Chapter 5
Generative AI Adoption and Use by Micro-enterprises: Validation of the Measurement Instrument

Artur Strzelecki, Małgorzata Pańkowska, and Mariia Rizun

Abstract Artificial intelligence and all AI-based tools have recently become a crucial part of everyday life both for individual users and businesses. Yet, with it have come the doubts and distrust toward AI, as well as the lack of awareness of the ways of using this tool. Inspired by the scale of research dedicated to the use of Technology Acceptance Models like TAM or UTAUT2, the authors have developed the Technology Readiness Index—Environment-Organization-Use (TRIEOUS) framework to measure the usage and adoption of generative AI, specifically for micro-enterprises. This paper presents the content of this framework and the procedure of validation of the framework with the help of EFA and CFA analysis methods. Results of the statistical validation, based on the pilot testing data, show that the TRIEOUS framework, combining TAM, TOE, and TRI models, in its current format, does not sufficiently match the phenomena it is supposed to analyze. Modifications of the framework, beginning with the decrease in the number of analyzed items, are required.

5.1 Introduction

In 2016, during the 46th World Economic Forum it was announced that current economics, in the era of the 4th Industrial Revolution is being led by the artificial intelligence (AI) [1]. Indeed, AI has been used by individuals and companies in various fields, introducing permanent changes into our activity. AI-based technologies are being used in manufacturing, finance, medicine, education, music, and many other spheres of our life. However, both individuals and whole companies tend to be hesitant about accepting AI in its full potential. That is why it is crucial to explore users' acceptance and attitudes regarding AI, generative AI and all AI-based tools. It is essential to reveal the factors influencing users' acceptance of AI and their willingness to use it for professional or private tasks [2].

A. Strzelecki (✉) · M. Pańkowska · M. Rizun
Department of Informatics, University of Economics in Katowice, Katowice, Poland
e-mail: artur.strzelecki@ue.katowice.pl

J. L. Reis et al. (eds.), *Marketing and Smart Technologies*, Smart Innovation, Systems and Technologies 438, https://doi.org/10.1007/978-981-96-3077-6_5

One of the most frequently used tools to access users' acceptance of technology presently are the Technology Acceptance Model, proposed in 1989 [3], and further developed into TAM2 [4] and TAM3 [5], and the Unified Theory of Acceptance and Usage of Technology (UTAUT) model, proposed in 2003 [6] and later changed into the UTAUT2 [7]. For instance, only in the year 2024 (as the year of publication), the search of the keywords "Technology Acceptance Model" OR "TAM" gives 22 papers in the IEEE Xplore database, 432 papers in Scopus, 16 069 papers in ScienceDirect database. "UTAUT" OR "UTAUT2" results in 12 papers in IEEE Xplore, 200 papers in Scopus, and 164 papers in ScienceDirect. These models have been frequently verified to work as efficient tools to assess acceptance of various kinds of technologies (as well as AI) by various groups of users. Moreover, there exist other models, developed separately or on the basis of TAM and/or UTAUT, as well as there are adoptions of these models created for usage in particular areas. However, much fewer research works present the combination of more than two different models into one research tool.

The authors of this paper have made an attempt of combining the Technology Acceptance Model, Technology Readiness Index and Technology–Organization–Environment model into one tool. Thus, the paper presents the Technology Readiness Index—Environment-Organization-Use (TRIEOUS) framework, developed for the assessment of the usage and adoption of generative artificial intelligence by micro-enterprises, as well as the procedure of this framework's validation, conducted with the Exploratory Factor Analysis and the Confirmatory Factor Analysis. The objective of the validation is to reveal whether the suggested tool fits the data of the phenomenon that it is supposed to measure.

The paper is structured as follows: the next section provides the theoretical background of AI application by enterprises, and presents the review of the approaches toward AI acceptance assessment, presented in literature; Sect. 5.3 introduces the conceptual model developed by the authors; Sect. 5.4 present the process of statistical validation of the model and the results of this validation; the final section (discussion) draws conclusions on the results of the study, and argues on their possible implications.

5.2 Theoretical Background

5.2.1 Problem Identification

Digital transformation of business organizations is a continuous process, where information communication technologies change processes, business models, and corporate relationships. Business organizations want, using the digital transformation, to stay relevant on their markets, speed up decision-making, improve customer service, automate robotic processes, and reduce business risks. Digital transformation is a highly complex endeavor that impacts the whole organization and covers various technologies. In this study, the authors focus on the factors having impact on the generative AI technologies implementation and usage in business units.

According to Weber [8], AI is the science of creating intelligent machines, and particularly intelligent computer programs. This discipline is related to the activities of using a computer to understand human intelligence. It is not a uniform discipline, but nowadays, there are plenty of AI sub-domains, i.e.:

- Natural language processing (NLP), for modeling the human computer interaction and analyzing large amounts of natural language data.
- Robotics, including mechanical engineering, electrical engineering, information technology, and computer science for construction robots supported with sensors and able to perform designed tasks.
- Cognitive system development to approximate biological cognitive processes.
- Knowledge engineering to support diagnosing and reasoning of computerized systems.
- Machine learning for solving problems through good training data and usage of large amounts of data for reasoning.

Niemi et al. [9] highlight also other sub-disciplines, such as:

- Speech, voice, and image recognition.
- Autonomous agents use as software bots.
- Data mining for diagnosing, predicting, socio-emotional well-being analysis, and fraud detection.

The authors aim to evaluate the intention of micro-enterprises' managers to use the AI solutions. That technologies' usage is assumed to depend on the socio-economic and environmental contexts. Micro-enterprises have from one to nine employees. The managers of such companies are unique, because they have an opportunity to direct and control all employees and all business assets. They impact the application of technical knowledge and skills, client orientation, customer satisfaction, achieving results, knowledge sharing and internal cooperation, managing staff, and development of trust and integrity. They should be competent enough to make decisions on investment into AI technologies.

5.2.2 Literature Review

The origin of AI goes back to 1950s, when the artificial neural networks were developed. Although the AI solutions are highly technical, requiring computer science knowledge and mathematical reasoning, the simplicity and intuitiveness of the mass production solutions easily accessible for citizens may inspire to implement and usage the AI software and devices.

This study presents a novel framework of the AI acceptance and contestation. This study results in identification of the factors influencing the willingness and fears of using AI. The authors conclude that statistical models are useful for policy decision makers and business managers who are involved in the promotion of the AI solutions implementation in business organizations [10].

The study aims to estimate the AI determinants and their impact on the AI technologies intention to use. Authors began from the literature survey on the AI modeling. The search query used to search titles, keywords, and abstracts was: "Artificial Intelligence" and "Exploratory Factor Analysis" and "Confirmatory Factor Analysis." The authors reviewed a number of repositories and found a large number of papers: IEEEXplore—28 papers, Scopus—44 papers, ScienceDirect—441 papers, PubMed—9 papers, Association for Information Systems electronic Library (AISeLib)—36 papers, Springer Nature—228 papers, and Sage Journals—104 papers. The papers were published within 2015 and 2024. The search included articles and conference proceedings written in English. The literature survey allowed for the identification of two approaches to the conceptual model formulation:

- Development of a novel framework from scratch [11–16].
- Modifying existing sociometric or psychometric frameworks by combining them, introducing new constructs, or removing those previously included by other authors [17–19].

In the conceptual model provided by [17], the attitudes toward adoption are positively related to the perceived ease of use (PEOU) and perceived usefulness (PU). The other construct included in the conceptual model are as follows: perceived self-efficacy (PSE), facilitating condition (FC), perceived risk (PR), and behavioral intention to adopt (BI). Poushneh et al. [18] developed the perception–action model of empathy (PAM) to understand how the empathetic response and narcissism can attract a person's attention, which in turn facilitates information exploration and results in consumer satisfaction and the use of voice AI. Chakraborty et al. [19] have integrated the Elaboration Likelihood Model (ELM) and Status Quo Bias (SQB) theory to develop the Unified Framework for Trust on Technology Platforms.

This study novel framework is driven by theoretical background including the Theory of Reasoned Action (TRA) and Theory of Planned Behavior (TPB). The TRA provides a background of behavioral intention on attitude and behavior [20]. The TPB offers a connection between principles and behavior. The TRA and TPB explain that behavioral response is driven by how great the intention or motivation is [21].

Chronologically, the oldest framework proposal was provided by Fishbein and Ajzen, who developed the Theory of Reasoned Action (TRA) [20]. Later, Rogers [22] provided the Innovation Diffusion Theory. In 1989, Davis [3] proposed the Technology Acceptance Model (TAM), which was further developed as TAM2 [4] and TAM 3 [5]. In 2003, Venkatesh et al. [6] published the Unified Theory of Acceptance and Usage of Technology (UTAUT) model, which was further changed into the UTAUT2 model [7]. In this study, the authors propose the conceptual model, which covers three latent variables, also included in the TAM model. They are as follows: perceived usefulness (PU), perceived ease of use (PEO), and continuance intention to use (CITU). For that constructs' identification, the authors used the Revised Technology Adoption Model (RTAM) provided by Chukwuere et al. [23].

According to them, perceived usefulness means confidence in information technology to increase user productivity, effectiveness, and task performance. Perceived ease of use (PEOU) variable is understood as a personal judgment that technology can be used in a comfortable way. Intentions to use include personal willingness and desires to use a particular technology. The RTAM summarizes the development of the TAM development and its modifications. The RTAM framework can be considered as set of conceptual models, in which independent and dependent variables have been identified and relationships among variables have been proposed and estimated.

Chittopaka et al. [24] considered the Technology–Organization–Environment (TOE) model as different from TAM, TPB or UTAUT model. The technology perspective covers the following variables: relative advantage, compatibility, trust, and security. Organizational (ORG) perspective covers variables such as firms' IT resources, higher authority support, firm size, and monetary resources. Finally, the Environment (ENV) perspective comprises the rivalry pressure, business partner's pressure, and regulatory support. In this study, the authors included the technology variables in the TAM and TRI models.

Ullah et al. [25] define Technology Readiness (TR) as a four-dimensional construct covering optimism, innovativeness, insecurity, and discomfort. Parasuraman [26] constructed the Technology Readiness Index (TRI) including just those four dimensions. The optimism (OPT) means a positive view of technology and perception of benefits. Innovativeness (INN) refers to the role of a technological leader. Discomfort (DIS) refers to a perceived lack of control over technology and a feeling of being stressed while a technology usage. Finally, insecurity (INS) is a certain skepticism about technology, concerning about its potential harmful consequences [26]. The TR demands positive evaluation of technology in terms of quality, value, and satisfaction. Those motivators increase the technology usage, while inhibitors, i.e., discomfort and insecurity, lead to the technology rejection. According to Mahmud et al. [27], the TR represents the psychographic profile of the individuals based on the perceptions of the technology value.

Although TAM is a widely used framework for evaluation of user intention to accept innovative technology, the model does not use a social influence variable for Technology Acceptance. Hence, in the proposed framework, the Technology Readiness Index (TRI) is included. Although TRI with TAM can provide a better perspective on the Technology Acceptance, a need to understand the users' context for perception of innovative technology encouraged the authors to combine TRI with selected variable of TOE framework, i.e., environment and organization. Thus, in this study, the authors proposed the conceptual framework, Technology Readiness Index—Environment-Organization-Use, as a combination of TRI, TOE, and TAM models.

5.3 Conceptual Model

With the objective to measure the potential of adoption and acceptance of generative artificial intelligence by micro-enterprises, the authors developed an instrument, i.e., the conceptual framework, Technology Readiness Index—Environment-Organization-Use (TRIEOUS). Its model is presented in Fig. 5.1.

The authors pursue to determine the influence between constructs, so they indicate that a questionnaire survey is the appropriate research method for verification of theoretical linkages and interaction between the observable variables (i.e., items). Thus, the following steps were followed:

1. Prepare online questionnaires based on the selected measurement items.
2. Include introductory information to explain the purpose of the survey to respondents.
3. Conduct a pilot test of the questionnaire with a group of 24 selected respondents.
4. Distribute the questionnaires to relevant managers in Poland.
5. Collect data and assess its completeness.
6. Apply Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) to estimate the conceptual model.
7. Analyze the validity and reliability of the estimated model.
8. Evaluate the structural model.

The items of the developed instrument (TRIEOUS model) are presented in Table 5.1. The initial version of the instrument was made up from three subscales. First scale were the Environment (ENV) and Organization (ORG) dimensions from TOE framework containing twelve and eleven items, respectively, second scale was the TRI index containing dimension like Optimism (OPT), Innovativeness (INN), Discomfort (DIS), and Insecurity (INS) made up of a total of 23 items, classified into four dimensions. The third scale was adapted from the Technology Acceptance Model and its later extensions to include three dimensions: perceived usefulness (PU), perceived ease of use (PEOU), and continuance intention to use (CITU). These dimensions have three, four, and three items, respectively. A 7-point Likert scale was used to measure the items. For all dimensions the value 1 was associated with the "strongly disagree" label, while the value 7 was associated with the "strongly agree"

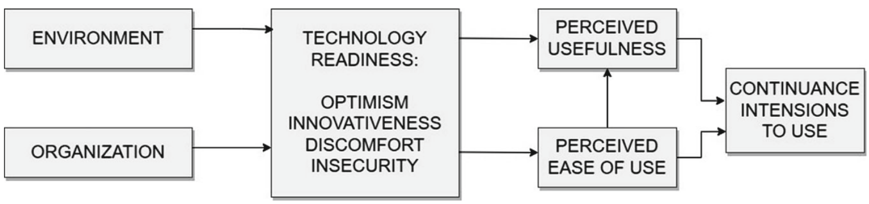

Fig. 5.1 TRIEOUS conceptual model

label. It is necessary to add here, that all litem questions (Table 5.1) consider generative AI technology. The phrase “generative AI” was not repeated in each statement to eliminate redundancy.

For a pilot testing of the survey questionnaire (step 3), a sample of 24 respondents from micro-enterprises were randomly chosen in Silesia region, Poland. This preliminary research allowed eliminating some observable variables, which were not valuable in the study. Later (in step 4), 229 complete questionnaires were gathered in a two-month lasting survey. The questionnaire was divided into three parts: the first part gave a brief explanation of the research’s purpose and guaranteed respondents’ anonymity and confidentiality; the second part asked questions about the respondents’ industry and number of work years at the surveyed company, company’s size (i.e., number of employees) and age; and the third part asked the stakeholders to provide feedback on the results of adoption of digital transformation.

The survey was conducted by collecting the data from the 229 micro-enterprises. In Poland, a micro-enterprise is an enterprise employing fewer than ten employees and for which the annual turnover and/or annual balance sheet total does not exceed Euro 2 million. The interviewed companies have one to three employees. The average number of employees in the sample companies was two persons. The surveyed companies’ age was two years at minimum and 98 years at maximum. The average age of the company stay on the market was 17 years. The questionnaires were provided to the micro-enterprises managers. Minimum number of manager work years in the micro-enterprise was one year, maximum—four years, and average—two years. The managers were asked to declare the industry, which the company belongs to. Hence, there were 67 commerce firms, 79 service firms, 70 production firms, and 13 high-tech firms.

5.4 Results

To perform steps 6–7 of the model development procedure (as presented in the previous section) and, thus, to conclude on the validity of the TRIEOUS model, the authors began with the Exploratory Factor Analysis (EFA), then followed by the Confirmatory Factor Analysis (CFA). This analysis was achieved after several attempts, resulting in a final survey instrument containing 52 questions divided into nine dimensions.

The EFA was conducted using IBM SPSS and the oblique Promax rotation method with Kaiser normalization [35]. This method allows for correlations between factors. Items with loadings below 0.3 were removed to ensure that the criterion guaranteed the adequacy of saturation and relevant factors [36]. This happened to items ENV11, ORG8, INN6, DIS6, and DIS7. The Kaiser–Meyer–Olkin (KMO) test result was 0.931, indicating the adequacy of the sample for factor analysis, while Bartlett’s test of sphericity was significant ($\chi 2 = 8122.580$; df $= 1326$; $p < 0.001$), supporting the reliability of the data for EFA. The final version of the factor analysis explained 58.51% of the true variance in the responses provided by the study participants.

Table 5.1 Items in the instrument

Construct	Item	Item question	References
ENV	ENV1	The utilization of technology in the company will enable making the right decisions and executing the appropriate tasks	[28, 29]
	ENV2	Technology allows for significantly faster decision-making and action execution	
	ENV3	Technology provides greater control over company operations	
	ENV4	Friends and colleagues influence my decisions to use technology	
	ENV5	The application of technology enhances the coordination of activities within business partner networks	
	ENV6	Our company's business partners recommend the adoption of technology	
	ENV7	Technology providers are actively encouraging us to purchase technology	
	ENV8	Current legal regulations are adequate for data management using technology	
	ENV9	Government organizations inspire me to trust technologies	
	ENV10	Government organizations support the implementation of technology	
	ENV11	Legal frameworks are necessary to address issues arising from the use of technology	
	ENV12	Legal regulations are sufficient to ensure the safe use of technology	
ORG	ORG1	The top management in my company supports the implementation of technology	[30, 31]
	ORG2	The top management provides the necessary resources for technology implementation	
	ORG3	The top management is willing to take the risks associated with technology adoption	
	ORG4	High acquisition costs discourage the adoption of technology	
	ORG5	Financial resources are critical for the adoption of technology	
	ORG6	Only highly profitable companies can afford to adopt technology	
	ORG7	Compatibility of technology with current company operations encourages its adoption	
	ORG8	Technology is not compatible with the processes in my company	
	ORG9	The hardware and software in my company are compatible with the technology requirements	

(continued)

Table 5.1 (continued)

Construct	Item	Item question	References
	ORG10	The technology aligns with the work culture and values in my company	
	ORG11	My company provides me with access to knowledge and training to use technology	
OPT	OPT1	Technology makes me work more efficiently	[26, 32, 33]
	OPT2	Technology gives me the ability to control my daily work	
	OPT3	Technology motivates me to take action and enhances my knowledge	
INN	INN1	I am willing to purchase technology even if I am not fully familiar with it	
	INN2	The changes required due to technology are consistent with current practices in the company	
	INN3	My company is ready to acquire people with the necessary technical and managerial skills for technology implementation and operation	
	INN4	I usually use technology without the help of others	
	INN5	I understand the significance of technology in my work environment	
	INN6	The skills required to use technology are beyond my reach	
	INN7	Using technology is an experiment; I learn it through practice	
	INN8	The results of using technology are widely visible, which encourages its adoption	
DIS	DIS1	Technologies complicate company procedures	
	DIS2	I avoid using technology for fear that something might go wrong	
	DIS3	I believe that technology might eliminate me from the job market	
	DIS4	I believe that technology threatens the protection of my privacy	
	DIS5	I trust technology and the decisions made with its help	
	DIS6	I believe that technologies are not designed for people without technical education	
	DIS7	The instructions on how to use technology are not written in simple language	
INS	INS1	Technology reduces the quality of social relationships by diminishing direct contact	
	INS2	Technology causes my company's information to be potentially used without the company's consent	
	INS3	The security of technology is inadequate for processing our company's information	

(continued)

Table 5.1 (continued)

Construct	Item	Item question	References
	INS4	Traditional technologies are safer than the ones listed below	
	INS5	Technologies hinder work and can even be harmful	
PU	PU1	The use of technology has positive effects on the environment and society	[3]
	PU2	The use of technology improves my company's operations	
	PU3	The introduction of technology reduces hardware and software costs in my company	
	PU4	Using technology is enjoyable and fun	
PEOU	PEOU1	I am often confused about whether and when to use technology	[4]
	PEOU2	When using technology, I constantly check (will check) the user manuals	
	PEOU3	Working with a technical system requires (will require) significant mental effort on my part	
CITU	CITU1	I will use technology in the future	[3, 6, 34]
	CITU2	I will recommend (suggest) the use of technology to others	
	CITU3	I prefer using technology over rejecting it	
	CITU4	I plan to implement technology within the next year	

Subsequently, CFA was conducted to assess the difference between the observed data and the model's predictions, utilizing both correlation and covariance matrices. The maximum likelihood method was employed for this analysis, under the assumption that the items follow a multivariate normal distribution. The validity of this assumption was checked using the Mardia Coefficient, which is deemed acceptable if it is lower than the result obtained from the formula $p(p + 2)$ [37], where p is the number of items in the factor model. For our model, which included 57 items from the original instrument, the Mardia Coefficient was found to be 3321.636, indicating that the matrix is likely normal.

To evaluate the adequacy of the model, several indices have been considered. The first is the CFI coefficient (Comparative Fit Index) was 0.756, and the NFI coefficient (Normed Fit Index) was 0.653. These values suggests that the model does not adequately capture the relationships among the variables and may require modification or a different model structure to better represent the data [38]. For the Root Mean Square Error of Approximation (RMSEA) index, a value between 0.05 and 0.08 would indicate a reasonable approximation error [39]. In this study, the result from CFA was 0.081, within the acceptable range. Finally, the Tucker-Lewis coefficient (TLI) is incremental fit indicator. Value close to 1 indicate a very good fit [40]. In this analysis in CFA, coefficient TLI = 0.738 was obtained, indicating further investigation and possible revisions to improve the model's fit to the data.

Concerning the reliability and validity of the constructs, the average variance extracted (AVE) values should surpass 0.50, following the criterion. To assess the

Table 5.2 Dimensions validity and reliability

Dimension	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Environment	0.894	0.906	0.919	0.655
Organization	0.903	0.909	0.923	0.633
Optimism	0.891	0.892	0.932	0.822
Innovativeness	0.803	0.808	0.871	0.629
Discomfort	0.696	0.765	0.827	0.620
Insecurity	0.836	0.867	0.888	0.667
PU	0.721	0.727	0.840	0.637
PEOU	0.742	0.759	0.853	0.659
CITU	0.861	0.869	0.906	0.708

internal consistency of Fornell–Larcker the measurement scale, both Cronbach's alpha and composite reliability were utilized. The literature generally suggests that these coefficients should be above 0.7, although some scholars, such as Hair [41], argue that a threshold of 0.6 can also be acceptable. Table 5.2 displays the reliability and validity measures for both samples, with all indices meeting satisfactory levels.

5.5 Discussion and Conclusions

In this paper, the authors present an instrument developed to measure the usage and attitude toward generative AI within micro-enterprises. The instrument represents a questionnaire with statements and the 7-point Likert scale to evaluate these statements. In the suggested instrument, the authors combined the dimensions from the Technology–Organization–Environment (TOE) framework, the Technology Readiness Index (TRI), and the Technology Acceptance Model (TAM). The developed framework was called Technology Readiness Index—Environment-Organization-Use (TRIEOUS). The TOE gave the environment and organization dimensions. The Environment refers to the external and internal conditions that affect the adoption and acceptance of technology in an organization. The Organization refers to internal factors within a company (e.g., management support, financial resources, culture, etc.) that influence the adoption and acceptance of technology. From TRI the authors took: Optimism (the positive perception that technology enhances personal efficiency, motivation, and knowledge), Innovativeness (an individual's willingness to embrace and experiment with new technologies), Discomfort (the negative perceptions and anxieties associated with technology), and Insecurity (concerns about technology compromising social interactions, data security, and overall safety). Finally, the TAM model engagement resulted in using: perceived usefulness (confidence of an individual in information technology to increase their productivity, effectiveness, and task performance), perceived ease of use (perception that technology can be used in a comfortable way), and continuance intention to use (a commitment to ongoing technology use, including future usage plans and recommendations to others). Overall, the developed questionnaire initially contained 57 questions within nine dimensions.

The instrument was validated with the Exploratory Factor Analysis (EFA), and then—with the Confirmatory Factor Analysis (CFA). The EFA revealed the loadings below 0.3 for five items (to be found in Table 5.1): ENV 11 (Environment dimension), ORG8 (Organization dimension), INN6 (Innovativeness dimension), DIS6 and DIS7 (Discomfort dimension). This means that these five items had to be removed from the list to make sure that the remaining items were strongly associated with the factors (dimensions) and that the factors (dimensions) themselves were meaningful and relevant. This led to the final number of items in the questionnaire being 52.

The CFA was further used to verify how well the proposed instrument matches the observed phenomenon. Out of four coefficients used (CFI, NFI, RMSEA, and TLI), only one (RMSEA) indicated a reasonable fit; the other three indices showed that the instrument needs revision because it does not fit the observed data. Taking into consideration the fact that all the applied models (TOE, TRI, and TAM) separately have been widely applied are known mostly to match the observed phenomena, the authors would conclude that it is the combination of three models that results into the instrument not passing the verification. Nine dimensions from three models, with a maximum of eleven items for one dimension (ENV), and 52 items in general—all that together may have resulted in the instrument being "too much" and too complex for analyzing the issue of generative AI usage by micro-enterprises. This leads to the conclusion that aiming to develop an efficient instrument to measure the potential of GAI in micro-enterprises, the authors will need to experiment with other versions of connecting the Technology–Organization–Environment framework, the Technology Readiness Index, and the Technology Acceptance Model into one research tool.

To support the idea by similar studies, the authors have searched for the works published within the last five years, for they analyze the acceptance of the most recent technology available for the enterprises. The revealed papers use the TAM and UTAUT/UTAUT2 model, or their combination, to explore the Technology Acceptance in micro-enterprises. For instance, Bonfanti et al. [42] apply TAM to study the intentions of microentrepreneurs' to use social networking sites, while Buvár and Gati [43] study the adoption of digital marketing by micro-enterprises. In both cases the Structural Equation Modeling was used to verify the results of the applied questionnaires. Validation of the model itself was not required. The authors Anton et al. [44] in their paper use the UTAUT2 model in combination with the Diffusion of Innovation (DOI) model and Business Model Canvas (BMC), obtaining their TAMC—Technology Adoption Model Canvas. The TAMC is stated to serve as a framework for assessing both the readiness to adopt smart technology and the effectiveness of the implemented technology, using qualitative and quantitative approaches. Yet, the paper does not provide any statistical validation of the model being fit to assess smart technology adoption. Thus, it cannot be fully compared with the results of the work presented in our paper.

The authors believe that the preliminary results of the Technology Readiness Index—Environment-Organization-Use (TRIEOUS) model validation, presented in the paper, would contribute to the theory and practice of Technology Acceptance analysis. Regardless the fact that the suggested instrument presently requires improvement, it can serve as the basis for further developments of other similar tools for the exploration of Technology Acceptance and use not only by micro-enterprises, but also by enterprises of other size. Based on the conducted research, it appears that the UTAUT2 model may still be considered a standard. Despite having been present in the research field for over a decade and some of its shortcomings being noted, it remains attractive for determining the willingness to accept new technologies, such as artificial intelligence.

Future research aimed at further developing this topic could focus on validating the scale by selecting observed variables that accurately and reliably define latent variables. Another potential direction for research could involve using data not from micro-enterprises but from larger enterprises that also use AI tools.

References

1. Skilton, M., Hovsepian, F.: The 4th industrial revolution: responding to the impact of artificial intelligence on business. Springer International Publishing, Cham (2018)
2. Na, S., Heo, S., Han, S., et al.: Acceptance model of artificial intelligence (AI)-based technologies in construction firms: applying the technology acceptance model (TAM) in combination with the technology–organisation–environment (TOE) framework. Buildings **12**, 90 (2022). https://doi.org/10.3390/buildings12020090
3. Davis, F.D.: Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q. **13**, 319 (1989). https://doi.org/10.2307/249008
4. Venkatesh, V., Davis, F.D.: A theoretical extension of the technology acceptance model: four longitudinal field studies. Manag. Sci. **46**, 186–204 (2000). https://doi.org/10.1287/mnsc.46.2.186.11926
5. Venkatesh, V., Bala, H.: Technology acceptance model 3 and a research agenda on interventions. Decis. Sci. **39**, 273–315 (2008). https://doi.org/10.1111/j.1540-5915.2008.00192.x
6. Venkatesh, V., Morris, M.G., Davis, G.B., Davis, F.D.: User acceptance of information technology: toward a unified view. MIS Q. **27**, 425–478 (2003). https://doi.org/10.2307/30036540
7. Venkatesh, V., Thong, J.Y.L., Xu, X.: Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. MIS Q. **36**, 157–178 (2012). https://doi.org/10.2307/41410412
8. Weber, F.: Artificial intelligence for business analytics. Springer Fachmedien Wiesbaden, Wiesbaden (2023)
9. Niemi, H., Pea, R.D., Lu, Y.: Introduction to AI in learning: Designing the future. In: AI in learning: designing the future, pp. 1–15. Springer International Publishing, Cham (2023)
10. Strzelecki, A., ElArabawy, S.: Investigation of the moderation effect of gender and study level on the acceptance and use of generative AI by higher education students: comparative evidence from Poland and Egypt. Br. J. Educ. Technol. **55**, 1209–1230 (2024). https://doi.org/10.1111/bjet.13425
11. Faruk, L.I.D., Pal, D., Funilkul, S., et al.: Introducing CASUX: a standardized scale for measuring the user experience of artificial intelligence based conversational agents. Int. J. Human-Comput. Interact. (2024). https://doi.org/10.1080/10447318.2024.2359206
12. Orden-Mejía, M., Carvache-Franco, M., Huertas, A., et al.: Modeling users' satisfaction and visit intention using AI-based chatbots. PLoS ONE **18**, e0286427 (2023). https://doi.org/10.1371/journal.pone.0286427

13. Koverola, M., Kunnari, A., Sundvall, J., Laakasuo, M.: General attitudes towards robots scale (GAToRS): a new instrument for social surveys. Int. J. Soc. Robot. **14**, 1559–1581 (2022). https://doi.org/10.1007/s12369-022-00880-3
14. Tjebane, M.M., Musonda, I., Okoro, C.: Organisational factors of artificial intelligence adoption in the South African construction industry. Front. Built. Environ. (2022). https://doi.org/10.3389/fbuil.2022.823998
15. Li, Y.: Relationship between perceived threat of artificial intelligence and turnover intention in luxury hotels. Heliyon **9**, e18520 (2023). https://doi.org/10.1016/j.heliyon.2023.e18520
16. Stevens, A.F., Stetson, P.: Theory of trust and acceptance of artificial intelligence technology (TrAAIT): an instrument to assess clinician trust and acceptance of artificial intelligence. J. Biomed. Inform. **148**, 104550 (2023). https://doi.org/10.1016/j.jbi.2023.104550
17. Nguyen, T.H.D., Nguyen, X.T., Le, T.H.T., Bui, Q.A.: Determinants influencing the adoption of artificial intelligence technology in non-life insurers. Corp. Gov. Organ. Behav. Rev. **8**, 205–212 (2024). https://doi.org/10.22495/cgobrv8i1p17
18. Poushneh, A., Vasquez-Parraga, A., Gearhart, R.S.: The effect of empathetic response and consumers' narcissism in voice-based artificial intelligence. J. Retail. Consum. Serv. **79**, 103871 (2024). https://doi.org/10.1016/j.jretconser.2024.103871
19. Chakraborty, D., Kumar Kar, A., Patre, S., Gupta, S.: Enhancing trust in online grocery shopping through generative AI chatbots. J. Bus. Res. **180**, 114737 (2024). https://doi.org/10.1016/j.jbusres.2024.114737
20. Fishbein, M., Ajzen, I.: Belief, attitude, intention, and behavior: an introduction to theory and research. Addison Wesley, MA (1975)
21. Ajzen, I.: From intentions to actions: A theory of planned behavior. In: Action control, pp. 11–39. Springer, Berlin Heidelberg, Berlin, Heidelberg (1985)
22. Rogers, E.M.: Diffusion of innovations, 5th edn. Free Press, NY (2003)
23. Chukwuere, J.E., Ntseme, O.J., Shaikh, A.A.: Toward the development of a revised technology acceptance model. In: The International Conference on Electronic Business. pp 551–561. (2021)
24. Chittipaka, V., Kumar, S., Sivarajah, U., et al.: Blockchain technology for supply chains operating in emerging markets: an empirical examination of technology-organization-environment (TOE) framework. Ann. Oper. Res. **327**, 465–492 (2023). https://doi.org/10.1007/s10479-022-04801-5
25. Jan, I.U., Ji, S., Kim, C.: What (de) motivates customers to use AI-powered conversational agents for shopping? The extended behavioral reasoning perspective. J. Retail. Consum. Serv. **75**, 103440 (2023). https://doi.org/10.1016/j.jretconser.2023.103440
26. Parasuraman, A.: Technology readiness Index (Tri): a multiple-Item scale to measure readiness to embrace new technologies. J. Serv. Res. **2**, 307–320 (2000). https://doi.org/10.1177/109467050024001
27. Mahmud, H., Islam, A.K.M.N., Mitra, R.K.: What drives managers towards algorithm aversion and how to overcome it? Mitigating the impact of innovation resistance through technology readiness. Technol. Forecast. Soc. Change **193**, 122641 (2023). https://doi.org/10.1016/j.techfore.2023.122641
28. Awa, H.O., Ojiabo, O.U., Emecheta, B.C.: Integrating TAM, TPB and TOE frameworks and expanding their characteristic constructs for e-commerce adoption by SMEs. J. Sci. Technol. Policy Manag. **6**, 76–94 (2015). https://doi.org/10.1108/JSTPM-04-2014-0012
29. Low, C., Chen, Y., Wu, M.: Understanding the determinants of cloud computing adoption. Ind. Manag. Data Syst. **111**, 1006–1023 (2011). https://doi.org/10.1108/02635571111161262
30. Chatterjee, S., Rana, N.P., Dwivedi, Y.K., Baabdullah, A.M.: Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. Technol. Forecast. Soc. Change **170**, 120880 (2021). https://doi.org/10.1016/j.techfore.2021.120880
31. Zhu, K., Kraemer, K.L., Xu, S.: The process of innovation assimilation by firms in different countries: a technology diffusion perspective on e-business. Manag. Sci. **52**, 1557–1576 (2006). https://doi.org/10.1287/mnsc.1050.0487

32. Tsikriktsis, N.: A technology readiness-based taxonomy of customers: a replication and extension. J. Serv. Res. **7**, 42–52 (2004). https://doi.org/10.1177/1094670504266132
33. Walczuch, R., Lemmink, J., Streukens, S.: The effect of service employees' technology readiness on technology acceptance. Inf. Manag. **44**, 206–215 (2007). https://doi.org/10.1016/j.im.2006.12.005
34. DeLone, W.H., McLean, E.R.: Information systems success: the quest for the dependent variable. Inf. Syst. Res. **3**, 60–95 (1992). https://doi.org/10.1287/isre.3.1.60
35. Grieder, S., Steiner, M.D.: Algorithmic jingle jungle: a comparison of implementations of principal axis factoring and promax rotation in R and SPSS. Behav. Res. Methods **54**, 54–74 (2021). https://doi.org/10.3758/s13428-021-01581-x
36. Thomas, C.L., Hayes, A.R.: Using exploratory structural equation modeling to investigate the construct validity of the critical thinking disposition scale. J. Psychoeduc. Assess. **39**, 640–648 (2021). https://doi.org/10.1177/0734282921990564
37. Bollen, K.A.: Structural equations with latent variables. Wiley (1989)
38. Zhang, M.F., Dawson, J.F., Kline, R.B.: Evaluating the use of covariance-based structural equation modelling with reflective measurement in organizational and management research: a review and recommendations for best practice. Br. J. Manag. **32**, 257–272 (2021). https://doi.org/10.1111/1467-8551.12415
39. Shi, D., DiStefano, C., Maydeu-Olivares, A., Lee, T.: Evaluating sem model fit with small degrees of freedom. Multivar. Behav. Res. **57**, 179–207 (2022). https://doi.org/10.1080/00273171.2020.1868965
40. Schumacker, R., Lomax, R.G.: A beginner's guide to structural equation modeling, 4th edn. Routledge, New York, NY (2016)
41. Hair, J.F.: Multivariate data analysis. Prentice Hall (2009)
42. Bonfanti, R.C., Tommasi, F., Ceschi, A., et al.: The antecedents of the technology acceptance model in microentrepreneurs' intention to use social networking sites. Eur. J. Investig. Heal. Psychol. Educ. **13**, 1306–1317 (2023). https://doi.org/10.3390/ejihpe13070096
43. Buvár, Á., Gáti, M.: Digital marketing adoption of microenterprises in a technology acceptance approach. Manag. Mark. **18**, 127–144 (2023). https://doi.org/10.2478/mmcks-2023-0008
44. Anton, T.S., Trupp, A., Stephenson, M.L., Chong, K.L.: The technology adoption model canvas (TAMC): A smart framework to guide the advancement of microbusinesses in emerging economies. Smart Cities **6**, 3297–3318 (2023). https://doi.org/10.3390/smartcities6060146