

MAIN DRIVERS OF CHATGPT ADOPTION BY ROMANIAN COMPUTER SCIENCE STUDENTS

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Abstract

The use of artificial intelligence technologies in education has huge potential to improve teaching and learning by providing personalised learning experiences, on-demand academic support, and automated feedback. The emergence of generative artificial intelligence has introduced a new category of educational technology that is changing how students search for information, solve problems, and engage with course materials. This transformation is especially relevant for computer science students, who can benefit from using AI tools not only for learning but also for programming. The purpose of this research was to investigate the main drivers influencing the adoption of the ChatGPT tool among Romanian students enrolled in a computer science educational program. An extended technology acceptance model (TAM) that includes output quality and perceived impact as external variables has been specified and tested with a sample of 165 university students. The results show that perceived enjoyment and perceived usefulness have the strongest direct influence on the behavioural intention to use ChatGPT. The influence of perceived ease of use on perceived usefulness and behavioural intention was not significant, suggesting that it is not a relevant variable for computer science students. Another finding is that taking into consideration indirect effects, perceived impact of AI tools on education and future professions, and perceived enjoyment emerge as equally important for the adoption of ChatGPT.

Keywords: ChatGPT, computer science, university students, TAM, AI tools

Introduction

Education is facing rapid transformation due to the availability and proliferation of AI tools. The use of digital technology in higher education has expanded substantially over the last two decades, moving from supplementary resources such as learning management systems and e-learning platforms to more interactive and intelligent tools that support both teaching and learning activities. This trend was further accelerated by the COVID-19 pandemic, which forced a rapid shift toward online and blended learning and made digital tools a central part of everyday academic practice. More recently, the emergence of generative artificial intelligence has introduced a new category of educational technology that does not merely deliver content but actively produces explanations, examples, summaries, and code on demand, thereby changing how students search for information, solve problems, and engage with course materials.

Among AI tools, ChatGPT, released by OpenAI in November 2022, has been adopted at an unprecedented pace by university students worldwide. A large-scale global study covering 23,218 students from 109 countries reported that a majority of higher education students were already using ChatGPT in early 2024, primarily for brainstorming, summarising texts, and supporting academic writing (Ravšelj et al., 2025). Beyond ChatGPT, students are increasingly

using a range of complementary AI tools, such as Gemini, Copilot, Claude, and specialised coding assistants, often in combination with each other. This rapid and broad uptake raises important pedagogical and institutional questions regarding how these tools are integrated into learning, how their use affects academic integrity and skill development, and what factors drive students' decisions to continue using them.

Computer science students are a particularly relevant target group in this context. On the one hand, they are among the most intensive users of AI tools, employing them not only for general academic tasks but also for discipline-specific activities such as writing and debugging code, explaining algorithms, generating test cases, and producing documentation (Yilmaz & Karaoglan Yilmaz, 2023). On the other hand, they are also the future developers and integrators of such tools, which makes their attitudes and adoption behaviours particularly important for understanding the longer-term evolution of AI in education and in professional practice. Despite this dual role, empirical evidence on how computer science students perceive and adopt ChatGPT in specific national contexts, and particularly in Central and Eastern European higher education, remains limited.

The fast development of AI tools in the last decade raised several research directions, among which investigating the main factors driving the adoption of these tools in education gained significant attention in recent years (Balaskas et al., 2025; Dahri et al., 2024; Ma et al., 2025; Vázquez-Parra et al., 2024). The Technology Acceptance Model (TAM) can explain and predict technology adoption across various computer platforms and devices (Davis, 1989). The underlying theory, rooted in the theories of reasoned action and planned behaviour, posits that behavioural intention to use a technology is driven by two key beliefs: perceived ease of use and perceived usefulness. Later, TAM was extended by Davis et al. (1992) to include intrinsic motivation, conceptualised as perceived enjoyment.

Theoretical Background

Related Work

The use of artificial intelligence technologies in education has huge potential to improve teaching and learning by providing personalised learning experiences, on-demand academic support, and automated feedback. Since the public release of ChatGPT in November 2022, generative AI tools have been rapidly adopted by university students across disciplines, reshaping the way they seek academic help, generate ideas, and engage with content. A recent literature review commissioned by OECD concluded that digital technologies can support student learning when integrated in pedagogically sound ways, but that outcomes depend strongly on the quality of implementation and on learner characteristics (Forsström et al., 2025). In the specific case of computer science students, ChatGPT is used not only as a general study aid but also for writing and debugging code, explaining algorithms, and generating documentation (Yilmaz & Karaoglan Yilmaz, 2023).

To explain the adoption of information technologies, the Technology Acceptance Model (TAM) proposed by Davis (1989) has become one of the most widely used theoretical frameworks. TAM posits that behavioural intention to use a technology is driven by two key beliefs, perceived usefulness and perceived ease of use, both of which are also influenced by external variables. The model was subsequently extended to incorporate intrinsic motivation in the form of perceived enjoyment (Davis et al., 1992), which is particularly relevant to hedonic information systems (van der Heijden, 2004). A systematic literature review by Granić and Marangunić (2019) confirmed that TAM remains the most widely used model for explaining the adoption of educational technologies, with perceived ease of use and perceived usefulness consistently emerging as the strongest predictors of behavioural intention across a variety of learning domains and types of users.

Over the years, TAM has been progressively extended to better capture the determinants of perceived usefulness and perceived ease of use. The extended model TAM2 (Venkatesh & Davis, 2000) introduced social influence processes (subjective norm, voluntariness, image) and cognitive instrumental processes (job relevance, output quality, result demonstrability) as antecedents of perceived usefulness, while TAM3 (Venkatesh & Bala, 2008) further articulated the determinants of perceived ease of use, including computer self-efficacy, computer anxiety, and perceived enjoyment. In parallel, Wixom and Todd (2005) proposed a theoretical integration of user satisfaction and technology acceptance, in which object-based beliefs, such as information and system quality, are linked to behavioural beliefs about the system, providing a strong theoretical justification for treating output-related variables as antecedents of the core TAM constructs. Alternative frameworks have also been used to study generative AI adoption, in particular the Unified Theory of Acceptance and Use of Technology (UTAUT) and its extension UTAUT2 (Venkatesh et al., 2003; Venkatesh et al., 2012), which emphasise performance expectancy, effort expectancy, social influence, hedonic motivation, and habit. Although UTAUT2 has been successfully applied to ChatGPT acceptance, TAM and its extensions remain particularly suitable for educational contexts, where parsimonious models built around perceived usefulness, perceived ease of use, and perceived enjoyment offer a clear interpretation of the cognitive and motivational drivers of student behaviour (Granić & Marangunić, 2019; Ma et al., 2025).

The widespread uptake of ChatGPT has motivated a growing number of TAM-based studies that investigate its acceptance in higher education. Vázquez-Parra et al. (2024) highlighted the importance of students' perceptions of AI tool adoption and training, reporting that prior experience and perceived utility shape attitudes and behaviours toward ChatGPT. Dahri et al. (2024) extended TAM in a mixed-methods study. They found that metacognitive self-regulated learning, together with the core TAM beliefs, significantly influences the acceptance of ChatGPT for educational purposes. Ma et al. (2025) confirmed the central role of perceived usefulness and perceived ease of use in driving user adoption of ChatGPT, while also emphasising the importance of perceived enjoyment. Balaskas et al. (2025) extended TAM with perceived trust and perceived risk as mediating constructs. They reported that the core TAM beliefs, together with perceived intelligence, are significant determinants of ChatGPT adoption intentions in higher education.

A complementary stream of research has examined ChatGPT acceptance across different national and cultural contexts, highlighting both common patterns and country-specific differences. Strzelecki (2024), in a study of 503 Polish state university students based on an extended UTAUT2 model, reported that habit, performance expectancy, and hedonic motivation were the strongest predictors of behavioural intention, while effort expectancy and social influence had only modest effects. A subsequent comparative study by Strzelecki and ElArabawy (2024) across Polish and Egyptian universities showed that, although the core determinants of acceptance are largely shared, gender and study level moderate some of the relationships, indicating that socio-cultural and demographic factors should not be ignored. The large-scale global study by Ravšelj et al. (2025), based on responses from more than 23,000 students in 109 countries, confirmed that the perceived usefulness, ease of use, and enjoyability of ChatGPT are central across regions, but that students' concerns regarding accuracy, academic integrity, and over-reliance vary substantially with the local educational context. Despite this growing body of cross-cultural evidence, studies focusing specifically on Central and Eastern European higher education and on computer science students remain scarce.

A complementary line of research has focused specifically on the use of ChatGPT in programming education. Yilmaz and Karaoglan Yilmaz (2023) reported that computer science students perceive ChatGPT as useful for obtaining fast and mostly correct answers, facilitating debugging, and improving self-confidence in programming. Xue et al. (2024) found, in a

quasi-experimental study, that ChatGPT-facilitated programming modes change students' programming behaviours and improve their perceived usefulness and attitudes, with students regarding the tool as both beneficial and enjoyable. Concerns about the accuracy and reliability of generated code and the risk of over-reliance have nevertheless been consistently reported, suggesting that, even when students value the tool, the trustworthiness of its output remains an important factor shaping its acceptance.

Beyond ChatGPT, computer science students increasingly rely on a broader ecosystem of AI tools, including specialised coding assistants such as GitHub Copilot, Cursor, and Claude, alongside general-purpose chatbots such as Gemini and DeepSeek. Empirical studies on AI coding assistants in computer science education have reported substantial productivity gains for students working on programming tasks, with reductions in task completion time, fewer manual searches, and higher solution quality (Shihab et al., 2025). At the same time, these studies caution that excessive dependence on AI suggestions can lead to a superficial understanding of programming concepts and a decline in independent problem-solving skills (Shihab et al., 2025; Xue et al., 2024). Such findings indicate that the acceptance of generative AI tools by computer science students should be understood not in isolation but as part of a wider repertoire of AI-supported learning practices, in which different tools are combined for different tasks.

A fourth, increasingly visible strand of research examines the risks associated with the use of ChatGPT in higher education, focusing on academic integrity, over-reliance, and the trustworthiness of generated content. Cotton et al. (2024) discussed how the convenience of ChatGPT may blur the boundary between legitimate academic support and academic misconduct, calling for institutional policies that clarify acceptable uses and assessment practices. Sullivan et al. (2023) and Ravšelj et al. (2025) similarly argued that students' willingness to use ChatGPT is shaped by their perceptions of risk, including concerns about plagiarism, fairness in assessment, and the impact on the development of higher-order skills. In programming-related contexts, additional concerns have been raised about the correctness of generated code and about the possibility that students accept AI suggestions without sufficient critical evaluation (Yilmaz & Karaoglan Yilmaz, 2023; Xue et al., 2024).

Problem Statement and Research Questions

While the core TAM beliefs explain a large part of technology adoption, the case of generative AI tools such as ChatGPT raises additional considerations that are not fully captured by perceived usefulness, perceived ease of use, and perceived enjoyment alone. Two aspects appear particularly relevant for computer science students. The first is the quality of the output produced by the tool, that is, the accuracy and reliability of the answers and code it generates, which is a recurring concern in technical and programming-related tasks where incorrect suggestions can be costly. The second is the perceived impact of AI tools on education. For future professionals, computer science students are not only users but also prospective developers of such technologies, and their beliefs about the long-term role of AI are likely to shape their current adoption behaviour. For this reason, the present study extends the classical TAM with two external variables, output quality and perceived impact, in order to obtain a more complete picture of what drives the continued use of ChatGPT in this population.

Despite the growing body of literature on ChatGPT adoption, most existing studies have been conducted on heterogeneous samples of students from various disciplines or have focused on contexts outside of Central and Eastern Europe. Evidence on computer science students, who are both potential developers and power users of such tools, remains limited, as does evidence from Romanian higher education. The present study contributes to filling these gaps by specifying and testing an extended TAM, enriched with output quality and perceived impact, on a sample of Romanian undergraduate students enrolled in a computer science program.

The purpose of this study was to answer two research questions:

RQ1: To what extent are Romanian undergraduate students enrolled in computer science programs using ChatGPT and other AI tools in their studies?

RQ2: What are the main drivers influencing the adoption of ChatGPT by Romanian computer science students?

To answer these questions, an extended Technology Acceptance Model (TAM) has been specified and tested with a sample of 165 computer science students from the University of Craiova.

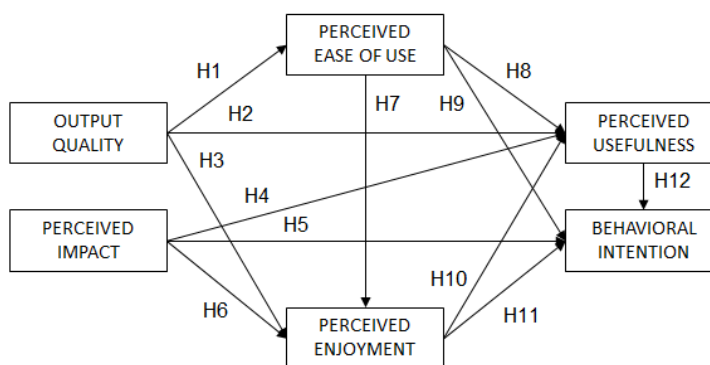
Research Methodology

Model and Hypotheses

The proposed research model is an extended TAM that includes three drivers of the behavioural intention (BI) to continue using ChatGPT: perceived ease of use (PEU), perceived enjoyment (PE), and perceived usefulness (PU). Additionally, it includes two external variables that deserve particular attention in the context of ChatGPT adoption: the output quality (OutQ) and the perceived impact of AI tools on education and the future profession (PI).

Davis (1989) defined the perceived ease of use (PEU) as a belief “that using a particular system would be free of effort” and the perceived usefulness as a belief that „using a given technology will improve job performance”.

Figure 1
Research Model



Output quality refers to the accuracy and reliability of the responses returned by the system. It was originally introduced as a determinant of perceived usefulness in the extended technology acceptance model (TAM2) by Venkatesh and Davis (2000). It was later integrated as an antecedent of the key TAM beliefs in the unified user satisfaction and acceptance model proposed by Wixom and Todd (2005). According to this perspective, when a system consistently returns accurate and trustworthy outputs, users find it more useful for their tasks, easier to interact with, and more enjoyable to use. In the case of ChatGPT, recent studies have confirmed this pattern, showing that the perceived quality of responses positively influences the perceived usefulness and the overall acceptance of the tool (Ma et al., 2025). At the same time, several studies have reported that students remain cautious about the correctness of ChatGPT’s answers, especially for technical and programming-related tasks (Xue et al., 2024; Yilmaz & Karaoglan Yilmaz, 2023). Therefore, it is supposed that output quality (OutQ) positively influences the key TAM beliefs: perceived ease of use, perceived enjoyment, and perceived usefulness (Ma et al., 2025; Venkatesh & Davis, 2000; Wixom & Todd, 2005).

- H1: Output quality has a positive influence on the perceived ease of use ($OutQ \rightarrow PEU$)*
H2: Output quality has a positive influence on the perceived usefulness ($OutQ \rightarrow PU$)
H3: Output quality has a positive influence on the perceived enjoyment ($OutQ \rightarrow PE$)

The perceived impact refers to the role AI tools will play in education and the future computer science profession. Perceived impact (PI) is a relevant external variable, since students who believe AI will play an important role in their future careers tend to display more positive attitudes and a stronger intention to use such tools (Dahri et al., 2024; Vázquez-Parra et al., 2024). Drawing on the extrinsic and intrinsic motivation framework proposed by Davis et al. (1992), it is expected that this future-oriented belief will operate both as an extrinsic motivator, by reinforcing the practical value students attach to ChatGPT for their academic and professional development (perceived usefulness), and as an intrinsic motivator, by making the engagement with the tool more meaningful and enjoyable (perceived enjoyment). A direct effect on the behavioural intention is also expected, in line with previous TAM-based studies on the adoption of AI tools by students (Dahri et al., 2024; Vázquez-Parra et al., 2024).

- H4: Perceived impact of AI tools positively influences perceived usefulness ($PI \rightarrow PU$)*
H5: Perceived impact of AI tools positively influences behavioural intention ($PI \rightarrow BI$)
H6: Perceived impact of AI tools positively influences perceived enjoyment ($PI \rightarrow PE$)

The remaining hypotheses concern the core relationships among the TAM constructs. The positive influence of perceived ease of use on perceived usefulness and behavioural intention, as well as the positive influence of perceived usefulness on behavioural intention, are central to the original TAM (Davis, 1989; Davis et al., 1989) and have been widely confirmed in educational technology contexts (Granić & Marangunić, 2019), including recent TAM-based studies on ChatGPT acceptance (Balaskas et al., 2025; Ma et al., 2025). Perceived enjoyment was added to TAM as an intrinsic motivator by Davis et al. (1992) and shown to be particularly relevant for hedonic and learner-facing systems (van der Heijden, 2004). In educational settings, Lee et al. (2005) demonstrated that perceived enjoyment positively influences perceived usefulness and behavioural intention, while perceived ease of use, by reducing cognitive effort, also fosters enjoyment of the interaction. Since ChatGPT is used by computer science students both as a practical aid for academic and programming tasks and as an engaging conversational tool, perceived enjoyment is hypothesised to act both as a consequence of perceived ease of use and as an antecedent of perceived usefulness and behavioural intention.

- H7: Perceived ease of use positively influences perceived enjoyment ($PEU \rightarrow PE$)*
H8: Perceived ease of use positively influences perceived usefulness ($PEU \rightarrow PU$)
H9: Perceived ease of use positively influences behavioural intention ($PEU \rightarrow BI$)
H10: Perceived enjoyment positively influences perceived usefulness ($PE \rightarrow PU$)
H11: Perceived enjoyment positively influences behavioural intention ($PE \rightarrow BI$)
H12: Perceived usefulness positively influences behavioural intention ($PU \rightarrow BI$)

The measures of the latent variables presented in Table 1 were adapted from existing scales in the literature. The items for perceived ease of use (PEU), perceived usefulness (PU), and behavioural intention (BI) were adapted from the original TAM scales validated by Davis (1989) and Davis et al. (1989).

Table 1
Evaluation Instrument

Item	Statement
OutQ1	The output I get from ChatGPT is of high quality.
OutQ2	ChatGPT provides accurate information.
OutQ3	ChatGPT's responses are reliable.
PI1	AI tools will play an important role in education.
PI2	AI will play an important role in the development of my profession.
PEU1	My interaction with ChatGPT is clear and understandable.
PEU2	It is easy for me to become skilful at using ChatGPT.
PE1	I find using ChatGPT enjoyable.
PE2	Using ChatGPT is attractive.
PU1	Using ChatGPT enhances my effectiveness on tasks.
PU2	Using ChatGPT increases my productivity.
PU3	ChatGPT helps me complete tasks more quickly.
BI1	I intend to continue using ChatGPT in the future.
BI2	I will frequently use ChatGPT for my tasks.

The items for perceived enjoyment (PE) were adapted from the intrinsic motivation scale proposed by Davis et al. (1992) and from the educational TAM extension introduced by Lee et al. (2005). The output quality (OutQ) items were adapted from the information and output quality scales used in the integrated user satisfaction and acceptance model of Wixom and Todd (2005) and the TAM2 framework of Venkatesh and Davis (2000), with wording adjusted to capture the perceived accuracy and reliability of ChatGPT's responses. The perceived impact (PI) items were developed for this study by drawing on the conceptualisation of students' perceptions of AI tools and their professional relevance proposed by Vázquez-Parra et al. (2024). With one exception, items were rephrased to refer explicitly to ChatGPT.

Sample

The target population of the study consisted of the undergraduate students enrolled in the computer science program of the Faculty of Automation, Computers and Electronics at the University of Craiova in the academic year 2025/2026. The questionnaire was implemented as a Google Form and posted in the Google Classroom spaces of the courses attended by the students in years 1, 2, 3 and 4 of the program, so that the sampling frame was formed by the approximately 329 students enrolled in those courses. No sample was drawn from this frame: the invitation was addressed to all of them, and the students decided individually whether to respond. Participation was voluntary and anonymous, no incentive was offered, and the resulting sample is therefore a self-selected convenience sample. A total of 165 complete questionnaires were returned, which corresponds to a participation rate of approximately 50% of the students who had access to the announcement.

Most of the participants were male (120 male, 45 female, 72.73%), which reflects the gender distribution of the program itself. Ages ranged from 19 to 39 years ($M = 21.25$, $SD = 2.11$). The respondents were distributed across the first (10), second (65), third (43), and fourth (47) year of study.

No a priori power analysis was performed, since the questionnaire was addressed to the whole accessible population rather than to a sample of a predetermined size. The adequacy

of the resulting sample was therefore assessed against the requirements of covariance-based structural equation modelling. The measurement model comprises six latent constructs measured by 14 indicators, which gives a ratio of 11.8 observations per indicator, above the ratio of 10:1 commonly recommended for maximum likelihood estimation. Hair et al. (2006) indicate a minimum of approximately 150 observations for models that contain seven or fewer constructs, have item communalities above .50 and contain no underidentified construct; all three conditions are satisfied here, since every standardised loading exceeds .50, composite reliability exceeds .70 and average variance extracted exceeds .50 for all six constructs. The acceptable fit obtained for both the measurement and the structural model provides further evidence that the sample supports stable parameter estimates. The single-institution and self-selected character of the sample is nevertheless a limitation, and it is addressed in the Discussion.

Data were collected between October and December 2025. The instrument consisted of the 14 statements presented in Table 1, rated on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Two additional open-ended questions asked the students to name the other AI tools they use and the tasks for which they use them. Before starting the questionnaire, the students were informed about the purpose of the study, about the fact that participation was voluntary and that the answers were collected anonymously, and they gave their informed consent. The returned questionnaires were screened for completeness, and only the fully completed ones were retained for analysis.

Data Analysis

Unidimensionality of latent variables has been assessed by analysing factor loadings. Convergent validity has been assessed according to the recommended thresholds in the literature (Fornell & Larcker, 1981; Hair et al., 2006), specifically in terms of loading magnitude, construct reliability (CR), and average variance extracted (AVE). Discriminant validity has been assessed with the criterion of the squared correlation test (Fornell & Larcker, 1981).

The model fit with the data has been assessed by using the goodness of fit (GOF) indices, as recommended by Hair et al. (2006): chi-square (χ^2), degrees of freedom (df), the ratio χ^2/df , comparative fit index (CFI), non-normed fit index (NNFI), the goodness of fit index (GFI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR).

The model was estimated with LISREL 9.3 for Windows (Mels, 2006) using maximum likelihood estimation. The empirical validation followed the two-step procedure recommended by Anderson and Gerbing (1988): (1) testing the measurement model to analyse construct validity, and (2) testing the structural model to check hypotheses.

Research Results

Measurement Model

The measurement model showed an acceptable fit with the data: $\chi^2 = 106.90$, $df = 62$, $p = .00040$, $\chi^2/df = 1.72$, RMSEA = .066, CFI = .957, NNFI = .937, GFI = .919, SRMR = .0516. The descriptive statistics and the factor loadings are presented in Table 2. All factor loadings exceeded .50, which indicated the unidimensionality of the latent variables.

The mean values of the output quality measures were relatively low, close to the neutral value, and the reliability of ChatGPT's responses obtained the lowest mean of the whole instrument. The mean values of the remaining measures fell in the range 3.18–3.70. Overall, the respondents expressed a positive perception of ChatGPT and the intention to continue using it.

With respect to the AI tools used, 150 students (90.91%) reported that they currently use ChatGPT. The other tools mentioned were Gemini (59.39%), Copilot (30.30%), Claude (28.48%), DeepSeek (13.94%), and Cursor (7.88%), while 41 students (24.85%) mentioned further tools. The number of AI tools reported by a student ranged from 1 to 7 ($M = 2.65$, $SD = 1.34$).

With respect to the tasks carried out with the help of AI tools, 155 students (93.94%) mentioned explaining algorithms, 133 (80.61%) writing code, 113 (68.48%) generating text, and 77 (46.67%) inserting comments into computer programs.

Table 2
Descriptives and Factor Loadings (N = 165)

Construct	Item	M	SD	Loading
OutQ	OutQ1	2.92	0.64	.85
	OutQ2	3.01	0.61	.78
	OutQ3	2.84	0.71	.79
PI	PI1	3.61	0.60	.78
	PI2	3.54	0.67	.79
PEU	PEU1	3.60	0.62	.96
	PEU2	3.72	0.48	.57
PE	PE1	3.40	0.66	.80
	PE2	3.18	0.79	.73
PU	PU1	3.59	0.59	.88
	PU2	3.48	0.72	.72
	PU3	3.70	0.56	.68
BI	BI1	3.55	0.61	.83
	BI2	3.29	0.73	.87

The estimation of convergent and discriminant validity is presented in Table 3, where the values in bold represent the square root of the average variance extracted (AVE). Convergent validity was good for all latent variables, since composite reliability (CR) exceeded .70 and average variance extracted exceeded .50. Discriminant validity was also good, since for every pair of constructs the square root of AVE was higher than the correlation between them, in line with the criterion of Fornell and Larcker (1981).

Table 3
Convergent and Discriminant Validity (N = 165)

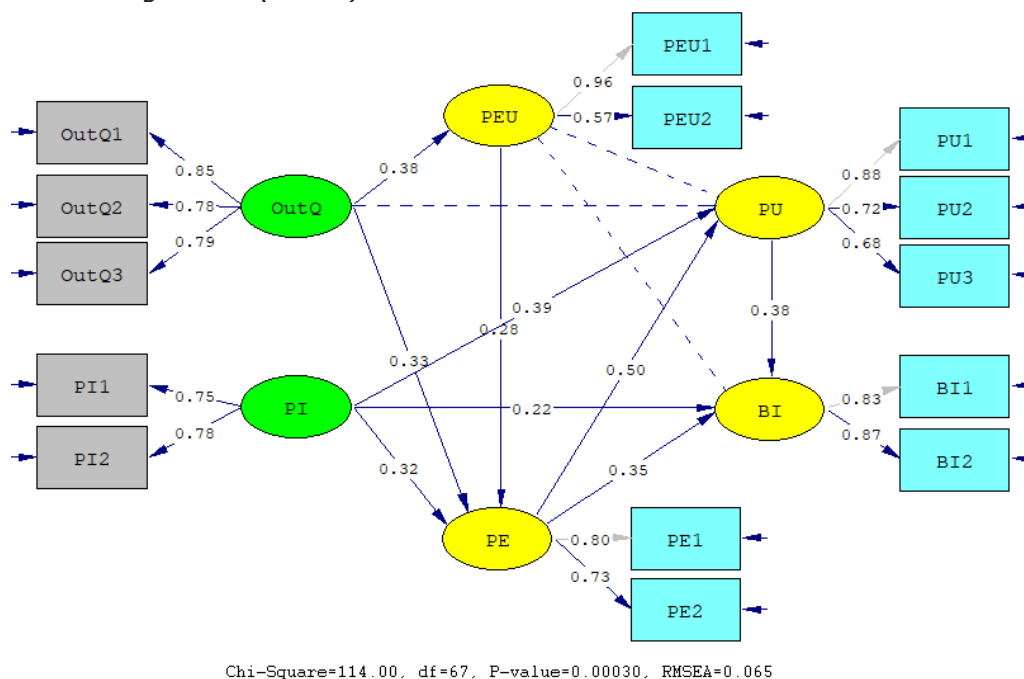
	CR	AVE	OutQ	PI	PEU	PE	PU	BI
OutQ	.849	.652	.807					
PI	.738	.585	.314	.765				
PEU	.756	.623	.325	.379	.789			
PE	.739	.586	.504	.548	.507	.766		
PU	.807	.585	.646	.389	.392	.695	.765	
BI	.839	.723	.631	.355	.329	.745	.755	.850

Structural Model

The structural model testing results are depicted in Figure 2. The goodness of fit indices showed a good fit of the model with the data: $\chi^2 = 114.00$, $df = 67$, $p = .00030$, $\chi^2/df = 1.70$, $RMSEA = .063$, $CFI = .954$, $NNFI = .937$, $GFI = .937$, $SRMR = .0636$.

The path from OutQ to PU was not significant, so hypothesis H2 was not supported; output quality influenced perceived usefulness only indirectly, through perceived ease of use and perceived enjoyment. The paths from PEU to PU and from PEU to BI were not significant either, so hypotheses H8 and H9 were not supported. This suggests that ease of use is not a problem for computer science students.

Figure 2
Model Testing Results (N=165)



Hypotheses H1, H3, H4, H5, H6 and H7 were supported, since the paths from OutQ to PEU ($\beta = .38$, $p < .001$), from OutQ to PE ($\beta = .33$, $p = .001$), from PI to PU ($\beta = .39$, $p = .00X$), from PI to BI ($\beta = .22$, $p = .031$), from PI to PE ($\beta = .32$, $p = .001$) and from PEU to PE ($\beta = .28$, $p = .013$) were all significant. Perceived impact therefore acted as an antecedent of both perceived enjoyment and perceived usefulness, and it also had a direct effect on the continuance intention.

Perceived enjoyment had a significant positive influence on perceived usefulness ($\beta = .50$, $p < .001$) and on behavioural intention ($\beta = .35$, $p = .003$), so hypotheses H10 and H11 were supported. The influence of perceived usefulness on behavioural intention was also significant ($\beta = .38$, $p = .004$), which supported hypothesis H12.

The model explained 14.4% of the variance in perceived ease of use, 45.8% of the variance in perceived enjoyment, 58.7% of the variance in perceived usefulness, and 66.7% of the variance in the intention to continue using ChatGPT.

The influence on behavioural intention can be analysed further through the indirect and total effects, which are presented in Table 4.

Table 4
Indirect and Total Effects (N = 165)

	Indirect effects					Total Effects				
	PI	OutQ	PEU	PE	PU	PI	OutQ	PEU	PE	PU
PEU							0.38			
PE	.	0.11				0.32	0.44	0.28		
PU	0.16	0.22	0.14			0.55	0.22	0.14	0.50	
BI	0.32	0.24	0.15	0.19		0.54	0.24	0.15	0.54	0.38

Perceived impact and perceived enjoyment had the strongest influence on behavioural intention, mediated by perceived enjoyment and perceived usefulness in the first case and by perceived usefulness in the second. Output quality and perceived ease of use were less important predictors.

Discussion

This study contributes to the growing body of research on the acceptance of generative AI tools in higher education by specifying and testing an extended TAM enriched with two external variables, output quality and perceived impact, on a sample of Romanian undergraduate students enrolled in a computer science program. The findings provide insights both at the descriptive level, regarding actual patterns of AI tool usage, and at the explanatory level, regarding the cognitive and motivational drivers of the intention to continue using ChatGPT.

In response to the first research question, the results show that ChatGPT is broadly adopted, with 90.91% of the students currently using it, and that it is rarely used in isolation. On average, students reported using 2.65 AI tools, with Gemini, Copilot, Claude, DeepSeek, and Cursor mentioned as complementary tools. This pattern is consistent with recent international evidence indicating that university students typically combine several generative AI tools in their study workflow (Ravšelj et al., 2025) and suggests that the question of acceptance should increasingly be framed in terms of an ecosystem of AI tools rather than a single application.

The most frequent tasks for which AI tools are used by Romanian computer science students, namely explaining algorithms (93.94%), writing code (80.61%), text generation (67.40%), and inserting comments into computer programs (46.47%), confirm that for this population AI tools are integrated into both general study activities and discipline-specific programming work, in line with previous findings on the use of ChatGPT in programming learning (Yilmaz & Karaoglan Yilmaz, 2023; Xue et al., 2024).

Regarding the second research question, the structural model accounts for 66.7% of the variance in the behavioural intention to continue using ChatGPT, supporting the relevance of the proposed model for this population. The strongest direct predictors of behavioural intention are perceived usefulness ($\beta = 0.38$), perceived enjoyment ($\beta = 0.35$), and perceived impact ($\beta = 0.22$). At the same time, perceived enjoyment also acts as a strong antecedent of perceived usefulness ($\beta = 0.50$).

When indirect paths are taken into account, perceived impact and perceived enjoyment emerge as the strongest overall drivers of the continuance intention, with total effects of 0.54 each, followed by perceived usefulness (0.38), output quality (0.24), and perceived ease of use (0.15). Together, these results suggest that, for computer science students, the decision to continue using ChatGPT is shaped less by usability concerns and more by a combination of pragmatic value (usefulness for academic and programming tasks), intrinsic motivation (enjoyment of interacting with the tool), and a forward-looking belief about the role of AI in education and in the future profession.

A noteworthy finding is that the paths from perceived ease of use to perceived usefulness (H8) and to behavioural intention (H9) are not significant. This contrasts with the typical pattern reported in TAM studies on more heterogeneous student populations (Balaskas et al., 2025; Ma et al., 2025), but it is consistent with the specific profile of the respondents. Computer science students are familiar with command-line tools, programming environments, and conversational interfaces, and the model also explains only 14.4% of the variance in perceived ease of use, indicating that this construct is not a major source of differentiation in this group. In other words, ease of use appears to act as a hygiene factor: it is taken for granted by these students and therefore does not discriminate between those who plan to continue using ChatGPT and those who do not. A similar interpretation has been suggested in studies of programming-oriented users of ChatGPT, where utility, output quality, and engagement, rather than usability, dominate the acceptance pattern (Yilmaz & Karaoglan Yilmaz, 2023).

The role of output quality also deserves attention. The direct path from output quality to perceived usefulness (H2) is not significant. However, output quality has a significant positive effect on perceived ease of use (H1) and perceived enjoyment (H3), as well as a non-trivial total effect on the behavioural intention (0.24). At the same time, the descriptive results show that output quality items have the lowest mean values in the model, with perceived reliability being the lowest. Computer science students appear to clearly recognise the limits of AI tools, particularly regarding the correctness of generated code and explanations, while still finding them useful and enjoyable. This nuanced perception is consistent with prior findings reporting that programming students value ChatGPT but remain cautious about the accuracy of its outputs (Yilmaz & Karaoglan Yilmaz, 2023; Xue et al., 2024) and suggests that, in the case of generative AI, output quality should be modelled primarily as an antecedent of the affective and usability beliefs rather than as a direct driver of usefulness.

The strong role of perceived impact (total effect 0.54 on BI) is one of the most distinctive findings of this study. Perceived impact significantly influences perceived enjoyment, perceived usefulness, and behavioural intention directly, suggesting that the way students project the future role of AI tools in their education and in the computer science profession shapes their current adoption behaviour. This extends previous findings on the importance of students' perception of AI tools and of training in such tools (Dahri et al., 2024; Vázquez-Parra et al., 2024) by showing that future-oriented professional beliefs operate alongside, and not only through, the classical TAM constructs.

Placing these results in an international context helps to separate what is specific to the present sample from what is shared across educational systems. The central role of perceived enjoyment converges with the evidence reported by Strzelecki (2024) for 503 Polish state university students, where hedonic motivation, the UTAUT2 counterpart of perceived enjoyment, emerged as one of the strongest predictors of behavioural intention, and with the global study of Ravšelj et al. (2025), in which enjoyability was one of the three perceptions that proved central across regions. The affective component of ChatGPT use therefore appears to be a stable driver of adoption rather than a feature of one particular national context.

The picture is different for the effort-related beliefs. Strzelecki (2024) reported that effort expectancy had only a modest effect on behavioural intention among Polish students, and the present results take this pattern one step further: for Romanian computer science students, perceived ease of use has no significant effect either on perceived usefulness or on behavioural intention, and the model explains only 14.4% of its variance. Studies conducted on discipline-heterogeneous samples, such as those of Balaskas et al. (2025) and Ma et al. (2025), consistently report perceived ease of use as significant. Taken together, these findings suggest that the explanatory power of ease of use decreases as the technical fluency of the population increases and approaches zero in a population trained to work with programming environments and command-line interfaces. Acceptance results obtained on mixed student samples should therefore not be transferred uncritically to computing disciplines.

Ravšelj et al. (2025) also reported that students' concerns regarding the accuracy of ChatGPT's output vary substantially with the local educational context. In the present sample, these concerns are clearly visible: the three output quality items obtained the lowest means of the whole instrument, and the perceived reliability of the responses was the lowest rated item overall. What is notable is that this scepticism does not translate into a weaker intention to use the tool. Output quality influences behavioural intention indirectly, through perceived ease of use and perceived enjoyment, while its direct path to perceived usefulness is not significant. Romanian computer science students thus appear to have developed a calibrated form of use, in which the tool is valued and used intensively while its output is not automatically trusted, a pattern consistent with the cautious attitudes towards generated code reported by Xue et al. (2024) and by Yilmaz and Karaoglan Yilmaz (2023).

The strongest contrast with previous work concerns perceived impact. The extensions of TAM and UTAUT2 applied to ChatGPT so far have added constructs that describe the tool or the user's current relation to it: trust and risk (Balaskas et al., 2025), metacognitive self-regulated learning (Dahri et al., 2024), or habit and social influence (Strzelecki, 2024; Venkatesh et al., 2012). The present results show that a belief which refers neither to the tool nor to the current learning situation, but to the future of the profession, has a total effect on behavioural intention equal to that of perceived enjoyment (.54) and larger than that of perceived usefulness (.38). For students who are at the same time users and prospective developers of these technologies, adoption is therefore also an anticipatory professional decision and not only a judgement about the immediate utility of the tool. This is the main respect in which evidence from a computer science population differs from the evidence accumulated on general student samples, and it adds a Central and Eastern European data point to a comparative literature that so far covers this region only through Poland (Strzelecki, 2024) and through the Polish–Egyptian comparison of Strzelecki and ElArabawy (2024).

From a theoretical perspective, the results support the relevance of extending TAM with external variables that capture system-related characteristics (output quality) and broader, future-oriented beliefs (perceived impact). They also confirm the central role of perceived enjoyment as both a direct predictor of behavioural intention and a strong antecedent of perceived usefulness, which is consistent with conceptualisations of educational tools as having a significant hedonic component (Ma et al., 2025; van der Heijden, 2004).

At the same time, the non-significance of the perceived ease of use paths suggests that, for technically advanced user groups such as computer science students, the explanatory weight of TAM shifts away from usability and toward motivational and contextual factors. In this respect, given the widespread use of educational platforms, a motivational model seems more appropriate than TAM for explaining students' adoption of educational technologies.

From a practical perspective, the findings have several implications for educators and curriculum designers in computer science programs. First, since perceived enjoyment plays a central role both directly and indirectly through perceived usefulness, integrating ChatGPT-supported activities in a way that is engaging, and not only efficient, is likely to sustain its use as a learning aid. Second, the strong role of perceived impact suggests that explicitly addressing the role of AI in the future profession, for example, through dedicated lectures, seminars, or laboratory exercises on the responsible use of AI in software engineering, can reinforce students' intention to use such tools as part of their professional development. Third, given that students perceive output quality (particularly reliability) as the weakest aspect of ChatGPT, instructional approaches should explicitly train students to critically evaluate and validate AI-generated outputs, especially code, rather than relying on them uncritically.

Several limitations of this study should be acknowledged. First, the research is exploratory and based on a relatively small sample of 165 students from a single institution, which limits the generalizability of the findings to the broader population of Romanian and Central and Eastern

European computer science students. Second, the sample is unbalanced in terms of gender, with male students being clearly over-represented, as is common in computer science programs. Third, data were collected at a single point in time, which precludes any conclusions about the evolution of perceptions and behaviours as students gain more experience with generative AI tools. Fourth, behavioural intention was used as a proxy for actual continued use, in line with the standard TAM tradition.

Future research could replicate the study with larger and more diverse samples across multiple universities, include additional external variables (such as perceived risk, trust, AI literacy, or self-efficacy in working with AI), adopt a longitudinal design, and complement self-reported behavioural intention with objective indicators of actual use.

Conclusions and Implications

The current research aimed to examine the main drivers of ChatGPT adoption among Romanian undergraduate students enrolled in a computer science program by specifying and testing an extended technology acceptance model that includes two external variables: output quality and the perceived impact of AI tools on education and the future profession. Data collected from 165 students at the University of Craiova showed that ChatGPT is broadly used (90.91%), typically alongside other AI tools, and is integrated into both general academic tasks and discipline-specific programming activities such as algorithm explanation, code writing, and code documentation.

The empirical results show that the extended TAM explains 66.7% of the variance in the behavioural intention to continue using ChatGPT, with perceived usefulness, perceived enjoyment, and perceived impact emerging as significant direct predictors. When indirect paths are also considered, perceived impact and perceived enjoyment have the strongest overall effects on the behavioural intention. Perceived ease of use, in contrast, did not significantly predict either perceived usefulness or behavioural intention, which suggests that for computer science students, who are familiar with conversational and command-line interfaces, ease of use functions as a baseline expectation rather than a discriminating factor. Output quality affects the behavioural intention indirectly, primarily through perceived ease of use and perceived enjoyment, while students rate the reliability of ChatGPT's responses lowest among all measured items.

Theoretically, the study contributes to the literature by providing evidence that, for technically advanced students using generative AI tools, the explanatory weight of TAM shifts from usability toward motivational and contextual factors, and by demonstrating the value of perceived impact as an external variable that captures forward-looking professional beliefs. Practically, the findings suggest that integrating ChatGPT into computer science education in a pedagogically sound way requires more than ensuring access to the tool: it calls for activities that support enjoyable and meaningful use, explicit reflection on the role of AI in students' future professions, and dedicated training in critically evaluating the output of generative AI systems. By focusing on a Romanian computer science cohort, the study also adds evidence from a Central and Eastern European context that has so far been underrepresented in the literature on ChatGPT adoption in higher education.

Declaration of Interest

The authors declare no competing interests.

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