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Higher Education Students' Perceptions of GenAI Tools for Learning

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Abstract: Students' perceptions of tools with which they learn affect the outcomes of this learning. GenAI tools are new tools that have promise for students' learning, especially higher education students. Examining students' perceptions of GenAI tools as learning tools can help instructors better plan activities that utilize these tools in the higher education context. The present research considers four components of students' perceptions of GenAI tools: efficiency, interaction, affect, and intention. To triangulate data, it combines the quantitative and the qualitative methodologies, by using a questionnaire and by conducting interviews. A total of 153 higher education students responded to the questionnaire, while 10 higher education students participated in the interview. The research results indicated that the means of affect, interaction, and efficiency were significantly medium, while the mean of intention was significantly high. The research findings showed that in efficiency, affect, and intention, male students had significantly higher perceptions of AI tools than female students, but in the interaction component, the two genders did not differ significantly. Moreover, the degree affected only the perception of interaction of higher education students, where the mean value of interaction was significantly different between B.A. and Ph.D. students in favor of Ph.D. students. Moreover, medium-technology-knowledge and high-technology-knowledge students differed significantly in their perceptions of working with AI tools in the interaction component only, where this difference was in favor of the high-technology-knowledge students. Furthermore, AI knowledge significantly affected efficiency, interaction, and affect of higher education students, where they were higher in favor of high-AI-knowledge students over low-AI-knowledge students, as well as in favor of medium-AI-knowledge students over low-AI-knowledge students.

Keywords: artificial intelligence; higher education; students' perceptions; GenAI

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1. Introduction

GenAI bots populate the educational panorama, as they attract the attention of educators from various disciplines [1–4]. Students' perceptions towards the use of GenAI bots in learning affect the outcomes of this learning in terms of cognitive, social, and affective aspects of learning. The present research is interested in students' perceptions of GenAI bots, where these perceptions are associated with the three previous aspects of learning. The cognitive aspect of learning is associated with the efficiency of learning, while the social aspect of learning is associated with AI–human interactions. The affective aspect of learning addresses the confidence to work with GenAI bots as well as other variables like learners' motivation to engage in this work. In addition, the present research is interested in students' intention to learn with GenAI bots.

Below, we address previous studies that address the four components of students' perceptions of GenAI tools, and then we describe the research rationale and goals, which lead us to the research questions.

1.1. Efficiency of Learning with GenAI

One issue of efficiency of learning with GenAI is related to performing tasks with GenAI. Owens [5] commented that GenAI can help perform various tasks such as writing essays, brainstorming research ideas, conducting literature reviews, enhancing papers, and writing computer codes. Moreover, Bernabei et al. [6] reported that large language models (LLMs) helped students produce good essays, suggesting that LLMs affected their performance positively. LLMs also supported the students in their understanding of the topics during oral presentations, but this was not the same for all students, where some students did not sufficiently rework and discuss the text produced by ChatGPT. In addition, Bernabei et al. [6] reported that students recognized the potential benefits of LLMs in improving task performance, enhancing understanding, and supporting teachers.

Teachers can also benefit from using GenAI in the educational setting. Kasneci et al. [7] reported that teachers used ChatGPT for lesson planning, student assessment, and professional development.

Not only can humans benefit from the efficiency of learning with GenAI, but the GenAI bot improves itself too. Van Dis et al. [8] claim that receiving new data through user interactions, the abilities of ChatGPT are expected to rapidly expand.

Working efficiently with GenAI bots can be confronted with some obstacles. Researchers highlighted the multiple key challenges in using GenAI bots. Kasneci et al. [7] mentioned copyright issues, bias, fairness, excessive reliance on GenAI of students and teachers, lack of expertise in integrating this technology in teaching, the difficulty of distinguishing model-generated from student-generated answers, cost of training and maintenance, data privacy and security, and sustainable usage.

1.2. Interactions in the GenAI Environment

One issue of interaction associated with GenAI is human-like interaction. Dasborough [9] says that ChatGPT is specifically designed and fine-tuned for conversational usage to produce human-like responses by drawing on its wealth of information and knowledge.

Iqbal et al. [10] reported that university faculty were generally cautious in interacting with ChatGPT, where they had a negative perception towards interacting with ChatGPT. They were afraid that such an interaction would lead to cheating and plagiarism, but at the same time, they were aware that this interaction could lead to facilitating lesson planning and assessment.

GenAI interacts with users through prompts. Bozkurt and Sharma [11] argue that by strategically approaching a conversational generative AI bot, with clear purpose, tone, role, and context, a prompt-based conversational pedagogy can be established, enabling communication and interaction, which facilitates teaching and learning effectively.

Liu et al. [12] reported that students struggled with the issue of formulating prompts to make the GenAI model generate the desired images.

Interaction with GenAI bots can lead to positive educational outcomes. Huang et al. [13] reported that utilizing GenAI bots in language learning enhanced feedback provision, stimulating student interest, participation, and satisfaction. Sabzalieva and Valenini [14] reported that ChatGPT offered personalized feedback to students derived from information supplied by students or teachers, potentially enhancing their learning motivation.

1.3. Affect in the GenAI Environment

Researchers emphasize that students' self-confidence is very effective in the learning process and has positive impacts on their learning processes and outcomes. This shows the main role of self-confidence and other affect variables in students' learning.

Akbari and Sahibzada [15] reported that students' self-confidence affected their participation, goal seeking, and developing interest in lessons, and it decreased students' anxiety. Moreover, GenAI bots can enrich students' confidence to learn. Chiu et al. [16] reported that GenAI bots enhanced students' confidence and reduced their anxiety to learn English. Kelly et al. [17] found that students' confidence in their ability to use GenAI ethically increased with experience using GenAI.

Motivation is another affect variable that affects students' learning outcomes. Daher [18] reported that the robotics-based mathematics class positively influenced students' motivation to learn mathematics in terms of interest, mastery, and self-efficacy. Chiu et al. [16] reported that intrinsic motivation and competence to learn with the chatbot depended on both teacher support and student expertise, while teacher support better satisfied the need for relatedness, but it less satisfied the need for autonomy.

Hmoud et al. [19] found that despite the satisfaction with tasks performed using ChatGPT 3.5, feelings of anxiety prevailed among some students, where this anxiety was attributed to several reasons, including a lack of substantive trust in the program's information and fear that the task would be labelled as "cheating".

1.4. Research Rationale and Goals

The emergence of GenAI bots, particularly ChatGPT, has captured the attention of educators and educational researchers. Students' perceptions play a crucial role in the adoption of these tools in education. This study focuses on higher education students' views of GenAI, examining how factors like gender, degree, technological knowledge, and AI knowledge influence these perceptions.

Iqbal et al. [10] suggest that future research should employ quantitative methods to explore students' perceptions of GenAI tools in teaching and learning. This study responds to the call, investigating students' perceptions of GenAI bots for learning across four aspects: cognitive, social, affective, and intention to use. These aspects have been identified by researchers as key components of students' learning [5,9,19].

While previous studies have touched on some elements of students' perceptions of GenAI tools [20,21], there is a lack of quantitative research in this area [10]. This study pioneers the use of quantitative data to describe students' perceptions, complemented by qualitative data for a more comprehensive analysis. This mixed-method approach enhances the study's validity and depth.

The quantitative component assesses the level of students' perceptions and analyzes significant differences based on background variables. The qualitative part provides insights into the functions of GenAI tools.

The research questions address the level of higher education students' perceptions, the significance of differences due to background variables, and evidence for the functions of GenAI bots in higher education students' learning.

1.5. Research Questions

1. What are the levels of higher education students' perceptions of learning with GenAI bots?
2. Are there significant differences, due to gender, in higher education students' perceptions of learning with GenAI bots?
3. Are there significant differences, due to degree, in higher education students' perceptions of learning with GenAI bots?
4. Are there significant differences, due to technological knowledge, in higher education students' perceptions of learning with GenAI bots?
5. Are there significant differences, due to GenAI knowledge, in higher education students' perceptions of learning with GenAI bots?
6. What are students' perceptions of the functions of GenAI tools in their learning?

Below, we address the methodology followed in the present research to answer the research questions, then we present the findings and the discussion. At the end, we present the conclusions, recommendations, and limitations of the present research.

2. Methodology

2.1. Research Context and Participants

The sample was a convenient one. We wrote the questionnaire as an online document, requesting participants from three universities in Palestine to fill in the questionnaire, whose link we gave the students. Some of the participants were from humanistic disciplines, while others were from scientific disciplines.

A total of 153 higher education students participated in the research. A total of 89 students were from the humanistic disciplines, while a total of 64 students were from the scientific disciplines. Table 1 describes the quantitative sample in terms of gender and education stage.

Table 1. The quantitative sample frequency in terms of gender and education stage.

		Education Stage			Total
		B.A.	M.A.	Ph.D.	
gender	male	20	16	9	45
	female	46	30	32	108
Total		66	46	41	153

The high number of female students is related to female students outnumbering male students in humanistic disciplines. Table 2 shows the distribution of gender across disciplines.

Table 2. Distribution of gender across disciplines.

		Gender		Total
		Male	Female	
Specialty	Humanistic discipline	19	70	89
	Scientific discipline	26	38	64
Total		45	108	153

The frequencies in Table 2 represent the situation of gender in the university. This is acknowledged worldwide, as researchers report more female presence in humanistic disciplines than in scientific disciplines [22].

We interviewed ten higher education students regarding the different components of their perception of GenAI tools for their learning. Five of the interviewees were from humanistic disciplines, while the other five were from scientific disciplines. The answers of the interviewees were not different because of their disciplines. The interviewees are described in Table 3.

Table 3. The interviewees' characteristics.

Participant	Age	Education Stage	Discipline
Salam	21	B.A.	Scientific
Amir	20	B.A.	Humanistic
Ali	22	B.A.	Humanistic
Walid	22	B.A.	Scientific
Amira	26	M.A.	Scientific
Samira	28	M.A.	Humanistic
Sami	30	M.A.	Humanistic
Alaa	30	Ph.D.	Scientific
Samar	40	Ph.D.	Scientific
Sana	45	Ph.D.	Humanistic

The participants reported that they used mainly ChatGPT, Bard (now called Gemini), and Claude. Moreover, the participants reported that the universities' regulations of the use of GenAi tools by the students concerned only the transparency of this use, so the students had to report any use they made of GenAI to carry out their university tasks.

2.2. Data Collection Tools

The quantitative data were collected using a questionnaire due to Shoufan [23] with four components of higher education students' perceptions: efficiency, interaction, affect, and intention. The efficiency component has ten items, such as "It will really help in solving everyone's problems". The interaction component has nine items, such as "It feels like having a smart friend who you can ask anything". The affect component has seven items, such as "I find it very motivating to work with a GenAI tool". The intention component has two items, such as "I intend to use GenAi tools in my future learning".

Computing Cronbach's alpha yielded 0.716 for efficiency, 0.750 for interaction, 0.725 for affect, and 0.786 for intention. These values ensured reliability of the questionnaire. In addition, computing Pearson correlation between the items of each scale and the whole scale gave values between 0.651 and 0.842, indicating validity of the four scales. Computing Pearson correlation between each scale and the whole questionnaire yielded values between 0.711 and 0.873, also indicating the validity of the questionnaire.

The qualitative data were collected through interviews. The interview questions addressed the four components of perception of GenAI tools. Examples of these questions are as follows:

Introductory questions: What GenAI tools do you use in your university study? What regulations does the university administration put on your use of GenAI tools in your study?

Main questions: When do you use GenAI tools? Why do you use GenAI tools? How do you interact with GenAI tools? What do you feel about working with GenAI tools? What about your intention to use GenAI tools in the future?

We were interested in pursuing our questions with the participants to arrive at in-depth information regarding the studied phenomenon, i.e., higher education students' perceptions of GenAI for their learning. To do that, we adopted the interview [24] as a collecting tool, rather than writing open questions in the questionnaire.

2.3. Data Analysis Tools

To answer the first research question, we examined the normality of scores for each component of perceptions. The results indicated that students' perception scores were normally distributed, as assessed by the Kolmogorov–Smirnov test ($p > 0.05$). There were no outliers in the data, as assessed by the inspection of boxplots. To find the level of each component of students' perceptions, we adopted the following division: 1–2.333 for low, 2.333–3.667 for medium, and 3.667–5 for high. These intervals resulted from the computation (5–1)/3 = 1.333, indicating the length of each level. To verify the significance of the level of each component of perception, we ran a one-sample *t*-test, as the scores, for each scale, were normal.

To answer the second research question, we first examined the normality of the scores for each component of perceptions over gender. The results indicated that students' perceptions scores were normally distributed over the gender variable, as assessed by the Kolmogorov–Smirnov test ($p > 0.05$). Thus, we ran an independent sample *t*-test to examine the significance of the differences in students' perceptions of GenAI between males and females.

To answer the third research question, we first examined the normality of the scores for each component of perceptions over degree. The results indicated that students' perceptions scores were normally distributed over the degree variable, as assessed by the Kolmogorov–Smirnov test ($p > 0.05$). In addition, homogeneity of variance, computed by Levene's test, indicated that the scores of each scale were homogenous over the degree variable ($p > 0.05$). Thus, we ran a one-way ANOVA to examine the significance of the differences in students' perceptions of GenAI between the different degrees. Moreover, when the ANOVA's results indicated a significant difference, the Scheffe post hoc test for multiple comparisons was run to determine which significant differences between the categories of the degree variable yielded the overall significant difference.

To answer the fourth research question, we followed a similar procedure to that of the second research question, while to answer the fifth research question, we followed a similar procedure to that of the third research question.

In addition to the above, the general guidelines for interpreting the effect size for Cohen's d were as follows: 0.2 = small effect, 0.5 = moderate effect, and 0.8 = large effect. Moreover, the following guidelines were followed for interpreting the Partial Eta Squared: η2: 0.01= small effect, 0.06= medium effect, 0.14= large effect.

To answer the sixth research question, we conducted inductive content analysis. In this analysis, the coder examines the data (here, interview transcripts) and codes relevant segments into categories and subcategories through an iterative process [25]. This is performed by reading through the data several times, coding relevant portions, and grouping similar codes into broader themes or categories [26]. In collecting and analyzing the data, we arrived at saturation when we reached the ninth interview. After analyzing the ninth interview, we noticed that no additional category or theme and no additional property of any category emerged [27].

3. Results

We will present the results of the research for each research question.

3.1. First Research Question

What are the levels of higher education students' perceptions of learning with GenAI bots?

To answer the first research question, we computed the descriptive statistics of the four components of higher education students' perceptions of AI. We noticed that three of the four means (efficiency, interaction, and affect) indicate a medium level of perceptions (2.33–3.66), while the fourth (Intention) indicates a high level. We thus ran a one-sample *t*-test, with the critical point of 3.66. Table 4 shows the results of the one-sample *t*-test for each component of higher education students' perceptions.

Table 4. Means, standard deviations, and one-sample *t*-test.

	M	SD	*t*	*p*	95% CI	
					Low	High
Efficiency	3.194	0.611	17.510	0.000	0.767	0.962
Interaction	3.301	0.610	19.685	0.000	0.873	1.068
Affect	3.521	0.639	23.071	0.000	1.089	1.293
Intention	3.850	1.005	18.703	0.000	1.360	1.680

Table 4 shows that the means of affect, interaction, and efficiency are significantly medium, while the mean of intention is significantly high.

3.2. Second Research Question

Are there significant differences in higher education students' perceptions of learning with AI tools due to gender?

To answer the second research question, we ran an independent sample *t*-test. Table 5 describes the results of this test.

Table 5. Independent sample *t*-test for differences due to gender (number of males = 45, number of females = 108).

	Gender	M	SD	t	*p*	95% CI	
						Low	High
Efficiency	male	3.3611	0.58401	2.207	0.014	0.025	0.448
	female	3.1250	0.61070				
Interaction	male	3.4056	0.61304	1.337	0.085	−0.065	0.362
	female	3.2569	0.60610				
Affect	male	3.6698	0.54298	1.876	0.031	−0.011	0.433
	female	3.4590	0.66694				
Intention	male	3.6963	0.73794	1.746	0.041	−0.032	0.524
	female	3.4506	0.81435				

Table 5 shows that male and female students differed significantly in their perceptions of learning with AI tools, due to gender, in three of the four perception components (efficiency, affect, and intention), while they did not differ in the interaction component. Male students perceived the AI tools better than female students. Cohen's d effect size of gender was between 0.603 and 0.633, for efficiency, interaction, and affect, indicating a moderate effect size, while it was 0.793 for intention, i.e., closer to a high effect size.

3.3. Third Research Question

Are there significant differences in higher education students' perceptions of learning with AI tools due to degree?

To answer the third research question, we ran a one-way ANOVA. Table 6 describes the results of this test.

Table 6. Differences due to degree (number of B.A. students = 66, number of M.A. students = 46, number of Ph.D. students = 41).

				95% CI	F	*p*
Efficiency	B.A.	3.125	0.643	2.967–3.283	1.754	0.177
	M.A.	3.160	0.5996	2.982–3.338		
	Ph.D.	3.345	0.555	3.169–3.520		
Interaction	B.A.	3.119	0.652	2.959–3.280	5.883	0.003
	M.A.	3.383	0.5752	3.212–3.554		
	Ph.D.	3.500	0.498	3.343–3.657		
Affect	B.A.	3.394	0.6868	3.225–3.563	2.570	0.080
	M.A.	3.575	0.6428	3.384–3.765		
	Ph.D.	3.666	0.5167	3.502–3.829		
Intention	B.A.	3.444	0.864	3.232–3.657	0.735	0.481
	M.A.	3.630	0.777	3.340–3.861		
	Ph.D.	3.529	0.711	3.304–3.753		

Table 6 shows that the degree affected only higher education students' perception of interaction. The Scheffe post hoc test for multiple comparisons found that the mean value of interaction was significantly different between B.A. and Ph.D. students ($p = 0.006$, 95% C.I. = [0.090, 0.671]). The eta squared effect size of degree was 0.073, indicating a moderate effect size.

3.4. Fourth Research Question

Are there significant differences in higher education students' perceptions of learning with AI tools due to technology knowledge?

The number of participants who reported a low technology level was relatively very low (5), so we decided to consider only the participants who reported medium and high technology knowledge. To answer the fourth research question, we ran an independent sample *t*-test. Table 7 describes the results of this test.

Table 7. Differences due to technology knowledge (number of students with medium technology knowledge = 65, number of students with high technology knowledge = 81).

	Level of Technology Knowledge	M	SD	t	*p*	95% CI	
						Low	High
Efficiency	Medium	3.156	0.572	−1.154	0.250	−0.314	0.083
	High	3.272	0.627				
Interaction	Medium	3.200	0.608	−2.440	0.016	−0.434	−0.044
	High	3.440	0.575				
Affect	Medium	3.475	0.574	−1.773	0.078	−0.369	−0.020
	High	3.649	0.603				
Intention	Medium	3.523	0.837	−0.318	0.751	−0.294	0.213
	High	3.564	0.710				

Table 7 shows that the medium and high students differed significantly in their perceptions of learning with AI tools in the interaction component only, where this difference was in favor of the high students. The Cohen's d effect size of technology knowledge was between 0.590 and 0.769, indicating a moderate effect size.

3.5. Fifth Research Question

Are there significant differences in higher education students' perceptions of learning with AI tools due to AI knowledge?

To answer the fifth research question, we ran an ANOVA. Table 8 describes the results of this test.

Table 8 shows that AI knowledge significantly affected three perception components (efficiency, interaction, and affect) of higher education students. The Scheffe post hoc test for multiple comparisons found that the mean value of each of the three components was significantly different between low-AI-knowledge students and middle-level-AI-knowledge students, in favor of middle-level-AI-knowledge students. Moreover, the mean value of each of the three components was significantly different between low-AI-knowledge students and high-AI-knowledge students, in favor of high-AI-knowledge students. No significant difference was found between middle-level-AI-knowledge and high-AI-knowledge students in any of the three perception components.

The eta squared effect size of the AI knowledge was between 0.149 and 0.186, indicating a strong effect size.

Table 8. Differences due to AI knowledge (number of low-AI-knowledge students = 42, number of medium-AI-knowledge students = 91, number of high-AI-knowledge students = 20).

		M	SD	95% Confidence Interval for Mean		F	*p*
				Lower	Upper		
Efficiency	Low	2.824	0.679	2.613	3.036	13.144	<0.001
	Medium	3.302	0.535	3.191	3.414		
	High	3.481	0.435	3.278	3.685		
Interaction	Low	2.893	0.529	2.728	3.058	16.668	<0.001
	Medium	3.419	0.587	3.297	3.541		
	High	3.619	0.447	3.410	3.828		
Affect	Low	3.099	0.700	2.88	3.317	17.086	<0.001
	Medium	3.633	0.536	3.52	3.744		
	High	3.900	0.489	3.67	4.129		
Intention	Low	3.492	0.817	3.237	3.747	0.047	0.954
	Medium	3.531	0.810	3.362	3.700		
	High	3.550	0.736	3.206	3.894		

3.6. Sixth Research Question

What are students' perceptions of learning with GenAI tools?

The interview with the higher education students revealed that categories appearing from the interview analysis were related to the four categories of perceptions, where different sub-categories emerged for each category. Below, we report these categories and their sub-categories.

3.6.1. Efficiency of AI Tools

The participants mentioned the following sub-categories of the category 'efficiency of AI tools': problem solving, content enriching, verification of answers, justification and support. Below, we describe each sub-category with examples of students' statements.

A. Problem solving:

Talking about problem solving, the participants mentioned the 'Ability to solve problems' and 'Solving only part of the problems'. For example, Salam said, "ChatGPT can help us solve problems, generally not difficult problems. It helped me solve a mathematical problem given to us by the instructor of Linear Algebra". Amir said, "Not all problems can be solved by ChatGPT or Gemini. Sometimes they are not able to solve even easy problems". Thus, the participants did not agree on the ability of GenAI tools to solve problems.

B. Content enriching:

The participants agreed that GenAI tools can enrich their content knowledge. Ali said, "AI tools can enrich the content you know. I generally approach AI tools to get more information about topics that we take in the university courses. Most of the time I get interesting information". Thus, Ali's experience influenced his perception of AI tools as giving interesting information.

C. Verification of answers:

Some of the participants reported that they use GenAI tools to verify their answers. Walid said, "You can use ChatGPT to verify your answer, especially when you are in doubt about it. Not only me but my classmates think so too". Thus, the participant mentions not only himself but also his classmates as perceiving GenAI tools as able to verify answers of problems met in the higher education context.

D. Justification:

Some of the participants reported that they use GenAI tools to justify scientific claims. Amira said, "AI tools can justify or refute given claims. I say that depending on my experience". Here too, experience led to specific perceptions.

E. Support

Some of the participants expressed their perceptions of GenAI tools as a source for references that supported a scientific or an educational issue written by them. Samira said, "Perplexity can reference scientific texts. We, higher education students, believe that it is suitable for such goal". In this case, the student speaks not only in her own name but also in the name of her classmates.

3.6.2. Interaction with GenAI Tools

The participants mentioned the following sub-categories of the category 'interaction with GenAI tools': human-like interaction, ways of addressing users, utilization of pre-interaction, interaction prompts, and learning from interaction. Below, we describe each sub-category with examples of students' statements.

A. Human-like interaction:

When talking about the interaction with GenAI tools, the participants talked about the familiarity of this interaction. Sami said, "I think it is just easy to interact with Chatbots because they interact like humans, and we are familiar with this way of interaction.". So, this human-like interaction made the students perceive the interaction with GenAI tools as easy.

B. Way of addressing users:

When talking about the way GenAI tools address users, the participants talked about the mutuality of this addressing. Alaa said, "AI tools address you as you address them, so you are the one who decides the characteristics of interaction". Thus, the participants believe that the user affects the way of interaction with GenAI tools.

C. Utilization of pre-interaction:

Talking about the utilization of pre-interaction, some participants talked about taking advantage of pre-interaction. Amira said, "AI tools can work from the point you need them to work. They can interact with the content in a pre-interaction". For Amira, utilizing the pre-interaction is an advantage for the discussants.

D. Interaction prompts:

The participants were generally aware of the importance of prompts when working with GenAI tools. Here, they talked about two issues: 'Friendly prompts' and 'introducing oneself'. Ali said, "If you want an AI bot to be friendly with you, you need to be friendly with it. You can do that using prompts. For example, you can say: Hello, how are you? And then ask the question". Walid said, "Introducing oneself to the bot can help the bot better know what you need". Thus, the participants were aware of the impact of prompts, including the way you talk with GenAI tools, on their interaction with the user.

E. Learning from interaction:

Some of the participants talked about improving the bots' responses based on the interaction. Samar said, "Chatbots learn from the interaction with humans and improve their responses depending on this interaction". Samar, here, is aware of machine learning and how it affects the consequences of bot–human interaction.

3.6.3. GenAI Tools and Affect

The participants mentioned the following sub-categories of the category 'GenAI tools and affect': comfort, motivation, belief, values, and attitudes. Below, we describe each sub-category with examples of students' statements.

Comfort

The participants talked about comfort as characterizing their work with GenAI tools. Sana said, "Claude makes one feels comfortable because it helps the person asking in a way or another". Here, Sana explains that GenAI tools positively affect their emotions while learning with these tools.

A. Motivation:

The participants described their motivation to learn using GenAI tools. Walid said, "Gemini can make you enthusiastic to work with because it does not complain when you ask it several questions on the same topic". Here, Walid talked specifically about enthusiasm as an indicator of motivation to work with GenAI tools in order to learn in higher education courses.

B. Belief:

The participants described their beliefs regarding learning using GenAI tools. This included the future of education. Sami said, "I believe that AI tools will be the future of education, especially after the emergence of generative ones". It also included the belief that chatbots would be the most used bots in the future in education. Salam said, "Chat bots are probably the most AI tools that would take part in education, because of their chat property that enables students to argue with them and consult them before taking educational decisions". Thus, the participating students were convinced that GenAI tools, especially chatbots, would have a major role in the future of education.

C. Values:

Talking about values related to their learning with GenAI tools, the participants referred mostly to the value of respect and the value of apology that they believe GenAI tools have. Samira referred to respect as a value that GenAI tools show in their interaction humans. She said, "ChatGPT has the value of respect. It respects this who talks to it, and words that indicate this respect". Amira referred to the value of apology: "ChatGPT has the value of apology when it makes a mistake or even when it is not precise. We humans need to learn this property from it". Thus, the participants expressed valuation of the positive values that GenAI tools show, whether when addressing the user with respect or when making a mistake or producing an inaccurate answer for which they apologize.

D. Attitude:

The attitude of the participants towards GenAI tools included whether they were for or against bots' use in higher education learning. Sami said, "I'm with the implementation of AI technology because it is a promising one". Alaa was not so sure about her attitude towards this use. She said, "I am not sure whether I am for or against bots' use to write my university assignments. Working with it, I saw that it helped me sometimes, but sometimes it gave me wrong answers." Thus, not all the participants had the same attitude towards the use of bots in the educational setting, though none of them expressed refusal of this use.

3.6.4. Intention to Use GenAI Bots

The participants mentioned the following sub-categories of the category 'Intention to use GenAI bots': assisting in problem solving, assisting the conceiving of content and assisting research. Below, we describe each sub-category with examples of students' statements.

A. Assisting problem solving:

Talking about GenAI tools' assistance in problem solving, the participants referred to assistance in performing assignments. Sana said, "I will use Chatbots in my learning. They can assist me in all types of assignments". Thus, Sana intends to use chatbots in her learning because of their ability to support the completion of assignments in general.

B. Assisting the conceiving of content:

Talking about GenAI tools' assistance in conceiving content, the participants referred to these tools' assistance in introducing a specific concept. Amir said, "I will use Claude to give me an introduction to the topic that I want to know". Some students mentioned GenAI tools in general as able to assist them in the conceiving of content. Sana said, "All Generative Artificial Intelligence tools can assist you in conceiving the content you want to learn. This is because they depend on a large amount of data. So, I will keep using them in conceiving content". Thus, it seems that the participating students saw the GenAI tools' ability in content as a powerful property.

C. Assisting research:

Other students mentioned perplexity as a tool that can be trusted in research. Walid said, "Perplexity is advantageous in writing research essays. Though it is in its first steps, I will use it to write such essays". Though Walid is aware that bots are in their early stages, he intends to use them to support his learning. Other students talked about using GenAI tools to obtain guidance for writing literature in a new study. Salam said, "I will use AI to provide me with a direction regarding writing a literature review for my research". Thus, higher education students had a positive intention to use GenAI tools in writing literature essays.

4. Discussion

The present research aimed to study higher education students' perceptions of GenAI tools as learning tools. The research results indicated that the means of affect, interaction, and efficiency were significantly medium, while the mean of intention was significantly high. The previous results could indicate the characteristics of students' perceptions of new technologies such as AI bots. Work with these bots has not yet been established as a tool in higher education, and students are meanwhile practicing and attempting to verify the new tools' potentialities. This explains the medium level of efficiency, interaction, and affect. Still, the students in higher education intend to continue using AI bots in their learning, probably due to the benefits of this use, especially as they know that the potentialities of these bots improve continuously [19].

Ayanwale and Ndlovu [28] reported that there were no direct relationships between perceived usefulness and perceived ease of use, concluding that there were other influencing factors or dynamics in the adoption of chatbots for educational purposes. Here, though the level of students' perceptions of AI bots was medium, their intention to use them was high. Thus, other influencing factors could be involved. We claim that the factors here could be the changing potentialities of AI bots in learning practices.

The research findings showed that in three of the four perception components (efficiency, affect, and intention), male students had significantly higher perceptions of AI tools than female students, but in the interaction component, the two genders did not differ significantly. Tondeur et al. [29] found that women had a less positive attitude towards computers in general, but not towards computers for educational purposes, where the attitude towards computers for educational purposes did not differ significantly due to gender [29]. The present research addressed the educational context of GenAI tools. It agrees with that of Tondeur et al. [29] in one component only. The present results here agree in particular with the results of Tondeur et al. [29] regarding technology in general.

An alternative explanation for the gender differences might be found in the frequency of GenAI bots' use. Nyaaba et al. [30] reported that male pre-service teachers used these tools significantly more often than their female counterparts. This frequent usage could logically lead to more positive perceptions of GenAI tools for learning among male students. This interpretation suggests that exposure to and familiarity with GenAI tools may play a crucial role in shaping perceptions, which potentially explain the observed gender differences in this study.

There was no significant gender difference in how students perceived their interaction with AI bots. This similarity could be attributed to the fact that both male and female students likely use comparable prompts when engaging with these bots. These prompts are often sourced from widely shared online resources, suggesting a standardized approach to bot interaction across genders. Additionally, AI bots are designed to provide consistent feedback across users, which may contribute to the uniform perception of interaction among students of different genders [30].

The research findings showed that the degree variable affected only the perception of interaction of higher education students, where the mean value of interaction was significantly different between B.A. and Ph.D. students in favor of Ph.D. students. This significant difference could indicate that Ph.D. students have richer means of interaction with AI bots. This is especially true as follow-up interactions are needed when learning with GenAI bots [31]. In addition, the results show similar perceptions of AI bots regarding their efficiency and affect, in addition to similar intention to use them in students' learning [32].

The research findings showed that the medium-technology-knowledge and high-technology-knowledge students differed significantly in their perceptions of working with AI tools in the interaction component only, where this difference was in favor of the high-technology-knowledge students. Here too, the findings indicate that higher education students of the two technology knowledge levels perceived similarly the efficiency and affect related to GenAI bots, in addition to similar intention to use these GenAI bots. The significant difference in the perception of interaction indicates that high-technology-knowledge students have richer means of interaction with the GenAI bots. This aligns with Rodrigues et al. [33], who say that students' technological skills are crucial to their personal, social, and professional futures, as well as to the relationships between students, teachers, and institutions.

The research findings showed that AI knowledge significantly affected three perception components (efficiency, interaction, and affect) of higher education students, where multiple comparisons found that the mean value of each of the three components was significantly higher in favor of high-AI-knowledge students over low-AI-knowledge students, as well as in favor of medium-AI-knowledge students over low-AI-knowledge students. Thus, when you are a low-AI-knowledge student, you do not perceive the efficiency, interaction, and affect related to GenAI bots similar to a medium- or a high-AI-knowledge student. Getting more experience in working with GenAi bots can increase your perception of the efficiency, interaction, and affect related to GenAi bots. Rodrigues et al. [33] say that students need knowledge and skills to take advantage of the digital age. Thus, a low level of AI knowledge would negatively affect students' perceptions of them. Moreover, the previous results are in line with studies that highlight students' ability as needed in educational settings to achieve the learning goals (ex., [34]).

The qualitative results enabled the investigation of specific incidences of higher education students' perceptions related to the use of GenAi in their learning. These incidences showed the reasons behind students' perceptions. For example, students feel comfortable because they perceive GenAi bots as helpful in one way or another. They feel enthusiastic to work with GenAi bots because they perceive their ability not to complain when you ask them several questions on the same topic. Moreover, the students addressed different aspects of affect in learning by talking about issues related to learning emotions, attitudes, beliefs, motivation, and values, which agrees with previous studies that showed students' involvement with the different aspects of learning with technology [35–37].

5. Conclusions, Recommendations, and Limitations

The present research intended to study students' perceptions of GenAI tools for learning, where these perceptions included four components: students' efficiency, interaction, affect, and intention. The research findings showed that the mean of affect, interaction, and efficiency was significantly medium, while the mean of intention score was significantly high. Together, these findings show that there is room to increase students' affect, interaction, and efficiency. This increase could be obtained through different means. For example, instructors can increase them by discussing with the students their utilization of GenAI tools, so the students develop their skills in how to utilize those tools effectively and efficiently. This utilization is expected to increase their perceptions of the GenAI tools.

The research findings also showed that each background variable affected part of the components (efficiency, affect, and intention), so we need to take these background variables into consideration when planning the use of GenAI tools in educational settings. The present research was not interested in the age of students as a background variable, so future research is requested to find how this variable affects students' perceptions of GenAI tools for their learning.

A potential limitation of this study is the gender imbalance among participants, with female students outnumbering male students by nearly 2:1. While we have provided an explanation for this disparity, future research should strive for an equal gender representation to enhance validity.

Although overall saturation was achieved, the qualitative component of this study is limited by the small sample size from each academic discipline. Future research should focus on achieving saturation within each specific discipline when examining higher education students' perceptions of GenAI tools, which will provide more robust discipline-specific insights. In addition, future research can utilize focus group discussions as another qualitative collecting tool. This utilization will enrich the validity of results through the critical discussion in the groups [38].

To conclude, future studies should investigate GenAI perceptions among specific sub-populations, defined by individual background variables and their intersections (e.g., female higher education students in humanities). This approach would yield more nuanced, population-specific findings, providing a stronger foundation for understanding students' perceptions of GenAI tools within these distinct groups.

The qualitative data revealed themes, such as motivation, values, beliefs, and attitudes in the affect category. The theoretical framework we adopted did not explicitly address all of these categories. Future research is needed to incorporate these emergent themes into a new questionnaire, enhancing the measurement of students' perceptions of GenAI tools in university learning.

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