SILESIAN UNIVERSITY OF TECHNOLOGYPUBLISHING HOUSE

SCIENTIFIC PAPERS OF SILESIAN UNIVERSITY OF TECHNOLOGY 2025
ORGANIZATION AND MANAGEMENT SERIESNO. 227

EXPLORING THE ACCEPTANCE OF THE CHATGPT ARTIFICIAL INTELLIGENCE TOOL IN TEACHING PROGRAMMING

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Purpose: This article presents the results of an acceptance study of artificial intelligence, in the form of the ChatGPT tool in programming education. The purpose of this study was to identify factors influencing the acceptance of AI technology in the form of ChatGPT in programming education among students. The study involved 383 pupils and students learning programming in educational classes.
Design/methodology/approach: Data obtained through a survey questionnaire were analysed, which measured the impact of constructs such as performance expectancy, effort expectancy, innovation characteristics, social influence, psychological needs and trust on acceptance. Questions defining each construct were prepared according to previous studies. The subjective degree of feeling was given by the user on a seven-point Likert scale (1 - strongly agree, 7 - strongly disagree). The seven-point scale has also been used in many other works on similar topics. Correlation studies were carried out using the partial least squares (PLS) method. Calculations were performed using Excel, SPSS, and the SmartPLSv3 application.
Findings: The results indicated that the most significant influence on acceptance was expected effort and expected performance. Trust in the technology appeared to be next. On the other hand, psychological needs, social influence and innovation characteristics although present, have a less significant impact on respondents' decision to accept the ChatGPT tool.
Research limitations/implications: Future research should focus on continuous improvement of measurement models and adaptation to the studied environment.
Practical implications: The results obtained may have practical implications for staff creating and managing the education process and for software developers.
Social implications: Building awareness of the impact of various factors on the behaviour of users of information systems.
Originality/value: The paper analyses the factors influencing software acceptance, which is of relevance to management and quality sciences.
Keywords: ChatGPT, technology acceptance, artificial intelligence in education, TAM, UTAUT, programming education.
Category of the paper: Research paper.

1. Introduction

Modelling technology acceptance is a key aspect of research into the[1] factors that determine users' choice of IT tools. Research on the acceptance of artificial intelligence (AI) in education, management, economics can bring tangible social and financial benefits. First of all, the acceptance of AI technology by pupils and students is crucial for the very process of its implementation in education and for the full exploitation of AI's potential in the learning process. On the other hand, knowledge of the determinants of acceptance of the ChatGPT tool, can influence the management of the educational process, as well as the evaluation of curricula in educational institutions. Several relevant theories of technology acceptance can be distinguished in the literature.

One of the first models used in technology acceptance research was the theory of reasoned action (TRA). Developed by Fishbein and Ajzen (1980), it indicates that both attitudes[2], and social norms[3], are crucial in shaping behavioural intentions. Behavioural intentions, in turn, directly influence users' behaviour, creating a predictable relationship between attitudes and behaviour. The next step in technology acceptance research was the development of the theory of planned behaviour (TPB), which added another construct, perceived behavioural control (PBC). According to Ajzen (1985), a sense of control over a given action influences both users' intentions and behaviour, allowing better prediction of users' decisions in situations where there are technical or psychological constraints (Ajzen 1985). Other theories that have influenced current models of technology acceptance include innovation diffusion theory (IDT) (Wani, Ali, 2015; Rogers, 2003) and self-determination theory (SDT) (Ryan, Deci, 2013; Berkowitz, Bier, McCauley, 2017).

One of the most important, widely used and cited technology acceptance models is the technology acceptance model (TAM) proposed by Davis (1989). In the TAM model, two key factors, perceived usefulness (PU) and perceived ease of use (PEOU), influence user attitudes and intentions to use technology (Davis, 1989). Research based on TAM indicates that high levels of usability and ease of use increase the acceptance and effectiveness of technological tools in education.

An extension of this model is the unified theory of acceptance and use of technology (UTAUT), developed by Venkatesh et al. (2003). UTAUT combines elements from several previous theories, including TRA, TPB and TAM, introducing four main constructs: performance expectancy, effort expectancy, social influence and facilitating conditions. The UTAUT model also takes into account moderating variables such as: age, gender, and experience, making it a comprehensive tool for analysing technology acceptance across

[1] The work also uses the concept of construct as a component of the model.
[2] Reflecting on positive or negative evaluations of a given behaviour.
[3] Other people's expectations and willingness to meet them.

different demographic groups (Venkatesh et al., 2003). Subsequent extensions such as UTAUT 2 and UTAUT 3 introduced new constructs such as: hedonic motivation, value for money and habit, which are particularly useful in consumer technology research (Venkatesh et al., 2003). UTAUT 3 also adds the element of personal innovation in technology use as a factor that supports the acceptance of new IT solutions (Farooq et al., 2017).

In fact, each new study implies new constructs from previous models in order to even better predict user behaviour (Blunt, Chong, Tsigna, Zayyad, Tsigna, Venkatesh, 2022; Radomski, 2017). Also, the construct of trust in a technology has long been analysed in many technology acceptance studies (Alharbi, 2014; Rajasingham, Premarathne, 2018; Chen, Fan, Azam, 2024). Constructs such as: performance expectancy, effort expectancy, social influence, characteristics of the innovation, psychological needs or trust are key to understanding the reasons for technology acceptance.

2. Acceptance of AI tools in education

Current research on the use of the ChatGPT tool and other artificial intelligence (AI) systems in education, provides important insights into the potential benefits and challenges affecting their acceptance. The analyses mentioned below present the possibility of combining factors from different models, which in many cases expands the possibilities for prediction.

Almogren and Aljammaz's (2022) study, based on the technology acceptance model (TAM) and social cognitive theory (SCT) (Bandura, 1986), showed that the integration of SCT and TAM models is effective in identifying predictors that identify students' attitudes and intentions towards m-learning. The study used the popular SPSS and Smart-PLS software for analysis. In contrast, Adel, Ahsan and Davison (2024) analysed the complexity of the challenges posed to education using generative AI. The authors suggest that the use of ChatGPT in education can be useful in the learning process, especially by tailoring educational content to individual student needs and abilities.

Another example of recent research is the work, by Almogren, Al-Rahmi and Dahri (2024). The results of the analyses showed that perceived ease of use and perceived usefulness[4], are significant predictors of user attitudes towards the ChatGPT tool in smart education. Predictors such as user attitudes and behavioural intentions also have a significant impact on the acceptance of ChatGPT in education. In contrast, Dempere, Modugu, Hesham and Ramasamy (2023) provide perspectives on the potential of ChatGPT in education. Among the important benefits, they included: research support, the possibility of automated assessment and improved human-computer interaction.

[4] In UTAUT as expected effort, expected outcome.

In conclusion, artificial intelligence, in the form of ChatGPT, has the potential to significantly transform education, provided that appropriate ethical and legal standards are met and the educational process is properly organised. To ensure the safe and effective use of AI, the authors of many publications suggest the development of specific guidelines and tools to support the responsible use of these technologies in the teaching process.

3. Research model

By combining theories and models from the fields of technology acceptance, education and psychology, a comprehensive research framework model can be developed (Ofosu-Ampong, Acheampong, Kevor, Amankwah-Sarfo, 2023). The proposed model distinguishes six key constructs[5] relevant to the analysis of students' acceptance of AI (ChatGPT) in programming education:

- performance expectancy *(PE) - this construct is derived from the TAM and UTAUT models and emphasises the importance of students' and pupils' feelings about the usefulness of artificial intelligence (AI)-based tools in programming education (Davis, Glikson, Woolley, 2020). These perceptions play a key role in shaping the acceptance of AI in educational contexts;*
- *effort* expectancy *(EE) - a construct defined as the level of perceived difficulty of mastering a given system. Derived from the UTAUT model, it is often used in studies of the acceptance of learning tools;*
- social *influence (SI)* **-** *a construct derived from UTAUT theory; emphasises the influence of social factors (the influence of peers, mentors and environment on an individual's behaviour), on the acceptance of AI in education (Sahu, Padhy, Dhir, 2020);*
- *innovation characteristics (IC) - this construct is derived from innovation diffusion theory (IDT) (Wani, Ali, 2015) and emphasises the characteristics of the AI innovation itself (Rogers, 2003), communication channels and the role of opinion leaders and social networks in the diffusion and acceptance of AI in education (Ofosu-Ampong, Acheampong, Kevor, Amankwah-Sarfo, 2023);*
- *psychological needs (PN) - a construct derived from self-determination theory (SDT), identifies the intrinsic motivation, autonomy and competence of individuals in accepting AI in education (Ryan, Deci, 2013; Berkowitz, Bier, McCauley, 2017). This construct recognises the importance of supporting students' and pupils' psychological needs for autonomy and competence in order to stimulate acceptance;*

[5] Constructs that explain user behaviour.

- *trust (TR) - a construct that was among the first to be used by Cody-Allen and Kishore (2006). In this paper, trust is defined as the degree to which a user feels that an AI solution is safe, is not afraid of AI algorithms and the risks of using the system.*

Based on the above six factors and the acceptance of AI, six research hypotheses were proposed as shown in the figure below.

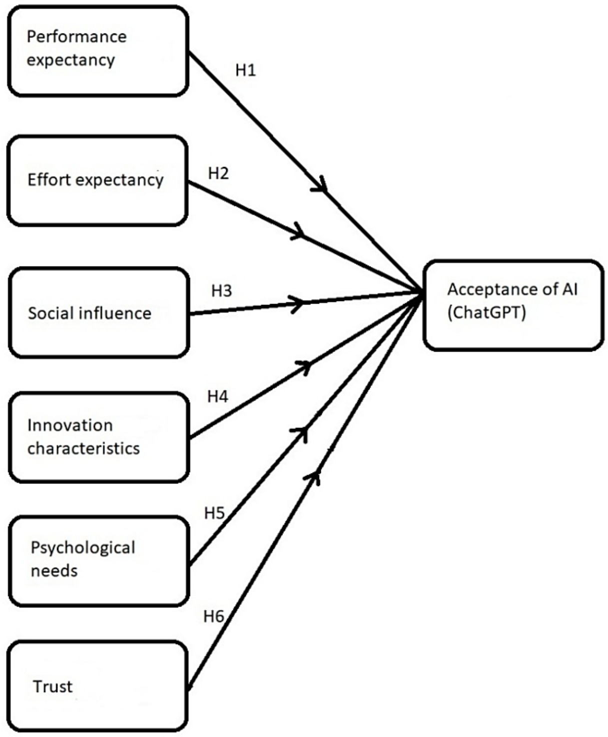

Figure 1. Research model.

Source: own study.

4. Description of the research procedure and design of the questionnaire

Questions defining each construct were prepared according to previous studies (Davis, 1989; Rogers, 2003; Ofosu-Ampong, Acheampong, Kevor, Amankwah-Sarfo, 2023). The subjective degree of feeling was given by the user on a seven-point Likert scale (1 - strongly agree, 7 - strongly disagree). The seven-point scale has also been used in many other works on similar topics (Venkatesh, Morris, Davis, Davis, 2003).

Correlation studies were carried out using the partial least *squares* (PLS) method. Calculations were performed using Excel, SPSS, and the SmartPLSv3 application.

Descriptive statistics were used to describe the sociodemographic characteristics of the students, while PLS was used to evaluate the measurement model to assess the reliability and correlation between the constructs and their indicators.

The study population consisted of pupils and students from four secondary schools (high school and technical high school) and three higher education institutions in the Pomeranian Voivodeship who participated in programming classes. The research was conducted over a two-week period in October 2024 using an online questionnaire among the class participants. The selection of the group was made at random.

The designed questionnaire consisted of 27 questions divided into two blocks. The first block consisted of questions on basic information about the interviewee. The variables investigated were: gender, age, employment, education level, feelings about using ChatGPT for programming.

The second block of the questionnaire asked respondents to indicate their feelings about the research model. The questions (indicators) in this block were divided into seven groups reflecting the other variables of the research model. The first three questions related to the expected outcome (PE) variable, with a further three reflecting expected effort (EE). Further groups of three questions were related to social influence (AI), innovation characteristics (IC), psychological needs (PN) and trust (TR), respectively. Two indicators were prepared for the acceptance factor AI (AA).

5. Findings

A total of 384 pupils and students completed the survey questionnaire. Of these, more than half (n = 194, 50.5%) were aged between 15 and 18 years and there were 173 respondents (45%) in the 19 to 25 age range. Over 25 years old were 17 respondents (4.5%). The majority of respondents were male (n = 200, 53.6%), but the prevalence was slight. Greater acceptance of the AI tool (in the form of ChatGPT) in programming was shown by a slightly higher percentage of men (n = 174, 87%), compared to women (n = 157, 85%). In terms of employment status, 63 (16.4%) students were employed - these were part-time students. The vast majority of students used ChatGPT in their programming studies (n = 331, 86.2%). Furthermore, the majority of them (n = 300, 66.1%) reported positive feelings in using the chatbot analysed.

Of the 384 students who took part in the survey, the vast majority (n = 308, 77.6%) expressed acceptance of AI and a desire to continue using it in education, while a small group of respondents (n = 4, 8.9%) indicated a lack of acceptance of AI (Table 1). This is a small percentage, mainly due to a lack of knowledge regarding AI, concerns arising from previous experiences.

Table 1.
Demographic profile of respondents

Variable	Category	n (%)	Acceptance of AI		p-value
			No n (%)	Yes n (%)	
Gender	Woman	184 (46.4)	27 (15.0)	157 (85.0)	0.217
	Male	200 (53.6)	26 (13.0)	174(87.0)	
Age (years)	15-18	194 (50.5)	24(12.4)	170 (87.6)	0.015**
	19-25	173 (45.0)	25 (14.4)	148 (85.6)	
	>25	17 (4.5)	4 (23.5)	13 (76.4)	
Employment	Unemployed	321 (83.6)	33 (10.3)	288 (89.7)	0.237
	Employed	63 (16.4)	20 (31.7)	43 (68.3)	
Level of education	Secondary school	199 (51.8)	31 (15.6)	168 (84.4)	0.029**
	College	185 (48.2)	22 (11.9)	163 (88.1)	
Using ChatGPT in programming	Yes	331 (86.2)	0(0)	331 (100)	0.141
	Not	53 (13.8)	53 (100)	0 (0)	
Feelings about using ChatGPT	Positive	300 (66.1)	0 (0)	300 (100)	0.211
	Indifferent	26 (25.0)	0 (0)	76 (100)	
	Negative	5 (8.9)	4(100)	1(0)	
Declaration of ChatGPT reuse in programming	Yes	308 (77.6)	0(0)	308(100)	0.234
	Maybe	19 (13.5)	2 (16.0)	17 (84.0)	
	Not	4 (8.9)	4 (100)	0 (0)	

*p < 1;** p < 0.05.

Source: the authors' own development.

Due to the model's assumptions, further analysis used data from 331 surveys of pupils and students who used artificial intelligence in the form of ChatGPT in programming education.

6. Evaluation of the measurement model

In order to determine the factors influencing acceptance of AI (ChatGPT), reliability and relevance tests were conducted for each model relationship. As shown in Table 2, all coefficients of composite construct reliability (CR) and Cronbach*'s* alpha (CrA) were above the recommended minimum threshold of 0.7 (ranging from 0.812 to 0.976). This indicates good internal consistency between the measurement elements in the model design. In addition, Table 2 shows the mean response value for all questions included in the model constructs, ranging from 0.234 to 0.41.

Table 2.
Structural equation modelling

Construct	Question	Average	CrA	CR
Performance expectancy	PE1	0.345	0.812	0.976
	PE2	0.393		
	PE3	0.421		
Effort expectancy	EE1	0.467	0.832	0.936
	EE2	0.543		
	EE3	0.456		

Cont. table 2.

Social influence	SI1	0.478	0.935	0.912
	SI2	0.234		
	SI3	0.454		
Innovation characteristics	IC1	0.431	0.876	0.934
	IC2	0.382		
	IC3	0.456		
Psychological needs	PN1	0.434	0.867	0.945
	PN2	0.325		
	PN3	0.393		
Trust	TR1	0.318	0.834	0.918
	TR2	0.367		
	TR3	0.345		
Acceptance of AI	AA1	0.234	0.821	0.965
	AA2	0.470		

Source: the authors' own development.

7. Evaluation of the conceptual model

The next step was to evaluate the structural model using the path coefficient. Table 3 shows the results of the PLS-SEM analysis performed using SmartPLSv3. The main indicator is the path coefficient, which determines the 'strength' of the effect of one construct on another as shown in Figure 1. In addition, the variance inflation factor (VIF) was estimated to assess the issue of collinearity. As shown in Table 3, the VIF values ranged from 1.381 to 3.873. All coefficients were therefore below the recommended threshold of 5, indicating that there was no collinearity issue in this study. The results presented in Table 3 indicate that each of the six hypotheses is statistically significant. This is evidenced by the path coefficient values, as well as the T-statistic and p-values below 0.05.

Table 3.
Evaluation of the structural model

Hypothesis	Model relationships	Path coefficient	VIF	T statistics	p-value
H1	*PE→AA*	*0.789*	*3.347*	*3.123*	*0.02*
H2	*EE→ AA*	*0.834*	*2.875*	*4.357*	*0.00*
H3	*SI→ AA*	*0.688*	*3.873*	*2.689*	*0.01*
H4	*IC→ AA*	*0.679*	*1.381*	*2.235*	*0.03*
H5	*PN→ AA*	*0.567*	*2.745*	*1.732*	*0.03*
H6	*TR→ AA*	*0.776*	*3.014*	*3.345*	*0.04*

Source: the authors' own development.

Very strong associations, expressed by the path coefficient, were observed for effort expectancy (EE) with acceptance (AA) - (0.834), performance expectancy (PE) with acceptance (AA) - (0.789), and trust (TR) with acceptance (AA) - (0.776). The lowest path coefficient value was observed for hypothesis *H5* (0.567), i.e. the association of psychological needs (PN) with acceptance (AA).

8. Summary

The research conducted on the acceptance of the ChatGPT tool in programming education, presents great potential for AI in transforming the learning process. The analysis results obtained for all hypotheses are statistically significant. The research shows that effort expectancy (EE) and performance expectancy (PE) are key factors influencing students' and pupils' acceptance of the ChatGPT tool. This thesis is also supported by a large number of previous studies. A very high path coefficient was also obtained in the TR→AA relationship (H6), showing that trust (TR) in the new technology plays an increasingly important role in its acceptance. Social influence (SI) and innovation characteristics (IC) also play an important role showing that peers' opinions and willingness to experiment with new technologies are important in the implementation of AI in programming learning. Hypothesis H5 is also statistically significant, although the effect of psychological needs (PN) on acceptance (AA) is not as clear as for the other relationships of the model. This may suggest that pupils and some students, due to their young age, lack sufficient intrinsic motivation, autonomy and sufficient competence. Research indicates that the technology serves and can serve both as a tool to support individual learning and as an element to build interactivity and engagement in the teaching process. Tools such as ChatGPT can support the solving of programming problems, the translation of complex concepts and the generation of task ideas, providing important support for both students and teachers. AI in the management of programming education offers opportunities for personalisation, efficiency and scalability of education.

In the future, it would be worth conducting a study with a larger research sample to increase the possibility of generalising conclusions, which is one of the key limitations of this type of research. A further step could be to include variables such as the level of knowledge about AI and the level of sophistication in programming. It would also be worth focusing on the trust factor, which in the study had a large impact on the acceptance of the chatbot under analysis - despite the fact that it is a relatively new technology. This could allow a more precise identification of the factors influencing the acceptance of the ChatGPT tool by different user groups in the programming education process. Understanding the research questions can also be a limitation. Inappropriate wording of survey questions can lead to errors of interpretation, which will affect the quality of the data obtained.

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