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Antecedents of students' behavioural intention to use generative artificial intelligence: Quantitative research

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A B S T R A C T

Objective: The article aims to identify factors that influence students' behavioural intentions to use generative artificial intelligence (GenAI).

Research Design & Methods: We proposed a research model based on the theory of planned behaviour, the technology acceptance model and a literature review.

Findings: The results show that attitude, perceived usefulness, perceived quality, and perceived support from higher education institutions positively impact students' behavioural intention to use GenAI.

Implications & Recommendations: The findings allowed us to propose two practical implications for academic teachers and managers of higher education institutions. Firstly, we recommend supporting students in terms of their knowledge, skills and conscious use of GenAI. Comprehensive education and other forms of training may be of use here. Secondly, we recommend that educational establishments clearly define their expectations regarding students' use of GenAI, particularly how and when they can safely use GenAI, not only during their studies.

Contribution & Value Added: Our study offers a new multilevel model of students' behavioural intentions to use generative GenAI. It enables the synthesis of our research results and the organisation of variables influencing students' behavioural intention to use GenAI, as well as the relations between them. Furthermore, as far as we are aware, we are the first to encompass aspects of the perceived quality and ethics of students using GenAI in our research.

Article type: research article
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INTRODUCTION

Since the launch of Chat GPT in November 2022 (https://chat.openai.com; retrieved on October 29, 2023), a conversational language model based on GenAI developed by Open AI, GenAI as 'a machine learning model that uses unsupervised and supervised learning techniques to understand and generate human-like language' (Lund & Wang, 2023, p. 1) has become one of the most intensively explored topics (Wach *et al*., 2023), in particular from the perspective of higher education institutions (HEI) (Gill *et al*., 2024).

Increasing numbers of studies show that GenAI can be particularly useful for students in obtaining teaching materials, providing personalized learning experiences, offering virtual personal tutoring, creating outlines, brainstorming ideas, assisting in creating educational content, learning a foreign language, translating texts, and writing assignments (Perera & Lankathilaka, 2023). Moreover, GenAI can prove significant in improving teaching and learning outcomes, expanding knowledge, saving time and achieving educational goals.

Despite the research intensity (Gill *et al*., 2024), the literature emphasises the need to look again at the reasons for using GenAI from the perspective of key stakeholders, students in particular (Gill *et al*., 2024). Such reasons are understood to be antecedents, *i.e.,* factors that precede and influence the results of a specific event. Antecedents represent pre-existing conditions and behaviours before an individual considers performing a specific activity. Previous findings regarding the antecedents of GenAI focus on research into public opinion, consumers, public health, government services, finance and professional developers (Singh & Singh, 2023). Although the antecedents of the intentions of students to use GenAI have gained attention, previous research has its limitations. These mainly refer to small sample sizes (Bonsu & Baffour-Koduah, 2023; Strzelecki, 2023) and use one selected theory (Bonsu & Baffour-Koduah, 2023; Foroughi *et al*., 2023; Raman *et al*., 2023; Strzelecki, 2023; Yilmaz *et al*., 2023). We conducted the research using a qualitative approach and quantitative research (Bonsu & Baffour-Koduah, 2023; Choudhury & Shamszare, 2023; Foroughi *et al*., 2023; Raman *et al*., 2023; Strzelecki, 2023; Yilmaz *et al*., 2023). These have their limitations, especially with regard to the specifics of qualitative research per se, but also relating to extant quantitative research, *i.e.,* number of participants (Bonsu & Baffour-Koduah, 2023), focus on the Anglo-Saxon (Choudhury & Shamszare, 2023), or Asian context (Foroughi *et al.,* 2023), the use of a single theoretical lens (Foroughi *et al*., 2023; Raman *et al*., 2023), state universities (Strzelecki, 2023), and students studying programming (Yilmaz *et al*., 2023).

Despite findings on factors that may influence students' intentions to use GenAI, there are still calls for research to reveal other factors (Bonsu & Baffour-Koduah, 2023). In response to the indicated challenges, we aimed to identify factors that influence students' intentions to use GenAI. In this study, we understand intention as 'the degree to which a person has formulated conscious plans to perform or not perform certain future behaviours' (Warshaw & Davis, 1985, p. 214). Unlike previous studies, which examined the antecedents of intentions to use GenAI among students on a single-level basis (Bonsu & Baffour-Koduah, 2023; Dwivedi *et al*., 2023; Foroughi *et al*., 2023; Raman *et al*., 2023; Strzelecki, 2023; Yilmaz *et al*., 2023), we perceive them on many levels at the individual, group, and organizational level. The literature recommends this approach for concepts that change and depend on different contexts (Kozlowski & Klein, 2000).

The literature has not yet provided guidance on selecting and applying appropriate theories that considering the intention to do something (Kwon & Silva, 2020). However, considering the formulated research question, we decided to choose two theories, *i.e.*, the theory of planned behaviour (TPB) (Ajzen, 1991) and the technology acceptance model (TAM) (Davis, 1989). We made this choice for two reasons. Firstly, these theories are the two most popular ones that are widely used to explain intentions regarding broadly understood technology (Kwon & Silva, 2020), such as GenAI. Secondly, the choice of the TPB resulted from the fact that it is widely used in research on intentions and behaviours related to the adoption of new technologies (Ajzen, 1991). However, it is necessary to treat this theory as a starting theory, as subsequent applications allow it to be extended to new contexts (Conner & Armitage, 1998). Therefore, we decided to use the TAM.

Our study is a response to the challenge presented in the literature regarding the identification of the antecedents to students' intentions to use GenAI (Dwivedi *et al*., 2023). Firstly, we adopted a multilevel approach, which the literature recommends in the case of antecedent research. This allows for the improvement of theoretical development and the understanding of concepts in various contexts. Secondly, our study considers aspects of the perceived quality and ethics of students using GenAI, which has so far been omitted in other studies, but has been postulated and recommended (Panagopoulou *et al*., 2023).

The subsequent part of this article is organized as follows. The first section of this paper provides an overview of the literature on antecedents of students' intention to use GenAI, research model, and hypotheses development. The next section covers the sample and data collection procedure, the adopted research tool, and data analysis. Next, the results section presents the descriptive statistics and matrix correlation results, the confirmatory factor analysis, the discriminant validity, and the PLS-SEM analysis. Finally, the conclusion summarizes the results, theoretical and practical implications, limitations, and potential future research.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Antecedents of Students' Intention to Use GenAI

Previous studies have explored factors that influenced students' intention to use GenAI, drawing on various theoretical frameworks. Foroughi *et al*. (2023) applied the extended unified theory of acceptance and use of technology (UTAUT2) to identify key determinants influencing the intention to use GenAI for educational purposes, including performance expectancy, effort expectancy, hedonic motivation, and learning value. Using the same theory as Foroughi *et al.* (2023), Strzelecki (2023) found that performance expectancy, habit, personal innovativeness, and hedonic motivation are positively associated with behavioural intention. Scholars have also found a weak positive effect of expected effort and social influence on behavioural intentions. Other researchers have used the TAM to explain why students use GenAI (Bonsu & Baffour-Koduah, 2023; Yilmaz *et al*., 2023). Based on mixed sequential research, Bonsu and Baffour-Koduah (2023) determined that students' perception of GenAI is not related to the intention to reach for it and use it. However, the experience of using technological innovations increases students' intention to use GenAI. In turn, adopting the perspective of the TAM, Yilmaz *et al*. (2023) found a positive perception of GenAI among students, as well as the importance of all the adopted factors on the behavioural intention of students. Taking the perspective of the perceived attributes of the diffusion of innovation theory, Raman *et al*. (2023) conducted research among 288 students. They found that relative advantage, compatibility, ease of use, observability and trialability significantly influenced the adoption of GenAI by students.

Moreover, the literature provides different results regarding the importance of age, gender, and study level in students' behavioural intention to use GenAI. For example, Bonsu and Baffour-Koduah (2023) found that students over 26 years of age showed a greater tendency to use GenAI than in the case of their younger colleagues. However, Yilmaz *et al*. (2023) found no significant differences for behavioural intention between different age groups of students. Regarding gender, according to Bonsu and Baffour-Koduah (2023), the intention to use GenAI is greater among male students than female students. Yilmaz *et al.* (2023) found that gender matters in students' behavioural intention to use GenAI. In detail, their findings are similar to those of Bonsu and Baffour-Koduah (2023) – male students showed stronger levels of intention to use GenAI. In turn, Raman *et al.* (2023) believe that gender does not matter for behavioural intention, but gender differentiates the reasons for using GenAI. According to the authors, male students will choose GenAI due to its compatibility, ease of use, and observability. In turn, ease of use, compatibility, relative advantage and trialability may be important for female students. On the other hand, Strzelecki (2023) states that gender does not matter in students' behavioural intention to use GenAI. With regard to study level, Bonsu and Baffour-Koduah (2023) state that the higher the level of study, the greater the intention to use GenAI. The results of the research conducted by Strzelecki (2023) do not confirm these findings, and the study level does not matter in students' behavioural intention to use GenAI.

Research Model and Hypotheses Development

To develop a robust model for the factors influencing students' behavioural intention to use GenAI, we conducted pilot studies. Initially, we compiled a list of potential antecedents based on the two theoretical frameworks used in our research, as suggested by existing literature, *i.e.*, the theory of planned behaviour (TPB) (Ajzen, 1991) and the technology acceptance model (TAM) (Davis, 1989). Moreover, we incorporated factors such as perceived quality (Niu & Mvondo, 2024), ethical perception (Paul *et al*., 2023), and HEI support (Stahl & Eke, 2024), as recommended in prior research. To measure those antecedents, we adopted established measurement scales from the TPB, TAM, and studies by Stone-Romero *et al*. (1997) and Michaelidou *et al*. (2021) (Table 3). To ensure respondents understood the term GenAI, we provided the adopted definition at the beginning of the questionnaire. We did not include a filtering question to differentiate between GenAI users and non-users, as our goal was to capture students' opinions, perceptions, and attitudes regarding their intention to use GenAI. A seven-point Likert scale was used to assess all variables, ranging from ‘1 – strongly disagree‘ to ‘7 – strongly agree,‘ as McKelvie (1978) suggests that reliability is maximized with that scale.

We conducted the pilot study in April 2023 at a conveniently selected private higher education institution in one of Poland’s largest cities. We hosted the questionnaire on the Webankieta.pl platform (https://www.webankieta.pl, retrieved April 1, 2023). The sample comprised 3000 people, with 60 fully completed questionnaires returned. To assess the reliability and suitability of our research tool, we performed the McDonald’s omega reliability coefficient test (ω) (McDonald, 1999), which is considered more general than Cronbach’s alpha and is a more optimal measure of reliability (Hayes & Coutts, 2020). The overall reliability of the tool was 0.939, indicating high reliability (McDonald, 1999).

Moreover, we tested the raw data for common method bias using Harman’s single-factor test (Podsakoff *et al*., 2003). The results showed that the variance explained by the single factor was 61.80%, which was below the 70% threshold, indicating no common method bias. We assessed the composite reliability (CR) and convergent validity of the measurement using the average variance extracted (AVE) method (Hair *et al*., 2011). The CR for the antecedents – attitude, perceived usefulness, perceived quality, ethical perception, perceived subjective norms, and HEI support – exceeded the threshold of 0.7. Regarding AVE, the required threshold of ≥ 0.5 was met for attitude and perceived usefulness. We then conducted exploratory factor analysis (EFA) using the principal component method with Promax rotation and Kaiser normalization to explore the underlying data structure.

Before performing the EFA, we verified the statistical assumptions necessary for the analysis by conducting the Kaiser-Meyer-Olkin (KMO) test and Bartlett’s test of sphericity. The KMO value was 0.915, indicating excellent adequacy (Kaiser, 1974), while Bartlett’s test of sphericity was significant ($p < 0.001$), confirming that the data was suitable for factor analysis (Field, 2009). The EFA revealed that the 40-item tool with six factors had factor loadings of 0.40 or greater (Watkins, 2018) and explained 82.98% of the variance. This led to the final version of the questionnaire, which included the antecedents attitude, perceived usefulness, perceived quality, ethical perception, perceived subjective norms, and HEI support for further analysis. We excluded from further analyses two constructs that were included in TAM and TPB (mostly perceived ease of use and perceived behavioural control), because the factor loading was less than the predefined value. Next, following the multilevel approach (Kozlowski & Klein, 2000), we grouped the proposed antecedents into three levels: individual, group, and organizational.

Individual Level

The individual level refers to features associated with a given person. At this level, we adopted the following four antecedents: attitude, perceived usefulness, perceived quality, and ethical perception.

Attitude refers to a person’s attitude towards certain phenomena, expressing their views and way of acting or behaving towards specific phenomena, events or people (Ajzen, 1991). Previous research shows that a positive attitude is recognized as a factor influencing the behavioural intention to use GenAI (Yilmaz *et al*., 2023), and is crucial to its successful adoption (Yilmaz *et al*., 2023). In light of the above considerations, we therefore expected that students’ behavioural intention to use GenAI would depend on their attitudes.

H1: Attitude positively impacts students’ behavioural intention to use GenAI.

Perceived usefulness refers to ‘degree to which a person believes that using a particular system would enhance their job performance‘ (Davis, 1989, p. 320). Therefore, the decision to take action is primarily driven by the perceived advantages or the belief that one’s needs will be satisfied. Previous studies suggest that perceived usefulness is linked to students’ intention to adopt technology that can boost their productivity, efficiency, and effectiveness (Algahtani & Mohammad, 2015). According to Yilmaz *et al*. (2023), students are more likely to use GenAI if they believe it will improve their academic performance. Similarly, Bonsu and Baffour-Koduah (2023) found that students’ behavioural intention to use GenAI is influenced by its perceived usefulness. These findings led us to the following hypothesis:

H2: Perceived usefulness positively impacts students’ behavioural intention to use GenAI.

Perceived quality refers to customers’ cognitive and emotional reactions to a specific project or service (Stylidis *et al*., 2020). As indicated by Xu *et al.* (2023), perceived quality positively impacts the intention to use GenAI. In turn, Tlili *et al.* (2023) found that students perceived GenAI as a valuable element of educational transformation, but also showed concerns about the quality of the content it generated. Therefore, if potential users believe that GenAI will provide good quality benefits, this may have a direct impact on their intention to use it. These findings lead us to the following hypothesis:

H3: Perceived quality positively impacts students' behavioural intention to use GenAI.

Ethical perception refers to the degree to which a person can recognize whether a given behaviour is moral from their perspective or not (Dwivedi *et al*., 2023). From the perspective of students, concerns are highlighted about the quality of the obtained data, copyright infringement (Stokel-Walker, 2023) and the sharing of sensitive or personal data. In this regard, viewing GenAI from an ethical perspective seems to be important for students' behavioural intention to use it. These findings lead us to the following hypothesis:

H4: Ethical perception positively impacts students' behavioural intention to use GenAI.

Group Level

The group level pertains to how an individual views their own actions as well as those of others. At this level, we identified subjective norms, which involve a person's belief that significant individuals or groups (as perceived by the person) will endorse and encourage a particular behaviour (Ajzen, 1991). Previous research on GenAI has shown a significant and positive relationship between subjective norms and behavioural intention to use it (Foroughi *et al*., 2023; Strzelecki, 2023; Yilmaz *et al*., 2023). In this approach, if a person tends to adapt to the expectations of others to strengthen relationships with group members or other people important to them, they may develop the intention to use GenAI. With the above in mind, we hypothesised:

H5: Subjective norms positively impact students' behavioural intention to use GenAI.

Organizational Level

The organizational level refers to the scope of responsibility, authority or other activities from the point of view of the organization in which a given person is located. At this level, we adopted HEI support. This refers to the student's perception that the university acknowledges their efforts, appreciates their contributions, and prioritizes their overall well-being (Rhoades & Eisenberger, 2002). In this approach, we may associate HEI support with students' behavioural intention to use GenAI (Dwivedi *et al*., 2023; Stahl & Eke, 2024). Therefore, we hypothesised:

H6: Higher education institutions' support positively impacts students' behavioural intention to use GenAI.

Figure 1 shows our proposed research model.

RESEARCH METHODOLOGY

Sample and Data Collection

We conducted the main research using the final verified version of the questionnaire. We conducted the main research from May to June 2023 at a conveniently selected private higher education institution in one of Poland's largest cities. We distributed our online questionnaire to all part-time bachelor's and master's students, with a total sample size of 3 000 people. To determine the minimum sample size, we factored in the acceptable margin of error (5%) and the assumed confidence level ($\gamma = 0.95$; $\alpha = 1.96$; $d = 0.05$). Based on those parameters, we concluded that the minimum sample size needed was 341 participants.

We received a total of 1125 completed questionnaires, but we discarded 355 due to incomplete data. Ultimately, we included 770 valid questionnaires in the analysis, yielding a response rate of 25.67% and meeting the minimum sample size requirement. The majority of respondents were women (66.36%), over 25 years of age (44.30%), and first-year students (55.30%) (Table 1).

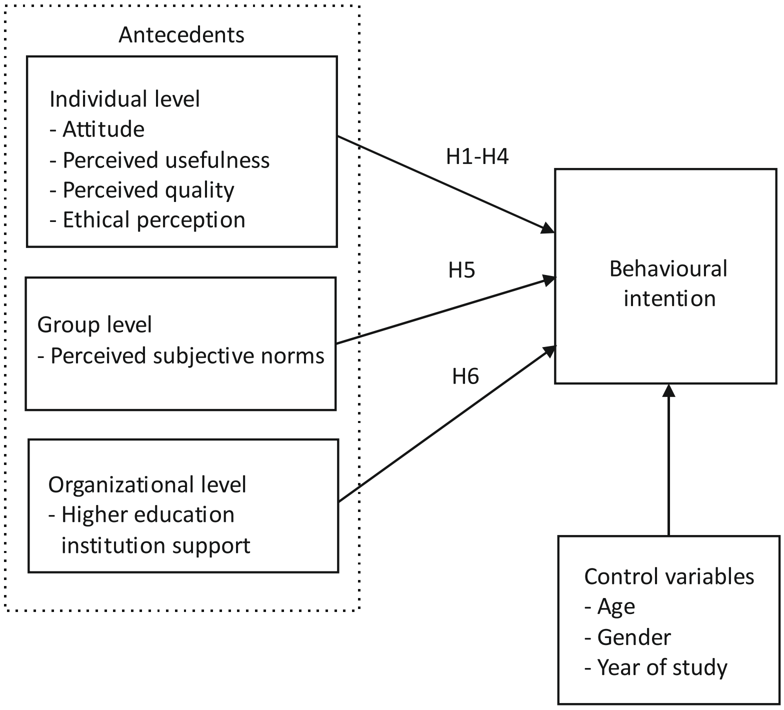

Figure 1. A theoretical multilevel model of students' behavioural intentions to use GenAI
Source: own elaboration.

Table 1. Respondents' main features

Demographic variables		Frequency (n)	Percentage (%)
Gender	Male	511	66.36
	Female	234	30.39
	I don't want to disclose my gender	25	3.25
Age	19-20	138	17.90
	21-22	149	19.40
	23-24	142	18.40
	> 25	341	44.30
Year of study	1	426	55.30
	2	107	13.90
	3	83	10.80
	4	85	11.00
	5	69	9.00

Source: own study.

Variable Description and Measurement

To measure the adopted antecedents of the intention to use GenAI among students divided into individual, group and organizational levels, using behavioural intention and control variables, we adopted an approach taken from the literature (Table 3). To measure age, we adopted the following categories: 19-20, 21-22, 23-24, 25 and above. Such categories are consistent with previous research conducted among students (Yilmaz *et al.*, 2023) as the age category is emphasized by other researchers (Strzelecki, 2023). To measure the year of study, we adopted the range 1-5 in accordance with the higher education system (Bonsu & Baffour-Koduah, 2023).

Data Analysis

We performed correlation analysis, as well as convergent and discriminant procedures. We used correlation analysis to measure the association between the antecedents and students' behavioural intention to use GenAI. As part of the convergent and discriminant validation procedures, we performed confirmatory factor analysis (CFA), McDonald's omega reliability coefficient, and Harman's single factor test. To test our hypotheses, we employed PLS-SEM (Hair *et al*., 2011). We chose this method, because it enables the estimation of theoretical constructs, their reliability and validity, as well as testing the directional relationships between complex constructs (Chin, 2010). We conducted the analysis using PS Imago Pro 9 and SmartPLS 4 software.

RESULTS AND DISCUSSION

Table 2 presents the descriptive statistics and correlation analysis results. The findings indicate that, out of the mean values, perceived usefulness had the highest mean (4.651), while perceived quality had the lowest mean (3.171). We also observed minor differences between the means for perceived quality (4.108) and HEI support (4.270). To examine the linear relationship between two variables and assess its strength and nature, we conducted a correlation analysis using the Pearson r correlation coefficient. As shown, not all antecedents positively correlated with behavioural intention, such as ethical perception (-0.033). It is also important to note the weak correlations for perceived subjective norms (0.288). A strong correlation was found in the case of attitude (0.701). To check for multicollinearity, we calculated the variance inflation factor (VIF) for each variable. The results ranged from 1.687 to 4.841, which aligns with the required tolerance range of 0.20 to 5.0 (Hair *et al*., 2011).

Table 2. Descriptive statistics and matrix correlation

No.	Variables	Summary statistics			Variable						
		Mean	SD	ω	ATT	PU	PQ	PE	SNO	POS	BI
1.	Attitude	4.394	1.456	0.853	1						
2.	Perceived usefulness	4.651	1.420	0.913	0.727	1					
3.	Perceived quality	4.108	0.919	0.897	0.410	0.444	1				
4.	Ethical perception	3.171	1.381	0.820	-0.012	-0.070	-0.061	1			
5.	Perceived subjective norms	3.601	1.216	0.821	0.265	0.363	0.373	0.078	1		
6.	Higher education institution support	4.270	1.320	0.753	0.570	0.638	0.510	0.052	0.497	1	
7.	Behavioural intention	3.420	1.651	0.904	0.701	0.639	0.466	-0.033	0.288	0.567	1

Source: own study.

To perform the reliability analysis, we calculated McDonald's omega reliability coefficient (ω) (Table 2). The overall tool achieved a value of 0.914, indicating very high reliability. Individual antecedents and behavioural intention also exhibited high internal consistency. Since we gathered data for all variables from a single source, we conducted Harman's single-factor test with Promax rotation (Podsakoff *et al*., 2003) to assess common method variance. The results revealed that the first factor accounted for only 28.233% of the data variability, indicating no risk of common method variance, as the explained variance was below 50% (Podsakoff *et al*., 2003).

We used confirmatory factor analysis (CFA) to evaluate the measurement model and assess the fit of the proposed factor structure (Table 3). We used the following criteria with the established thresholds: root mean square error of approximation (RMSEA) with a close fit < 0.05 (Brown, 2015), goodness-of-fit index (GFI) > 0.9, and adjusted GFI (AGFI) > 0.8 (Bagozzi & Yi, 1988). The overall fit indices for the measurement model were RMSEA = 0.020, GFI = 0.929, and AGFI = 0.910, indicating an adequate fit. Moreover, SmartPLS includes the standardized root mean square residual (SRMR) as a fit criterion for PLS path modelling, with a recommended value of less than 0.08 (Hu & Bentler, 1999). The SRMR for our final structural model was 0.072, indicating an acceptable fit.

The findings presented in Table 3 reveal that the factor loadings for the 40 items ranged from 0.188 to 0.914. In most cases, the loading factor exceeds 0.70 (Hair *et al*., 2011), indicating good reliability (Hair *et al*., 2011). However, a loading factor of 0.50 is also considered acceptable (Hulland, 1999). Based on these guidelines, we removed eight items (PE2, PE3, PE4, PE6, PE7, SNO5, SNO6, POS1). Next, we evaluated the composite reliability of the antecedents (CR) and the convergent validity of the measurement using average variance extracted (AVE) (Hair *et al*., 2017). After these adjustments, all con-

Table 3. Confirmatory factor analysis results

Variable	Indi-cator	Items	Factor loading	CR	AVE
Attitude (Ajzen, 1991)	ATT1	Using GenAI when studying has more advantages than disadvantages.	0.807	0.857	0.694
	ATT2	GenAI matters when studying.	0.840		
	ATT3	GenAI makes a difference in achieving better academic results.	0.845		
	ATT4	If there were any possibility, I would use GenAI.	0.839		
Perceived usefulness (Davis, 1989)	PU1	Speeding up the completion of my assignment will encourage me to use GenAI.	0.822	0.919	0.632
	PU2	Increasing the chances of getting a better grade for passing the subject will encourage me to use GenAI.	0.815		
	PU3	Speeding up the search for information requested by the lecturer will encourage me to use GenAI.	0.828		
	PU4	The need to look for information that is useful during my studies will encourage me to use GenAI.	0.770		
	PU5	Being able to quickly get answers to questions I may have while studying will encourage me to use GenAI.	0.817		
	PU6	The ability to access unlimited sources of knowledge will encourage me to use GenAI.	0.766		
	PU7	The possibility of saving time while writing final papers will encourage me to use GenAI.	0.826		
	PU8	The opportunity to save time while preparing for exams will encourage me to use GenAI.	0.710		
Perceived quality (Stone-Romero *et al.*, 1997)	PQ1	I believe that the information provided by GenAI is reliable.	0.822	0.907	0.769
	PQ2	I believe that GenAI ensures the security of the information I post.	0.912		
	PQ3	I believe that my personal data is protected when using GenAI.	0.861		
	PQ4	I believe that when I use GenAI, I can be confident in the privacy of the information I post.	0.909		
Ethical perception (Michaelidou *et al.*, 2021)	PE1	The use of GenAI does not violate generally accepted ethical principles at the university.	0.828	0.767	0.548
	PE2	All the data I receive from GenAI is real.	-0.759		
	PE3	I can sign as the creator of a study written by GenAI.	0.188		
	PE4	The use of GenAI influences human ethical behaviour.	0.328		
	PE5	The use of GenAI gives you permission to cheat while studying.	0.625		
	PE6	Lecturers should lower grades for students using GenAI.	-0.495		
	PE7	I believe that using GenAI is ethical.	-0.780		
	PE8	I find it absurd that some universities ban students from using GenAI.	0.782		
Perceived subjective norms (Ajzen, 1991)	SNO1	People who are significant to me will encourage me to use GenAI.	0.741	0.900	0.547
	SNO2	The lecturer's recommendations will encourage me to use GenAI.	0.789		
	SNO3	My college friends who also use GenAI will encourage me to use it.	0.555		
	SNO4	The opinions of my university friends will encourage me to use GenAI.	0.535		
	SNO5	My university's promotion of GenAI use will motivate me to use it.	0.451		
	SNO6	University regulations regarding GenAI use will encourage me to use it.	0.440		
	SNO7	The absence of a ban from my university will encourage me to use GenAI.	0.866		
	SNO8	People who are significant to me will encourage me to use GenAI.	0.855		
Higher education institution support (Eisenberger *et al.*, 1997)	POS1	The technical support offered by my university will encourage me to use GenAI.	0.270	0.828	0.725
	POS2	The chance to participate in a training course on how to use GenAI will motivate me to use it.	0.821		
	POS3	The university's expectations for students to use GenAI will encourage me to do so.	0.871		
	POS4	I will be encouraged to use GenAI by my lecturers' inclusion of GenAI in the curriculum.	0.856		
Behavioural intention (Azjen, 1991)	BI1	I think it is very likely that I will use GenAI to prepare for classes within the next month.	0.878	0.908	0.773
	BI2	I will recommend that my friends use GenAI to prepare for their studies.	0.914		
	BI3	I will make every effort to make the use of GenAI the norm during my studies.	0.888		
	BI4	My means of learning is by using GenAI.	0.836		

Source: own study.

structs exceeded the CR threshold of 0.7, demonstrating strong reliability (Hair *et al*., 2011). The square roots of the AVE for each construct were above the minimum value of 0.60, confirming that all constructs met the criteria for satisfactory convergent validity (Fornell & Larcker, 1981). Moreover, to assess discriminant validity, we applied the heterotrait-monotrait ratio (HTMT), which is considered more robust than the Fornell-Larcker criterion (Henseler *et al*., 2015). In our HTMT analysis (Table 4), all variables showed results of < 0.90, confirming adequate discriminant validity (Henseler *et al*., 2015).

Table 4. Discriminant validity

No.	Variables	ATT	PU	PQ	PE	SNO	POS	BI
1.	Attitude	1						
2.	Perceived usefulness	0.821	1					
3.	Perceived quality	0.464	0.506	1				
4.	Ethical perception	0.277	0.314	0.136	1			
5.	Perceived subjective norms	0.302	0.407	0.414	0.152	1		
6.	Higher education institution support	0.556	0.423	0.125	0.345	0156	1	
7.	Behavioural intention	0.795	0.742	0.516	0.236	0.311	0.457	1

Source: own study.

To assess the overall predictive power of the structural model, we calculated the coefficient of determination (R^2) (Chin, 1998). The values were as follows: attitude – 0.570 (moderate), perceived usefulness – 0.367 (moderate), perceived quality – 0.123 (small), ethical perception – 0.330 (moderate), perceived subjective norms – 0.319 (moderate), and HEI support – 0.688 (substantial).

For the overall assessment of model fit, we calculated the standardized root mean square residual (SRMR). The model estimation was 0.086, confirming an acceptable fit based on the reference point of 0.1 for SRMR. We applied structural equation modelling (SEM) to the measurement model (Table 5). To test the significance of the path coefficients, we used a nonparametric bootstrapping procedure with 5 000 samples (Hair *et al*., 2011).

Table 5. Results of PLS-SEM analysis

Hypothesis and path	Path coefficient	*T-statistic* (sig. level)	*p-values*
H1. Attitude -> behavioural intention	0.399	11.232	0.000
H2. Perceived usefulness -> behavioural intention	0.120	3.099	0.002
H3. Perceived quality -> behavioural intention	0.111	3.358	0.001
H4. Ethical perception -> behavioural intention	-0.067	0.934	0.350
H5. Perceived subjective norms -> behavioural intention	0.051	1.682	0.093
H6. Higher education institution support -> behavioural intention	0.198	5.473	0.000

Source: own study.

The results revealed that attitude (path = 0.399, T = 11.232, $p < 0.005$), perceived usefulness (path = 0.120, T = 3.099, $p < 0.005$), perceived quality (path = 0.111, T = 3.358, $p < 0.005$), and HEI support (path = 0.198, T = 5.473, $p < 0.005$) had the most significant influence on students' behavioural intention. Therefore, we found support for hypotheses H1, H2, H3, and H7. Moreover, we found that ethical perception (path = -0.067, T = 0.934, $p > 0.005$) and perceived subjective norms (path = 0.051, T = 1.682, $p > 0.005$) had no effect on students' behavioural intention, leading to the rejection of hypotheses H4 and H5.

To further validate our findings and assess their robustness, we conducted additional analyses of control variables such as age, gender, and level of study. We used a one-way ANOVA test for this purpose, allowing for the comparison of the means of two or more independent groups to determine if there is statistical evidence of significant differences between the groups (Ross & Willson, 2017). This test is suitable for analysing sub-samples with different numbers of respondents, as it has less stringent assumptions compared to parametric tests, making it applicable to various measurement scales.

The results indicated significant differences in students' behavioural intentions to use GenAI across the different age groups, $F(28.133) = 73.825$, $p < 0.001$. The Student's t-test for independent samples revealed no statistically significant differences between women and men t(743)=-5.304, p>0.05, students aged 24 and younger versus those aged 25 and older t(285)=-0.696, p>0.05, and by level of study t(531)=-1.751, p>0.05. To further explore these findings, we performed bootstrapping using the Gabriel test. The results showed no significant differences between male and female students across specific age groups (19-20, 21-22, 23-24, 25 and above) (0.008; 5.27). However, the average behavioural intention was slightly higher for students aged 21-22 years (3.596) and 23-24 years (3.569) compared to students aged 25 and older (3.268) and 19-20 years (3.455), and for men (3.891) compared to women (3.213). We also noted small differences between third-year students (3.903) and first-year students (3.252).

Based on the TPB and the TAM, we aimed to identify factors influencing students' intentions to use GenAI. By examining antecedents at different levels individual (attitude, perceived usefulness, perceived quality, ethical perception), group (perceived subjective norms), and organizational (HEI support), as well as control variables like age, gender, and year of study, the study found support for four of the proposed hypotheses. Specifically, we confirmed that attitude (H1), perceived usefulness (H2), perceived quality (H3), and HEI support (H6) positively influence students' intentions to use GenAI. Conversely, ethical perception (H4) and perceived subjective norms (H5) did not affect students' behavioural intention to use GenAI, leading to the rejection of these hypotheses.

At the individual level, the findings indicated that attitude significantly impacts students' intention to use GenAI. This aligns with prior studies (Yilmaz *et al*., 2023). Furthermore, perceived usefulness positively affects students' intentions, which corroborates earlier research (Bonsu & Baffour-Koduah, 2023; Yilmaz *et al*., 2023). The results suggest that students were more likely to use GenAI when they perceive it as a tool that can help them complete assignments faster, search for information, get personalized answers quickly, and access unlimited knowledge sources, all contributing to better academic performance and time savings.

Perceived quality also plays a crucial role at the individual level. The study found that students' belief in the quality of information from GenAI influences their intention to use it, consistent with findings from other researchers (Tlili *et al*., 2023). This belief is often shaped by feedback from other users or academic publications on the topic.

However, ethical perception did not positively influence students' behavioural intentions to use GenAI, contrary to the expectations set by prior research (Stokel-Walker, 2023). This is likely due to the widespread admiration of GenAI's advantages at the time of the study. Ethical concerns, including issues like plagiarism or copyright infringement, have only recently gained attention (Stahl & Eke, 2024). This emerging concern represents a challenge for academic instructors, who now face the responsibility of identifying potential plagiarism (Khalil & Er, 2023). Researchers have called for further studies to better understand these issues and to guide future policy development (Stahl & Eke, 2024).

Secondly, at the group level, we found that perceived subjective norms do not have a positive impact on students' intention to use GenAI. Our findings did not confirm the previous findings of other researchers (Foroughi *et al*., 2023; Strzelecki, 2023; Yilmaz *et al*., 2023). However, our results are not surprising, and we can explain them by the fact that over half of our respondents (53.3%) were first-year students. Moreover, we conducted research among students following extra-mural studies, in which a considerable proportion of the classes were conducted online (80% remote learning). Face-to-face classes did not take place more than once a month. This means that our respondents had limited contact with their peers from the same year. Thus, their acquaintances from their studies could have had a limited impact on their decision to reach for GenAI. Finally, our results confirmed previous findings in the literature, which found that in the case of new technologies, subjective norms had a smaller impact on the intention to use them (Lee *et al*., 2010).

Thirdly, our results show that at the organizational level, HEI support had a positive impact on students' behavioural intention to use GenAI. These findings are consistent with Stahl and Eke (2024), who emphasize the importance of student support. Our research confirms that universities should conduct workshops and training on what GenAI is, how it works, and what its capabilities and limitations are. Discussions should be organized regarding the ethical aspects of using such tools in an academic context. This includes issues of plagiarism, academic dishonesty, and verifying information obtained from GenAI.

Including demographic variables in the models allowed us to confirm and extend previous conclusions from the literature. We found that age does not matter for students' behavioural intention to use GenAI. Our results confirmed the findings of Yilmaz *et al*. (2023). Our next result showed that gender does not matter for the behavioural intention to use GenAI among students, which confirms the findings of Raman *et al*. (2023) and Strzelecki (2023). Finally, our results showed that the level of study does not matter for the behavioural intention among students to use GenAI, which is consistent with Strzelecki (2023).

Ultimately, based on our research results, we propose a multilevel conceptual framework of students' behavioural intentions to use GenAI (Figure 2).

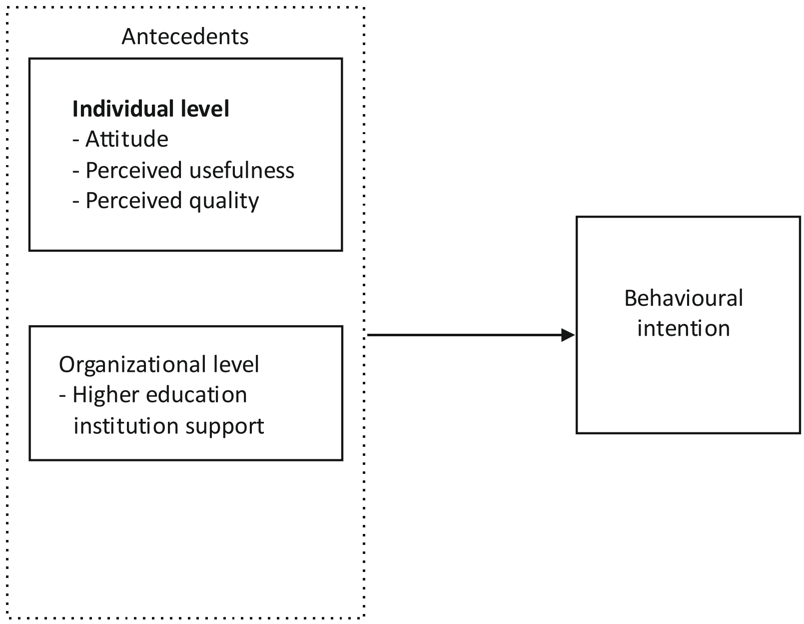

Figure 2. Multilevel conceptual framework of students' behavioural intentions to use GenAI
Source: own elaboration.

Our conceptual framework integrates students' behavioural intentions to use GenAI with its antecedents, which stem from our research findings. At the individual level, these are attitude, perceived usefulness, and perceived quality, while at the organizational level, it is HEI support. This framework not only consolidates the factors at both individual and organizational levels and their relationships with students' intentions to use GenAI, but it also serves as a foundation for future research. It offers a basis for further investigation that could deepen and expand the current understanding of students' behavioural intentions regarding GenAI usage.

CONCLUSIONS

Our research contributes to refining and developing theory on the antecedents to students' behavioural intention to use GenAI (Dwivedi *et al*., 2023) by developing a multilevel model of antecedents of students' behavioural intention to use GenAI. Our research showed that students' behavioural intention to use GenAI requires various factors and actions at various levels to intensify such intention. At the individual level, these are attitude, perceived usefulness, and perceived quality. Meanwhile, at the group level, students' intention to reach for GenAI is intensified by perceived subjective norms, while at the organizational level, this effect is achieved by HEI support. In summary, our study expands the current understanding of why students choose GenAI. From a theoretical point of view, our study contributes to and is the first step towards a multilevel approach to the antecedents of students' use of GenAI.

Our findings allow us to propose two practical implications for academic teachers and managers of HEI. These refer to the identified antecedents of the behavioural intention among students to use GenAI. Firstly, since attitude, perceived usefulness and HEI support are important for students' intention to use GenAI, it is important to provide them with support in terms of knowledge and skills. Therefore, there is a need to build and raise students' awareness of the critical use of GenAI. It is important to provide comprehensive training and other forms of improving competencies in the conscious use of GenAI. This may require universities to provide additional academic resources in the form of guides, instructional materials, videos or training to support critical use of GenAI.

Secondly, considering that perceived quality positively impacts students' behavioural intention to use GenAI, we recommend that universities clearly define their expectations regarding students' use of GenAI. These expectations may take the form of regulations or standards that address the benefits and risks of students' use of GenAI. Therefore, we encourage universities to explain to students how and when they can safely use artificial intelligence (Chan & Hu, 2023). Of course, we should also mention the threats of GenAI resulting from the indiscriminate use of GenAI, such as hallucinations, intellectual property infringement and the uncertainty of personal data security. Moreover, we believe that the academic community should start discussing comprehensive ways of identifying incidents of intellectual property infringement.

This study has several limitations that may serve as inspiration for future research. Firstly, the sample comprises Polish students from a conveniently selected private education institution located in one of the largest cities in Poland. This can be a limitation for the generalisation and application of the results. A limitation regarding the sample is that over half the respondents (53.3%) were first-year students. However, we conducted the research on a large sample, which increases the chances of counteracting and overcoming potential risks in sample selection. However, the context is important in research on behavioural intention, so future studies should be comparative, conducted in different countries, and consider different types of schools (public, private) and fields of study.

Secondly, our research referred to the opinions and observations of both male and female students, which could have influenced the conclusions drawn. In general, questionnaires measuring perception may be subject to errors of subjectivity and bias. Moreover, both the independent variables and the dependent variable were measured using the same scale, which may be subject to common method bias. This may lead to false conclusions. Therefore, to identify potential common method bias, we performed Harman's single-factor test (Podsakoff *et al*., 2003). Based on the result, we can conclude that there was no common method bias in our research (28.233%). Moreover, the results of the McDonald's omega reliability coefficient (ω) confirm the reliability of our tool. However, qualitative research may be helpful in the future to explore the opinions and perceptions of GenAI among students further. This would make it possible to identify and explain other reasons why students use GenAI. Moreover, perception changes over time, so future research should be longitudinal.

Thirdly, although we included control variables in our research (age, gender, level of study), our findings are not clear in this respect. Although men (66.36%) above 25 years of age (44.3%) dominated our sample, this does not constitute a threat to interpretation of the results. However, building on previous studies, future research could expand our findings to include personality traits and personality innovativeness.

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Conflict of Interest

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