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Research Article

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The Relationship Between Perceptions and Uses of Generative AI Among Students Testing the Unified Theory of Acceptance and Use of Technology in The Context of Generative AI in Academia

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Abstract

Using an adapted UTAUT model (Venkatesh et al. 2003), this research examines how students' individual characteristics and their representations of generative AI influence their use of this technology. Data collected from 1,209 French students reveal that the intention to use is strongly determined by expected performance, which mediates between other representations and actual adoption, nuancing the relationships predicted by the UTAUT model. They reveal links between academic anxiety and preference for AI, as well as between naive representations of this technology and the adoption of unethical behaviors.

Introduction

In 2024, the Digital Education Council Global AI Student Survey reports that 86% of students use AI for their studies. However, the relationship between students and AI is understudied (Wang et al., 2024). Initial research shows that students have varied uses and applications for AI (Genre and Similowski, 2024), or that they perceive it positively (Molina et al., 2024), even though they remain aware of the risks and possible abuses (Pudasaini et al., 2024).

The research question posed in this article aims to supplement these initial findings and provides insight into how representations of generative AI and students' individual characteristics influence the use of this technology in an academic setting. After reviewing the state of the art on the uses and representations of generative AI among students, an adapted version of the UTAUT (Unified Theory of Acceptance and Use of Technology) model initiated by Venkatesh and his colleagues in 2003 is presented. This model explains the intention to use AI by mobilizing variables such as expected performance, perceived ease of use, hedonic motivation, and social influence. The uses of AI (effective, ethical, social) are then linked to intentions to use it.

1. Context and theoretical framework of the research

1.1. The rise of generative AI and its spread in higher education

Artificial intelligence (AI) has established itself as one of the most significant technological innovations of the 21st century. If we focus more specifically on so-called generative AI, i.e., applications capable of producing original content, the most telling example is undoubtedly ChatGPT. Released in late 2022 by OpenAI, this large language model has enabled the general public to generate text and code or summarize several pages of a book in a matter of seconds using simple instructions. Less than two years after its launch, ChatGPT has more than 122 million active users (Singh, 2025). The application has quickly established itself as a predominant tool in academia. Indeed, the proportion of students familiar with ChatGPT rose from 60% in 2023 to 97% in 2024, with a usage rate of 86% (Janzen et al., 2024; Digital Education Council Global AI Student Survey, 2024). However, this adoption has not been uniforming across the university population. Variations in usage have been observed according to students' fields of study, gender, and social background (Arum et al., 2025; von Garrel and Mayer, 2023; Urmeneta and Romero, 2024). In this context of rapid but uneven adoption, our research aims to characterize students' uses of generative AI and the representations that guide them, and to compare them with their individual characteristics.

1.2. Representations and uses of generative AI among students

Students' perceptions of AI are generally favorable. They associate it with flexibility, speed, and quality of responses, while emphasizing its compliance with academic standards (Yan, 2023). Several studies indicate that they perceive it as effective and enjoyable to use, particularly for language and writing skills (Polyzi and Moussiades, 2023). However, this positive view is accompanied by reservations: some criticize the density and complexity of the responses, or doubt their reliability and transparency (Maheshwari, 2023). Others express ethical and social concerns related to algorithmic bias, academic fairness, or dependency (Digital Education Council, 2024; Urmeneta and Romero, 2024; Yan, 2023), with nearly one in two students reporting that they depend on ChatGPT for their success (Forman et al., 2023; Digital Education Council, 2024).

Some research has already looked at what motivates students to use these tools, despite the reservations they may express about them. A key factor seems to be the trust placed in the application, driven by the perceived quality of the responses, their relevance, and the benevolent tone of these systems (Choudhury and Shamszare, 2023; Peng and Wan, 2024). The expected performance, i.e., the perception of concrete benefits for academic success, also positively influences the willingness to adopt these tools, as does their perceived ease of use (Shahzad et al., 2024; Tummalapenta et al., 2024). Furthermore, some research highlights a form of curiosity and intrinsic pleasure

associated with the use of these applications, described as a hedonic motivation positively associated with the use of a chatbot (Tummalapenta et al., 2024). Entertainment is also a stated purpose of use for one-third of respondents in certain surveys (Choudhury and Shamszare, 2023).

With regard more specifically to students' use of AI, surveys converge to show widespread but heterogeneous adoption: nearly two-thirds of students in Germany report using generative AI for their studies (Urmeneta and Romero, 2024), and 77% in Canada (Janzen et al., 2024). Some cohorts reach almost universal levels: during an educational hackathon, 99% of engineering students used these tools, mainly ChatGPT (88%), with 30% having a paid subscription (Pôle Léonard de Vinci et al., 2024). The frequency of use varies: at Harvard, 25% of students report daily use (Hirabayashi et al., 2024), while in engineering schools, which are more tech-savvy, this rate reaches 30% (Pôle Léonard de Vinci et al., 2024). Internationally, 24% of students report daily use (Digital Education Council, 2024).

By focusing on the nature of usage, studies show that these practices are predominantly academic and utilitarian. Students use generative AI for writing, structuring, correcting, or producing drafts (Bazile et al., 2024; Digital Education Council, 2024). They also use it to clarify concepts, search for information, translate, correct text, or generate summaries (Molina et al., 2024). Part of the use involves treating these systems as conversational search engines to obtain targeted answers (Genre and Similowski, 2024). There are variations between disciplines: STEM students use these tools more for problem solving and code generation, while those in the arts favor documentary research and writing (Molina et al., 2024). Translation, on the other hand, remains cross-disciplinary (Molina et al., 2024).

2. Research objectives: how do representations of generative AI and students' individual characteristics influence the use of this technology in a university setting?

2.1. Linking representations to uses

The diversity of uses for generative AI is accompanied by an equally marked plurality of representations. In a context of mass dissemination, it seems relevant to examine how these two dimensions interact. Representations shape the way students perceive, interpret, and use these tools; they constitute frameworks of understanding that guide technological appropriation and give meaning to practices. Studying these links makes it possible to identify the underlying logic behind the use of AI, as well as the levers for action that can promote more responsible and ethical practices. These issues are not only technical or pedagogical in nature: they also involve ethical, cognitive, emotional, and social dimensions.

From an ethical and cognitive perspective, the rise of generative AI brings back old issues such as plagiarism and cheating (Nguyen et al., 2024; Pudasaini et al., 2024; Compilatio, 2023). Furthermore, automation bias can encourage excessive confidence in the answers produced (Gratton, 2020), particularly when naive or fantasized representations of these tools are circulating (Cave and Dihal, 2019; Williams et al., 2023; Kim et al., 2023; Marx et al., 2024). This overconfidence undermines reflective thinking, hence the importance, highlighted by several authors, of training students to verify, question, and implement AI with a methodical skepticism (Abdelghani et al., 2023a; Abdelghani et al., 2023b; Kidd and Birhane, 2023).

Emotional and social dimensions also influence usage. When self-confidence is low, AI can help overcome writer's block, provide reassurance, or clarify an idea (Bandura, 1997; Desombre et al., 2016; Bazile et al., 2024; Genre and Similowski, 2024). For some, interacting with a chatbot even seems more comfortable than interacting with peers. Anthropomorphizing helps reinforce this feeling of benevolent, even friendly interaction (Peng and Wan, 2024; Curiale et al., 2022; Brandtzaeg, 2022). However, this relationship often remains taboo and can be accompanied by feelings of guilt, linked to the idea that the help is "too easy" or "unfair" (Adnin et al., 2025). This discomfort leads some students to minimize or hide their use of these tools (Nguyen et al., 2024; Pôle Léonard de Vinci et al., 2024).

These different dimensions invite us to analyze the relationships between representations and uses in greater detail. Representations function as filters: they combine beliefs, knowledge, and emotions, structuring the way AI is understood and used (Sandrin-Berthon, 2002; Dortier, 2002). Judging AI to be useful, simple, reliable, or enjoyable is therefore not just a matter of describing a tool, but of expressing an interpretive framework that guides practices. These representations are also social: they are constructed in the "social laboratories" described by Moscovici (1961), stabilize shared norms about what is legitimate or excessive, and shape everyday uses (Moscovici, 1961; Jodelet, 1993).

From this perspective, analyzing representations and uses together provides a better understanding of the meaning students attribute to their practices and identifies levers for intervention to support more ethical uses. Our research is part of this approach and aims to articulate these dimensions around the following question: How do representations of generative artificial intelligence and students' individual characteristics influence their use of this technology in an academic setting?

2.1. In search of a model of technological acceptance that combines uses, representations, and personal characteristics

In this research, we seek to link learners' representations, uses, and individual characteristics. We therefore deemed it relevant to develop a technology acceptance model that would allow us to articulate these different dimensions. To build this model, we drew on the *Unified Theory of Acceptance and Use of Technology* (UTAUT) developed by Venkatesh and his colleagues (2003), which aims to explain an individual's intention to use a technology as well as their actual usage behavior. We found this framework particularly suitable for analyzing students' representations and uses, while testing the validity of the model in the context of generative AI in higher education.

In the UTAUT model, Venkatesh et al. (2003) identified three dimensions explaining the intention to use (or behavior) of a technology and one dimension exerting a direct effect on actual use (usage behavior), as shown in the following diagram:

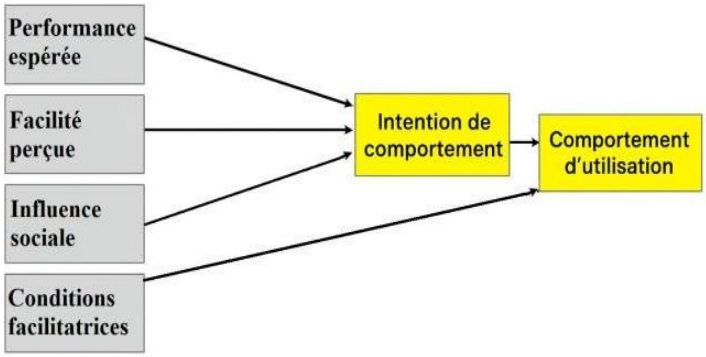

Figure 1: Representation of the UTAUT model, without control variables, Venkatesh et al. (2003) - Diagram created with ChatGPT 4o.

Expected performance corresponds to the belief that using a technology improves performance (Davis, 1989; Venkatesh, Thong, and Xu, 2012; Tran et al., 2019). It is one of the main determinants of intention to use. Perceived ease refers to the idea that a tool is simple to use and requires little effort (Davis, 1989). Social influence refers to an individual's perception of the expectations of those around them regarding the use of a technology (Venkatesh et al., 2003). Finally, enabling conditions refer to the perception of organizational and technical support that facilitates the use of the technology (Venkatesh et al., 2003).

To design our own research model, we adapted the structure of the UTAUT model. We did not include facilitating conditions, as access to generative AI is simple and usually free for students. However, we did incorporate hedonic motivation, a concept from the UTAUT2 model corresponding to the pleasure of use, which seems to play a decisive role in the adoption of these tools (Venkatesh et al., 2012). Two other dimensions seemed interesting to test in this model: false representations of AI and the unethical practices that may be associated with them, as well as the preference for human assistance over artificial assistance. Certain control variables that help to explain these uses were also included (socio-professional category, field of study, gender, and age of students).

3. Research hypotheses and methodology used

3.1. Research hypotheses

We then sought to verify whether students' representations in terms of expected performance, perceived ease of use, social influence, and hedonic motivation do indeed have a positive and direct influence on the intention to use generative AI, as predicted by the UTAUT model (Venkatesh et al., 2003). Thus, the following hypotheses were proposed:

- H1: Students who consider generative AI useful for their studies have a greater intention to use it.
- H2: Students who perceive generative AI as easy to use have a greater intention to use it.
- H3: Students who perceive social support in the use of AI have a greater intention to use it.
- H4: Students who perceive the use of generative AI as fun and enjoyable have a greater intention to use it.

In addition, we tested the link between intention to use and actual use of these technologies, also predicted by Venkatesh et al. (2003):

- H5: Students with a strong intention to use generative AI report more intensive use of these technologies.

In addition, we incorporated into the model a dimension on preference for AI over human assistance. Several studies (Peng and Wan, 2024; Bazile et al., 2024; Nguyen et al., 2024) show that low self-efficacy, fear of failure, or academic stress can encourage the use of AI over human assistance. Thus:

- H6: Students who are anxious in an academic environment prefer to obtain help from generative AI rather than from a human.

Finally, we considered a link between students' false or naive representations of AI and the less ethical practices associated with these technologies. A limited understanding of how AI works could lead some students to consider AI outputs as reliable without questioning them, reflecting a lack of critical perspective (Kidd & Birhane, 2023). This relationship with technology could thus encourage unethical uses, such as plagiarism or cheating. We therefore formulate the following hypothesis:

- H7: Students with naive representations of generative AI adopt a less critical stance towards it.

These seven hypotheses are summarized in this adapted UTAUT model:

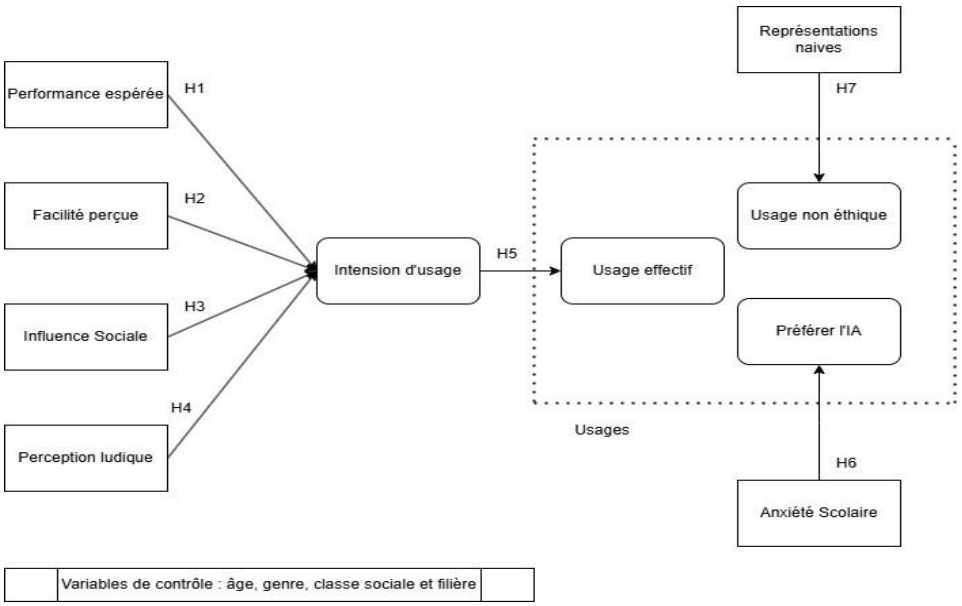

Figure 2: Complete representation of our research model.

3.2. Methodological elements

We adopted a quantitative hypothetical-deductive approach in order to empirically test the links between representations and uses, while taking individual characteristics into account. To do this, an anonymous quantitative questionnaire was administered on a large scale to students at the University of Burgundy Europe. Its distribution (from L1 to M2) via institutional mailing lists, in two successive waves, enabled us to collect 1,209 usable responses out of 20,856 recipients. Free and informed consent was obtained by means of an introductory text. Participation was voluntary and revocable; the data was anonymized upon collection and the analysis files were secured by encryption.

The questionnaire first collected the individual characteristics of the respondents (age, gender, field of study, and socio-professional category). It then focused on the academic uses of generative AI, the intention to use it, and the various representations associated with it. Expected performance, perceived ease, hedonic motivation, and social influence were measured using 5-point Likert scales adapted from reference models (Venkatesh et al., 2003; Venkatesh et al., 2012). Social influence was enriched with items relating to perceived valuation and feelings of competence (Meyer and Piché, 2024). Naive representations were assessed using a set of false statements about how AI works (Kim et al., 2023; Bewersdorff et al., 2023; Marx et al., 2024). Preference for human assistance or AI was measured using three items and two open-ended questions. School anxiety, considered multidimensional, combined four tests: social anxiety (Liebowitz, 1987), self-efficacy (Schwarzer and Jerusalem, 1995; Saleh, Romo, and Camart, 2016), sense of integration (Zimet et al., 1988), and test anxiety (Driscoll, 2007). Finally, a last section focused on unethical practices, through items relating to the declaration of use, content verification, and concealment in the context of prohibition.

4. Research results

4.1. Characteristics of respondents and initial descriptive elements

The sample selected comprises 1,209 students. Female respondents account for 65.8% (n = 796), which can be explained in part by the high proportion of female students in the humanities and social sciences (30.8%). Other fields of study are also represented: business, law, and administration (21.2%), science and technology (16%), health (9%), and education (8.6%). Certain disciplines, such as computer science (4.9%), engineering (6.2%), and information and communication (2.6%), are less represented, but Shannon's entropy index (H = 0.88) confirms good overall diversity. The distribution by level of education is balanced, from Bac+1 to Bac+5 (approximately 20% per level). The average age is 21.47, with a few extreme values above 50. In terms of the parents' socio-professional category, the privileged classes are in the majority (44.7% for parent 1 and 40.9% for parent 2), while the middle classes are less represented (≈ 12% and 9.5%). Nevertheless, the relative entropies (H = 0.90 and H = 0.89) indicate sufficient diversity. These results suggest that the sample presents sufficient variety for quantitative analysis.

Generative AI appears to be widely adopted among respondents: 89.4% say they have already used it for their studies. Among them, 10.8% use it daily and 50.7% at least once a week. Conversely, only 10.6% have never used it, the majority of whom (93.3%) do not plan to do so. The intensity of use seems to have reached a local maximum: 54% of students do not plan to increase their frequency of use and 30.8% say they want to reduce it. ChatGPT is by far the most frequently cited tool (85%) and its use is diverse: explanation of concepts (60%), information search (46.4%), text summarization (43.8%), correction (39.5%), and translation (32.4%). More specific uses are also mentioned, such as administrative assistance (11.8%), verifying information (11.2%), and finding solutions to relationship or stress-related problems (10.2%). This diversity is reflected in academic work: 71.7% of students say they have already submitted work generated at least in part by AI, including 8.1% who say it was generated entirely by AI.

However, 82.8% admit that they do not mention the use of AI in their work, 18.2% use it despite a ban, and 6.5% say they have cheated during an assessment. Nevertheless, a majority (71.6%) say they verify the information produced, reflecting a reflective attitude towards these tools.

The majority of students (74.3%) consider generative AI useful for their studies and believe that it speeds up task completion (67.4%). However, they are less

Many attribute productivity gains (43.7%) or improved results (32.7%) to it. Its ease of use is widely recognized: 82.4% find it simple to use and 68.7% find interactions clear. In terms of enjoyment, its use is perceived as fun (51.2%), but less often as pleasant (39.5%) or immersive (34.9%). Social and institutional support remains limited: 19.9% of respondents mention encouragement from their institution and 10.2% mention support from teachers. Furthermore, 70.1% do not perceive the use of AI as socially rewarding and 76.1% do not consider that it makes them feel recognized or competent. The preference for human assistance remains clear: 66.4% prefer a friend and 70% a teacher rather than artificial assistance. The open-ended responses show that the main drivers of use are the speed and availability of the systems, which allow users to get immediate answers and ask questions in quick succession without waiting. Students also highlight the low social cost of these interactions, as they can ask simple questions without fear of being judged. AI is perceived as an effective support for routine tasks, verification, reformulation, and comprehension: step-by-step explanations, structuring of ideas, or clarification of poorly understood concepts. Finally, time pressure, atypical schedules, or the need for confidentiality reinforce the appeal of private support that is available at any time. Adherence to naive representations remains low: the responses reflect a realistic and pragmatic perception of generative AI.

4.2. Explaining the intention to use generative AI

Our research aims to understand how students' representations and characteristics influence their use of generative AI. We seek to verify the links between the different dimensions of the model constructed, inspired by the UTAUT model of Venkatesh et al. (2003). To quantitatively test these relationships, we performed statistical regressions, i.e., we sought to explain a dependent variable using several explanatory variables. We will therefore present the various regression models obtained, which indicate the weights and significance of the different variables likely to explain generative AI usage behaviors.

Our first four hypotheses assumed that expected performance, perceived ease, hedonic motivation, and social influence could explain the intention to use generative AI. To verify this, we performed a linear regression with the scores for these four dimensions as explanatory variables, the two items on self-esteem and sense of competence that complement social influence, and the individual characteristics of the students:

Model 1: Intention to use = f*(Expected performance, Perceived ease, Social influence, Hedonic motivation, Item "using AI is rewarding," Item "using AI = recognized competence," Field of study, Gender, Age, Parent 1's socio-professional category, Parent 2's socio-professional category, University cycle*)

Table 1: Net effects of representations of generative AI on students' intention to use it.[1]

INDEPENDENT VARIABLES			
Item		***Coeff.***	***Sign***
Expected performance score		**0.164**	*******
Perceived ease score		0.009	ns
Hedonic motivation score		0.013	ns
Item “I find the use of AI rewarding”		0.058	ns
Item “I find that using AI makes me feel competent”		-0.009	ns
Social influence score		0.005	ns
CONTROL VARIABLES			
Reference modality	***Active modality***	***Coeff.***	***Sign***
Is a man	Is a woman	-0.028	ns
Social sciences and humanities	Education	-0.069	ns
	Info-com stream	0.403	*
	Law program	0.286	***
	Computer science	0.413	**
	Science	0.187	*
	Engineering	0.240	ns
	Healthcare program	0.043	ns
Parental socio-professional category 1 Disadvantaged	Socio-professional category of parent 1: advantaged	-0.049	ns
	Parental socioeconomic status 1: Middle class	-0.051	ns
Parental socioeconomic status 2 Disadvantaged	Socio-professional category of parent 2: advantaged	0.051	ns
	Parental socioeconomic status 2: Middle	-0.185	ns
Bachelor's degree	Master's degree	-0.038	ns
Age		0.004	ns
Constant		0.00	6
Adjusted R^2		**28.3**	

[1]Reading grid:
- * : Variable significant at the 10% threshold ($p < 0.10$).
- **: Variable significant at the 5% threshold ($p < 0.05$).
- ***: Variable significant at the 1% threshold ($p < 0.01$).
- ns: Non-significant variable ($p \geq 0.10$).

For quantitative variables, such as scores or age, the coefficients indicate how much the intention-to use score varies for an additional unit of that variable. For example, a student with an expected performance score of 3 will have a usage intention score that is 0.164 points higher than a student with a score of 2. For qualitative variables, the coefficients express the difference from a reference category. Thus, being a law student is associated with a difference of 0.286 points compared to students in the social sciences and humanities.

In this first regression, only expected performance appears to be significant. This means that students who perceive AI as useful for their studies have a higher intention to use it, and that this effect is strong enough to render other representations insignificant in this model. We also observe differences according to field of study: students in information and communication, law, science, and computer science have a higher intention to use AI than those in social sciences and humanities.

In order to understand why perceived ease, hedonic motivation, and social influence components become insignificant when expected performance is included in the model, we performed an additional regression analysis to explain the latter based on students' perceptions and characteristics.

Model 2: Expected performance = f*(Perceived ease, Social influence, Hedonic motivation, Item "using AI is rewarding," Item "using AI = recognized skill," Field of study, Gender, Age, Parent's socioeconomic status parent 1, Socio-professional category of parent 2, University cycle*)

Table 2: Net effects of representations of generative AI on students' expected performance, adjusted for nonsignificant variables.

		Model 2 *N = 1, 209*	
INDEPENDENT VARIABLES			
Item		***Coeff.***	***Sign***
Perceived ease score		0.365	***
Hedonic motivation score		0.296	***
Item “I find the use of AI rewarding”		0.648	***
Item “I find that using AI makes me feel competent”		0.608	***
Social influence score		0.161	***
	CONTROL VARIABLES		
Reference modality	***Active modality***	***Coeff.***	***Sign***
SHS program	Computer science	0.776	**
	Science stream	1.218	***
	Engineering	1,030	**
	Age	0.097	*
	Constant	-0.3	41
	Adjusted R^2	**35.9**	

In this model, where we have not presented the effects of insignificant variables in order to make it easier to read, we find that perceived ease, hedonic motivation, and social influence components all have a positive and highly significant effect ($p < 0.001$). Furthermore, students in computer science, science, and engineering programs consider generative AI to be more useful for their studies than those in the humanities and social sciences. A similar trend is also observed among older students.

The fact that expected performance is the only significant dimension when analyzed in conjunction with perceived ease, hedonic motivation, and social influence, combined with the finding that these three dimensions positively and significantly predict expected performance, led us to formulate a mediation hypothesis. In other words, expected performance could play a mediating role between these three representations and the intention to use:

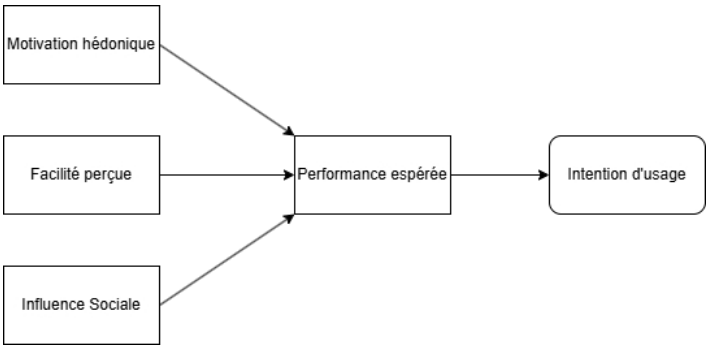

Figure 3: Diagram explaining the mediating effect of expected performance.

To examine this hypothesis, we tested the direct and indirect (i.e., mediated by expected performance) effects of the three representations on usage intention. To do this purpose, we used the PROCESS 4.2 extension in SPSS to estimate a mediation model. The results obtained are presented in the following table:

Table 3: Direct and indirect effects of perceived ease, hedonic motivation, and social influence on usage intention, mediated by expected performance.

DIRECT EFFECT			INDIRECT EFFECT	
Variable	***Coeff.***	***Sign. (p value)***	***Coeff.***	***Sign. (95% CI)*** [2]
Perceived ease score	0.0124	0.34 (ns)	0.1018	[0.0839; 0.1192]
Hedonic motivation score	0.0197	0.11 (ns)	0.1059	[0.0890; 0.1229]
Social influence score	0.0093	0.47 (ns)	0.0694	[0.0528; 0.0870]

We observe that the direct effects of these representations are not significant, while their indirect effects, mediated by expected performance, are all significant. However, it is important to note that in this type of calculation, the variables are considered independently of each other: PROCESS 4.2 does not allow for the simultaneous estimation of the indirect effects of several variables or the integration of control variables. These results thus highlight the mediating role of expected performance between these three representations and the intention to use.

4.3 Explaining the actual use of generative AI

Our fifth hypothesis postulated the existence of a direct and positive link between the intention to use generative AI and its actual use by students. To test this, we performed a linear regression incorporating the different representations, intention to use, and student characteristics as independent variables in order to explain their actual usage score:

*** Model 3:** Actual usage = f*(Intention to use, Expected performance, Perceived ease, Social influence, Hedonic motivation, Item "using AI is rewarding," Item "using AI = recognized skill," Field of study, Gender, Age, Socio-professional category of parent 1, Socio-professional category of parent 2, University cycle*)

[2]The PROCESS 4.2 module does not provide a p-value for indirect effects, only a 95% confidence interval.

17/33 We obtained the following results:

Table 4: Net effects of representations of generative AI, intention to use, and student characteristics on their actual use, adjusted for insignificant variables.

		Mode ***N = 1,***	**l 3** ***209***
INDEPENDENT VARIABLES			
Item		***Coeff.***	***Sign***
Intention to use		**0.377**	*******
Expected performance		0.385	***
Perceived ease score		0.058	**
Hedonic motivation score		0.079	***
CONTROL VARIABLES			
Reference modality	***Active modality***	***Coeff.***	
SHS program	Computer science	1.169	***
Parent's socio-professional category 2 Disadvantaged	Parent's socio-professional category 2: Middle class	-0.407	*
Age		0.089	**
Constant		2.582	
Adjusted R²		**45.7**	

In accordance with the UTAUT model developed by Venkatesh et al. (2003), intention to use appears here as a positive and significant predictor of actual use. Students with a higher intention to use engage with generative AI more intensively and in more diverse ways. Furthermore, high scores for expected performance also predict greater use of this technology. Perceived ease and hedonic motivation point in the same direction, but with a less pronounced effect.

These results are modulated by several variables: computer science students use generative AI more than those in the social sciences and humanities; students whose "Parent 2" belongs to an average socio-professional category report less use than those from disadvantaged backgrounds; finally, age is also positively associated with use.

It should also be noted that expected performance has a greater weight than intention to use in explaining the actual use of AI. This suggests a direct link between this representation and actual use. To test this hypothesis, we performed a mediation test with PROCESS 4.2 to estimate both the direct effect of expected performance on actual use and its indirect effect through intention to use. The results obtained are as follows:

Table 5: Direct and indirect effects of expected performance on actual use, mediated by intention to use.

DIRECT EFFECT			INDIRECT EFFECT	
Variable	***Coeff.***	***Sign. (p value)***	***Coeff.***	***Sign. (95% CI)***
Expected performance score	0.4333	0.001	0.0656	[0.0455; 0.0890]

Thus, expected performance has both a direct positive and significant effect on actual usage, as well as a weaker indirect effect, mediated by intention to use. These results confirm the idea that the expected performance of generative AI plays a central role in its adoption by students. Finally, we did not consider it relevant to test for mediation of perceived ease or hedonic motivation via intention to use, since we showed earlier that their direct effects on this intention were not significant once expected performance was taken into account.

4.4 Explaining the preference for generative AI

The sixth hypothesis postulated that a high level of academic anxiety would be associated with a preference for human assistance rather than artificial assistance. As a reminder, we constructed an academic anxiety score based on four components: social anxiety, self-efficacy (SEP), sense of integration, and test anxiety. To test this hypothesis, we performed two linear regressions: the first incorporated the overall school anxiety score, and the second, more precise, distinguished the four individual components of this score.

Model 4: Preference for human assistance = f(School anxiety score, Expected performance, Perceived ease, Item "using AI is rewarding," Item "using AI = recognized skill," Social influence, Hedonic motivation, Field of study, Gender, Age, Socio-professional category of parent 1, Socio-professional category of parent 2, University cycle)

Model 5: Preference for human assistance = f(Social anxiety, SEP, Sense of belonging, Test anxiety, Expected performance, Perceived ease, Social influence, Item "using AI is rewarding," Item "using AI = recognized skill," Hedonic motivation, Field of study, Gender, Age, Socio-professional category of parent 1, Socio-professional category of parent 2, University cycle).

We obtained the following results:

Table 6: Net effects of representations of generative AI and school anxiety on preference for human assistance, adjusted for non-significant variables.

		Model 4 N = 1,209		**Model 5** N = 1,209	
INDEPENDENT VARIABLES					
Item		***Coeff.***	***Sign***	***Coeff.***	***Sign***
Expected performance score		-0.304	***	-0.300	***
Hedonic motivation score		-0.114	***	-0.115	***
Item “I find the use of AI rewarding”		-0.173	*	-0.181	**
Item “I find that using AI makes me feel competent.”		-0.185	*	-0.188	**
Overall school anxiety score		**-0.014**	****	/	/
Specific social anxiety score		/	/	**-0.021**	**ns**
Specific self-efficacy score		/	/	**-0.075**	****
Specific score for sense of integration		/	/	**-0.130**	****
Specific score for test anxiety		/	/	**0.044**	****
CONTROL VARIABLES					
Reference modality	***Active modality***	***Coeff.***	***Sign.***	***Coeff.***	***Sign***
Is a man	Is a woman	-0.283	*	-0.419	***
Social sciences and humanities	Science stream	0.550	***	0.481	**
	Information and Communication Sciences	0.840	*	0.778	*
	Engineering program	0.817	***	0.727	**
Constant		3.524		2.939	
Adjusted R^2		**32.2**		**34.6**	

First, let us recall that the dependent variable measures a student's level of preference for human assistance. A low value therefore indicates a preference for using generative AI in academic tasks. The academic anxiety score and its various components are coded negatively: a high value reflects an unfavorable state for the student, i.e., high social anxiety, low self-efficacy, low sense of integration, or high-test anxiety, depending on the component considered.

In the first model, we observe that school anxiety is negatively associated with a preference for human help. In other words, students with high levels of school anxiety are more likely to turn to artificial help. A more detailed analysis of the components in the second model shows that social anxiety is not significant in explaining this preference. On the other hand, low self-efficacy and low integration are associated with a stronger preference for AI. Conversely, high test anxiety is linked to an increased preference for human assistance.

In both models, expected performance, hedonic motivation, and the two secondary components of social influence are significant and associated with a preference for AI. This result is consistent with previous analyses, which showed that these dimensions predicted a higher intention to use AI. We also observe a gender effect: women appear more inclined to seek artificial assistance. Conversely, students in science, information-communication, and engineering fields are more likely to turn to human assistance than those in the social sciences and humanities.

Even though social anxiety is not significant in quantitative models, some responses to open-ended questions suggest that it still plays a role. When asked what motivates them to seek help from AI rather than humans, several students say they prefer AI because they don't dare ask humans questions for fear of appearing incompetent, disturbing them, or because they are shy. Here are some examples of these responses:

"When I don't dare ask a question, afraid that it might be 'stupid,' obvious, or that I should already know the answer from my studies."

"In a context of social isolation, shyness, difficulty approaching others easily."

"When I am alone and want to continue alone."

"That way, I don't bother people."

"In cases of social laziness"

4.5 Explaining unethical behavior

Finally, our seventh and final hypothesis posited that a naive and erroneous representation of AI would be associated with less critical and less ethical behavior towards it. To test this hypothesis, we conducted a linear regression including different representations of generative AI, the naive perception score, dimensions of school anxiety, and student characteristics.

Model 6: Unethical usage score = f(Naive representations score, Social anxiety, SEP, Sense of belonging of integration, Test anxiety, Expected performance, Perceived ease, Item "using AI is rewarding," Item "using AI = recognized skill," Social influence, Hedonic motivation, Field of study, Gender, Age, Socio-professional category of parent 1, Socio-professional category of parent 2, University cycle).

Table 7: Net effects of representations of generative AI, naive representations, and school anxiety on the unethical behavior score, adjusted for non-significant variables.

		Mo N =	**del 6** 1,209
INDEPENDENT VARIABLES			
Item		***Coeff.***	***Sign***
Expected performance score		0.158	***
Perceived ease score		0.047	***
Item “I find that using AI makes me feel competent”		0.080	*
Social influence score		-0.025	*
Naive perception score		**0.036**	***
Specific social anxiety score		-0.027	**
Specific self-efficacy score		0.023	**
CONTROL VARIABLES			
Reference modality	***Active modality***	***Coeff.***	***Sign***
Is a man	Is a woman	-0.0221	**
Social sciences and humanities	Info-com stream	0.854	***
	Law program	0.336	***
	Computer science	0.972	*
	Science	-0.212	***
	Engineering	0.300	*
Constant		1.7	60
Adjusted R^2		**31**	**.2**

First, a high score for unethical behavior indicates that a student has previously submitted a document written primarily by generative AI, checks less often for information produced and rarely mentions its use to their teachers. The model shows that naive representations are positively and significantly associated with this score: students with misconceptions about AI are therefore more likely to adopt less ethical practices. Perceiving AI as useful or easy to use, as well as feeling competent or valued when using it, also leads to less critical use. A low sense of self-efficacy also seems to encourage this type of behavior.

Conversely, positive social influence and high social anxiety are associated with more ethical practices. A gender effect also appears: on average, men adopt less critical practices than women. In terms of academic disciplines, students in information and communication, law, engineering, and computer science are generally less critical than those in the social sciences and humanities, while science students are more critical.

We then estimated two additional models to analyze what motivates or discourages students from mentioning their use of AI or verifying the information generated, using two binary logistic regressions:

Model 7: Verifying the information generated = f(*Social anxiety, SEP, Sense of belonging, Test anxiety, Expected performance, Perceived ease, Social influence, Item "using AI is rewarding " Item "using AI = recognized skill," Hedonic motivation, Naive representations, Field of study, Gender, Age, Socioprofessional category of parent 1, Socio-professional category of parent 2, University cycle*)

Model 8: Mentioning the use of AI = f (*Social anxiety, SEP, Sense of belonging, Test anxiety, expected performance, perceived ease, Social influence, Item "using AI is rewarding," Item "using AI = recognized skill," Hedonic motivation, Naive representations, Field of study, Gender, Age, Socioprofessional category of parent 1, Socio-professional category of parent 2, University cycle*)

Table 8: Net effects of representations of generative AI, naive representations, and school anxiety on mentioning the use and verifying the information generated, adjusted for non-significant variables.

		Model 7 N = 1,209		**Model 8** N = 1,209	
INDEPENDENT VARIABLES					
Item		***Coeff.***	***Sign***	***Coeff.***	***Sign***
Expected performance score		-0.060	*	0.102	***
Perceived ease score		-0.002	ns	0.082	**
Social influence score		-0.018	ns	-0.150	***
Naive perception score		**0.**128	*******	**0.076**	*******
Specific self-efficacy score		0.072	***	0.019	ns
Specific test anxiety score		-0.029	**	-0.012	ns
CONTROL VARIABLES					
Reference modality	***Active modality***	***Coeff.***	***Sign***	***Coeff.***	***Sign***
Social sciences and humanities	Info-com program	-1.595	**	-0.765	*
	Education sector	0.527	**	0.173	ns
	Health sector	0.579	**	0.320	ns
Age		-0.131	***	-0.068	ns
Constant		**2.534**		**3.297**	
Nagelkerke R^2		**13.4**		**13.5**	

First, note that the items "verification" and "mention" are negatively coded binary variables: the value "1" corresponds to a generally rare mention of AI use or less verification of generated content. Here too, we observe that naive and erroneous representations of AI are associated with less verification and less transparency.

The effect of expected performance varies depending on the practice in question: perceiving AI as useful increases the likelihood of verifying information, but reduces the likelihood of mentioning its use. A low sense of self-efficacy is associated with less verification, which may reflect excessive confidence in the answers generated when students doubt their own abilities. Positive social influence tends to encourage greater transparency, unlike considering AI to be easy to use, which seems to discourage mention.

Finally, test anxiety increases the likelihood of verifying answers provided by generative AI. We also observe an effect related to the field of study: students in education and health check and mention their use less often than those in social sciences and humanities, while students in information and communication stand out for their significantly higher level of verification. Finally, older students appear to be more critical: they check content more and mention their use more often.

To refine the analysis of unethical practices, we then performed two additional binary logistic regressions to explain, on the one hand, the hidden use of AI during an assignment or midterm

exam and, on the other hand, the use of AI in an explicitly prohibited context.

Model 9: Concealed use = f(*Social anxiety, SEP, Sense of belonging, Anxiety about tests, Expected performance, Perceived ease, Social influence, Item "using AI is rewarding," Item "using AI = recognized skill," Hedonic motivation, Naive representations, Field of study, Gender, Age, Socioprofessional category of parent 1, Socio-professional category of parent 2, University cycle*)

Model 10: Prohibited use = f(*Social anxiety, SEP, Sense of belonging, Test anxiety, Expected performance, Perceived ease, Social influence, Item "using AI is rewarding," Item "using AI = recognized skill," Hedonic motivation, Naive representations, Field of study, Gender, Age, Socioprofessional category of parent 1, Socio-professional category of parent 2, University cycle*)

Table 9: Net effects of representations of generative AI, naive representations, and academic anxiety on covert use and use during a ban, adjusted for insignificant variables.

		Model 9 N = 1,209		**Model 10** N = 1,209	
INDEPENDENT VARIABLES					
Item		***Coeff.***	***Sign***	***Coeff.***	***Sign***
Expected performance score		0.195	***	0.185	***
Perceived ease score		0.054	ns	0.085	**
Item “I find the use of AI rewarding”		-0.166	ns	-0.217	**
Item “I find that using AI makes me feel competent.”		0.136	ns	0.238	**
Social influence score		-0.138	***	-0.112	***
Naive perception score		**0.080**	****	0.035	ns
Specific test anxiety score		-0.049	**	-0.005	ns
CONTROL VARIABLES					
Reference modality	***Active modality***	***Coeff,***	***Sign.***	***Coeff.***	***Sign***
Social sciences and humanities	Law program	0.689	*	0.254	ns
	Computer science program	1.720	***	0.819	**
	Information and Communication Technology	0.975	ns	1.043	**
	Health sector	1.010	**	0.307	ns
Constant		-1.258		-1.586	
Nagelkerke R^2		**21.3**		**17.7**	

Here too, the two scores studied, concealed use and prohibited use, are negatively coded binary variables. The value "1" indicates that the student has already used AI in these conditions considered unethical. Once again, naive perception is positively and significantly associated with covert use, although it is not significant for prohibited use. Expected performance, perceived ease, and feeling competent thanks to AI are also positively linked to these unethical practices. Positive social influence, on the other hand, tends to reduce these behaviors. Anxiety about tests also seems to discourage covert use.

In terms of academic disciplines, students in law, computer science, information and communication, and health sciences appear to be more inclined toward these practices than those in the social sciences and humanities. Thus, naive representations and misconceptions about generative AI remain associated with less ethical practices, unlike positive social influence.

5. Discussion

5.1. Validation of research hypotheses

Our model posited that expected performance, perceived ease, hedonic motivation, and social influence determined intention to use, which then influenced actual use. The results partially confirm this pattern: only expected performance has a direct effect on intention to use, with the other variables having an indirect effect through it. Thus, only hypothesis H1 is retained, while H2, H3, and H4 are rejected.

We also showed that actual usage depends directly on the intention to use and, directly or indirectly, on expected performance. Hypothesis H5 is therefore retained. Expected performance appears to be the central pivot of the model: it is what organizes, absorbs, and relays the effect of other representations to guide the intention and actual use of generative AI. These relationships can be represented in the following diagram:

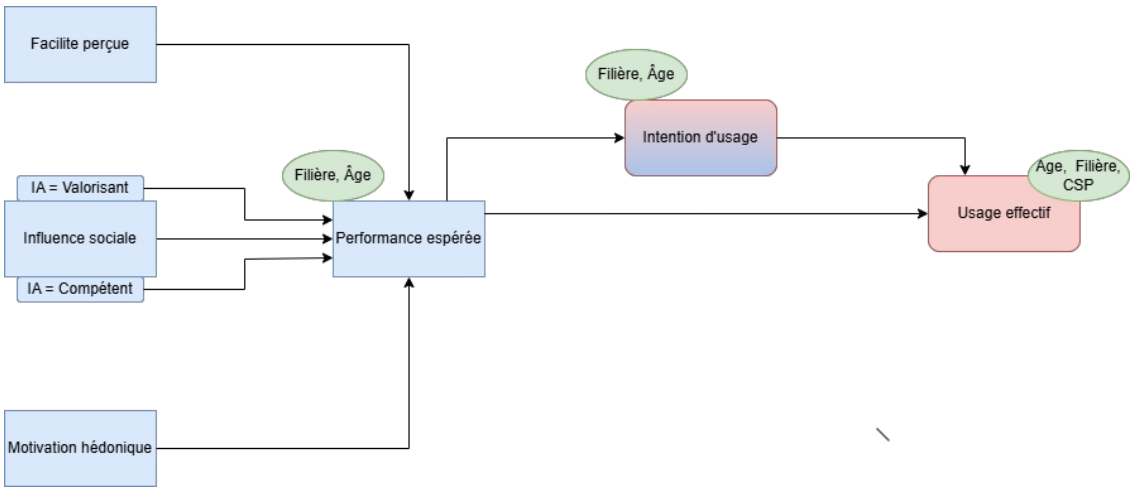

Figure 4: Modeling interactions between representations and uses of generative AI. The green ovals represent the control variables moderating the effects.

Regarding the preference between human assistance and AI, a low sense of self-efficacy and a low sense of integration steer students more toward AI, while test anxiety reinforces the preference for human assistance. Despite these nuances, the overall effect of academic anxiety remains significant and supports hypothesis H6, which is therefore confirmed. Finally, since naive representations are positively associated with unethical behavior, hypothesis H7 is also retained.

5.2 Interpretation of results

Expected performance appears to be a key predictor of behaviors and perceptions related to generative AI: students use it to gain a perceived advantage. However, a paradox remains: 74.3% consider AI useful, but only 32.7% believe it increases their chances of achieving better results. This discrepancy could be explained in part by its use for repetitive tasks and time-saving, by its perceived unreliability, which requires verification and thus reduces its net effectiveness, and by its low social value and lack of institutional encouragement. Nevertheless, 71.7% say they have already submitted work that was partially generated or modified using AI. We can view this from a cost-benefit perspective: a simple, fast, and accessible tool with mainly social and ethical costs. This strategy is part of a utilitarian approach to education, as described in *L'Emprise scolaire* (Dubet & Duru-Bellat, 2024): AI is seen as a pragmatic means of achieving a result, sometimes at the expense of learning, leading to unethical practices. Finally, beyond its immediate usefulness, some perceive mastery of these tools as a necessary skill, particularly in computer science, from an academic and professional competitiveness perspective.

Emotionally and relationally, low self-efficacy and integration tend to lead to a preference for AI, which is sometimes used as a discreet validator to confirm an idea without exposing oneself to the judgment of others. Conversely, test anxiety is associated with a preference for human assistance and more critical behavior. Two forms of school anxiety seem to stand out: one internal (low self-efficacy, reduced integration) and the other external (test anxiety and social anxiety). Students in the first group place greater trust in AI, sometimes to the point of checking the information produced less rigorously. This reflects an excessive confidence in the technological tool, combined with an underestimation of their own abilities. Conversely, students whose anxiety stems from external pressure, such as test anxiety, prefer human assistance and generally adopt more critical and ethical behaviors toward AI: they check the generated content more thoroughly and are less likely to use AI covertly. In addition, a significant majority of students say they use polite language with generative AI, with 65.5% saying they do so more than rarely. Some also use it in relational contexts, to simulate conversations, resolve interpersonal issues, or ask personal questions they would not dare to ask.

address humans. These uses reveal notable relational mechanisms between students and AI. However, as our literature review shows, this use remains largely taboo and socially devalued. Our results indicate that 82.8% of respondents never explicitly mention their use of AI, while 70.1% believe that using it is not socially valued. Thus, although perceived as a reassuring emotional resource for some, AI remains associated with a form of secrecy in academic practices.

Finally, we can highlight the central role of academic institutions and teachers in students' relationship with generative artificial intelligence. Our results show that perceived social influence, when positive, tends to reduce unethical behavior. In other words, students who perceive their institution or teachers as supporting the use of AI are more inclined to be transparent. They are more open about their use of these tools and are less likely to use them inappropriately, particularly during assessments or despite explicit prohibitions. A supportive academic environment, where standards of use are clarified and valued, thus promotes more thoughtful and less transgressive use. We have also shown that naive representations of AI were systematically correlated with uncritical practices, such as failure to verify generated content or covert use of the tool. This link suggests that a lack of technical and conceptual understanding of AI weakens critical practices. In this sense, offering instruction on how generative AI actually works, its limitations, its biases, and its role in academic work could help reduce naive or abusive use in favor of more measured and reflective practices.

5.3 Limitations

Like all research, this study has several methodological and analytical limitations. In terms of data collection, there is likely to be a selection bias: the questionnaire explicitly mentioning AI may have attracted more students interested in this subject. Distribution via the internal digital environment may have excluded those who are less connected, and the sample is overrepresented in terms of women (65.8%) and humanities and social sciences (30.8%), while computer science remains underrepresented. The external scope of the study remains limited to the context of the University of Burgundy Europe, and social desirability bias is possible with regard to unethical uses, despite the guarantee of anonymity. In addition, the length of the questionnaire may have affected the quality of some responses. In terms of operationalization, the naive representations were based on deliberately false statements, which may have introduced a framing bias, and the manual classification of fields of study and parental professions may have generated errors. From a theoretical point of view, certain dimensions of the UTAUT model, such as facilitating conditions or student experience, were excluded, although they could have enriched the analysis.

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