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ARTIFICIAL INTELLIGENCE IN WARTIME UKRAINE: BUSINESS ADOPTION, INVESTMENT INTENTIONS, AND LABOUR-MARKET EXPECTATIONS

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Abstract. This *study examines* the factors that determine whether firms adopt AI and are ready to invest, and explores labour-market and employment-related expectations in wartime Ukraine. *Methodology.* The study is based on original survey data collected in a frontline region of Ukraine during wartime. The sample comprises 300 respondents from various socio-economic backgrounds. The empirical analysis uses descriptive statistics, nonparametric tests and ordinal and binary logistic regression models. The study also presents an original composite AI-readiness index (ranging from 0 to 100) which assesses preparedness for AI adoption by integrating organisational, behavioural and investment-related dimensions. All statistical analyses were conducted using R statistical software. *Results.* The findings suggest that organisational readiness plays a key role in determining current AI adoption and firms' willingness to invest in AI. Expected efficiency gains from AI greatly increase investment intentions, while prior AI adoption has a cumulative effect on further investment readiness. Furthermore, adaptive capacity is positively associated with more favourable perceptions of AI in wartime. The fear of losing one's job to AI is significantly higher among employees engaged in routine-intensive tasks, but this effect is significantly reduced by higher education, which confirms the moderating role of human capital. Perceived AI-driven efficiency gains vary considerably across social groups, with citizens being more optimistic than business representatives and workers. The proposed AI-readiness index reveals significant differences in AI readiness among firms of different sizes, sectors, and geographic scopes. *Practical implications.* The results are relevant to business decision-making and economic policy in wartime. The findings show that the adoption of artificial intelligence in business is primarily determined by organisational capacity, institutional support and adaptive capability rather than technological accessibility alone. For firms, this highlights the importance of taking a systemic approach to the use of artificial intelligence in strategic planning. In frontline regions, human capital policy – including digital education, reskilling and regional co-operation between enterprises and educational institutions – is particularly relevant, as it can support economic adaptation and mitigate employment-related risks. *Value/Originality.* This article makes a contribution to the body of research on the adoption of artificial intelligence and employment-related perceptions under wartime conditions. Unlike previous empirical studies, which were conducted in contexts of institutional stability and predictable market environments, this study examines decision-making related to artificial intelligence in a border region of Ukraine that is close to active hostilities. Here, economic expectations, investment behaviour and perceptions of employment risks are all shaped by ongoing security threats. The study's originality lies in its integration of firm-level determinants of artificial intelligence (AI) adoption with individual-level economic expectations and employment-related responses. By incorporating organisational readiness, investment intentions and labour-market perceptions into a single analytical framework, the article broadens the scope of existing AI adoption approaches by considering organisational, economic and socio-behavioural factors in a wartime context.

Keywords: artificial intelligence, AI adoption, AI readiness, investment intentions, labour-market expectations, employment risk perceptions.

JEL Classifications: O33, J24, L26

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1. Introduction

Against the backdrop of ongoing digital transformation, artificial intelligence is evolving from a standalone technological tool into a systemic driver of economic development. It is shaping productivity, business competitiveness and the transformation of labour markets. However, the adoption of AI remains uneven, depending on factors such as organisational readiness, human capital availability, trust levels, and the institutional environment. These dependencies are particularly important in situations of uncertainty, where economic decisions are made in environments characterised by high risk and limited resources. For Ukraine, these dependencies are of particular significance under martial law, where economic decisions must be made despite substantial security and resource constraints. On the one hand, the war intensifies the need to improve business process efficiency, managerial flexibility and organisational adaptability. On the other hand, it highlights concerns relating to data security, labour shortages and increased social anxiety. These concerns may limit investment in digital technologies and lead to a cautious or ambivalent attitude towards artificial intelligence among businesses, employees and society as a whole.

Despite the growing number of studies devoted to the implementation of artificial intelligence (AI) and its impact on labour markets, the literature still lacks a comprehensive analysis of firms' readiness to invest in AI and of expectations regarding its employment-related effects across different social groups in wartime Ukraine. This study therefore aims to analyse the factors shaping firms' readiness to adopt and invest in AI, and to examine expectations regarding the labour market and employment effects of AI in wartime Ukraine.

The study adopts an institutional and behavioural perspective, conceptualising the adoption of artificial intelligence as a multi-level process shaped by the interaction of organisational resources, expected economic benefits, trust and individual adaptive capacity.

2. Literature Review

2.1 Artificial Intelligence and its Adoption in Business

Contemporary research no longer views the adoption of artificial intelligence (AI) in business as a purely technological solution. Instead, it is considered a complex organisational process that depends on a firm's strategic, resource-based and cognitive readiness (Wang, 2019; Haenlein & Kaplan, 2019; Soni et al., 2020; Martins, 2025). Artificial intelligence provides businesses with the opportunity to optimise processes, improve the quality of managerial decision-making and develop new products and services. However, realising this potential requires purposeful organisational change (Kolomiyets et al., 2025).

Despite the growing interest in artificial intelligence, many firms are still in the early stages of adopting it. According to studies by MIT Sloan and BCG, many organisations have a discrepancy between their stated strategic ambitions for AI and the actual extent to which they use it (Ransbotham et al., 2017; Ransbotham et al., 2025). Most corporate AI projects deliver only minor efficiency improvements rather than radical business model transformations, and AI is often only used at an operational level (Davenport & Ronanki, 2018; Borges et al., 2020). The key barriers to scaling up remain a shortage of qualified personnel, organisational inertia and risks relating to data confidentiality (Benbya, Davenport & Pachidi, 2020).

In this context, the concept of organisational readiness for the adoption of artificial intelligence has received increasing attention. Research indicates that successful AI adoption and use are shaped by the interaction of technological resources, managerial support, human capital and organisational flexibility (Alsheibani, Cheung & Messom, 2018; Jöhnk, Weißert & Wyrtki, 2021; Baabdullah et al., 2021; Perez-Andersson et al., 2024; Flavián et al., 2022; Lichtenthaler, 2019; Bharadiya, Thomas & Ahmed, 2023). Further empirical studies emphasise that investments in artificial intelligence are only effective when technological solutions are combined with appropriate organisational capabilities and adapted business processes, rather than through the isolated adoption of individual tools (Wamba-Taguimdje et al., 2020). In the Ukrainian context, Kubatko et al. (2024) report a generally positive attitude towards the potential of artificial intelligence among businesses, while also identifying algorithmic bias as a significant obstacle. This highlights the importance of establishing ethical standards to promote fairness and trust.

Taken together, these results allow AI readiness to be conceptualised as a multidimensional construct that combines technological resources, human capital, and organisational flexibility, and shapes both the current use of artificial intelligence and companies' readiness for further investment in these technologies.

2.2. AI and Economic Development

Contemporary literature increasingly discusses economic development in the context of digital transformation through the effects of artificial intelligence on productivity, production structures, and resource allocation efficiency (Vinuesa et al., 2020; Sergun et al., 2025; Dubyna et al., 2025). The impact of AI on social development trajectories is characterised as ambivalent: while it can support progress towards achieving many of the Sustainable Development Goals, it can also exacerbate risks of inequality and bias

(Vinuesa et al., 2020; Yeh et al., 2021). In this regard, macroeconomic outcomes are shaped not only by technological potential but also by social receptivity to innovation. Empirical studies demonstrate that public trust and individuals' propensity to accept new technologies have a substantial impact on the economic returns from AI investment. Despite the presence of advanced digital infrastructure, the effects of AI adoption remain constrained in environments characterised by low levels of trust and inadequate digital competencies (Androshchuk, 2021; Brauner et al., 2023; Vu & Lim, 2022). Perceptions of artificial intelligence are shaped by both expected economic benefits and the extent to which the technology is perceived as transparent and fairly regulated (Brauner et al., 2023; Robles & Mallinson, 2023).

At the macroeconomic level, there has been an increasing focus on the role of the institutional and legal environment in shaping the long-term effects of artificial intelligence. Research confirms that economic growth associated with artificial intelligence investments depends on more than just access to technology; it also hinges on the quality of regulation and the stability of governance institutions (Saba & Ngepah, 2024; Reiter et al., 2026). Well-designed regulatory frameworks enhance the predictability of rules and facilitate the adoption of technologies (Corea et al., 2022; Robles & Mallinson, 2023). In this context, models of artificial intelligence governance at both the supranational and national levels have gained particular importance. The European Union's unified regulatory framework aims to reconcile incentives for innovation with safety considerations and the protection of citizens' rights (European Parliament and Council of the European Union, 2024). At the policy level, Ukraine has taken steps towards institutionalising artificial intelligence governance by adopting strategic and programme documents (The Order of the Cabinet of Ministers of Ukraine "On Approval of the Concept for the Development of Artificial Intelligence in Ukraine"; The Order of the Cabinet of Ministers of Ukraine "On Approval of the Action Plan for the Implementation of the Concept for the Development of Artificial Intelligence in Ukraine for 2025–2026"). Despite the existence of these strategic documents, regulatory fragmentation persists, creating a certain degree of legal uncertainty for economic agents (Halaburda et al., 2025). In the Ukrainian context, the regulation of artificial intelligence is further complicated by martial law conditions, intensifying concerns relating to data security and trust in digital solutions (Tarasenko et al., 2024; Androshchuk, 2021; Oliinyk, 2025).

Thus, the economic effects of artificial intelligence are shaped by the interaction between technological innovation and institutional frameworks. Not only do regulation and public trust determine the permissible boundaries of AI use, they also influence the expectations and adaptive capacity of economic agents.

2.3 Artificial Intelligence, Work, and Employment

The adoption of artificial intelligence (AI) is reshaping the nature of work, creating new opportunities for increased productivity and raising concerns among workers. Recent studies describe the impact of AI on the labour market as a multidimensional transformation, with tasks and skills becoming the primary units of change. Therefore, assessing the consequences of technological innovation requires consideration of the structure of work activities and the heterogeneity of occupational roles (Frank et al., 2019; Lane & Saint Martin, 2021; Brynjolfsson & Mitchell, 2017).

Empirical evidence generally does not support the idea that automation will lead to the rapid and large-scale displacement of workers. Instead, the main changes observed are in the structure of employment and shifting demand for skills, which leads to an uneven distribution of benefits and risks among different groups of workers (Graetz & Michaels, 2018; Georgieff & Hyee, 2022; Humlum, 2022). One of the most consistent findings in this context is the growing demand for workers capable of performing analytical, creative and coordination-intensive tasks, while routine activities are more likely to be automated (Georgieff & Hyee, 2022; Gao et al., 2026).

An increasing amount of organisational research highlights the complementary nature of human labour and artificial intelligence capabilities (Jarrahi, 2018; Makarius et al., 2020; Krakowski et al., 2023). In the age of artificial intelligence, the future of work is often described as a reconfiguration of tasks and skills. The overall outcome depends on the balance between substitution and complementarity, as well as the institutional capacity to support occupational transitions and renew human capital through education and lifelong learning systems (Acemoglu & Restrepo, 2018; Lane & Saint Martin, 2021; Manyika et al., 2017; Portocarrero Ramos et al., 2025). As AI becomes more widely adopted, the need for continuous reskilling is increasingly recognised as a key way to mitigate the risks of technological unemployment and strengthen individuals' competitiveness in the labour market (Manyika et al., 2017; Coombs et al., 2020). Research indicates that the impact of AI on employment varies and is largely influenced by the nature of the tasks performed, educational level, and workers' ability to adapt to technological change.

A review of contemporary literature suggests that the adoption of artificial intelligence (AI) is a multi-level process influenced by organisational, institutional and individual factors. These approaches together form the conceptual basis of this study, enabling an empirical analysis of the determinants of AI readiness, firms' investment intentions and perceptions of technological change in wartime.

2.4. Research Hypotheses

Based on the literature review and theoretical considerations, the following hypotheses (H1-H6) are proposed and empirically tested in the study:

H1: There is a positive association between a higher level of organisational readiness and the likelihood of adopting AI in business processes.

H2: The higher the perceived potential of AI for improving business efficiency, the more likely firms are to invest in it.

H3: The current adoption of AI is positively associated with firms' readiness to invest in its further use.

H4: The way in which people perceive artificial intelligence in a wartime context is associated with their capacity to adapt to technological change.

H5: The effect of task routineness on the fear of losing one's job to AI is stronger among employees with lower levels of education.

H6: The perceived impact of artificial intelligence on efficiency varies significantly among business representatives, workers and citizens.

3. Methodology

The study is based on a comprehensive theoretical and methodological framework. This framework is intended to explain the factors that drive the adoption of artificial intelligence in wartime, and to assess related economic expectations and perceptions of changes in employment. This approach combines an institutional-behavioural perspective with the logic of digital transformation. This allows the simultaneous consideration of the technological, organisational and social factors that influence business and employee decision-making in wartime. The study integrates theoretical synthesis, empirical measurement and statistical testing of the formulated hypotheses.

The empirical basis of the study was formed through an online survey conducted in Ukraine during martial law, targeting respondents living and working in a border region close to the combat zone. The sample comprised 300 participants, including business representatives, employees and citizens. The survey comprised sections covering experience with AI tools, intentions for further use, expected benefits and investment readiness, as well as socio-demographic and professional characteristics. Most indicators were measured using five-point Likert scales and multiple-choice formats. Descriptive and non-parametric statistical methods were employed to test the hypotheses. All statistical calculations were performed using R statistical software.

4. Findings

Organisational readiness is positively associated with firms' investment intentions in artificial intelligence (AI). Organisational readiness was measured using a composite index that captured the following: firms' perceived AI potential; the importance attributed to staff training; and team awareness of AI technologies. Investment intention, operationalised as the readiness to invest in AI implementation, was treated as an ordinal outcome variable. Spearman's rank correlation revealed a strong positive association between organisational readiness and firms' investment intentions over the next one to three years ($\rho = 0.77$, $p < 0.001$). Descriptive statistics show that the average levels of organisational readiness and investment intention are moderate (Mean = 2.98 and 2.16, respectively), with sufficient dispersion to justify ordinal modelling.

Ordinal logistic regression results show that higher organisational readiness is associated with a substantially greater likelihood of reporting higher investment intention categories ($b = 2.48$; $SE = 0.40$; $z = 6.21$; $p < 0.001$). The corresponding odds ratio (OR = 11.99) indicates a large effect size (see Table 1).

Table 1
Ordinal logistic regression predicting investment intention from organisational readiness

Predictor	b	SE	z	p	OR
OR_index	2,48	0,40	6,21	$5{,}31 \times 10^{-10}$	11,99

Figure 1 shows how the organisational readiness index is distributed across three levels of firms' investment intention in AI. There is a strong correlation between higher investment intention and substantially higher levels of organisational readiness.

Organisational readiness is also positively associated with the actual adoption of AI. Binary logistic regression results indicate that a one-point increase in organisational readiness significantly raises the likelihood of AI use by approximately 8.4% ($\beta = 0.0808$; $SE = 0.0156$; $z = 5.18$; $p < 0.001$). On a 0–100 scale, a one-point increase in organisational readiness is associated with an approximate 8.4% increase in the odds of AI adoption.

These results, when considered together, support Hypothesis 1.

The perceived potential of AI to improve business efficiency is strongly associated with firms' readiness to invest in artificial intelligence within the next one to three years. Descriptive results demonstrate a consistent pattern across levels of perceived AI potential. Firms that report high AI potential are predominantly ready to invest in AI (71.4%), whereas those with low perceived potential are not ready to invest and mainly express unwillingness to do so. Those with medium perceived AI potential most frequently

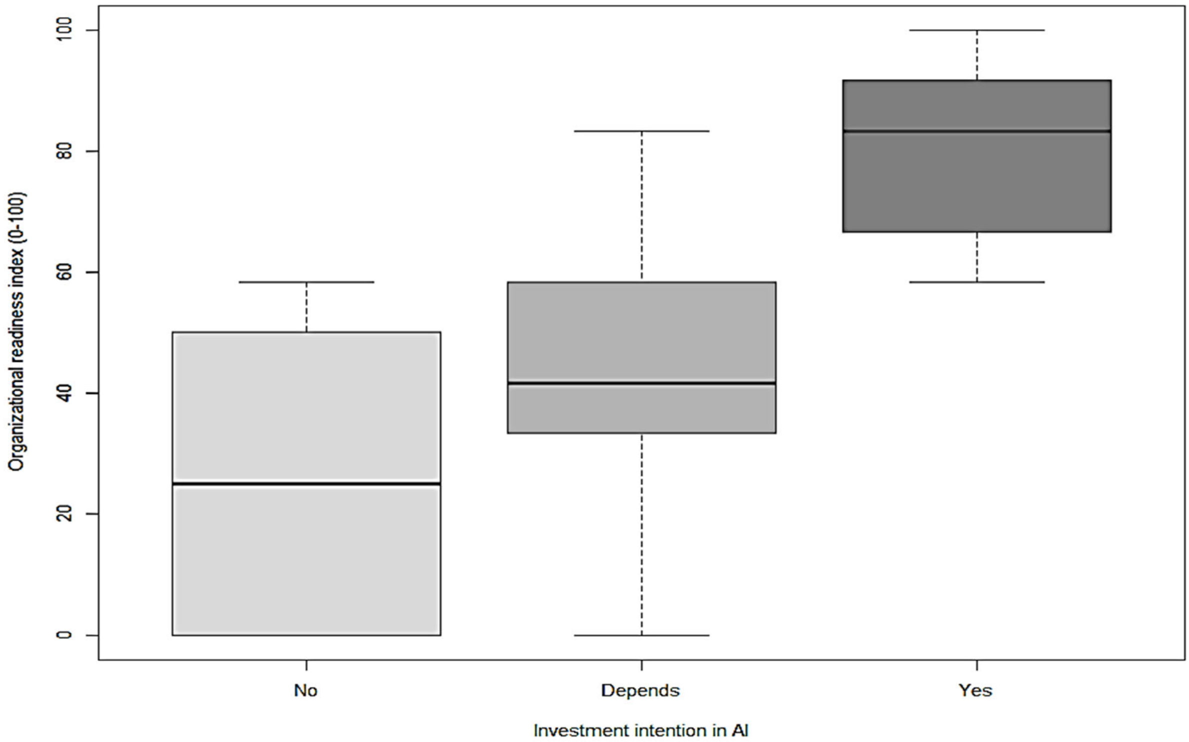

Figure 1. Organisational readiness and investment intention in AI

adopt a conditional position ("depends"), reflecting an intermediate level of investment intention.

A nonparametric analysis confirms a strong, positive, monotonic association between perceived AI potential and investment readiness (Spearman's $\rho = 0.768$, $p < 0.001$). Figure 2 further illustrates this relationship, showing a clear upward trend between perceived efficiency gains from AI and firms' willingness to invest.

Results from an ordinal logistic regression model further substantiate this association. Perceived AI potential was found to have a statistically significant positive effect on firms' investment readiness ($b = 3.68$; $SE = 0.57$; $z = 6.41$; $p < 0.001$). The estimated odds ratio (OR = 39.71; 95% CI [12.89; 122.33]) indicates a substantial increase in the likelihood of transitioning to higher investment-readiness categories as perceived AI potential increases (see Table 2).

Table 2
Ordinal logistic regression predicting firms' investment readiness in AI

Predictor	b	SE	z	p-value	OR (exp(b))	95% CI for OR
AI potential	3,68	0,57	6,41	<0,001	39,71	[12,89; 122,33]

Taken together, these findings suggest that the anticipated efficiency gains associated with artificial intelligence play a pivotal role in determining firms' investment readiness, thereby corroborating Hypothesis H2.

Current AI adoption is strongly associated with a firm's readiness to invest in further artificial intelligence implementation. As shown in Table 3, descriptive results indicate a clear contrast between firms that already use AI and those that do not.

Table 3
Current AI adoption and firms' investment readiness (row %)

AI adoption now	Investment readiness		
	No (1)	Depends (2)	Yes (3)
No	35,42%	64,58%	0,00%
Yes	1,92%	42,31%	55,77%

Among firms that do not use AI, investment readiness is concentrated in the "Depends" (64.6%) and "No" (35.4%) categories, with none reporting a definite intention to invest. In contrast, firms that already use AI predominantly report readiness to invest ("Yes", 55.8%), while explicit unwillingness to invest is almost non-existent (1.9%). This difference was statistically confirmed by a Mann–Whitney U test, which indicated a highly significant difference in investment readiness between AI adopters and non-adopters ($W = 380.5$; $p < 0.001$). Further confirmation of a strong association between current AI adoption and investment-readiness categories is provided by a chi-square test of independence ($\chi^2(2) = 44{,}66$; $p < 0{,}001$). This association is further supported by the strong, positive, monotonic relationship between current AI adoption

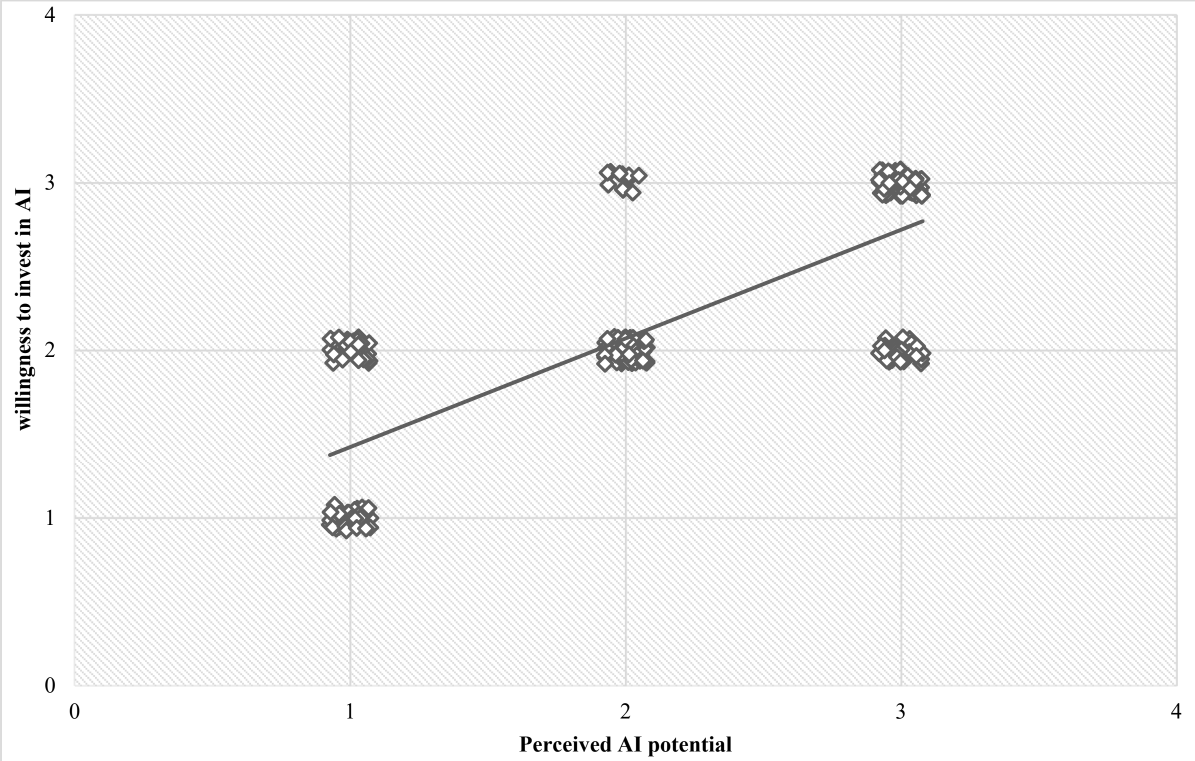

Figure 2. Relationship between perceived AI potential for business efficiency and firms' willingness to invest in AI

Note: Perceived AI potential is coded as Low = 1, Medium = 2, High = 3; investment readiness is coded as No = 1, Depends = 2, Yes = 3.

and investment readiness, as indicated by Spearman's rank correlation ($\rho = 0.664$; $p < 0.001$). Taken together, these results suggest that firms that have adopted AI are more likely to report higher investment readiness, thus supporting Hypothesis H3.

In the wartime context, adaptive capacity is positively associated with perceptions of artificial intelligence. AC is measured using a composite index that combines respondents' learning readiness (i.e., engagement in AI-related learning) and digital readiness (i.e., trust in AI). AI perceptions are captured by an index reflecting optimistic economic expectations regarding AI, as well as a lower emphasis on risks associated with employment displacement.

Spearman's rank correlation indicates a moderate-to-strong positive association between the Adaptive Capacity Index and the AI Perception Index ($\rho = 0.602$, $p < 0.001$; see Table 4).

Table 4
Association between adaptive capacity and AI perception

Variables	Spearman's ρ	p-value
Adaptive Capacity Index and AI Perception Index	0,602	<0,001

To further assess group-level differences, the respondents were divided into tertiles based on their adaptive capacity. A Kruskal–Wallis test revealed statistically significant differences in AI perception across these groups ($p < 0.001$). As illustrated in Figure 3, respondents in the high adaptive capacity group consistently report higher average AI perception scores than those in the medium and low capacity groups, forming a clear monotonic pattern.

Taken together, these results suggest that adaptive capacity is consistently linked to more favourable overall AI perceptions, whereas its direct correlation with specific employment expectations is weaker. These results provide empirical support for Hypothesis 4.

The fear of losing one's job due to AI is systematically associated with the routineness of one's tasks and one's level of education. An ordinal logistic regression model was used to predict the likelihood of fearing job loss (on an ordinal scale of 1–3) based on task routineness, level of education, and the interaction between these two factors. All predictors were mean-centred prior to estimation. Descriptive statistics indicate that employees engaged in more routine tasks perceive a higher level of job insecurity than those in less routine roles (Table 5).

Further confirmation of a positive association between task routineness and fear of job loss is provided by a Spearman rank-order correlation ($\rho = 0{,}227$; $p = 0{,}027$). The regression results indicate a positive and statistically significant main effect of task routineness on fear of job loss ($b = 1.37$; $p = 0.006$).

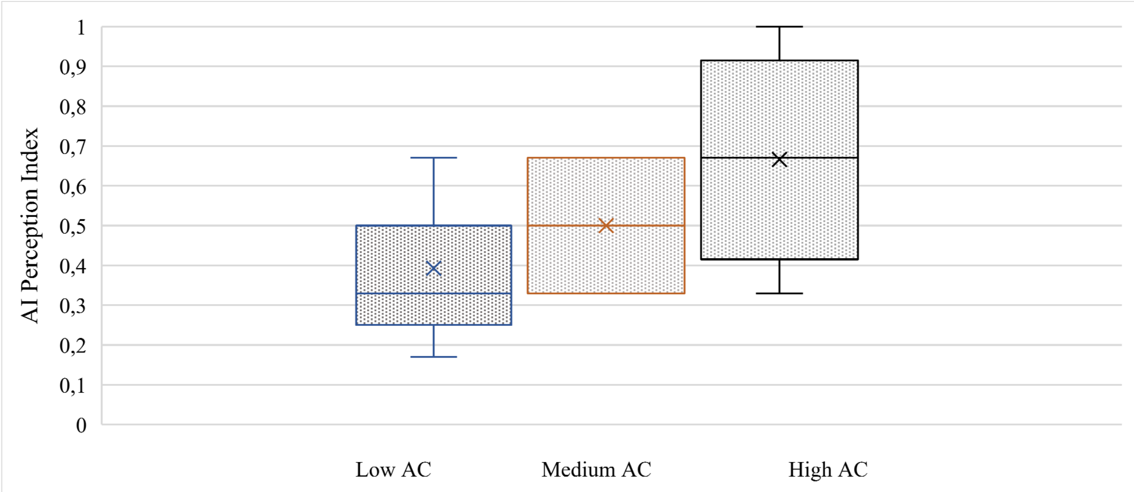

Figure 3. AI perception across tertiles of adaptive capacity

This suggests that employees in routine-intensive roles are more likely to experience anxiety about automation-related job loss. Education exhibits a significant negative main effect (b = -0.64; p = 0.017), suggesting that higher educational attainment is associated with lower perceived job insecurity. Importantly, the interaction between task routineness and education is also negative and statistically significant (b = -1.22, p = 0.017; see Table 6).

Table 5
Fear of job loss by task routineness

Task routineness level	Average fear of job loss	Std. dev.
Low routineness	2,07	0,73
High routineness	2,38	0,68
Total sample	2,24	0,74

Note: Fear of job loss measured on a 3-point ordinal scale (1 = no impact, 3 = high perceived risk).

This suggests that the positive impact of task routineness on the fear of job loss diminishes as educational attainment increases. Therefore, although routine-intensive work is generally associated with a higher perceived AI-related employment risk, a higher level of education substantially mitigates this effect. These findings provide support for Hypothesis H5. Figure 4 illustrates the moderating effect of education, showing that the association between task routineness and fear of job loss is much weaker among employees who have attained a higher level of education.

The perception of AI-driven efficiency gains varies considerably among business representatives, workers, and citizens. The perceived impact of AI on efficiency is measured using the AI impact index, which is normalised to a 0-100 scale. Higher values on this scale indicate stronger expected efficiency gains. The index was calculated separately for business representatives, workers, and citizens. Given the non-normal distribution of the AI impact index, intergroup differences were assessed using the Kruskal-Wallis H test. The results indicate statistically significant differences in the perception of AI-driven efficiency gains among business representatives, workers and citizens (χ^2 (2) = 38.39, p < 0.001). Post-hoc pairwise comparisons using Wilcoxon rank-sum tests with Holm adjustment were conducted to identify the sources of these differences.

Post-hoc analysis revealed significant differences between citizens and both business representatives and workers, with no statistically significant differences observed between the latter two groups. Citizens expressed substantially more optimistic expectations regarding AI-driven efficiency gains than economic actors who are directly involved in production and organisational processes. The pattern reflects an asymmetric structure of intergroup differences, with

Table 6
Ordinal logistic regression predicting fear of job loss due to AI: interaction between task routineness and education

Predictor	b (log-odds)	SE	z	p-value	OR	95% CI for OR
Task routineness	1,369	0,498	2,749	0,006	3,932	[1,48; 10,44]
Education level	-0,637	0,266	-2,397	0,017	0,529	[0,31; 0,89]
Task routineness x Education	-1,216	0,508	-2,396	0,017	0,296	[0,11; 0,80]

Note. The predictors are mean-centred. Higher values of fear of job loss indicate a stronger perception of AI-related employment risk.

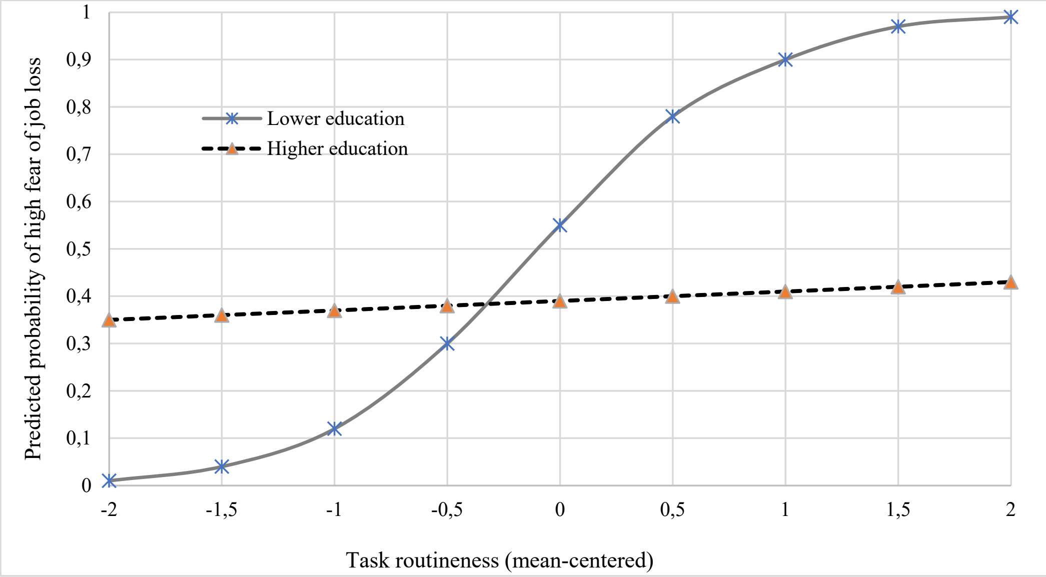

Figure 4. Predicted probability of high fear of job loss due to AI by task routineness and education level

**Note: Predictions are based on the ordinal logistic regression model reported in Table 6; task routineness is mean-centred*

citizens being the main source of divergence. This may be explained by differences in direct exposure to AI implementation, awareness of organisational and transformational costs, and varying levels of risk sensitivity associated with AI adoption. While business representatives and workers appear to adopt more cautious and pragmatic evaluations, citizens tend to emphasise potential benefits while underestimating implementation-related constraints. Taken together, these findings confirm hypothesis H6, indicating that the perceived impact of AI on efficiency differs significantly between business representatives, workers and citizens.

Table 7
Post-hoc pairwise comparisons (Wilcoxon test, Holm-adjusted p-values)

Comparison	p-value
Business – Citizens	$3{,}0 \times 10^{-9}$
Workers – Citizens	$4{,}9 \times 10^{-6}$
Business – Workers	0,22

Having tested individual hypotheses relating to the determinants of AI adoption, investment readiness and the behavioural responses of firms, it is necessary to synthesise these results into a coherent analytical framework using an integrated firm-level indicator. To address this, the study proposes an original AI readiness index designed to capture firms' preparedness for adopting artificial intelligence. The AI-readiness index was constructed by normalising the five survey components to a common scale of 0–100 and calculating their mean. These components are: (1) AI adoption; (2) AI potential; (3) investment readiness; (4) the perceived importance of training; and (5) team awareness of AI.

The AI-readiness index ranges from 0 to 100. With a mean value of 54.37 and a median of 55, it indicates an overall moderate level of AI readiness among the surveyed firms. The index reveals significant variation in the AI readiness of individual firms, with approximately one quarter demonstrating low preparedness and another quarter showing advanced readiness. The proximity of the mean and median suggests an absence of pronounced skewness, although dispersion remains high.

Table 8
Descriptive statistics of the AI-readiness index (0-100)

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0,00	40,00	55,00	54,37	80,00	100,00

The composite AI-readiness index, ranging from 0 to 100, was utilised to categorise firms into low (less than 40), medium (40-79), and high (more than 80) readiness groups (see Figure 5). The medium-readiness group constitutes the largest share of firms (48.4%), followed by high-readiness firms (28.4%) and low-readiness firms (23.2%). This classification underscores pronounced variation in the stages of AI adoption among firms, ranging from initial or hesitant engagement to advanced integration.

Table 9 presents the component-level structure of the AI-readiness index across firm characteristics. Clear and systematic differences emerge according to firm size, geographic scope of activity and industry. Larger firms consistently demonstrate higher values

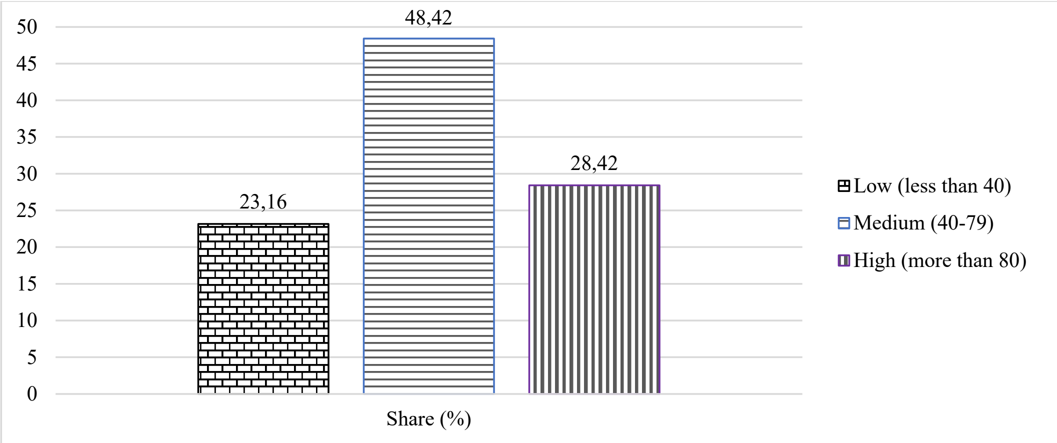

Figure 5. Firm classification by AI-readiness level

across all components of the index. Enterprises employing 100–200 workers show particularly strong performance in terms of actual AI adoption, investment readiness and the importance of training.

Geographic scope is associated with even more pronounced disparities. Firms operating in both Ukraine and international markets report the highest levels of AI readiness across all components, while those oriented towards local markets consistently demonstrate the lowest scores. The largest discrepancies are observed in terms of actual AI adoption and perceived AI potential, which suggests that international exposure is closely linked to both the practical use of AI and a forward-looking strategic orientation.

Sectoral patterns further reinforce the uneven nature of AI diffusion. IT and finance demonstrate the greatest readiness levels of all the components, reflecting their higher level of technological maturity and greater investment capacity. In contrast, traditional sectors such as services, retail, manufacturing and agribusiness are lagging behind.

Statistical testing confirms the presence of significant differences across firm characteristics. Variation is observed by firm size (Kruskal-Wallis H = 12,63; p = 0,0018; ε^2 = 0,11), industry (H = 46,07; p = 2,87 x 10^{-8}; ε^2 = 0,43), and geographic scope of activity (H = 45,64; p = 6,78 x 10^{-10}; ε^2 = 0,44). Post-hoc Mann-Whitney tests with Holm adjustment suggest that firms with 100–200 employees demonstrate significantly higher AI readiness than smaller enterprises. The most significant differences are observed in terms of geography: firms engaged in international activities have substantially higher readiness scores than those confined to local markets.

Table 9
Components of the AI-readiness index by firm size, market scope, and industry (mean values, 0-100)

Groups	AI-readiness	AI adoption	Investment readiness	Training importance	Team awareness	AI potential
Components of the AI-readiness index by firm size						
Less than 50 employees	53,6	68,2	53,2	48,4	40,9	58,2
51-100	38,2	35,7	50,0	42,9	33,9	28,6
100-200	80,6	88,9	83,3	94,4	52,8	83,3
Components of the AI-readiness index by geographic scope of activity						
Local market	32,9	29,4	38,2	35,3	32,4	26,9
Regional market	56,7	83,3	83,3	50,0	33,3	33,3
Ukraine only	44,1	58,5	39,4	39,1	37,2	45,7
Ukraine and International	80,5	93,3	85,0	80,8	53,3	90,0
Components of the AI-readiness index by industry						
IT	89,0	100,0	100,0	85,0	60,0	100,0
Finance	89,0	90,0	90,0	95,0	80,0	90,0
Other	74,6	85,7	82,1	75,0	48,2	82,1
Services	41,2	46,4	35,7	46,4	40,2	37,5
Retail trade	36,8	52,5	40,0	23,7	35,0	30,0
Manufacturing	47,3	59,1	50,0	43,2	25,0	59,1
Agribusiness	50,0	75,0	50,0	43,8	27,1	54,2

Table 10 further illustrates the difference between internationally active firms and locally oriented businesses at a component level, particularly with regard to AI adoption and perceived AI potential.

Table 10
Component-level AI-readiness gap by geographic scope

Component	Leader (UA and International)	Outsider (Local market)	Gap
AI adoption	93,3	29,4	63,9
AI potential	90,0	26,9	63,1
Investment readiness	85,0	38,2	46,8
Training importance	80,8	35,3	45,5
Team awareness	53,3	32,4	20,9

The AI-readiness index reveals significant differences in how prepared firms are for artificial intelligence, distinguishing those that are highly prepared from those that are either reluctant or cautious about engaging with AI technologies.

Overall, the empirical results suggest that the adoption of artificial intelligence and investment readiness are unevenly distributed among firms and social groups. The findings emphasise the pivotal role of organisational preparedness, anticipated efficiency gains, and prior AI experience in influencing firm-level behaviour. They also reveal significant disparities in perceptions of AI-related risks and benefits among workers, businesses, and citizens. The proposed AI-readiness index captures this heterogeneity further, revealing substantial structural disparities in preparedness for AI adoption across firm size, market scope, and industry.

Conclusions

The article examined the factors influencing the adoption of artificial intelligence and investment readiness, alongside economic expectations and employment-related perceptions among business representatives, employees and citizens in wartime Ukraine. The findings suggest that, while the use of AI in business does not cease under wartime conditions, it becomes more selective, primarily shaped by organisational capacities and pragmatic assessments of expected benefits.

The empirical analysis shows that organisational readiness is a key factor associated with both investment intentions in AI and the actual use of these technologies. Expected efficiency gains significantly strengthen firms' willingness to invest in AI, and prior experience of adopting AI is linked to a higher likelihood of further investment. This indicates a cumulative logic of digital transformation at the firm level. In a wartime context, adaptive capacity is associated with more positive perceptions of the economic effects of AI. In turn, task routineness is linked to stronger fears of job loss due to AI. However, higher levels of education mitigate this effect, highlighting the protective role of skills in the labour market.

The proposed AI-readiness index reveals significant differences in how prepared firms are for adopting artificial intelligence. Higher levels of readiness are typical of larger companies, businesses engaged in international activities and technology-intensive sectors. In contrast, locally oriented businesses demonstrate lower scores across the index's key components. This highlights the potential for structural gaps to widen in the context of digital transformation, emphasising the practical importance of policies that focus on human capital development, workforce training, and the enhancement of organisational capacities for AI implementation.

The results suggest that the use of artificial intelligence in wartime is influenced by organisational capabilities, anticipated efficiency gains and the adaptive capacity of individuals. This study makes a valuable contribution to existing literature on AI diffusion, providing an empirical basis for further research and policy discussions on digital transformation in unstable economic environments. Future research could build on this analysis by using panel data, making sectoral comparisons and examining institutional support mechanisms for AI adoption in wartime Ukraine in more depth.

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