KEY FACTORS INFLUENCING UNIVERSITY STUDENTS' INTENTION TO USE GENERATIVE AI AND ITS IMPACT ON SATISFACTION

Osvaldo Silva[1], Áurea Sousa[2]

[1]Universidade dos Açores, CICS.UAc/CICS.NOVA.UAc (PORTUGAL)
[2]Universidade dos Açores, CEEAplA and OSEAN (PORTUGAL)

Abstract

This study aims to explore the key determinants influencing university students' behavioural intention to use Generative Artificial Intelligence (BI_GAI) tools in educational settings, as well as the impact of this intention on student satisfaction (SS). Grounded in the Technology Acceptance Model (TAM), the research incorporates the traditional constructs of Perceived Ease of Use (PE) and Perceived Usefulness (PU) and extends the model by integrating Perceived Intelligence (PI), Perceived Trust (PT), Perceived Risk (PR), Expected Benefits (EB), and Technology Self-Efficacy (TSE).

Data were collected from 775 students at a Portuguese higher education institution through a questionnaire comprising 40 items across nine constructs (PE, PI, PU, PT, PR, BI_GAI, EB, TSE, and SS), alongside sociodemographic variables.

The data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The results reveal that PE and PI have a significant positive effect on Behavioural Intention to Use GAI (BI_GAI), whereas PU does not have a statistically significant direct influence. Perceived Trust (PT) emerges as a key mediating variable in the relationship between PU and BI_GAI, while Perceived Risk (PR) does not act as a significant mediator between the TAM constructs and BI_GAI. Behavioural Intention to Use GAI has the strongest direct influence on Student Satisfaction (SS), highlighting its central role in understanding students' engagement with GAI tools. Moreover, both EB and TSE significantly affect SS, both directly and indirectly through BI_GAI.

These findings support the development of an expanded TAM-based model that provides a more holistic perspective on the technological, psychological, and educational factors shaping GAI adoption in higher education. The inclusion of constructs such as PI, PT, and TSE offers deeper insights into the mechanisms through which students evaluate and adopt GAI for learning purposes, ultimately contributing to enhanced academic satisfaction.

Keywords: University students' perceptions, generative artificial intelligence, data analysis, PLS-SEM.

1 INTRODUCTION

Recent years have witnessed transformative shifts in higher education driven by technological innovations, particularly artificial intelligence (AI) and its applications in learning contexts [1]. Generative AI (GenAI) tools, such as ChatGPT, have become central to contemporary pedagogical strategies, offering opportunities to enhance instructional approaches and foster deeper student engagement [2, 3]. Evidence indicates that GenAI can support personalised learning, improve student satisfaction, and enable advanced tutoring and educational ecosystems [4, 5, 6]. However, the benefits of GenAI depend on institutional support, including infrastructure, training, and clear guidelines [7]. Without a structured framework, integration remains limited, and excessive reliance on technology may compromise critical thinking and learner autonomy [4, 8]. Ethical considerations—such as transparency and fairness—are essential for responsible GenAI use, while higher technological self-efficacy enhances students' confidence and engagement with these tools [9,10]. Understanding the interplay of these factors is crucial to optimise GenAI's effectiveness in higher education and ensure sustained, meaningful adoption [11].

Generative AI (GenAI) has increasingly transformed higher education, enhancing accessibility in teaching, learning, and research [12,13]. Tools such as ChatGPT and Gemini support tasks including essay writing, problem-solving, content creation, real-time feedback, and summarization, improving both academic performance and student satisfaction [14, 15]. GenAI fosters personalized, adaptive, and collaborative learning while promoting critical thinking, creativity, and technical skill development [16]. Students are inclined to use these tools for their efficiency in routine tasks, practical applications, and potential for innovation [17]. Effective integration into higher education requires understanding the key

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factors influencing students' intentions to use GenAI, as well as its impact on learning outcomes and overall satisfaction, ensuring meaningful and responsible adoption.

Perceived ease of use (PE) and perceived usefulness (PU), core constructs of the Technology Acceptance Model (TAM), are key predictors of users' attitudes, behavioural intentions, and engagement with new technologies [18, 19]. In this study, perceived ease of use refers to the extent to which students consider ChatGPT intuitive and straightforward, while perceived usefulness captures the degree to which the tools enhance academic performance in tasks such as writing, summarising, and idea generation [18, 20]. Both constructs are critical for understanding students' adoption of generative AI and are expected to influence satisfaction and continued use in higher education contexts.

Perceived Intelligence (PI) refers to users' perception of a generative AI system's cognitive capabilities, including its ability to understand context, generate relevant responses, and adapt to user needs. Higher PI is associated with increased trust and user engagement, which are critical for technology adoption [21]. Studies indicate that students' perceptions of an AI tool's intelligence significantly influence their intention to adopt it for academic tasks [22]. Therefore, PI is a key determinant in shaping students' behavioural intention (BI) to use GenAI tools in educational settings.

Expected benefits (EB) capture students' perceptions of the value of using generative AI (GenAI) tools in their academic practices. Drawing on Vroom's Expectancy Theory (1964) and the Technology Acceptance Model [23], research indicates that students are more likely to adopt GenAI when they anticipate gains in efficiency, engagement, personalisation, and innovation [14]. Empirical evidence confirms that recognising such benefits enhances both adoption and satisfaction [24]. Nonetheless, these effects are context-dependent, shaped by cultural and institutional settings. Therefore, EB is proposed as a key determinant of student satisfaction with GenAI tools.

While the Technology Acceptance Model (TAM) provides a solid basis for studying technology adoption [18, 19], incorporating trust and risk offers a more nuanced explanation of students' engagement with generative AI (GenAI). Perceived trust (PT) reduces uncertainty and fosters positive attitudes, thereby encouraging adoption [21], whereas perceived risk (PR) may limit use due to concerns over reliability, misuse, or ethical issues [25].

Technology self-efficacy (TSE), understood as confidence in the use of digital tools, is rooted in Bandura's self-efficacy theory (1983) and Ajzen's concept of perceived behavioural control (2002). Both frameworks suggest that self-efficacy strongly predicts behavioural intention (BI), a finding consistently supported in technology adoption research [11]. Recent studies confirm that students with higher TSE are more likely to engage effectively with generative AI (GenAI) tools, achieving superior learning outcomes, academic performance, and satisfaction [14]. TSE has also been associated with readiness for innovative pedagogical models, such as flipped learning. Accordingly, TSE emerges as a key determinant of both behavioural intention and student satisfaction in the context of GenAI adoption in higher education.

The present study builds on previous research conducted in Portugal on university students' perceptions of AI integration in higher education (e.g., [26]). It distinguishes itself from earlier work by proposing a conceptual model, represented through a path diagram within the framework of Partial Least Squares Structural Equation Modelling (PLS-SEM), and by drawing on more recent data. This study aims to identify the key determinants influencing university students' behavioural intention to use Generative Artificial Intelligence (BI_GAI) tools in educational settings, as well as to examine the mediating role of behavioural intention in the relationship between these determinants and student satisfaction (SS).

Section 2 outlines the research hypotheses and characterises the sample. It further details the constructs incorporated into the questionnaire employed for data collection, together with the conceptual model (path diagram) subjected to testing. Section 3 presents the key findings of the study. Finally, Section 4 summarises the main conclusions and highlights the practical implications of the research.

2 METHODOLOGY

The present study was conducted with a sample of Portuguese university students during the 2024-2025 academic year. Of the participants, 55.4% identified as female and 44.6% as male. Their ages ranged from 18 to 59 years (mean = 23.1, standard deviation = 1.8).

The statistical analysis method employed was Partial Least Squares Structural Equation Modelling (PLS-SEM), carried out using SmartPLS 4 software. The minimum required sample size was determined following the guidelines of Soper (2025) and Westland (2010), considering the number of observed variables (40) and latent constructs (9), the anticipated effect size (0.16), the desired statistical power

(0.80), and a minimum significance level of 0.05. This estimation indicated that at least 741 participants were necessary to ensure methodological robustness and to accommodate the complexity of the model. The final sample surpassed this threshold, comprising 775 valid responses, thereby reinforcing the statistical reliability of the results.

For data collection, a questionnaire was used that, in addition to sociodemographic variables, includes 40 items divided into nine constructs [Perceived Ease of Use (PE), Perceived Intelligence (PI), Perceived Usefulness (PU), Perceived Trust (PT), Perceived Risk (PR), Behavioural Intention (BI), Expected Benefits (EB), Technology Self-Efficacy (TSE) and Student Satisfaction (SS)] (see Appendix A - Table A1).

All 40 items across the nine constructs under analysis are self-report measures, each assessed using a seven-point Likert scale ranging from 1 (Strongly Disagree, SD) to 7 (Strongly Agree, SA), with 4 representing the midpoint. Perceived Ease of Use (PE) refers to the degree to which an individual believes that interacting with Generative Artificial Intelligence systems requires minimal effort, within the framework of the Technology Acceptance Model (TAM) [18, 19]. Perceived Usefulness (PU) refers to the degree to which an individual believes that using Generative Artificial Intelligence enhances their performance or effectiveness, a central determinant of technology adoption within the Technology Acceptance Model (TAM) [18, 19, 27 ,28]. Expected Benefits (EB) refers to the extent to which individuals anticipate positive outcomes and added value from using Generative Artificial Intelligence, such as increased efficiency, creativity, or productivity, complementing the core constructs of the Technology Acceptance Model (TAM) [18, 19, 28].

Perceived Intelligence (PI) captures the extent to which users ascribe human-like cognitive abilities to Generative Artificial Intelligence (GenAI). By fostering trust and reinforcing beliefs in GenAI's capacity to handle complex tasks, PI significantly enhances Behavioural Intention (BI) to adopt such technologies. Consequently, PI emerges as a key determinant in understanding GenAI acceptance.

A summary of all the relationships examined in the research conceptual framework is presented in Figure 1.

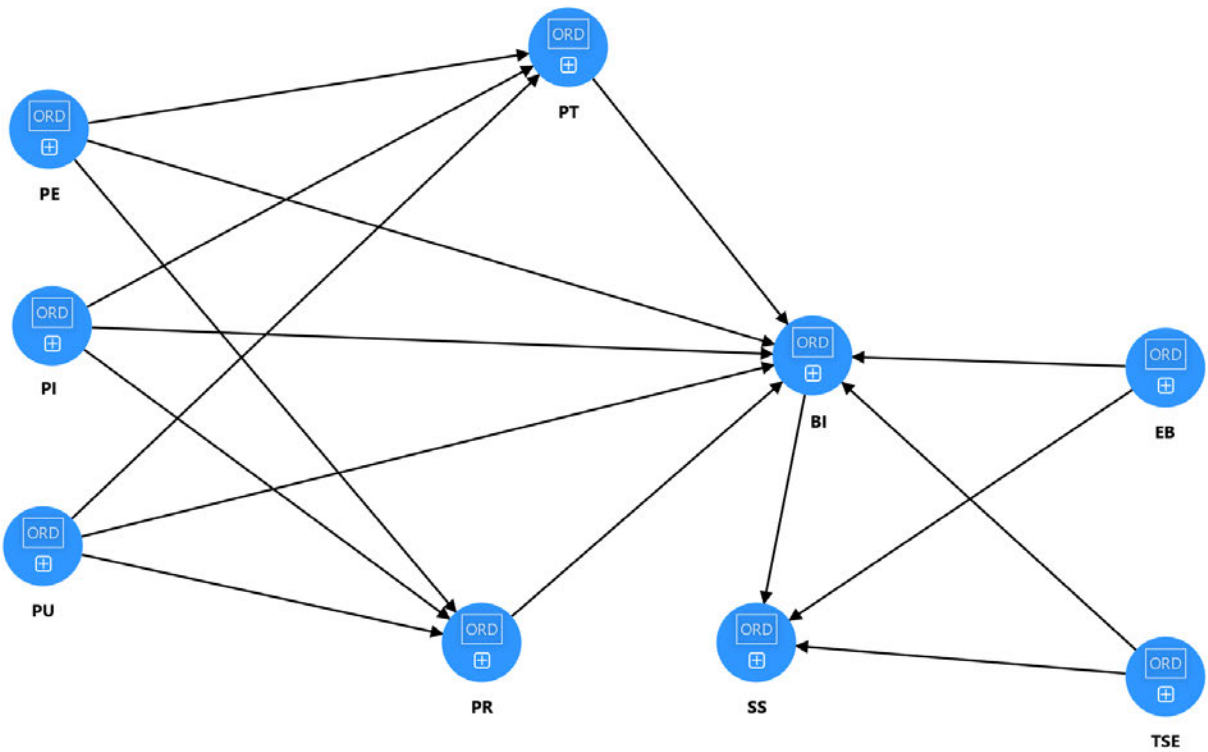

Figure 1. Conceptual model—path diagram.

This research attempts to test the following hypotheses:

H1. The perceived ease of use (PE) directly influences GAI adoption intention (BI) by university students.

H2. Perceived intelligence (PI) directly influences GAI adoption intention (BI) by university students.

H3. Perceived usefulness (PU) directly influences GAI adoption intention (BI) in by university students.

H4.1. Perceived trust (PT) directly influences GAI adoption intention (BI) in by university students.

H4.2. Perceived risk (PR) directly influences GAI adoption intention (BI) in by university students.

H5.1. Perceived trust (PT) mediates the relationship between the perceived ease of use (PE) and GAI adoption intention (BI) by university students.

H5.2. Perceived trust (PT) mediates the relationship between perceived intelligence (PI) and GAI adoption intention (BI) by university students.

H5.3. Perceived trust (PT) mediates the relationship between perceived usefulness (PU) and GAI adoption intention (BI) by university students.

H6.1. Perceived risk (PR) mediates the relationship between the perceived ease of use (PE) and GAI adoption intention (BI) by university students.

H6.2. Perceived risk (PR) mediates the relationship between perceived intelligence (PI) and GAI adoption intention (BI) by university students

H6.3. Perceived risk (PR) mediates the relationship between perceived usefulness (PU) and GAI adoption intention (BI) by university students.

H7. Expected benefits (EB) has a significant positive impact on student satisfaction (SS).

H8. Technology self-efficacy (TSE) has significant positive impact on student satisfaction (SS).

H9. GAI adoption intention (BI) by university students mediates the relationship between Expected benefits (EB) and student satisfaction (SS).

H10. GAI adoption intention (BI) by university students mediates the relationship between Technology self-efficacy (TSE) and student satisfaction (SS).

H11. GAI adoption intention (BI) by university students has a significant positive impact on student satisfaction (SS).

The research hypotheses outlined above were analysed using SmartPLS software (version 4) to conduct Partial Least Squares Structural Equation Modelling (PLS-SEM). This approach enabled the testing of all relationships depicted in the conceptual research framework shown in Fig. 1.

SmartPLS simultaneously provides results for both reflective measurement and structural models, including assessments of their reliability and validity [29]. In the present study, a reflective measurement model was applied, and the convergent and discriminant validity of the constructs under analysis were evaluated. Subsequently, the structural model is tested to assess the outcomes related to the formulated research hypotheses (H1 to H11).

3 RESULTS

Table 2 presents the assessment of the measurement model's reliability and validity. Cronbach's alpha values (ranging from 0.84 to 0.92) exceeded the threshold of 0.70 proposed by Hair et al. [30], indicating satisfactory internal consistency. Composite reliability (CR) values ranged from 0.91 to 0.94, all above the recommended 0.80 threshold [31]. Convergent validity was assessed using average variance extracted (AVE), defined as the extent to which a construct explains the variance of its items [30]. All AVE values exceeded the 0.50 criterion [18], supporting the adequacy of convergent validity. Overall, the internal consistency, reliability, and convergent validity of the measurement model are consistent with the psychometric requirements for reflective measurement models in SEM.

Table 2. Reliability and convergent validity indicators.

	Cronbach's Alpha	*Composite Reliability (CR)*	*Average Variance Extracted (AVE)*
BI	0,848	0,908	0,767
EB	0,910	0,930	0,690
PE	0,913	0,932	0,696
PI	0,878	0,916	0,732
PR	0,859	0,914	0,780
PT	0,891	0,925	0,754
PU	0,846	0,907	0,764
SS	0,913	0,932	0,696
TSE	0,920	0,940	0,759

Table 3 presents the results of the discriminant validity, which reflects the extent to which the constructs and their indicators are distinct from other constructs, thereby capturing phenomena not measured by others, and ensuring that the items represent a single latent construct [30]. Specifically, the table reports the values of the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio of correlations [31]. The Fornell–Larcker criterion [32] compares the square root of the AVE values with the correlations between the latent variables, whereby the square root of the AVE for each construct should exceed its highest correlation with any other construct.

The HTMT is defined as the geometric mean of the average correlations of items measuring the same construct, compared to the mean value of item correlations across constructs [19]. All values presented in Table 3 are below the recommended threshold of 0.90.

Table 3. Discriminant Validity – Fornell-Larker Criterion and Heterotrait-Monotrait Ratio (HTMT).

	BI	*EB*	*PE*	*PI*	*PR*	*PT*	*PU*	*SS*	*TSE*
BI	**0,876**	0,817	0,823	0,884	0,871	0,860	0,889	0,873	0,870
EB	0,843	**0,831**	0,896	0,883	0,847	0,843	0,884	0,896	0,825
PE	0,857	0,907	**0,834**	0,874	0,871	0,873	0,865	0,876	0,840
PI	0,867	0,880	0,891	**0,856**	0,833	0,802	0,871	0,884	0,866
PR	0,855	0,839	0,860	0,903	**0,883**	0,863	0,882	0,871	0,871
PT	0,879	0,851	0,879	0,887	0,878	**0,869**	0,894	0,873	0,869
PU	0,838	0,865	0,876	0,977	0,837	0,863	**0,874**	0,895	0,864
SS	0,857	0,908	0,889	0,890	0,860	0,878	0,875	**0,835**	0,860
TSE	0,857	0,848	0,863	0,868	0,863	0,878	0,851	0,862	**0,871**

Bold numbers indicate the square roots of the AVE values, while underlined numbers represent the HTMT ratios.

The results regarding the formulated research hypotheses (H1 to H11) are presented in Table 4.

Table 4. Testing the significance of hypotheses under investigation.

	Path coefficient (B)	*T Statistics*	*p-value*	*Supported*
H1: PE -> BI	0,111	2,441	0,015	Yes
H2: PI -> BI	0,277	2,750	0,006	Yes
H3: PU -> BI	-0,123	1,439	0,150	No
H4.1: PT -> BI	0,301	6,218	0,000	Yes
H4.2: PR -> BI	0,091	1,876	0,061	No
H5.1: PE -> PT -> BI	0,130	6,359	0,000	Yes
H5.2: PI -> PT -> BI	0,189	3,955	0,000	Yes

H5.3: PU -> PT -> BI	-0,038	1,496	0,135	No
H6.1: PE -> PR -> BI	0,027	1,833	0,067	No
H6.2: PI -> PR -> BI	0,150	1,867	0,062	No
H6.3: PU -> PR -> BI	-0,094	1,858	0,063	No
H7: EB -> SS	0,545	17,012	0,000	Yes
H8: TSE -> SS	0,223	7,520	0,000	Yes
H9: EB -> BI -> SS	0,023	3,054	0,002	Yes
H10: TSE -> BI -> SS	0,038	3,980	0,000	Yes
H11: BI -> SS	0,206	6,785	0,000	Yes

The constructs PE, PI, and PT show positive impacts on Behavioural Intention (BI), as expected, thus supporting Hypotheses H1, H2, and H4.1.

Perceived Usefulness (PU) and Perceived Risk (PR) do not exhibit a significant impact on Behavioural Intention (BI); therefore, H3 and H4.2 were not supported.

Perceived Trust (PT) plays a mediating role in the relationships between Perceived Ease of Use (PE) and Behavioural Intention (BI), as well as between Perceived Intelligence (PI) and Behavioural Intention (BI), thereby supporting Hypotheses H5.1 and H5.2.

Expected Benefits (EB) has a significant positive impact on Student Satisfaction (SS)) and Technology Self-Efficacy (TSE) have significant positive impacts on Student Satisfaction (SS), supporting Hypotheses H7 and H8.

Behavioural Intention (BI) mediates the relationships between Expected Benefits (EB) and Student Satisfaction (SS), as well as between Technology Self-Efficacy (TSE) and Student Satisfaction (SS). Therefore, Hypotheses H9 and H10 were validated.

Finally, Behavioural Intention (BI) has a significant positive effect on Student Satisfaction (SS), supporting H11. The remaining hypotheses were not supported.

4 CONCLUSIONS

As artificial intelligence becomes increasingly becomes, higher education institutions are compelled to adapt to this technological transformation. The successful integration of generative AI (GenAI) tools requires consideration of the determinants that shape user satisfaction, encompassing students, academics, and administrative staff alike.

This study aims to deepen understanding of university students' perceptions regarding the factors that shape their intention to adopt and integrate artificial intelligence tools, as well as their overall satisfaction with such tools in academic contexts. Several variables were incorporated into the Technology Acceptance Model (TAM), namely Perceived Intelligence (PI), Perceived Trust (PT), Perceived Risk (PR), Expected Benefits (EB), and Technology Self-Efficacy (TSE), to examine how they interact and influence, or fail to influence, Behavioural Intention (BI). In addition, the role of BI was tested as a mediating variable between students' perceptions of these constructs and their satisfaction with generative AI (GenAI) tools (SS). The findings indicate that students' satisfaction with GenAI tools is directly influenced by BI, EB, and TSE, and indirectly shaped by the mediating role of BI. Specifically, BI links both EB and TSE to SS, underscoring its pivotal role in shaping students' engagement with GenAI.

Higher education institutions should increasingly promote training initiatives and workshops to raise awareness within their academic communities regarding the appropriate use of artificial intelligence in educational settings. They should also periodically monitor the perceptions of all stakeholders, particularly students, in order to act proactively and ensure the development of essential competences, as well as the responsible and informed use of these tools.

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APPENDIX A

Table A1. Measurements used for data analysis

Perceived Usefulness (PU)	***Perceived Trust (PT)***
1. Using the GenAI tool improves the quality of my learning tasks. 2. Using the GenAI tool enhances my academic productivity. 3. The GenAI tool helps me accomplish learning tasks more effectively. 4. Overall, I find the GenAI tool useful for my coursework.	1. I trust the GenAI tool to provide reliable information. 2. I believe the GenAI tool acts in my best interest as a student. 3. I feel confident relying on the GenAI tool for academic support. 4. Overall, I trust the GenAI tool in the learning process.
Perceived Ease of Use (PE)	***Expected Benefits (EB)***
1. Learning to operate the GenAI tool is easy for me. 2. I find the GenAI tool easy to use. 3. It is easy for me to become skilful at using the GenAI tool. 4. My interaction with the GenAI tool is clear and understandable. 5. Completing tasks with the GenAI tool requires little effort. 6. Overall, I find the GenAI tool user-friendly.	1. The GenAI tool saves me time when working on academic tasks. 2. Using the GenAI tool increases my learning efficiency. 3. The GenAI tool helps me generate new ideas for assignments. 4. The GenAI tool supports my creativity and critical thinking. 5. Using the GenAI tool reduces stress in completing coursework. 6. Overall, I expect significant benefits from using the GenAI tool in my studies.
Perceived Risk (PR)	***Behavioural Intention (BI)***
1. I am concerned about the accuracy of information provided by the GenAI tool. 2. Using the GenAI tool may expose me to risks (e.g., errors, bias, plagiarism). 3. I worry that relying on the GenAI tool could negatively affect my learning outcomes.	1. I intend to continue using the GenAI tool for my coursework. 2. I will recommend the GenAI tool to other students. 3. I plan to use the GenAI tool frequently in the future.
Technology Self-Efficacy (TSE)	***Student Satisfaction (SS)***
1. I am confident in my ability to use the GenAI tool for coursework. 2. I can troubleshoot problems when using the GenAI tool. 3. I feel capable of learning advanced features of the GenAI tool. 4. Even without help, I can use the GenAI tool effectively. 5. I believe I have the skills needed to use the GenAI tool for my studies.	1. I am satisfied with my overall experience using the GenAI tool. 2. Using the GenAI tool meets my expectations as a learning support. 3. I feel pleased with the outcomes when I use the GenAI tool. 4. The GenAI tool improves my satisfaction with my coursework. 5. Overall, I enjoy using the GenAI tool in my studies. 6. My decision to use the GenAI tool has been a wise one.
Perceived Intelligence (PI)	
1. The GenAI tool provides intelligent responses to my queries. 2. I believe the GenAI tool demonstrates high knowledgeability. 3. The GenAI tool seems intelligent in handling my academic tasks.	