summarize the correlations between six reflective constructs. Findings reveal that students generally perceive AI positively, recognizing its potential to increase organizational efficiency and work productivity. Our research highlights the dual impact of AI, exploring students' perceptions of the effects of AI on society, organizations and the labor market and revealing the key links between these views and efficiency.

Keywords: artificial intelligence, labor market, productivity, skills, education, organizations.

JEL Classification: J01, E24, Q56, O33.

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1. Introduction

Recent technological transformations have triggered a digital revolution impacting every aspect of life. The emerging 5.0 era, which transcends industry 4.0, puts human innovation at the center to balance economic progress with social and environmental challenges (Tavares et al., 2023). In addition, artificial intelligence (AI) and other emerging technologies such as robotics, cloud systems and blockchain are reshaping the economic environment and, by extension, the labor market, with notable effects on productivity, wages and inequality, even if their full economic impact remains difficult to predict (Acemoglu, 2024).

A PwC study analyzing more than 500 million job advertisements in 15 countries shows that the use of AI is growing rapidly, particularly in the information, communications and financial services sectors (PwC, 2024). AI is expected to have a significant impact on all industries – particularly banking, advanced technologies and life sciences (Chui et al., 2023). However, as with previous technological changes, its growth has raised concerns about job displacement (Bárány & Siegel, 2020). The World Economic Forum's Future of Jobs Report 2023 predicts that while job losses may occur over the next five years, new opportunities in sectors such as agriculture, digital platforms, e-commerce and AI will eventually balance the decline, resulting in a net positive effect on employment (World Economic Forum, 2023).

Job vacancies for AI roles have increased seven-fold since 2012, while job vacancies overall have doubled and jobs requiring AI skills have grown 3.5 times faster (PwC, 2024). High-skilled roles such as business professionals, managers, CEOs, science and engineering professionals are most affected by AI advances, while lower-skilled jobs have less impact (Georgieff & Hyee, 2021). Meanwhile, companies are investing in AI to increase productivity and reduce labor costs, leading around 20% of workers in the financial and manufacturing sectors in OECD countries to express concern about potential job losses over the next decade (Lane et al., 2023). As AI and automation advance, repetitive tasks are increasingly automated, requiring workers to develop problem-solving, critical thinking and emotional intelligence skills. The rapid progress of AI is therefore reshaping the labor market, increasing productivity and creating new jobs opportunities, while at the same time posing risks such as job displacement and growing inequality. In this context, understanding the expectations of the public is essential for making informed decisions considering the potential multifaceted transformations (Pulkka, 2019). In addition, it should be considered that beyond short-term perceptions, the spread of AI may reshape wage structures, income distribution and sectoral employment over the coming decades (Acemoğlu et al., 2022).

Starting from such considerations, our paper aims to investigate the connections between individuals' perceptions of AI and its impact on the labor market, focusing on personal AI skills and the moderating role of perceived risks in the process of entering the labor market. This research aims to contribute to a more detailed understanding of how individuals' perceptions of AI and its impact on personal skills, productivity and efficiency influence their views on the economic effects of AI technologies, particularly in the context of the labor market. The paper also emphasizes how young people (business students) perceive the changes that may occur in the structure of labor demand, employment dynamics, and working conditions specific to the Romanian market, thus making valuable contributions to understanding their perspectives on the digital transition in the current context of the rapid development of AI. As a pilot study, this research focuses on students at Romania's leading economics-focused university to capture initial perceptions, recognizing that wider regional and sectoral heterogeneity requires further exploration. In addition, our research provides a subjective perspective on labor market transformations, which can be correlated in further research with objective economic data and established theories of economic growth, such as the Solow model or endogenous theories of economic growth. This combination could allow a deeper understanding of the way AI influences the fundamentals of output and income distribution in the long run. The second section of the paper provides a literature review of the impact of AI on productivity, job skills, organizational structures, and associated labor market risks – balancing the benefits of increased efficiency and automation with challenges such as adapting traditional skills and addressing job insecurity, inequality, and data privacy issues. Building on this analysis, the study hypothesizes on business students' perceptions of the impact of AI on the labor market. The third section presents the quantitative survey methodology used to explore these perceptions, while the fourth section analyses and discusses the findings. The final section concludes by summarizing the results and suggesting avenues for future research.

2. Literature review

2.1. The impact of AI on productivity and on organizations

AI is a transformative technology that significantly improves productivity, with research showing a strong correlation between AI training and work efficiency (Nurlia et al., 2023). Studies emphasize that by automating repetitive tasks and allowing employees to focus on creative and strategic work, AI improves decision-making and overall workplace efficiency (Nurlia et al., 2023; Chui et al., 2023). Moreover, AI improves efficiency, and facilitates knowledge sharing among employees (Tasheva & Karpovich, 2024). In addition, new AI tools have the potential to increase employee retention and facilitate learning, according to a study based on the gradual implementation of an AI-based generative conversational assistant using data from 5,179 customer service agents (Brynjolfsson et al., 2023). The same study indicates that having access to the AI indicated instrument resulted in an average productivity increase of 14%, as measured by the number of problems solved per hour. Furthermore, the integration of AI facilitated the dissemination of best practices among more proficient workers, thereby assisting new employees in accelerating their learning process (Brynjolfsson et al., 2023). Lane et al. (2023) also leads to similar conclusions, showing that employees and employers in the financial and manufacturing sectors have a largely positive perception of the influence of AI on productivity, with about 80% of AI users reporting improvements in job performance, while only 8% observed a negative impact.

Estimates of the impact of AI on productivity vary widely. Generative AI could increase US labor productivity by almost 1.5 percentage points per year over a decade, which could boost global GDP by 7% per year (Hatzius et al., 2023). However, its effect depends on task complexity and work automation. Other studies suggest that AI could contribute 0.1–0.6% per year to productivity growth by 2040, with automation technologies potentially adding 0.5–3.4 percentage points per year to the labor productivity growth rate (Chui et al., 2023).

Moreover, the impact of AI on the labor market intersects with broader economic growth frameworks. For example, the Solow model emphasizes how technological progress increases productivity primarily through capital deepening, while endogenous growth theories emphasize the role of human capital accumulation and innovation (Aghion & Howitt, 1992). Students' perceptions of their AI-related skills reflect this dimension of human capital; however, the integration of objective economic data is necessary for a more comprehensive analysis.

Damioli et al. (2021) provide empirical evidence that AI patent applications positively influence labor productivity, thus suggesting that firms implementing AI technologies experience enhanced economic performance. Similar findings are also presented in the study conducted by Pillai et al. (2024), who note that AI-based technologies in human resource management can lead to faster decision-making and improved employee performance, though the same study also highlights the fears that employees may feel about the constant adoption of technology.

The transformative effects of AI are not limited to increased productivity, as they also include changes in workplace dynamics and employee well-being. Kereopa-Yorke (2023) discusses the dual nature of the impact of AI, which can upsurge productivity while presenting risks such as technological stress and the erosion of creativity. At the same time, the introduction of AI technologies may increase wage inequality, as the benefits of productivity growths are often disproportionately distributed, favoring high-skilled workers (Klinova & Korinek, 2021; Lu & Zhou, 2019).

However, it is essential to consider the concept of the "productivity J-curve" in this context (Brynjolfsson et al., 2021), which shows that new technologies, especially general-purpose technologies, lead to productivity gains only after a period of investment in complementary intangibles such as business processes and new skills. To achieve substantial productivity gains, the widespread adoption of electricity and the initial wave of computers required several decades. Once again, concerns regarding job displacement, institutional inertia, and regulatory challenges may present substantial obstacles in sectors such as medicine, finance, and law (Baily et al., 2023). Nevertheless, in the context of AI, certain factors may accelerate the adoption process. Unlike physical automation, which often requires substantial investments in hardware and infrastructure, cognitive automation can be rapidly deployed through software solutions, this flexibility allowing organizations to implement AI technologies more swiftly and with fewer logistical barriers (Baily et al., 2023). Moreover, the impact of AI on organizations is a complex one, with research showing that exposure to new technologies generally increases job satisfaction by increasing task complexity (Bhargava et al., 2021). However, workers in the gig economy and those who fear job change report dissatisfaction and anxiety (Braganza et al., 2022). The adoption of AI also raises concerns about data privacy and job security, but favors flexibility, creativity, and innovation (Malik et al., 2021). In addition, AI in recruitment reduces human biases, improving hiring efficiency and labor market outcomes (Agan et al., 2023; Li et al., 2024).

2.2. The impact of AI on skills and education

Technology has significantly transformed, and will continue to significantly influence, the perception, requirements and boundaries of traditional work, as well as essential skills. The AI workforce exhibits distinct features in the case of the total employed population, as over 60% of employees hold at least a university degree, and in the top 10 occupations requiring advanced AI skills, this proportion rises to almost 80% for OECD member countries (Green & Lamby, 2023).

The spread of AI technologies necessitates a reassessment of the skill sets needed for success in the labor market (Ban et al., 2024), pointing to a dual transformation of work practices and skill requirements (Margaryan, 2023). Shaikh et al. (2023) argue that advances in AI require a continuous exchange of knowledge, which in turn increases employee productivity, especially in sectors such as healthcare, where the acquisition of new skills is essential (Shaikh et al., 2023).

Some types of tasks are more susceptible to automation than others, and the impact on human skills will depend on the specific requirements of such tasks. Research suggests that while AI may replace some jobs, it also creates demand for highly-skilled positions, especially in IT and analytics and also shows that critical thinking, creativity and problem solving are becoming increasingly valuable (Lu & Zhou, 2019; Acemoğlu & Restrepo, 2018). In this context of rapid digital progress, the time available for reskilling the workforce has shortened, requiring skills adaptation across all occupational sectors over the next five years, affecting both new and existing workers (Morandini et al., 2023). Moreover, lifelong learning becomes essential for adapting to changes in the labor market (Johnson et al., 2021).

Although the level of automation and the type of intelligence required may vary significantly between different jobs, once AI takes over repetitive tasks, the importance of activities that cannot be replaced by technology, namely those involving "thinking" and "feeling" skills, will increase (Huang et al., 2019). In this context, the evolution of companies in the near future will depend to a considerable extent on the ability of employees to adapt and hone their skills, which will lead to a redistribution of tasks towards activities requiring "feeling skills" rather than job losses (Strack et al., 2021). The findings also indicate that in order to adapt and thrive in a future marked by technological progress, individuals need to be able to emphasize a balance between transversal and digital skills (Zhironkin & Ezdina, 2023).

Thus, future skills will need to focus more on those facilitating the success in the digital environment (Badea et al., 2024). While some professions will require technical skills, most requirements will be geared towards soft skills – aspects that technology cannot fulfill (Marr, 2022). However, such skills are not sufficiently promoted in the current education system, which tends to underestimate their importance by focusing excessively on traditional academic subjects (Marr, 2022).

2.3. The impact of AI on the labor market – risks

The impact of AI on labor demand varies depending on the role of these systems, either as a substitute or as a support for employees. Substitution occurs when AI models take over most or all of the tasks of a job, while complementarity occurs when AI automates only some activities while retaining the need for human input (Baily et al., 2023). AI systems can also support human work by facilitating the performance of new tasks or improving the quality of existing work. In this context, two broad typologies of individuals can be observed in the labor market – some with the ability to adapt to new roles generated by the deployment of AI-based technologies, others who require training and education programs to acquire the necessary skills to collaborate effectively with AI systems (Li et al., 2023).

However, the impact of AI on the labor market cannot be seen as homogeneous across sectors or regions. Thus, industries such as technology, finance, and healthcare are experiencing rapid job growth involving the use of AI, while traditional sectors may face more significant job losses (Acemoğlu et al., 2022). In addition, the impact of AI differs by region, with some regions more susceptible to job losses than others due to differences in the specifics of local industries and workforce skills (Wang, 2023). It is also worth noting that based on recent adoption scenarios, which consider technological developments, economic viability and timeframes for implementation, it is estimated that around 50% of current work activities could be automated between 2030 and 2060, which may bring benefits but also concerns about job losses in some sectors (Chui et al., 2023). Worries also arise from research results indicating that about 80% of US employees could experience at least a 10% change in their work tasks with the introduction of large-scale language models, while about 19% of them could see changes in more than 50% of their activities (Eloundou et al., 2024).

Implementing AI may exacerbate socio-economic disparities, favoring highly educated workers, while the process may increase the risk of unemployment for low-skilled workers (McManus, 2023). Studies estimate that up to a quarter of current jobs could be replaced by AI, which could affect an estimated 300 million full-time jobs worldwide (Hatzius et al., 2023). However, some studies suggest that AI will primarily improve jobs rather than replace them, with significant effects in high- and middle-income countries (Gmyrek et al., 2023).

If one were to prioritize the risks associated with AI, the most prominent concern that would likely arise is the potential for human job displacement (Acemoğlu et al., 2022), seconded by others among which can be mentioned: exacerbation of social inequalities (Zajko, 2022; Acemoglu, 2024), compromising the right to privacy (Malik et al., 2021; Elliott & Soifer, 2022) and becoming an existential threat to humanity (Bonneau-Diesce & Chan, 2022).

It should not be overlooked that there is research showing that AI should be viewed from the complementarity perspective. Thus, Vaccaro et al. (2024), based on a systematic review evaluating the performance of humans, AI and combinations of the two, show that although human-IA collaboration is promising, in general, combinations of the two underperformed the most efficient entity taken separately, with losses in decision-making tasks and gains in creative ones. Results vary significantly, and the effectiveness of collaboration depends on which of human or AI outperforms, highlighting the need for further research to optimize these systems (Vaccaro et al., 2024). At the same time, beyond the risks, the potential of AI to support and enhance human work should be considered, emphasizing its role as a tool that complements, rather than replaces human skills. This view is supported both by favorable perceptions of workers and by the increasing use of AI in tasks requiring human-machine collaboration (Wang & Lu, 2025). The integration of AI is associated with significant benefits in terms of innovation, sustainability and operational efficiency, especially in areas such as green entrepreneurship and green technologies, where workers perceive it as an added value rather than a threat (Wang & Lu, 2025). However, AI-led productivity growth will also bring with it a number of complex challenges (Ioan-Franc & Gâf-Deac, 2024). Social protection programs and tax policies may require substantial revisions to reduce the social impact of labor market disruptions and to equitably distribute the benefits generated by AI, thereby preventing an excessive concentration of resources (Baily et al., 2023). In addition to these economic challenges, it is also essential to address associated risks, such as increased misinformation and social polarization, phenomena that can affect democratic stability, as well as security risks (Baily et al., 2023).

Thus, while the integration of AI into the labor market presents substantial opportunities to increase productivity and operational efficiency, it also raises important issues in terms of employee well-being, job security and changing the nature of work itself. The literature points to a complex interplay between the benefits of artificial intelligence and the challenges it raises, requiring a balanced approach to its implementation. From a practical point of view, the modern knowledge and technology-based economy is changing traditional job profiles, highlighting the need for new technological skills. In this context, organizations need to adopt workforce development strategies that include skills upgrading and effective knowledge management (Malik et al., 2021).

3. Research methodology

Based on the findings already discovered in the literature, our research aims to analyze the links between individuals' perceptions of AI and its impact on the labor market, focusing on the perception of personal skills in AI, how perceived risks influence the access to the labor market, as well as on the perspective of young people on the changes in the structure of labor demand and labor market conditions in Romania, thus contributing to a more detailed understanding of the economic effects of AI technologies and the digital transition. Our research was designed to explore the perspectives of a specific group characterized by young age (students), high educational attainment and advanced internet skills. Given that young people are the ones who will directly experience future labor market transformations (Hill et al., 2019), it is essential to explore their expectations and perceptions. Therefore, this study prioritizes the subjective perceptions of business students as potential employees or entrepreneurs. Although our research does not directly reflect objective market outcomes, it presents perceptions that can be used in shaping educational or policy solutions.

Following literature review, the following assumptions were formulated:

H1: Perception of acquired personal AI competences influence perception of the overall impact of AI.

H2: The influence between Perception of acquired personal AI competences and Perception of the overall impact of AI is moderated by the potential risk of not finding a job because of AI.

H3: Perception of the overall impact of AI influences Perception of the impact of AI on the labor market.

H4: Perception of the overall impact of AI influences Perception of increased organizational efficiency as a result of using AI.

H5: Perception of the overall impact of AI influences Perception of increased labor productivity as a result of using AI.

H6: Perception of increased labor productivity as a result of using AI influences Perception of the impact of AI on the labor market.

H7: Perception of increased organizational efficiency as a result of using AI influences Perception of AI's impact on the labor market.

This study was conducted as an empirical investigation employing a quantitative survey, administered via online interviews in November 2024. The sample consisted of business students from the Bucharest University of Economic Studies, selected through a convenience sampling method. A total of 344 respondents successfully completed the online survey.

A five-point Likert scale, ranging from 1 ("to a very small extent") to 5 ("to a very great extent"), was used for all items. The survey was designed around the following primary constructs: *AI Overall Impact* (reflective construct, three items, describes perceived AI impact in terms of positive effects on society overall), *Competences in Adapting to and Using AI* (reflective construct, two items, describes perceived skills gained to effectively leverage AI), *AI Impact on Organizational Efficiency* (reflective construct, three items, describes perceived impact of AI on enhancing decision-making, workplace flexibility, and job satisfaction), *AI Impact on Labor Productivity* (reflective construct, three items, describes perceived AI impact on increasing labor efficiency by decreasing labor time and monotony), and *AI Impact on the Labor Market* (reflective construct, three items, highlights perceived optimism about the labor market's ability to adapt to AI through increased flexibility and the creation of new jobs). Additionally, a single-variable construct was employed to assess the *Potential Risk of Not Finding Jobs due to AI* (outlines perceived concern that AI may displace traditional jobs), along with an item measuring the *Frequency of AI Technology Usage*. Most of the respondents admitted that they are using AI technologies on daily basis (36%) or at least weekly (44.2%), while only 1.2% admitted that they never used AI technologies.

For a better understanding of the tested assumptions, as well as the relationships among the constructs, a graphical representation has been provided, as depicted in Figure 1.

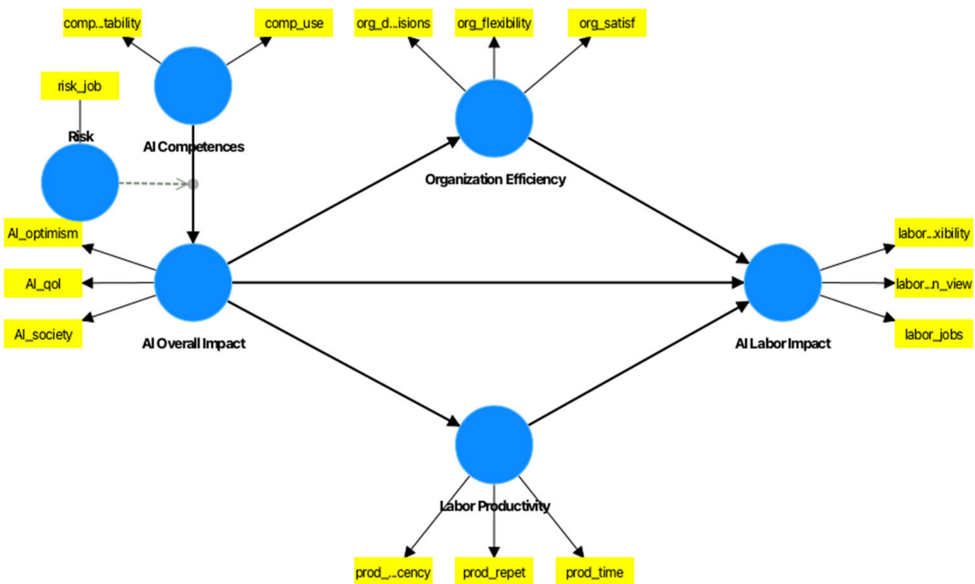

Figure 1. The relationship among the constructs (source: authors own calculations using SmartPLS)

Descriptive statistics of the items used in the model are shown in Table 1.

Table 1. Descriptive statistics (n = 344) (source: authors'own calculations)

Item	Mean	Std. Deviation	Skewness (Std. Error)		Kurtosis (Std. Error)	
AI_society	3.42	1.125	–.410	0.131	–.571	0.262
AI_qol	3.37	1.163	–.351	0.131	–.662	0.262
AI_optimism	3.42	1.183	–.339	0.131	–.734	0.262
comp_use	3.66	1.157	–.642	0.131	–.379	0.262
comp_adaptability	3.21	1.160	–.117	0.131	–.850	0.262
org_decisions	3.50	1.171	–.461	0.131	–.679	0.262
org_flexibility	3.60	1.099	–.492	0.131	–.486	0.262
org_satisf	3.40	1.157	–.390	0.131	–.611	0.262
prod_repet	3.87	1.203	–.803	0.131	–.418	0.262
prod_time	3.92	1.253	–.941	0.131	–.215	0.262

End of Table 1

Item	Mean	Std. Deviation	Skewness (Std. Error)		Kurtosis (Std. Error)	
prod_efficency	3.65	1.229	–.502	0.131	–.846	0.262
labor_flexibility	3.45	1.132	–.466	0.131	–.437	0.262
labor_gen_view	3.44	1.174	–.425	0.131	–.717	0.262
labor_jobs	3.07	1.350	–.094	0.131	–1.178	0.262
risk_job	3.20	1.238	–.225	0.131	–.815	0.262

The data were analyzed using SPSS version 25 and SmartPLS version 4. Hypothesis testing was conducted through structural equation modeling, utilizing a partial least squares (PLS) approach. One should consider that while PLS-SEM effectively captures the hypothesized relationships, it does not account for potential endogeneity, such as bidirectional effects between organizational effectiveness and the overall impact of AI, which could influence outcomes.

4. Results and discussions

4.1. Analysis of measurement model

The measurement model analysis assesses relationships between observed and latent variables (Hair et al., 2019), while reflective constructs were evaluated for validity and internal consistency as summarized in Table 2.

Table 2. Constructs and items (source: authors' own calculations using SmartPLS)

Construct	Item	Measure	Loading	Cronbach's alfa	CR	AVE
AI Competences	comp_adaptability	Acquired competences to be able to cope with AI challenges	0.887	0.753	0.756	0.890
	comp_use	Acquired competences to use effectively AI	0.903			
AI Overall Impact	AI_society	Perceived AI impact on improving society	0.869	0.867	0.867	0.919
	AI_qol	Perceived impact on improving quality of life	0.901			
	AI_optimism	Perceived overall optimism regarding AI	0.896			
Labor Productivity	prod_repet	Perceived impact of AI on reducing repetitive and monotonous tasks	0.866	0.856	0.857	0.912
	prod_time	Perceived impact of AI on reducing labor time	0.895			
	prod_efficency	Perceived impact of AI on labor efficiency	0.881			
Organization Efficiency	org_decisions	Perceived AI impact on decision-making process	0.846	0.795	0.795	0.880

End of Table 2

Construct	Item	Measure	Loading	Cronbach's alfa	CR	AVE
Organization Efficiency	org_flexibility	Perceived AI impact on workplace flexibility	0.843	0.795	0.795	0.880
	org_satisf	Perceived AI impact on workplace satisfaction	0.836			
AI Labor Impact	labor_flexibility	Perceived AI impact on labor market flexibility	0.854	0.772	0.784	0.867
	labor_gen_view	Overall perceived AI impact on the future of labor market	0.837			
	labor_jobs	Perceived AI impact on new jobs development	0.791			

All factor loadings exceed the minimum threshold of 0.70, satisfying the established criteria to demonstrate convergent validity (Hair et al., 2010). Reliability was assessed using Cronbach's alpha, which must surpass the threshold of 0.70 for confirmatory purposes (Henseler & Sarstedt, 2013). All Cronbach's alpha values exceeded 0.7, confirming the internal consistency of the model. Additionally, all AVE (Average Variance Extracted) values were greater than 0.5, indicating an adequate model fit (Chin, 1998) and further supporting the constructs' convergent validity. Composite reliability (CR) values were also above 0.70, reinforcing the reliability of the constructs (Hair et al., 2010).

Discriminant validity of the constructs was assessed using the Fornell–Larcker criterion (Fornell & Larcker, 1981), as presented in Table 3. According to the Fornell–Larcker criterion, the AVE value for each latent variable exceeds the correlation coefficients between that variable and all other distinct variables, supporting discriminant validity.

Table 3. Discriminant validity analyses (Fornell–Larcker) (source: authors' own calculations using SmartPLS)

	AI Competences	AI Labor Impact	AI Overall Impact	Labor Productivity	Organization Efficiency	Risk
AI Competences	0.895					
AI Labor Impact	0.468	0.828				
AI Overall Impact	0.531	0.657	0.889			
Labor Productivity	0.507	0.634	0.596	0.881		
Organization Efficiency	0.529	0.634	0.748	0.668	0.842	
Risk	0.170	–0.036	0.046	0.163	0.171	1.000

To further ensure that the constructs are not conceptually similar, the HTMT criterion was applied. Following Henseler et al. (2016), a threshold value of 0.9 was used. As shown in Table 4, all HTMT values were below 0.9, except one value which is 0.9, confirming the discriminant validity of the constructs.

Table 4. Discriminant validity analyses – Heterotrait–Monotrait (HTMT) (source: authors' own calculations using SmartPLS)

	AI Compe-tences	AI Labor Impact	AI Overall Impact	Labor Produc-tivity	Organi-zation Efficiency	Risk	Risk x AI Compe-tences
AI Competences							
AI Labor Impact	0.604						
AI Overall Impact	0.656	0.796					
Labor Productivity	0.636	0.768	0.690				
Organization Efficiency	0.685	0.799	0.900	0.811			
Risk	0.199	0.126	0.050	0.178	0.192		
Risk x AI Competences	0.284	0.316	0.317	0.319	0.371	0.076	

The collinearity levels of the items within the measurement model were evaluated for the dataset. All items demonstrated variance inflation factor (VIF) values below the threshold of 5, as recommended for collinearity analysis (Sarstedt et al., 2017).

4.2. Structural model analysis

A bootstrap procedure was employed to test the proposed hypotheses and examine the relationships among the latent variables (Hair et al., 2019; Ringle et al., 2022). The goodness of fit for the saturated model is deemed acceptable. The standardized root mean square residual (SRMR) of the saturated model is 0.062, satisfying the recommended threshold (<0.08). *AI Overall Impact, Labor Productivity* and *Organization Efficiency* explain 53.3% of the variance of *AI Labor Impact* (R^2 = 0.533). *AI Competences* explains 31.4% of the variance of *AI Overall Impact* (R^2 = 0.314), while *AI Overall Impact* explain 35.5% of the variance of *Labor Productivity* (R^2 = 0.355) and 56% of the variance of *Labor Productivity* (R^2 = 0.566). These results (see Figure 2) define a moderate prediction power of the structural model.

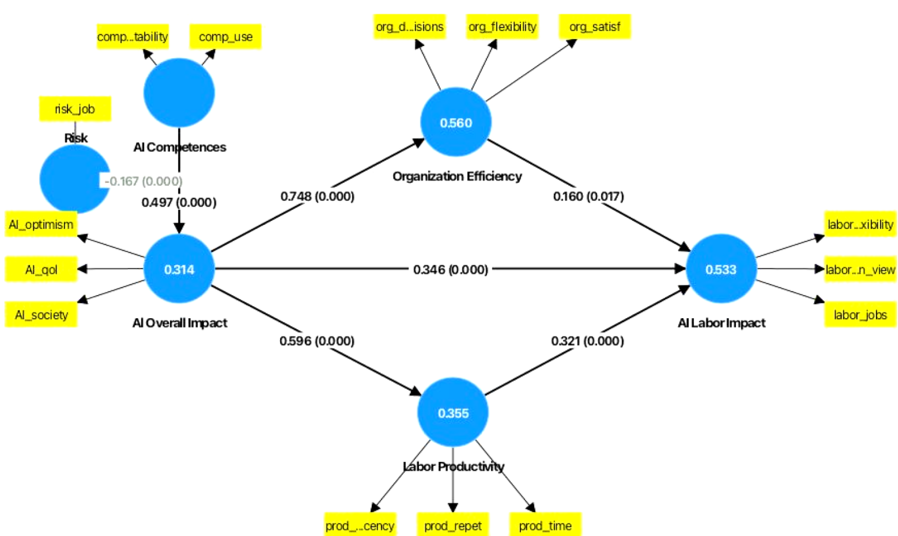

Figure 2. Results of structural model analysis (source: authors' own calculations using SmartPLS)

The results of the structural model analysis including path coefficients (beta), t statistics, and corresponding p-values were shown in Table 5. According to these results all seven hypotheses are statistically significant in the context of the current research.

Table 5. Results of structural model analysis (direct and moderating effects) (source: authors own calculations using SmartPLS)

Paths	Beta	SD	T stat.	P values	95% CI		Hypotheses
					LL	UL	
AI Competences → AI Overall Impact	0.497	0.047	10.481	0.000**	0.398	0.583	H1 supported
AI Overall Impact → AI Labor Impact	0.346	0.065	5.316	0.000**	0.222	0.478	H3 supported
AI Overall Impact → Labor Productivity	0.596	0.038	15.761	0.000**	0.514	0.664	H5 supported
AI Overall Impact → Organization Efficiency	0.748	0.027	27.669	0.000**	0.688	0.795	H4 supported
Labor Productivity → AI Labor Impact	0.321	0.058	5.495	0.000**	0.205	0.435	H6 supported
Organization Efficiency → AI Labor Impact	0.160	0.067	2.391	0.017*	0.027	0.289	H7 supported
Risk x AI Competences → AI Overall Impact	–0.167	0.046	3.665	0.000**	–0.256	–0.078	H2 supported

Note: $^{**}p < 0.01$, $^{*}p < 0.05$, based on a two-tailed test; $t = 1.96$.

As shown in Table 5, perception of the overall impact of AI on society as a whole has a significant positive effect on how respondents perceive the impact of AI on the labor market. Specifically, students' view on the overall benefits of AI drive their perspective on the positive impact of AI on labor market ($\beta = 0.346$, t-value = 5.316, $p < 0.001$). Thus, our research is in line with that of Nguyen et al. (2023), which showed that young people see AI as a catalyst for job creation, especially in fields that require advanced skills and innovative thinking (Nguyen et al., 2023). As AI technologies continue to advance, they are expected to generate new roles that did not previously exist, thus contributing to the expansion of the labor market. This view is supported by research that highlights the dual nature of AI's impact – while technologies and digitalization can displace those low-skilled jobs, they create opportunities in high-skilled sectors (Shan, 2023). In addition, AI's ability to amplify human skills is viewed favorably, with the potential to increase productivity and efficiency, which beneficially impacts the labor market (Xu et al., 2023).

Our model reveals that the strongest effect is observed between the perception of the overall impact of AI and its impact on organizational efficiency. The findings suggest that students perceive the overall benefits of AI as a significant driver of enhanced organizational efficiency ($\beta = 0.748$, t-value = 27.669, $p < 0.001$). Consistent with this finding, the analysis indicates a strong influence of the perceived overall impact of AI on perceptions of its effect on labor productivity. Specifically, students believe that the positive overall effects of AI implementation will also manifest in enhanced productivity ($\beta = 0.596$, t-value = 15.761, $p < 0.001$). However, one can notice that the perceived impact of AI on organizational efficiency, although statistically significant, does not strongly influence the perception of AI impact on labor market (β = 0.160, t-value = 2.391, $p < 0.05$). The same result is valid for the relationship between perception of impact of AI on labor productivity and the perceived impact of AI on labor market. There is a statistically significant influence of labor productivity construct on labor market construct, but this influence is rather week (β = 0.321, t-value = 5.405, $p < 0.001$).

Students' perceptions of the relationship between AI and organizational effectiveness are becoming increasingly relevant as AI technologies become more deeply integrated into various sectors of the economy. Many recognize that AI has significant potential to improve organizational performance by optimizing internal processes and enhancing decision-making capabilities. This view aligns with recent research findings, which suggest that the use of AI can make a substantial contribution to enhancing organizational competitiveness by providing businesses with the tools to quickly adapt to market changes and streamline their operations (Iwuanyanwu, 2021). In addition, students also place particular emphasis on the essential role of organizational support in the process of effective integration of AI technologies. Perceived organizational support can significantly contribute to reducing the negative impact of AI on employee morale and job satisfaction, thus highlighting the importance of a positive work environment to fully reap the benefits of these technologies (Xu et al., 2023). Moreover, research shows that organizations that use AI in HR have more effective recruitment and higher productivity, and that adapting to AI is associated with higher job satisfaction and lower staff turnover (Zhang, 2024). Positive perceptions of AI also contribute to higher organizational trust and increased employee engagement (Zhang, 2024).

Furthermore, our analysis focused on the mediating effects of *Perception of increased labor productivity* and *Perception of increased organizational efficiency* on the relationship between *Perception of the overall impact of AI* and *Perception of the impact of AI on the labor market*. As presented in Table 6, both constructs exhibit statistically significant mediating effects; however, the magnitude of these effects is relatively weak. Students who perceive a greater impact of AI on labor productivity tend to attribute slightly more significance to the influence of AI's overall impact on their perception of AI's effect on the labor market (β = 0.191, t-value = 5.007, $p < 0.001$). This evaluation becomes weaker and slightly less statistically significant when considering how students who perceive a greater impact of AI on labor productivity attribute significance to the overall impact of AI on their perception of its effect on the labor market (β = 0.120, t-value = 2.341, $p < 0.05$).

Table 6. Results of structural model analysis (mediating effects) (source: authors' own calculations using SmartPLS)

Paths	Beta	SD	T stat.	P values	95% CI		Mediating effect
					LL	UL	
AI Overall Impact → Organization Efficiency→ AI Labor Impact	0.120	0.051	2.341	0.019*	0.020	0.219	confirmed
AI Overall Impact → Labor Productivity → AI Labor Impact	0.191	0.038	5.007	0.000**	0.121	0.0271	confirmed

Note: $^{**}p < 0.01$, $^{*}p < 0.05$, based on a two-tailed test; t = 1.96.

The effect of AI on productivity can manifest itself through its ability to optimize operations and reduce costs, which can lead to an increase in output without a commensurate expansion of the workforce (Jawaid & Ahmed, 2023). In this context, scholars believe that as organizations integrate AI technologies, they will achieve significant improvements in efficiency, which will enable them to become more competitive in the marketplace (Ayoko, 2021). This perception is supported by research suggesting that organizations adopting AI can enhance service quality and improve operational coordination, which ultimately contributes to superior financial performance (Shan, 2023).

When it comes to the assumption that *Perception of acquired personal AI skills* influence *Perception of the overall impact of AI (H1)* the results shows that this hypothesis is confirmed. Students' perceptions of their acquired AI skills influence their views on AI's overall impact on society. This effect is statistically significant and moderately strong ($\beta = 0.497$, t-value = 10.481, $p < 0.001$).

Furthermore, our study analyzed the moderating effect of perceived risk of not finding a job due to AI on the relationship between acquired skills and perceived AI overall impact. The results confirmed the H2: The influence between *Perception of acquired personal AI skills* and *Perception of the overall impact of AI* is moderated by the *risk of not finding a job because of AI* ($\beta = -0.167$, t-value = 3.665, $p < 0.001$). The results indicate that students who perceive a high risk of job loss or difficulty finding employment due to AI are less likely to attribute significant influence to acquired AI skills on their perception of AI's overall impact.

While there is an urgent need to prepare the workforce for the new roles that will emerge with the development of AI technologies (Acemoglu et al., 2022), recent studies also show that young people have the ability to recognize the potential for AI to replace certain jobs, particularly those involving repetitive or routine tasks that can be effectively automated by emerging technologies (Arif, 2024). Moreover, Holm and Lorenz (2022) show that the impact of AI on workers depends on how the technology is used and their skill level. For high and medium-skilled workers, the use of AI in decision support can improve skills by supporting high-performance work practices such as teamwork and job rotation. Conversely, when AI orders workers, it limits the use of skills, reduces the quality of work and increases pace of work constraints, decreasing the autonomy of skilled workers and providing fewer learning opportunities for medium-skilled workers Holm and Lorenz (2022).

In addition, the need for specialized training in areas associated with AI is a major theme in students' views on their training for the job market. Many of them express concern that the education they are receiving does not sufficiently prepare them for the demands of a labor market that is becoming increasingly oriented towards the use of AI technologies (Ruiz-Talavera et al., 2023). This gap in academic training underlines the need for a review of the educational curriculum to integrate curricula that incorporate essential AI competencies to ensure that graduates will be equipped with the necessary skills to meet the challenges of a labor market transformed by new technologies (Tominc & Rožman, 2023). Thus, it is crucial that higher education institutions respond to these needs by offering training programs that prepare young professionals for a future in which technological skills and the ability to manage data will become fundamental elements of success in the labor market.

5. Conclusions

Our survey revealed complex and nuanced perspectives of students on the effects of the integration of AI into the labor market. Overall, the majority of respondents showed a favorable attitude, emphasizing the opportunities for increased productivity in organizations. However, concerns about possible job displacement and widening social inequalities were also highlighted, underlining the need for a continued debate on these topics.

AI could bring significant changes to our lives and work. Optimistically, it could boost productivity and help workers move into better paid roles. Conversely, a pessimistic view suggests that AI could lead to job elimination, pushing workers into less desirable roles and increasing demand for a small number of highly skilled workers while increasing organizations' profits. These views reflect a deep awareness that AI has a dual impact on the labor market, being perceived as both a driver of positive change and a risk factor. The recognition of the transformative potential of AI, together with the growing demand for an educational preparation adapted to these rapid changes, underlines a proactive and responsible attitude of students who wish to prepare themselves for a professional future characterized by an increasingly technological economic landscape. Thus, this attitude reflects the urgent need to integrate advanced competences in AI and related technologies into educational curricula to ensure that future professionals will be able to successfully navigate in a rapidly changing labor market influenced by technological developments.

One must notice that young people's perspectives highlight the need to rethink and reassess how work should be restructured in the context of human well-being to ensure long-term sustainability on the labor market. With these considerations in mind, it is paramount for the policy makers to develop educational policies addressing the vocational training needs of young people in order for them to be equipped to meet the challenges and opportunities of AI. Our study also recommends a broader research approach for the future, including investigating the perceptions of other demographic groups and conducting longitudinal studies to monitor how these perceptions vary over time. The topic of the impact of AI on the labor market is one with both short term and long-term implications. Further longitudinal research is therefore needed to assess lasting changes such as income redistribution or job reallocation between sectors.

This study is subject to several limitations arising from the analytical approaches and investigative methods employed. The first limitation stems from the use of a convenience sample. While the sample size was relatively large, all participants shared a common background, as they were selected from the same university. While our findings provide a valuable insight into the views of business students, they also reflect a specific demographic and institutional context, highlighting the need for more extensive studies addressing the macroeconomic heterogeneity of the Romanian labor market. Incorporating a more diverse range of participants in future research may enhance the generalizability and robustness of the study's findings. Another limitation of our research is that students' subjective perceptions may hinder direct inference about real market conditions, such as employment or productivity changes, which may differ due to economic, technological or political factors. Mixed methods approaches could fill this gap in future research. Furthermore, another potential limitation derives from the reliance on self-reported variables, as personal assessments are often susceptible to bias. To address this issue, future research could consider incorporating more objective measures or employing mixed-method approaches to complement and enhance the analysis.

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Author contributions

The authors conceived the study and were responsible for the design of the methodology, for data collection and interpretation.

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