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Students Planned Behavior and the Use of Generative Artificial Intelligence in Cameroon

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Abstract

This study explores the use of artificial intelligence (AI) by students, with a focus on the role of the theory of planned behavior (TPB). Partial Least Square structural equation modeling (PLS-SEM) was used to test a sample of 144 Cameroonian students. The results show that a positive attitude towards AI, supported by subjective norms and AI-favorable behavioral control, significantly influence adoption intention. Furthermore, this intention fosters a favorable disposition among students toward the use of generative AI. Notably, complexity is not perceived as a constraining factor. Recommendations are made to encourage the use of generative AI, by training students and making them aware of its advantages and limitations. This study offers a foundation for further research endeavors aimed at investigating the integration of AI in education in Cameroon.

Keywords: Generative AI, Students, Education, Cameroon.

Introduction

Generative artificial intelligence, based on machine learning technologies, is rapidly becoming an integral part of many sectors, performing tasks in a quasi-human way [1, 2]. Emerging with WaveNet in 2016 and popularized by tools such as ChatGPT in 2022, it promises advances as revolutionary as the steam engine or the Internet [3, 4]. In education, it opens up opportunities to enrich learning and optimize teaching practices, with tools offering personalized tutoring, instant feedback and learning flexibility for students [5, 6]. However, while these technologies potentially enhance learning, they also pose adoption challenges that the United Nations Educational, Scientific and Cultural Organization (UNESCO) recommends should be addressed in a reasoned manner [7, 8].

Existing research based on the theory of planned behavior indicates that factors such as social norms, personal attitudes, and perceived behavioral control influence AI adoption among students [9]. These studies are relevant because they reveal to what extent individuals in a student environment perceive AI and are influenced by it. However, this research is limited to developed geographical areas. It would be worthwhile to investigate the use of generative AI in a developing country context, where the education system is often marginalized and students do not always have access to the same resources. In such contexts, the TPB becomes particularly relevant, as it can provide a basis for understanding how students in these countries make decisions about generative AI and adopt the adoption behavior that can foster the integration of generative AI into academic practices. In order to fill this gap, we are interested in the Cameroonian environment. This study answers the following research question: What factors in the planned behavior of Cameroonian students guide their intention leading to the use of generative AI in their learning?

Our research makes theoretical contributions by enriching the framework of AI adoption in education with a dual behavioral and institutional perspective. On a practical level, it identifies behavioral levers for AI adoption to guide decision makers in the responsible integration of these technologies into higher education.

The remainder of this article is organized as follows: Section 1 presents a literature review on generative AI, followed by the presentation of the research model and the development of hypotheses in Section 2. The methodology used is described in Section 3. The results are described in Section 4. Discussions and implications of the study are presented in Section 5. Limitations of the study and future recommendations are presented in section 6.

Literature Review on Generative AI

The literature on generative AI is recent and continues to emerge as AI-related technologies evolve. In the field of education, research has emphasized the need to acquire AI knowledge through specific courses and hands-on experience, while highlighting the distinct advantages of generative AI, such as personalization and interactivity of educational content [10]. Further AI learning is likely to increase student engagement and academic achievement, providing a solid foundation for the strategic integration of these technologies into education [11]. From a TPB perspective, students' positive attitudes toward generative AI, subjective norms, and perceived behavioral control significantly influence their intention to use it [12]. However, students' self-efficacy may remain problematic in the formation of behavioral intentions [13].

The ethical implications of using AI in education are also discussed. In particular, AI-facilitated cheating in academia. Greitemeyer emphasizes the importance of attitudes, social norms, and perceived behavioral control in understanding this behavior. From a comparative perspective, Ivanov et al. apply TPB to explore the impact of benefits, weaknesses, and risks of generative AI tools on attitudes, subjective norms, and perceived behavioral control. They conclude that only perceived benefits positively influence these variables and argue for increased communication about the benefits of generative AI tools to improve their adoption in higher education. From a practical perspective, the research motivates academic integrity and discourages inappropriate use of AI tools. It recommends specific training and awareness campaigns that highlight the benefits and address the risks to encourage wider and ethical adoption of these tools. In addition, societal perceptions and individual expectations in the adoption of generative AI need to be monitored.

Research model and Hypotheses Development

The Theory of Planned Behavior, developed by Ajzen, examines how human behavior is influenced by three main factors: attitude, subjective norms, and perceived behavioral control. According to TPB, the intention to perform a behavior is the best predictor of actual behavior, and this intention is shaped by the individual's evaluation of the consequences of the behavior (attitude), the perceived expectations of others (subjective norms), and the individual's perceived ability to perform the behavior (perceived behavioral control). In the context of our study, the TPB allows us to understand how these factors influence students' intentions and actual use of generative AI, shedding light on the positive or negative attitudes toward AI, social influences, and perceptions of competence that condition their adoption of these tools. The integration of complexity enriches the analysis by taking into account perceived technological difficulty, which is absent from the TPB model. The Figure 1 below illustrates the research model.

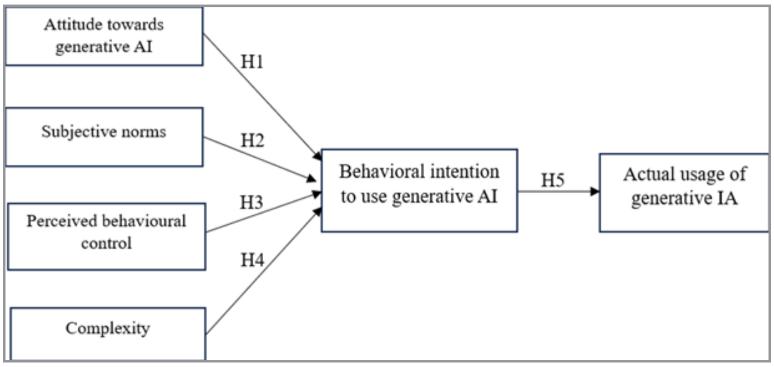

Figure 1: Research Model

Attitudes Towards Generative AI

In our study, students' attitudes toward generative AI are defined by their personal feelings about its use. Ajzen explains that beliefs about the consequences of a behavior influence its favorability, while Chai et al. point out that viewing AI as a social good can improve this attitude. Odai et al. add that when students see social benefits in AI, they are more likely to adopt it in other areas. We hypothesize the following:

H1: Attitude towards generative AI positively and significantly influences behavioral intention to use generative AI.

Subjective Norms

Ajzen defines subjective norms as the “perceived social pressure to perform or not to perform a behavior”. In our study, the opinions of people important to a participant may influence their intention to use generative AI, although some research, such as that by Chai et al. and Saxena and Doleck show that these norms have little impact on the intention to use ChatGPT or generative AI. However, subjective norms often influence the adoption of educational technologies, such as collaborative applications [13]. Kim et al. and Ursavaş et al. confirm their influence on the use of e-learning systems. Thus, although their effect is sometimes limited, subjective norms remain an important factor in the adoption of educational technologies. We hypothesize the following:

H2: Subjective norms positively and significantly influence behavioral intention to use generative AI.

Perceived Behavioral Control

Ajzen defines perceived behavioral control as an evaluation

of the ease with which a behavior can be performed, given the resources and skills available. It is based on self-efficacy and confidence, two factors that influence behavioral intentions. In the academic environment, students' skills and knowledge play an important role in the perception of behavioral control [13]. Shoufan has shown that students appreciate the ease of use of generative AI and its human interface, despite some inaccuracies. Chai et al. found that self-efficacy strengthens the intention to use AI in primary classrooms in China. Therefore, we hypothesize the following:
H3: Perceived behavioral control positively and significantly influences behavioral intention to use generative AI.

Complexity
In diffusion of innovation (DOI) theory, complexity refers to the degree to which a technology is perceived as difficult to understand and use [14]. The more complex an innovation is perceived to be, the greater the resistance to its adoption. This is especially true if the innovation requires new skills, a long learning curve, or major adjustments to current practices. In education, for example, a learning technology that is perceived as complex can slow adoption, even if it offers significant benefits. Reducing this perceived complexity by making

the technology intuitive and providing appropriate support is therefore essential to encourage adoption. We therefore formulate the following hypothesis:
H4: Complexity of generative AI has a negative and significant effect on behavioral intention to use generative AI.

Actual usage of Generative AI
For Ajzen, behavioral intention is a key indicator of the orientation of human actions, influencing motivation and the effort deployed to accomplish a task. Strong intention promotes intentional behavior [15]. An intention to adopt generative AI mobilizes resources and strengthens students' commitment, increasing the likelihood that they will actually integrate this technology into their academic activities. In fact, behavioral intention acts as a key lever, transforming the desire to use AI into actual use. In conclusion, behavioral intention is decisive for the effective use of generative AI in an academic context [15]. Therefore, we hypothesize the following:
H5: The behavioral intention to use generative AI positively and significantly influences the actual usage of generative AI.

Methodology
Based on a literature review, we developed a questionnaire comprising thirty-one (31) items corresponding to the six (06) constructs of our research model. Each item was measured using a 7-point Likert scale, ranging from strongly disagree to strongly agree. The questionnaire was pre-tested with five (05) people from a variety of backgrounds, including an IT engineer, three management and information systems master 's degree students, and a community manager. This pre-test ensured that the questions were clear and easy to understand.

The questionnaire was then designed using Google Forms and distributed online via WhatsApp, targeting student communities. The respondents were students from business and engineering schools living in Cameroon who were familiar with generative artificial intelligence tools in general and had used them. Participants were informed that the questionnaire was anonymous and that the data would be used exclusively for academic purposes. A pilot test was carried out on a sample of 60 responses in order to guarantee the reliability and validity of the construct measures. Once the stability of the model had been confirmed, the main data collection took place from August 16 to 26, 2024. A total of 144 valid responses were obtained after checking the consistency of the data. Analyses were carried out using SmartPLS version 4.1.0.2 [16]. This process included an evaluation of the measurement model to check the reliability and validity of the constructs, and an evaluation of the structural model to test the hypotheses of the research model [17].

Results
Demographic Profile
The sample is composed as follows: 53% male (77 people) and 47% female (67 people). In terms of age, the majority is between 21 and 23 years old (47%, or 67 people), followed by 24 to 27 years old (33%, or 48 people), 28 and older (13%, or 19 people), and 18 to 20 years old (7%, or 10 people). In terms of educational level, most respondents have a Master's degree (60%, or 86 people), while 35% (or 51 people) have a Bachelor's degree, 3% (or 4 people) have a Higher National Diploma, and 2% (or 3 people) have a PhD. Finally, regarding the type of school attended, 52% (75 people) of the participants came from an engineering school, compared to 48% (69 people) from a business school.

Model Assessment
Model assessment began with the analysis of the measurement model. This analysis aims to examine the following quality criteria: outer loadings, Cronbach's alpha, composite reliability, whose values must be greater than or equal to 0.7 and average variance extracted (AVE), whose values must be greater than or equal to 0.5 [18, 19]. Table 1 shows that the model constructs meet the recommended quality criteria, with the exception of the "COP1" item, which has an outer loading of 0.580, but which we have retained because it does not affect the convergent validity of this construct. These results confirm the internal consistency and convergent validity of the studied concepts.

On the other hand, the Fornell-Larcker criterion was used to evaluate the discriminant validity between the variables of the research model [20]. This criterion checks that the values on the diagonal of the correlation table are higher than those to the left and below. If this condition is met, it indicates that the constructs in the model are clearly distinct from each other. The results of this analysis, which satisfy the Fornell-Larcker criterion, are presented in Table 2.

We then proceeded to assess the structural model. Examination of the explanatory power of the model's dependent variables in Table 3 shows that the "IUT" construct has an R^2 value of 0.728, and for the "UTE" construct, an R^2 value of 0.552. These results suggest that the model provides a strong explanation of variance for "IUT" and a moderate explanation for "UTE". In addition, hypothesis testing was conducted using the bootstrapping method. The results in Table 4 show that hypotheses H1 ($\beta = 0.586$; $p < 0.001$), H2 ($\beta = 0.247$; $p < 0.001$), H3 ($\beta = 0.201$; $p < 0.05$) and H5 ($\beta = 0.743$; $p < 0.001$) are confirmed, indicating significant relationships between the concepts. However, H4 ($\beta = -0.077$; $p = 0.267$) is not supported because the p-value exceeds the 0.05

threshold, indicating a lack of significant influence.

Table 1: Construct's reliability and validity

Constructs	Items	Outer loadings	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Attitude towards generative AI	ATT 1	0.808	0.906	0.907	0.928	0.681
	ATT 2	0.767				
	ATT 3	0.819				
	ATT 4	0.830				
	ATT 5	0.859				
	ATT 6	0.864				
Perceived behavioral control	CCP 1	0.733	0.872	0.888	0.907	0.660
	CCP 2	0.809				
	CCP 3	0.839				
	CCP 4	0.861				
	CCP 5	0.815				
Complexity	COP 1	0.580	0.805	0.855	0.873	0.637
	COP 2	0.890				
	COP 3	0.835				
	COP 4	0.849				
Behavioral intention to use	IUT 1	0.794	0.905	0.910	0.927	0.679
	IUT 2	0.838				
	IUT 3	0.865				
	IUT 4	0.776				
	IUT 5	0.822				
	IUT 6	0.848				
Subjective norms	NOS 1	0.889	0.837	0.848	0.891	0.672
	NOS 2	0.859				
	NOS 3	0.757				
	NOS 4	0.766				
Actual usage of generative AI	UTE 1	0.806	0.792	0.794	0.865	0.615
	UTE 2	0.783				
	UTE 3	0.767				
	UTE 4	0.781				

Table 2: Discriminant validity

Constructs	ATT	CCP	COP	IUT	NOS	UTE
ATT	0.825					
CCP	0.631	0.813				
COP	0.667	0.581	0.798			
IUT	0.809	0.636	0.522	0.824		
NOS	0.548	0.380	0.327	0.622	0.820	
UTE	0.700	0.547	0.506	0.743	0.472	0.784

ATT= Attitude towards generative AI; CCP=Perceived behavioral control; COP= Complexity; IUT= Behavioral intention to use; NOS= Subjective norms; UTE= Actual usage of generative AI.

Table 3: Explanatory power

Dependent variables	R square	Adjusted R square
IUT	0.728	0.716
UTE	0.552	0.549

IUT= Behavioral intention to use; UTE= Actual usage of generative AI.

Table 4: Hypothesis testing

Hypotheses		Original sample (β)	P values	Sign. Level	Results
H1	ATT -> IUT	0.586	0.000	****	Supported
H2	NOS -> IUT	0.247	0.000	****	Supported
H3	CCP -> IUT	0.201	0.013	**	Supported
H4	COP -> IUT	-0.077	0.267	n.s	Rejected
H5	IUT -> UTE	0.743	0.000	****	Supported

ATT= Attitude towards generative AI; CCP=Perceived behavioral control; COP= Complexity; IUT= Behavioral intention to use; NOS= Subjective norms; UTE= Actual usage of generative AI.

Discussion and Implications

Our study validated four of the five hypotheses initially formulated and revealed important information about the planned behavior of business and engineering students in Cameroon towards the use of generative AI. Attitude, subjective norms, and perceived behavioral control showed a significant and positive influence on behavioral intention to adopt generative AI. The results also showed that this intention positively and significantly influences the use of generative AI. These results suggest that students who develop favorable perceptions and feel socially supported, while also feeling confident in their ability to use generative AI, are more likely to express an intention to adopt and integrate it into their academic practices. However, perceived complexity, often considered a barrier to technology adoption, did not show a significant effect in this context. The complexity of generative AI did not have a significant negative influence, as students found the technology easy to understand and use. This is due to the simplicity of its interface and students' increased familiarity with digital tools, which facilitates its integration into their academic practices.

These findings are part of an enriching theoretical perspective in that the Theory of Planned Behavior allows for an analysis of the factors influencing intention to use in marginal academic environments, helping to fill gaps in the existing literature. Furthermore, our study highlights contextual specificities, such as the importance of social norms in a culture where community interactions are often central, paving the way for future research to further explore the impact of cultural and institutional variables, such as the organizational structure of educational institutions, cultural values related to innovation, and the influence of traditional educational practices on technology adoption.

In practical terms, this study offers several recommendations for academic decision-makers and educational managers. Firstly, institutions should promote initiatives that improve students' attitudes towards generative AI. This could include interactive workshops, awareness campaigns, and concrete examples demonstrating the benefits of this technology for academic tasks. These efforts would help to reinforce positive perceptions and increase students' motivation to use generative AI. Secondly, to harness the influence of subjective norms, institutions can create an environment where the use of generative AI is valued. This can take the form of collaborative projects involving teachers and peers, or public recognition of students' technological initiatives. Finally, reinforcing perceived behavioral control is crucial to ensuring effective adoption. This involves making available technical resources, specific training and ongoing support to enable students to overcome the obstacles associated with mastering generative AI. In addition, strategies such as integrating AI into practical courses and partnerships with companies could reinforce behavioral intent and encourage real use. These measures, by creating a favorable framework, will not only increase the adoption of generative AI but also maximize its impact in the Cameroonian educational environment. The integration of generative AI in academia raises important ethical issues, particularly in terms of academic integrity and the confidentiality of sensitive data. Moreover, algorithmic biases and over-reliance on these technologies can limit the development of critical thinking, necessitating the establishment of clear guidelines for responsible use.

Limitations and Future Orientations

Our study has some limitations that can be taken into account when interpreting the results and guiding future research. First, our study is based on a general view of generative AI. It would be interesting for future research to compare the use of different existing generative AI tools to gain a deeper understanding of their specific impact. Second, certain factors were not taken into account. Future research could integrate complementary theories and examine factors such as trust, risk perception, and academic achievement, which could enrich our model and provide a broader view of the determinants of usage intention. These avenues could contribute to a more comprehensive and contextualized analysis of student behavior. We also recommend adopting a qualitative approach to explore more deeply the emotional and social dynamics surrounding the use of generative AI in the Cameroonian educational context. It would also be relevant to broaden the sample to include different student profiles. Furthermore, the integration of technological variables such as ease of use or security, as well as the analysis of cultural influences, would enrich our understanding of the determinants of the adoption of these technologies in educational settings.

Conclusion

This study examined the use of generative AI by business and engineering students in Cameroon, using the Theory of Planned Behavior to identify the determinants of this behavior. The results highlighted the significant role of positive attitudes, social norms, and perceived behavioral control in shaping students' intentions. Based on these findings, we propose practical recommendations to promote the integration of generative AI in education and argue for further research to broaden and deepen understanding of this emerging field [21-29].

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