ISSN 1611-1699/eISSN 2029-4433

JOURNAL of BUSINESS ECONOMICS & MANAGEMENT

2026
Volume 27
Issue 4
Pages 699–719

https://doi.org/10.3846/jbem.2026.28058

YOUTH ADOPTION OF ARTIFICIAL INTELLIGENCE IN CENTRAL AND EASTERN EUROPE: EVIDENCE FROM ROMANIA AND POLAND

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Article History:
- received 8 October 2025
- accepted 17 June 2026

Abstract. This study examines young people in Central and Eastern Europe adopting artificial intelligence (AI), focusing on Romania and Poland. It identifies main drivers of behavioral intentions toward AI by integrating micro, meso, and macro-level factors. Data from 502 respondents aged 18–34 were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Measurement invariance was tested with MICOM, and cross-country differences were assessed through Multi-Group Analysis (MGA). The model explains 39.5% of the variance in future AI use. Personal benefits were the strongest predictor, followed by AI integration and social environment, while perceived socio-economic benefits had a smaller but significant effect. Risk perceptions and gender showed no significant impact. MGA confirmed stronger effects of integration in Romania and benefits in Poland. The findings suggest country-tailored strategies: Romania should prioritize accessibility and ease of use, while Poland should emphasize career-related benefits and institutional resources. Universities and policymakers could support AI adoption by expanding AI literacy initiatives and by leveraging peer-based learning environments. The study contributes by applying a multi-level adoption framework to an underexplored region, highlighting how contextual factors shape AI adoption among Generation Z.

Keywords: artificial intelligence adoption, Generation Z, Central and Eastern Europe, PLS-SEM, MICOM/MGA, Romania and Poland.

JEL Classification: O33, M15, C38.

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1. Introduction

Artificial intelligence (AI) is transforming how organizations and societies function beyond research labs, raising questions about its integration into daily life. Understanding youth adoption of AI is crucial, as Generation Z is most immersed in digital environments (Göller et al., 2023). AI creates opportunities for productivity, personalization, and innovation (Kotler et al., 2023), while generating concerns about job displacement, inequality, and ethical issues (Camilleri, 2024; Rana et al., 2024). While research in advanced economies grows, Central and Eastern Europe (CEE) remains underrepresented, despite facing distinct challenges of slower digital integration and strong policy commitments to AI adoption (Gansser & Reich, 2021).

Generation Z, described as "the generation for which the world did not exist before technology" (Duse & Duse, 2017), has grown up in digital environments. They see minimal boundaries between virtual and real spaces (Persada et al., 2019; Tolstikova et al., 2023) and embrace technological novelty more than older cohorts (Guerra-Tamez et al., 2024). Their position at the labor market threshold makes them sensitive to digitalization disruptions, making them key for studying AI adoption dynamics. Technology adoption has been explained through models like the Technology Acceptance Model (Davis, 1989), Theory of Planned Behavior (Ajzen, 1991), and Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2012). These emphasize usefulness, ease of use, social norms, and facilitating conditions. Recent AI studies confirm the role of perceived benefits and peer influence (Dwivedi et al., 2021; Mou et al., 2023). However, macro-level perceptions rarely integrate with micro-level determinants, and comparative analyses of generational and regional contexts remain limited.

This study introduces a multi-level framing of AI adoption. At the micro level, we analyze knowledge, usage, benefits, and ease of use. At the meso level, we examine peer influence. At the macro level, we assess AI's socio-economic impact and resources. This framework explains adoption dynamics (Enríquez et al., 2024; Gu et al., 2023). The study contributes by validating adoption models through socio-economic integration, highlighting CEE youth specificity, and showing career and life quality expectations outweigh risks. The objectives are: O1: To assess AI integration among youth. O2: To analyze AI's economic and social impact. O3: To estimate future AI behavioral intentions. O4: To compare findings across Romania and Poland. The central research question examines how young people in CEE evaluate the opportunities and risks associated with AI.

The hypotheses proposed are as follows:

H1: Future behavior is influenced by AI integration.

H2: AI integration is shaped by interest in innovation and fundamental technical skills.

H3: AI integration is contingent upon access to educational and technical resources.

H4: Perceived ease of use affects integration.

H5: Perceived benefits determine both integration and future behavior.

H6: Future behavior is positively influenced by perceived socio-economic benefits.

H7: Future behavior is negatively influenced by perceived risks.

H8: The social environment influences AI adoption.

H9: Gender influences adoption intentions.

H10: Country differences moderate AI adoption patterns.

The remainder of the paper is structured as follows. Section two reviews relevant literature and identifies research gaps. Section three presents the methodology, including research design, data collection, and analysis. Section four reports empirical results. Section five discusses findings in light of existing theories and regional specificities. The final section concludes with implications, limitations, and future research directions.

2. Literature review

Artificial intelligence (AI), first introduced in 1956 (Hassani et al., 2020), has evolved rapidly, expanding beyond its initial scope to address complex tasks across industries and societies. With machine learning, robotics, and automation, AI has become a transformative force that scholars describe as a "new industrial revolution," reshaping production systems and daily life, with implications for global competitiveness and quality of life (W. Wang & Siau, 2019).

Literature underscores AI's dual nature. Its benefits are widely acknowledged: processing large datasets, generating predictive insights, and providing personalized services (Kotler et al., 2023). These advantages span healthcare, education, finance, and logistics, where AI tools optimize decisions and increase efficiency. However, concerns persist. Risks include job displacement, social inequalities, and existential threats (Kazi & Mandge, 2024; Stein et al., 2024). Privacy violations, algorithmic bias, and accountability questions shape public perceptions and regulations (Stahl, 2021). For younger generations, these tensions matter. Students and professionals view AI as valuable for education and careers but worry about fairness and discrimination (Chardonnens, 2025). While AI-based customer service grows, studies of user trust remain limited (Iancu & Iancu, 2023). Public trust depends on transparency, accessibility, and perceived fairness (Kozak & Fel, 2024).

Risk perceptions were included in the model as research suggests concerns about job displacement, inequality, cognitive dependency, privacy, and algorithmic bias may reduce trust and weaken technology adoption intentions. In technology acceptance contexts, such perceptions often act as inhibitors, particularly when users perceive low control or uncertain consequences. For younger users, however, these risks may be cognitively acknowledged but behaviorally discounted when perceived benefits are immediate. This tension makes risk perceptions theoretically relevant even if their empirical effect proves weak or non-significant.

Literature shows contrasting public attitudes toward AI. Optimistic views highlight AI's benefits for healthcare, education, and development (Kelley et al., 2021). However, privacy, ethics, and job concerns temper expectations (Fülöp et al., 2023). Studies show users favor algorithmic over human decisions with high digital literacy (Araujo et al., 2020), yet resistance exists in justice and healthcare (Ingrams et al., 2022; Lee, 2018; Smith, 2018). Trust combines technical reliability and ethical principles (Sigfrids et al., 2023). Scholars advocate governance frameworks with ethical safeguards (Gerlich, 2023; Lahusen et al., 2024), noting misalignment between public expectations and AI performance affects adoption. Technology acceptance models stress perceived ease of use and usefulness (Osman et al., 2024; Wu et al., 2024), with UTAUT2 extensions confirming the role of performance expectancy and social influence in students' adoption of generative AI (Sergeeva et al., 2025). Recent research includes digital skills, computational thinking (Celik, 2023), and AI literacy (Dusseault et al., 2025). Social influence affects behavior in education (Horodyski, 2023). Demographics influence AI perceptions, with urban youth showing higher acceptance (Golbabaei et al., 2020) and education correlating with healthcare AI trust (Zhang et al., 2020). Limited knowledge breeds skepticism (Mou et al., 2023). Infrastructure affects adoption (Abdo-Salloum & Al-Mousawi, 2025), raising questions about emerging economies (Gerlich, 2023). Gaps include limited evidence from Central and Eastern Europe and insufficient study of Generation Z (Göller et al., 2023; Guerra-Tamez et al., 2024).

This study examines Romania and Poland, two Central and Eastern European countries where AI adoption lags behind the EU average but is prioritized in national policies. By integrating the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and the Theory of Planned Behavior with constructs like socio-economic perceptions and trust (Shahzad et al., 2024), this study advances adoption research regionally. It proposes a framework covering micro-level determinants (knowledge, personal benefits, ease of use), meso-level influences (social environment), and macro-level factors (socio-economic impact, resources). The paper extends existing theories and provides a model of AI adoption among CEE youth, highlighting shared dynamics and country specificities. A summary of key themes, limitations, and gaps addressed is in Table 1.

Table 1. Summary of literature on AI adoption and research gaps (source: own synthesis based on reviewed literature)

Theme	Key Insights from Literature	Representative References	Identified Gaps / Relevance for This Study
Advantages of AI	Enhances productivity, personalization, efficiency across domains (healthcare, finance, logistics, education).	Kotler et al. (2023), Nguyen and Shaik (2024), W. Wang and Siau (2019)	Benefits are well-documented, but their role in shaping youth intentions in CEE remains underexplored.
Risks and controversies	Concerns over job displacement, inequality, privacy, algorithmic bias, ethical dilemmas.	Kazi and Mandge (2024), Stahl (2021), Stein et al. (2024)	Risk perceptions lack systematic testing for predictive relevance among Generation Z in CEE.
Trust in AI	Trust is multidimensional (technical reliability, fairness, transparency). Public ambivalence: optimism vs. skepticism.	Araujo et al. (2020), Lahusen et al. (2024), Lee (2018)	Few studies link trust to behavioral intentions in emerging European economies.
Determinants of adoption	Core TAM/UTAUT drivers: ease of use, usefulness; extended with AI literacy, digital skills, social influence.	Dusseault et al. (2025), Osman et al. (2024), Wu et al. (2024)	Lack of integration of micro (skills, use), meso (social influence), and macro (resources, perceptions) in a unified framework.
Demographic and contextual factors	Age, gender, education, and culture shape adoption; digital readiness mediates acceptance.	Abdo-Salloum and Al-Mousawi (2025), Golbabaei et al. (2020), Zhang et al. (2020)	Little empirical research on CEE youth as a distinct cohort, despite differences in digital infrastructure and policy agendas.
Theoretical gap	Global frameworks validated in advanced economies; limited studies in CEE, especially on Generation Z.	Göller et al. (2023), Guerra-Tamez et al. (2024), Shahzad et al. (2024)	Need for a regional, generational, and multi-level framework to explain AI adoption dynamics.

Based on the reviewed literature, the proposed framework organizes the determinants of AI adoption into three analytical levels. At the micro level, the model includes variables related to AI knowledge, use, perceived ease of use, personal benefits, and technological openness (V2, V6, V7, V10, V13, V14, V15). At the meso level, the analysis captures the role of peer influence and social environment (V28, V31). At the macro level, the model includes perceived socio-economic benefits and access to educational and technical resources (V11, V12, V16, V19). Risk-related perceptions (V20–V27) were included as a separate analytical block reflecting concerns that may inhibit adoption intentions.

3. Methodology

This study examines how young people in Romania and Poland perceive and use AI daily, and factors shaping future intentions. These countries were selected as digital technology use remains below EU average, while digital transformation is a policy priority (Y. Wang, 2024). This context enables analysis of adoption in emerging digital economies, where AI concerns vary across regions and demographics, making localized studies relevant (Enam et al., 2025; Scantamburlo et al., 2025). A quantitative survey was used, with a questionnaire covering three dimensions: AI integration in daily activities, perceptions of socio-economic impact, and behavioral intentions for future use. Items were measured on five-point Likert and Semantic Differential scales. Based on TAM, TPB, and UTAUT, the instrument included constructs for ease of use, usefulness, trust, risks, and socio-economic perceptions, with items on prior experience, competence, and social influence (Bunea et al., 2024; Kolar et al., 2024; Rana et al., 2024). The full instrument is presented in Appendix A.

The constructs included in the model were specified according to their conceptual nature as formative constructs. In formative measurement models, the indicators represent different facets that jointly define the construct rather than interchangeable manifestations of a single underlying concept (Hair et al., 2022). Consequently, the indicators are not expected to covary strongly, as each of them contributes a specific dimension to the construct.

This specification is appropriate because the indicators within each construct capture conceptually distinct facets of AI adoption. For example, AI_INT is formed by knowledge and frequency of use — related but non-redundant dimensions. Accordingly, model assessment focused on indicator collinearity, outer weights, and predictive relevance rather than internal consistency coefficients. The formative constructs were: AI Integration (AI_INT), Future Behavior (FB_AI), Basic Technological Skills and Innovation Interest (BT_II), Personal Benefits (PB), Access to Resources (AR_AI), Social Environment (SE_AI), and Socio-Economic Impact Opinion (AI_SEL).

The survey included 502 respondents aged 18–34, with balanced distribution between Romania and Poland. Respondents were recruited through online channels, including university networks, student groups, and social media platforms used by young adults in both countries. Participation was voluntary and anonymous, without financial incentives. This recruitment strategy reached digitally active respondents within the target age group, while reinforcing the non-probabilistic nature of the sample. Although non-probabilistic, the sample is sufficiently diverse for exploratory purposes and aligns with common practices in studies where the aim is to identify relationships rather than generate nationally representative estimates (Gerlich, 2023; Howell, 2024). Missing data were minimal and did not affect analytical consistency. Cases with incomplete key responses were excluded before model estimation. Data analysis proceeded in stages. Descriptive statistics characterized the sample, while t-tests and Chi-Square tests compared responses between countries. To explore relationships among latent constructs, we applied Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4, chosen for its suitability in exploratory research, ability to handle formative and reflective constructs, predictive orientation, and lenient assumptions regarding data distribution (Sanmukhiya, 2020; C. Wang et al., 2023). This allowed simultaneous estimation of measurement and structural models. The measurement model met recommended thresholds.

Because the constructs were specified as formative, internal consistency measures such as Cronbach's alpha or rho_A were reported only for transparency and were not used as the primary assessment criteria. Instead, following PLS-SEM guidelines for formative measurement, we examined multicollinearity through VIF values, as well as the significance and contribution of the indicators to their respective constructs. All VIF values were below 3.3, eliminating concerns about multicollinearity (Appendix B). The structural model was then assessed through path coefficients, R^2 values, effect sizes (f^2), and predictive relevance (Q^2). Bootstrapping with 5,000 resamples produced stable estimates of standard errors and significance levels, ensuring rigor and consistency (Cabrera-Sánchez et al., 2020).

Given the cross-country focus, we applied the MICOM procedure to establish measurement invariance (Henseler et al., 2016). Configural invariance was confirmed by specifying identical models, and permutation tests supported compositional invariance. Equality of means and variances showed partial invariance, which is sufficient for cross-group comparison (Hair et al., 2022). Multi-Group Analysis with permutation and PLS-MGA revealed that the path from Personal Benefits to Future Intention was stronger in Poland, while Ease of Use had greater influence in Romania; the Social Environment path showed no significant differences.

To reduce common method variance (CMV) risk, we ensured respondent anonymity, varied item formats, and avoided evaluative wording. Harman's single-factor test showed no factor explained more than 40% of variance, indicating CMV was unlikely to bias findings. The non-probabilistic sample restricts generalizability, and the cross-sectional design prevents causal inference. The methodological design combines descriptive, inferential, and structural modeling with invariance and group analysis. Future work should broaden the regional scope and apply longitudinal designs to capture evolving dynamics (Bădulescu et al., 2025; Naeem et al., 2024).

4. Results

4.1. Descriptive analysis

Analysis showed 73.9% of respondents used AI-based applications (V1), with significant differences between countries ($p < 0.001$) – higher in Poland (85.6%) versus Romania (62.3%). Knowledge of AI (V2) was moderate ($M = 3.18$), with significant differences ($p = 0.010$): Romanian respondents showed higher knowledge ($M = 3.27$) than Polish ones ($M = 3.10$). AI-related course participation (V3) was limited (10.2%), varying significantly between countries ($p = 0.029$): 13.1% in Romania versus 7.2% in Poland. For application types (V4), free versions dominated (58% exclusively free, 24.8% mostly free, 14.3% equally free and paid, 3% predominantly paid). Significant differences emerged ($p < 0.001$), with Romanian respondents using more paid applications (5.7% vs. 0.9%) (see Table 2).

Table 2. AI usage and knowledge by country (V1–V4)

Variable	Romania (%) / Mean (SD)	Poland (%) / Mean (SD)	Sig. (p)
V1: Use of AI applications (Yes)	62.3%	85.6%	0.000
V2: Knowledge about AI (1–5)	3.27 (0.88)	3.10 (0.92)	0.010
V3: Attended AI-related courses	13.1%	7.2%	0.029
V4: Type of AI applications used	More paid (5.7%)	More paid (0.9%)	0.000

Note: Independent-sample t-tests and Chi-Square tests applied as appropriate.

Romanian respondents showed higher engagement with paid tools, while adoption rates were higher in Poland, suggesting economic and cultural factors affect adoption. These findings align with research on contextual conditions shaping technology adoption (García et al., 2025; Li et al., 2024). For AI utilization (V5), respondents used AI for educational, professional, or entertainment purposes, with 80.1% using it for one purpose, indicating underutilization. AI use frequency (V6) showed 3.8% used AI several times daily, 10.5% every one to two days, and 17.5% weekly, with others using it less frequently (Figure 1). Chi-Square tests showed no significant cross-country differences. These findings reveal an adoption paradox: despite access, AI integration remains limited, indicating younger generations may be selective in AI adoption (Savin et al., 2024; Ward et al., 2025).

4.2. Perceptions regarding the impact of AI

Respondents showed optimism about AI's role in socio-economic development. They anticipated AI would catalyze new sectors and industries (V18 = 3.98), enhance high-tech domains (V17 = 3.83), advance scientific research (V19 = 3.70), and facilitate economic growth (V16 = 3.27). Significant differences emerged for V17 and V18: Polish respondents showed greater confidence in AI's capacity to propel advanced technologies ($M = 4.03$ vs. 3.62, $p < 0.001$) and foster new industries ($M = 4.13$ vs. 3.83, $p = 0.002$) (Table 3).

Table 3. Perceptions of AI's positive socio-economic impact (V16–V19)

Item	Romania Mean (SD)	Poland Mean (SD)	Sig. (p)
V16: AI supports overall economic development	3.27 (1.02)	3.28 (1.01)	n.s.
V17: AI strengthens high-tech fields	3.62 (0.94)	4.03 (0.91)	0.000
V18: AI stimulates new sectors and industries	3.83 (0.89)	4.13 (0.87)	0.002
V19: AI boosts scientific research	3.68 (0.96)	3.72 (0.95)	n.s.

Note: Likert scale 1 = strongly disagree, 5 = strongly agree.

Respondents showed concerns about AI's impact on cognitive abilities (V21 = 3.89), labor markets (V20 = 3.82), communication (V22 = 3.72), and evolution (V23 = 3.66). Polish youth expressed higher concern about job losses (V20, $p = 0.026$). On AI-based decisions, respondents were skeptical of AI replacing human thinking (V24 = 2.53), preferred human validation (V25 = 3.99), and considered AI better for repetitive tasks (V26 = 3.53) than complex ones (V27 = 3.66). Polish respondents showed higher trust in AI decisions for V25, V26, and V27. These findings reflect tension between AI potential and ethical concerns (Pérez-Velasco & Álvarez-Hernández, 2025; Thomson et al., 2024).

4.3. Working hypotheses

Drawing upon existing literature, we developed a Structural Equation Model (SEM) to assess the determinants of future behavior toward artificial intelligence (FB_AI). Future behavior was conceptualized as the intention to increase usage frequency (V32) and to seek additional knowledge (V33). Figure 1 illustrates the structural equation model estimated using the complete sample.

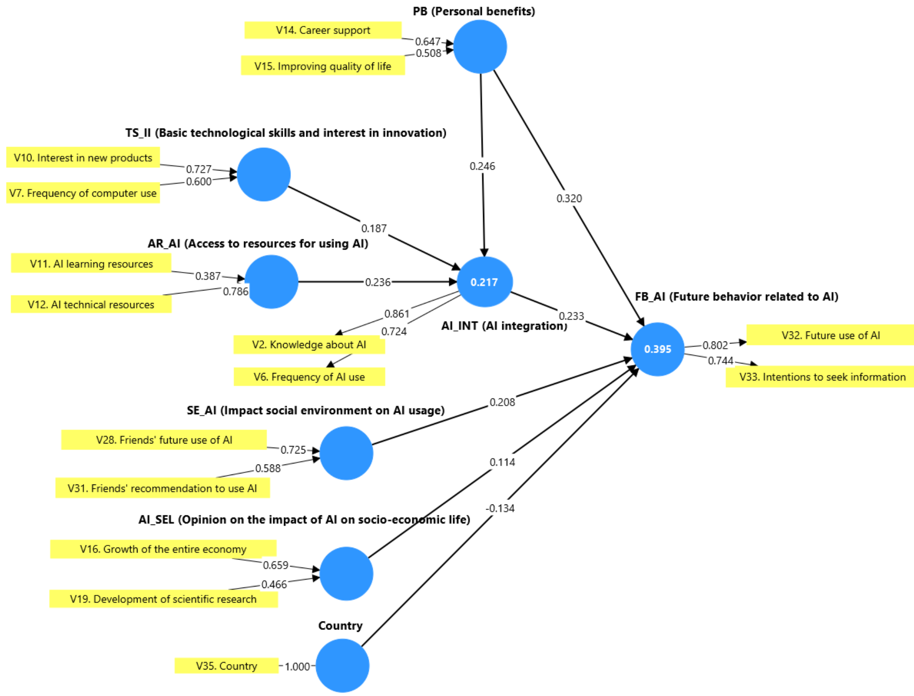

Figure 1. Structural Equation Model for entire sample (Poland and Romania) (source: own processing with SmartPLS 4)

The structural model was estimated to test the hypotheses formulated in the Introduction. The indicators (V7–V15, V28–V31) supported these assumptions. Romanian respondents showed greater interest in novelty (V10), task simplicity (V9), and feature discovery (V8). Perceived ease of use (V13) was stronger in Romania, while Poland had higher scores in perceived personal benefits (V14, V15). Social environment indicators were moderate in both groups, though Romanian respondents reported slightly higher anticipated peer engagement (V28, V31).

4.4. Model evaluation and PLS-SEM results

The model was estimated using PLS-SEM in SmartPLS 4. Tests confirmed no collinearity (VIF < 2) and established significance of outer weights and loadings ($p < 0.001$). Because the constructs were specified as formative, reliability measures such as Cronbach's alpha or AVE were not used as primary evaluation criteria. Instead, indicator collinearity and outer weights were examined. All VIF values remained below the recommended threshold (Appendix B), indicating that multicollinearity was not a concern. Table 4 summarizes the constructs included in the structural model, their measurement specification, and the indicators used to operationalize each construct.

The global model explained 39.5% of variance in future behavior ($R^2 = 0.395$), showing moderate power (Hair et al., 2022). Positive predictive relevance (Q^2) confirmed model robustness. Path coefficients showed: AI integration predicts future behavior ($\beta = 0.233$). Integration is influenced by personal benefits ($\beta = 0.246$), resources ($\beta = 0.236$), and basic skills/

innovation (β = 0.187). Personal benefits most strongly predict future behavior (β = 0.320). Social environment influences significantly (β = 0.208), while socio-economic benefits showed modest effect (β = 0.114). Risks and gender had no significant impact. These relationships appear in Table 5.

Table 4. Constructs, measurement type, and indicators included in the SEM model (source: authors' processing with SmartPLS 4)

Construct	Measurement type	Short description	Indicators
FB_AI	Formative	Future behavioral orientation toward AI use and learning	V32, V33
AI_INT	Formative	Current integration of AI in users' knowledge and practice	V2, V6
BT_II	Formative	Basic technological routine and openness to innovation	V7, V10
PB	Formative	Perceived personal advantages of AI	V14, V15
AR_AI	Formative	Perceived access to educational and technical AI resources	V11, V12
SE_AI	Formative	Social encouragement and peer orientation toward AI	V28, V31
AI_SEL	Formative	Perceived socio-economic contribution of AI	V16, V19
Country	Single-item observed variable	National group membership	V35

Note: All multi-item latent constructs were specified as formative because their indicators capture complementary dimensions of the broader concept rather than interchangeable manifestations of a single latent variable. The allocation of items to constructs is based on theoretical foundations from TAM/UTAUT and recent AI adoption studies (Dwivedi et al., 2021; Hair et al., 2022).

Table 5. Structural model results (PLS-SEM, full sample)

Hypothesis	Path	β	t-value	p-value	Supported
H1	AI_INT → FB_AI	0.233	4.82	0.000	Yes
H2	BT_II → AI_INT	0.187	3.21	0.001	Yes
H3	AR_AI → AI_INT	0.236	3.96	0.000	Yes
H4	Ease of use → AI_INT	0.229*	2.68	0.008	Partial
H5a	PB → AI_INT	0.246	5.03	0.000	Yes
H5b	PB → FB_AI	0.320	6.14	0.000	Yes
H6	AI_SEL → FB_AI	0.114	2.04	0.042	Yes
H7	Risks → FB_AI	n.s.	–	–	No
H8	SE_AI → FB_AI	0.208	3.88	0.000	Yes
H9	Gender → FB_AI	n.s.	–	–	No

Note: * indicates significance only in Romania's sub-model. R^2 (FB_AI) = 0.395.

These findings are consistent with previous evidence indicating that perceived utility and performance expectancy predominantly influence risk perceptions in the context of adoption (Cabrera-Sánchez et al., 2020; Dwivedi et al., 2021; Mou et al., 2023).

4.5. Cross-country measurement invariance and multi-group analysis

To ensure comparability, MICOM was employed as per Henseler et al. (2016). Configural invariance was achieved by specifying identical models. Compositional invariance was verified through permutation tests, while the equality of means and variances indicated partial invariance, which is sufficient for cross-country MGA. Table 6 presents the MICOM results.

Table 6. MICOM results (Romania vs. Poland)

Step	Construct	p-value	Invariance Established?
Step 2 – Compositional invariance	All constructs	> 0.05	Yes
Step 3 – Equality of means	AI_INT = 0.016	Partial	Some differences
	BT_II = 0.000	No	Significant mean difference
	Others > 0.05	Yes	Equality established
Step 3 – Equality of variances	SE_AI = 0.043	No	Significant variance difference
	AI_SEL = 0.017	No	Significant variance difference
	Others > 0.05	Yes	Equality established

Note: Partial measurement invariance confirmed, sufficient for MGA (Henseler et al., 2016).

A multi-group analysis (MGA) was conducted using permutation and PLS-MGA methodologies. The findings showed significant variations in certain pathways. The influence of AI integration on future behavior was stronger in Romania, while personal benefits were more evident in Poland (Table 7). Other pathways, such as social environment → future behavior, showed no significant differences across groups.

Table 7. Multi-Group Analysis (Romania vs. Poland)

Path	β (RO)	β (PL)	Difference	p-value	Significant?
AI_INT → FB_AI	0.302	0.133	0.170	0.020	Yes
PB → FB_AI	0.288	0.385	–0.097	0.271	No
SE_AI → FB_AI	0.204	0.233	–0.029	0.705	No
AI_SEL → FB_AI	0.332	0.195	0.137	0.128	No
AR_AI → AI_INT	0.276	0.147	0.129	0.141	No

Note: MGA results (Keil approach, 5,000 permutations). Significant difference observed for AI_INT → FB_AI.

To elucidate these distinctions, separate structural models were estimated for each country, as illustrated in Figure 2 (Poland) and Figure 3 (Romania).

4.6. Synthesis of results

The models demonstrated that AI adoption intentions among CEE youth are shaped by individual factors (knowledge, perceived benefits), social influences (peer norms), and contextual conditions (ease of use, resources). Polish participants prioritized tangible benefits and resources, while Romanian participants placed greater weight on ease of use and experiential familiarity. These differences underscore the need to tailor digital policies and educational initiatives to national contexts while developing shared European strategies promoting AI literacy and responsible adoption.

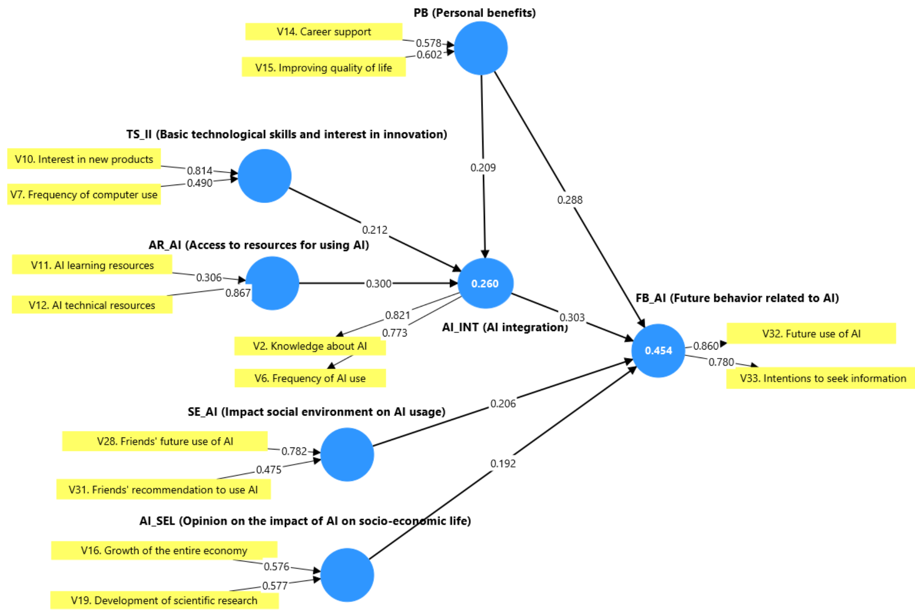

Figure 2. Structural equation model for Poland's subsample (source: own processing with SmartPLS 4)

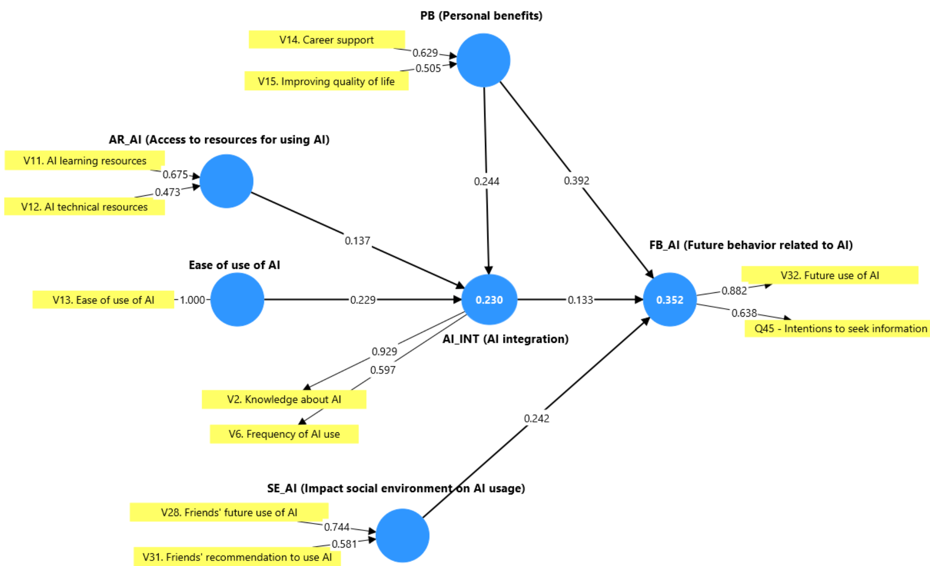

Figure 3. Structural equation model for Romania's subsample (source: own processing with SmartPLS 4)

5. Discussion

The PLS-SEM results reveal that AI adoption among Generation Z in Romania and Poland is shaped by perceived personal benefits, current integration experience, social influence, and broader socio-economic expectations.

The strongest predictor of future behavioral intentions is perceived personal benefit, consistent with the Technology Acceptance Model's emphasis on perceived usefulness. Respondents evaluate AI primarily through practical advantages such as career opportunities, learning support, and productivity gains, aligning with prior evidence that perceived utility dominates adoption behavior (Dwivedi et al., 2021). The positive relationship between current AI integration and future intentions further suggests that early exposure reduces uncertainty and strengthens adoption readiness.

Social dynamics also play a meaningful role in shaping behavioral intentions. The influence of peer perceptions and recommendations confirms the importance of social norms emphasized in the Theory of Planned Behavior (Ajzen, 1991). AI adoption is thus partly socially mediated: individuals are more likely to adopt new technologies when peers support or normalize their use (Davidaviciene & Al Majzoub, 2022).

Beyond individual and social factors, broader perceptions of AI's societal role also shape behavioral intentions. Respondents who associate AI with scientific progress, innovation, and economic development report stronger future use intentions, indicating that adoption is driven not only by personal utility but also by beliefs about AI's developmental potential.

A particularly noteworthy result is the non-significant effect of risk perceptions on behavioral intentions. Although respondents acknowledged risks such as job displacement and cognitive dependency, these concerns did not reduce stated intentions to use AI, suggesting that perceived opportunities carry greater behavioral weight than perceived threats.

Several factors may explain this pattern. Generation Z tends to approach digital technologies pragmatically, focusing on immediate academic and professional benefits. Individuals socialized in highly digital environments may perceive technological disruption as a normal condition rather than a deterrent. In the CEE context, emerging technologies are frequently associated with modernization and economic convergence, which increases the perceived salience of benefits relative to risks. Consistent with prospect theory (Kahneman & Tversky, 1979), anticipated gains associated with AI adoption appear to outweigh perceived losses at the level of stated behavioral intention.

The comparative analysis reveals broadly similar structural patterns across the two countries, with MGA indicating a stronger effect of AI integration on future intentions in Romania, where practical familiarity may be especially important given a still-evolving digital ecosystem. Other cross-country differences appear mainly at a descriptive level and should be interpreted cautiously.

Together, these results support a multi-level interpretation: micro-level personal benefits and experience, meso-level peer validation, and macro-level socio-economic context all contribute to AI adoption intentions among CEE youth. These relationships are synthesized in Table 8 and Figure 4.

Figure 4 offers a visual representation of this framework, illustrating the interaction among micro, meso, and macro dimensions in shaping future behavioral intentions. Notably, Romania and Poland exhibit distinct patterns in this context.

Table 8. Conceptual framework of AI adoption in CEE (source: own processing based on PLS-SEM and MGA results)

Level	Key factors	Role in adoption	Country differences
Micro	- AI knowledge & usage (AI_INT) - Personal benefits (PB) - Ease of use	Direct predictors of future behavior; benefits are strongest overall	Ease of use stronger in Romania
Meso	- Social environment (SE_AI) - Peer influence, recommendations	Social validation and group norms shape intentions, reinforcing adoption	Similar role in both countries
Macro	- Perceived socio-economic impact (AI_SEL) - National infrastructure/resources (AR_AI)	Legitimacy of AI at societal level supports adoption indirectly	Benefits & resources stronger in Poland
Outcome	- Future behavior (FB_AI): intention to use AI more frequently and seek further learning	Captures adoption potential and sustainability	Higher explanatory power in Poland (R^2 = 0.454) vs Romania (R^2 = 0.352)

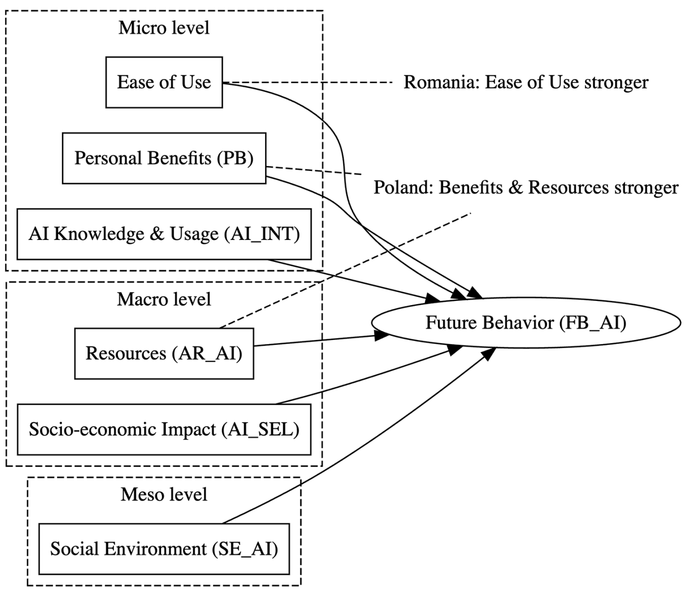

Figure 4. Conceptual framework of AI adoption in CEE (micro, meso, macro levels)

6. Theoretical and managerial implications

6.1. Theoretical implications

This study contributes to the literature on artificial intelligence adoption by extending established technology acceptance frameworks, including the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Unified Theory of Acceptance and Use of Technology (UTAUT). While these frameworks traditionally emphasize perceived usefulness, ease of use, and social influence, the present research integrates these elements within a broader multi-level analytical structure that incorporates micro-, meso-, and macro-level determinants.

At the micro level, the results highlight the importance of individual experience, perceived personal benefits, and perceived ease of use in shaping AI adoption intentions. At the meso level, peer influence and social validation emerge as relevant mechanisms. At the macro level, perceptions regarding the socio-economic role of AI and the availability of institutional resources contribute to shaping the adoption context. By integrating these dimensions, the study proposes a multi-level framework that captures the complex interplay between individual perceptions, social environments, and structural conditions in the adoption of emerging technologies.

Another theoretical contribution concerns the asymmetry between positive and negative AI perceptions. Although respondents acknowledged risks such as job displacement or cognitive dependency, these did not significantly predict behavioral intentions. Instead, perceived personal benefits exerted the strongest influence, suggesting that anticipated gains outweigh perceived risks for Generation Z – consistent with research indicating that motivation and utility can offset uncertainty in technology adoption contexts (Chang et al., 2025).

Finally, the comparative analysis provides empirical evidence from Central and Eastern Europe, a region that remains underrepresented in the AI adoption literature. Although the structural relationships appear broadly similar across the two countries analyzed, the results indicate some contextual differences in the relative importance of specific drivers. This contributes to a more nuanced understanding of how technology adoption models operate in emerging digital ecosystems.

6.2. Managerial and policy implications

The findings offer implications for educational institutions, organizations, and policymakers seeking to encourage responsible AI adoption among young users.

First, the strong influence of perceived personal benefits suggests communication strategies should emphasize practical advantages of AI. Universities should integrate AI competencies into curricula across disciplines, including non-technical fields. Second, policymakers should support initiatives expanding access to AI tools, learning platforms, and digital training, reducing barriers and supporting inclusive participation in digital innovation. Third, peer environments amplify adoption: student innovation labs, collaborative projects, and technology clubs can normalize responsible AI use in academic and professional contexts.

The comparative findings suggest adoption strategies should account for national contexts. Where digital ecosystems are still evolving, accessibility and usability improvements are most impactful; in more mature digital contexts, advanced training and institutional support take priority.

Finally, although risk perceptions did not significantly influence behavioral intentions in this study, policymakers and educators should not overlook ethical and societal concerns related to AI. Promoting responsible AI literacy, including awareness of privacy, fairness, and long-term societal implications, remains essential for ensuring balanced and sustainable technology adoption.

7. Conclusions and limitations

This study examined AI adoption among Generation Z in Romania and Poland. Perceived personal benefits emerged as the strongest predictor of future behavioral intentions, followed by current AI integration, resource access, and social influence. Although respondents acknowledged AI-related risks, these concerns did not significantly reduce stated adoption intentions.

Theoretically, the study integrates micro-, meso-, and macro-level determinants into a unified adoption framework and provides empirical evidence from a CEE region underrepresented in AI adoption research.

The results should be interpreted considering several limitations. First, the non-probabilistic sampling approach limits generalizability beyond the studied population. Second, the cross-sectional design captures perceptions at a single point and does not allow causal inference regarding long-term adoption behavior. Future studies could employ longitudinal designs to explore how AI perceptions evolve as technologies become more integrated into educational and professional environments. These findings align with prior evidence published in highly ranked outlets. The dominance of perceived personal benefits echoes results from Dwivedi et al. (2021), published in the International Journal of Information Management, who documented performance expectancy as a primary adoption driver across multiple digital technologies. The non-significant role of risk perceptions is consistent with Venkatesh et al. (2012), published in MIS Quarterly, where inhibiting factors were frequently offset by strong utility expectations. The multi-level framework further corroborates Camilleri (2024), published in Technological Forecasting and Social Change, who similarly found that perceived usefulness and ease of use outweigh concern-based barriers in AI adoption contexts. Country-level differences observed in this study extend the comparative logic applied by Scantamburlo et al. (2025) in IEEE Transactions on Artificial Intelligence, who documented heterogeneous AI attitudes across European nations, suggesting that regional digital maturity shapes adoption dynamics in ways that uniform frameworks may underestimate.

Although the model explains a substantial share of behavioral intentions (R^2 = 0.395), additional factors such as institutional trust, media exposure, or prior experience with advanced AI systems may further improve explanatory power in future research. From a practical standpoint, the findings carry concrete policy implications. Universities in Romania and Poland should prioritize embedding AI literacy into non-technical degree programs, since the strong influence of perceived personal benefits suggests that students respond to tangible, career-oriented framings of AI rather than abstract technological arguments. Policymakers should design national AI strategies that differentiate between access-oriented interventions (more relevant in Romania, where ease of use drives adoption) and competency-oriented interventions (more relevant in Poland, where benefit expectations dominate). At the European level, cohesion funding directed at digital infrastructure and open-access AI training platforms may help reduce the adoption gap between CEE and Western EU countries. Finally, because social environment exerts a consistent influence across both countries, peer-learning communities and student innovation networks represent cost-effective channels through which institutional actors can accelerate responsible AI adoption among Generation Z.

8. Practical recommendations

Based on these findings, educational institutions should integrate AI literacy across disciplines and support peer-learning environments such as student innovation communities. Organizations can accelerate adoption by emphasizing professional benefits and providing intuitive AI tools that reduce entry barriers. At the governmental level, policy initiatives should balance infrastructure investments with digital skills programs, ensure equitable access for disadvantaged groups, and promote responsible AI use through awareness of privacy, algorithmic transparency, and broader societal implications.

Author contributions

LT and BN conceived the study and were responsible for the overall design and methodology. LT and MD collected and curated the data. BN and MB performed the formal analysis and structural modelling. LZ contributed to the literature review, validation, and refinement of the theoretical framework. LT and BN prepared the first draft of the manuscript. LT, LZ, MB, and MD contributed to reviewing and editing the final version. All authors read and approved the submitted manuscript.

Disclosure statement

Authors declare no competing financial, professional, or personal interests from other parties.

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APPENDIX

A. Survey instrument

Section 1. AI Usage and Knowledge
V1	Used AI applications	Yes/No
V2	Knowledge about AI	1 = very low … 5 = very high
V3	Attended AI courses/training	Yes/No
V4	Type of AI applications used	1 = exclusively free … 5 = predominantly paid
V5	Purpose of AI use: education, professional, entertainment, other	Multiple-choice
V6	Frequency of AI use	1 = less than once/month … 5 = several times/day

Section 2. Perceived Benefits and Ease of Use
V7	Frequency of computer use	1 = very low … 5 = very high
V8	AI helps discover features	1 = strongly disagree … 5 = strongly agree
V9	AI makes tasks easier	1 = strongly disagree … 5 = strongly agree
V10	Interest in new technologies	1 = strongly disagree … 5 = strongly agree
V11	Educational resources for AI	1 = strongly disagree … 5 = strongly agree
V12	Technical resources for AI	1 = strongly disagree … 5 = strongly agree
V13	AI easy to use	1 = strongly disagree … 5 = strongly agree
V14	AI helps career development	1 = strongly disagree … 5 = strongly agree
V15	AI improves quality of life	1 = strongly disagree … 5 = strongly agree

Section 3. Socio-Economic Impact
V16	AI supports economic development	1 = strongly disagree … 5 = strongly agree
V17	AI strengthens high-tech fields	1 = strongly disagree … 5 = strongly agree
V18	AI stimulates new sectors	1 = strongly disagree … 5 = strongly agree
V19	AI boosts scientific research	1 = strongly disagree … 5 = strongly agree

Section 4. Risks and Trust
V20	AI may cause job losses	1 = strongly disagree … 5 = strongly agree
V21	AI may harm cognition	1 = strongly disagree … 5 = strongly agree
V22	AI erodes communication	1 = strongly disagree … 5 = strongly agree
V23	AI may evolve uncontrollably	1 = strongly disagree … 5 = strongly agree
V24	AI thinks better than humans	1 = strongly disagree … 5 = strongly agree
V25	Human validation needed	1 = strongly disagree … 5 = strongly agree
V26	AI suitable for routine decisions	1 = strongly disagree … 5 = strongly agree
V27	AI not suitable for complex decisions	1 = strongly disagree … 5 = strongly agree

Section 5. Social Environment
| V28 | Friends recommend AI | 1 = strongly disagree … 5 = strongly agree |
| V31 | Friends intend to use AI | 1 = strongly disagree … 5 = strongly agree |

Section 6. Future Intentions
| V32 | Intend to use AI more frequently | 1 = strongly disagree … 5 = strongly agree |
| V33 | Intend to seek more AI knowledge | 1 = strongly disagree … 5 = strongly agree |

Note: Items were measured using 5-point Likert or Semantic Differential scales unless specified. Constructs were operationalized per TAM, TPB, and UTAUT frameworks, extended with socio-economic perceptions and risk dimensions. Coding (V1–V33) aligns with model specification in Tables 3–6 of Results.

B. Measurement model assessment

To assess measurement model quality, we examined collinearity statistics (VIF), reliability, and validity indicators. The results are summarized in Tables A1–A2.

Table A1. Collinearity statistics (VIF) for outer model indicators

Construct / Indicator	VIF
Q50	1.000
V10. Interest in new products	1.016
V11. AI learning resources	1.017
V12. AI technical resources	1.316
V14. Career support	1.321
V15. Improving quality of life	1.321
V16. Growth of the entire economy	1.481
V19. Development of scientific research	1.481
V2. Knowledge about AI	1.080
V28. Friends' future use of AI	1.023
V31. Friends' recommendation to use AI	1.023
V32. Future use of AI	1.041
V33. Intentions to seek information	1.041
V6. Frequency of AI use	1.080
V7. Frequency of computer use	1.016

Note: All VIF values are below the threshold of 3.3 (Kock, 2015), indicating multicollinearity is not a concern in the outer model.

Table A2. Reliability and validity indicators of constructs

Construct	Cronbach's α	rho_A	Composite Reliability (CR)	AVE
AI_INT (AI integration)	0.428	0.452	0.774	0.633
FB_AI (Future behavior related to AI)	0.330	0.332	0.748	0.598

Note: Cronbach's alpha and rho_A are reported for transparency, but these coefficients are not the primary quality criteria for the formative constructs specified in this study. In formative measurement, indicators represent distinct dimensions of a construct and are therefore not expected to exhibit high internal consistency. For this reason, construct assessment relies primarily on multicollinearity diagnostics and indicator contribution. As shown in Table B1, all VIF values remain below the recommended threshold, supporting the adequacy of the formative measurement specification (Hair et al., 2022).