Research Report

Objective of the Sampling

During the research, probability sampling was conducted using quotas based on firm size and sector in Hajdú-Bihar and Bihor counties. The sample included 250 enterprises, each employing fewer than 250 people, with equal representation from both countries. The questionnaire consisted of three main sections: firm characteristics and the assessment of the general level of digitalization, latent variable groups, and a discussion of the primary barriers to the adoption of AI technologies. The assessment of latent variables was based on the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003). Using latent-variable measurement was essential because while AI technologies are widely recognized, their adoption and diffusion vary significantly. Consequently, many enterprises lack direct experience with these technologies and instead rely on their perceptions and expectations. These perceptions and expectations are shaped by complex technological and social factors that can be challenging to quantify. The essence of measuring latent variables is to approximate underlying factors using a set of interrelated questions that explore different aspects of the same construct. These question sets help capture abstract and hard-to-measure behavioral traits. In the UTAUT model, the primary components are Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. Therefore, the adoption of technology is influenced by an enterprise's expectations regarding the technology and the effort required to implement it. We enhanced this framework by adding two additional sets of supporting questions. The first group focused on AI explainability, specifically on how transparency in AI outcomes influences its adoption. The second group consisted of nine questions divided into three subdimensions: competence, integrity, and benevolence, which were designed to assess trust in AI. This categorization is based on the classic components of organizational trust as identified by Mayer et al. (1995). The key response variable was the measure of behavioral intentions to use advanced AI technologies.

Table 1: Descriptive Statistics of the Sample

	Hungary (N = 119 after data cleaning)	**Romania (N = 117 after data cleaning)**	**p-value**
Behavioral Intentions			0.20
= 1 (none or weak)	26.89%	38.46%	
= 2 (uncertain)	31.09%	27.35%	

= 3 (strong/very strong)	42.02%	34.19%	
Firm age	13.53 (8.57)	25.50 (10.93)	0.00
Size			0.00
micro	78.99%	43.59%	
small	19.33%	40.17%	
medium	1.68%	16.24%	
Share of exporters	15.13%	23.08%	0.12
Sector			0.00
Agriculture	5.04%	9.40%	
Construction	6.72%	9.40%	
Industry	11.76%	22.22%	
Services	60.50%	33.33%	
Trade	15.97%	25.64%	
IT department	12.61%	13.68%	0.80
Net sales revenue/employee	~8.67 million HUF (~18.5 million HUF)	~35.3 million HUF (~47.6 million HUF)	0.00
Missing	4	15	
Personnel cost ratio (%)	34.29 (24.04)	32.39 (20.82)	0.70

Note: For metric variables (age, NSR/employee, personnel cost ratio), the displayed values indicate the mean and standard deviation. The p-value refers to the statistical test according to the type of variable. Behavioral intention is the categorized version of the original 7-point scale.

Source: Authors' own compilation (2025)

Methodology

Several factors needed to be considered in the design of the methodology. First, due to the format of the survey, the questions are ordinal in nature. Although a 7-point scale is often treated as continuous, it is more effective to address AI adoption using categorical variables. Consequently, methods were required that could accommodate the ordinal nature of the responses. Second, examining the UTAUT items is not always feasible through latent modeling; therefore, methods that can manage a large number of strongly correlated ordinal variables were necessary. In the first phase of the research, we focused on a key policy question: What factors affect behavioral intention to use advanced AI technologies? To predict behavioral intention, we utilized two innovative algorithms: the ordinal random forest (Hornung, 2020; Hornung, 2024) and the frequency-adjusted borders ordinal random forest algorithm (Buczak, 2025a; Buczak, 2025b). Both methods are effective in managing a large number of correlated variables while accurately predicting outcomes that respect their ordinal nature. We evaluated prediction performance using stratified, repeated five-fold cross-validation and identified the main predictors using variable importance measures. In the second phase of the research, to understand the barriers to AI adoption, we employed a finite mixture algorithm capable of row, column, and biclustering (Matechou et al., 2016; Fernández et al., 2019; McMillan et al., 2025). This approach simultaneously identifies similar respondents (rows) and structurally coherent groups of questions (columns), providing significantly more information than traditional clustering algorithms. The method is based on the Proportional Odds ordinal model and the Expectation-Maximization (EM) algorithm. The results from the novel algorithms were further validated through data processing and visualization procedures (Wickham et al., 2019).

Main Results

The results revealed intriguing relationships between AI-related intention and regional differences. According to the ordinal forest algorithms, the most significant predictors influencing behavioral intention varied notably between Hungary and Romania. In Hungary, the strongest predictors were technical compatibility and performance expectations related to productivity, efficiency, and long-term business goals. Conversely, in Romania, supportive managerial attitudes, employees' knowledge levels, and preparedness related to the workforce and infrastructure were the most decisive factors. In both countries, behavioral intention was predominantly influenced by internal organizational factors, while external pressures, such as those from consumers or competitors, had little to no impact. This aligns with existing literature and emphasizes that the primary drivers behind digitalization and technology implementation stem from internal organizational forces rather than external influences. Additionally, the biclustering analysis uncovered noteworthy differences between potential AI adopters and non-adopters in Hungary and Romania, particularly in their evaluations of experienced challenges. Two sets of AI implementation barriers were identified across different dimensions in both countries. The first set encompassed traditional investment-oriented factors, such as technology costs, expected returns, data management, data security, and legal liability. The second set addressed compatibility issues between firms and technology, including economies of scale, employee skills and knowledge, financing challenges, and the availability of suitable AI solutions. Furthermore, in Hungary, regulatory and compliance difficulties emerged as a distinct group. Overall, our analysis identified legal liabilities and uncertainties regarding expected returns as the most pressing issues. Notably, AI adoption barriers could not be effectively explained by general firm-specific characteristics, such as firm size or sector, which are often regarded as primary drivers of AI adoption.

Policy Implications for Regional Development

The factors influencing technology and digital adaptation are more complex than previously thought, emphasizing the need for policymakers to create tailored solutions for small and medium-sized enterprises (SMEs). Predictive analyses indicate that internal organizational factors, such as workforce readiness and infrastructure compatibility, along with performance expectations, are more influential than external social factors. In other words, AI adoption primarily arises from internal motivations. Based on these findings, public policies should focus on reducing implementation barriers, mainly by providing financial and educational support. Policymakers should allow firms to determine their specific strategies, as one-size-fits-all policy interventions are likely to be less effective. Additionally, the regulatory environment needs to be more robust towards liability and data issues. Companies tend to evaluate AI adoption from an investment standpoint, and they see unpredictable returns and unclear legal and data management responsibilities as significant obstacles. As a result, firms often shy away from the risks associated with AI technologies; thus, the regulatory framework must address and reduce these uncertainties. While there are transnational initiatives aimed at creating a stable and predictable business environment for AI-based solutions, significant variability remains at both national and firm levels. The results indicate considerable region-specific differences, particularly at the firm level, although the most important barriers to adoption are largely consistent across regions.

References

BUCZAK, P. 2025a. fabOF: frequency adjusted borders Ordinal Forest. https://github.com/phibuc/fabOF.

BUCZAK, P. 2025b. Frequency-adjusted borders ordinal forest: A novel tree ensemble method for ordinal prediction. *British Journal of Mathematical and Statistical Psychology,* 78**,** 594-616.

FERNÁNDEZ, D., ARNOLD, R., PLEDGER, S., LIU, I. & COSTILLA, R. 2019. Finite mixture biclustering of discrete type multivariate data. *Advances in Data Analysis and Classification,* 13**,** 117-143.

HORNUNG, R. 2020. Ordinal Forests. *Journal of Classification,* 37**,** 4-17.

HORNUNG, R. 2024. ordinalForest: Ordinal Forests: Prediction and Variable Ranking with Ordinal Target Variables. https://cran.r-project.org/web/packages/ordinalForest/index.html.

MATECHOU, E., LIU, I., FERNÁNDEZ, D., FARIAS, M. & GJELSVIK, B. 2016. Biclustering Models for Two-Mode Ordinal Data. *Psychometrika,* 81**,** 611-624.

MAYER, R. C., DAVIS, J. H. & SCHOORMAN, F. D. 1995. An Integrative Model of Organizational Trust. *The Academy of Management Review,* 20**,** 709-734.

MCMILLAN, L., FERNÁNDEZ MARTÍNEZ, D., CUI, Y. & MATECHOU, E. 2025. clustord: Cluster Ordinal Data via Proportional Odds or Ordered Stereotype. R package version 1.3.4 ed. https://CRAN.R-project.org/package=clustord.

VENKATESH, V., MORRIS, M. G., DAVIS, G. B. & DAVIS, F. D. 2003. User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly,* 27**,** 425-478.

WICKHAM, H., AVERICK, M., BRYAN, J., CHANG, W., MCGOWAN, L. D. A., FRANÇOIS, R., GROLEMUND, G., HAYES, A., HENRY, L., HESTER, J., KUHN, M., PEDERSEN, T. L., MILLER, E., BACHE, S. M., MÜLLER, K., OOMS, J., ROBINSON, D., SEIDEL, D. P., SPINU, V., TAKAHASHI, K., VAUGHAN, D., WILKE, C., WOO, K. & YUTANI, H. 2019. Welcome to the Tidyverse. *Journal of Open Source Software,* 4**,** 1686.