education sciences

MDPI

Article

University Teachers' Views on the Adoption and Integration of Generative AI Tools for Student Assessment in Higher Education

Abstract: This study examines the factors that may impact the adoption of Generative Artificial Intelligence (Gen AI) tools for students' assessment in tertiary education from the perspectives of early-adopter instructors in the Middle East. Utilizing a self-administered online survey and the Unified Theory of Acceptance and Use of Technology (UTAUT) model to collect data from 358 faculty members from different countries in the Middle East. .Smart PLS software was used to analyze the data. The research identifies significant factors, namely performance expectancy, effort expectancy, social influence, and hedonic motivation in shaping educators' behavioral intentions and actual use of Gen AI tools to assess students' performance. The findings reveal both the potential advantages of Gen AI, namely enhanced student engagement and reduced instructor workload, and challenges including concerns over academic integrity and the possible negative impact on students' writing and thinking skills. The study emphasizes the significance of targeted professional development and ethical criteria for the proper integration of Gen AI in educational assessments.

Keywords: Assessment; AI literacy; AI in education; higher education

I miss into about RQ1 and RQ2

This manuscript is in a draft format

1. Introduction

Educators' interest in Generative Artificial Intelligence (Gen AI) has grown significantly (Stokel-Walker, 2022), particularly since OpenAI released ChatGPT3 in 2022. This is primarily due to of the tools' capacity to generate writings that resemble those produced by humans to the extent that texts generated by AI are hard for even specialists to recognize (Casal & Kessler, 2023). Furthermore, students have rapidly adopted Gen AI tools in their writings (Moorhouse et al., 2023).

Opponents of integrating Gen AI in education have expressed their concerns regarding the validity of assessments, particularly with respect to academic honesty and plagiarism (Swiecki et al., 2022; Hamamra et al. 2024). Students' use of AI tools to complete their assignments (Chan, 2023) could compromise academic integrity and eventually undermine the reputation of academic institutions. Furthermore, academics contend that if students rely too much on GAI, it might hinder the development of their writing and critical thinking abilities (Warschauer et al., 2023; Hamamra et al. 2024) and negatively impact the quality of instruction and learning outcomes for students (Chan & Lee, 2023).

Nevertheless, some academics argues that Gen AI can have positive effects on schooling (e.g., Chiu, 2023; Kohnke et al., 2023). For example, Mate and Weidenhofer (2021) point out that Gen AI can boost student participation in assignments, provide prompt feedback, facilitate collaboration, and make learning more accessible. One major advantage is the capacity to offer prompt and insightful feedback through automated marking. Similarly, Celik et al., 2022) found that Gen AI tools could assist educators in identifying and meeting their students' needs, as well as in automatic essay scoring and instantaneous student feedback, thereby reducing instructors' workload. Zhai and Nehm (2023) argue that the discussion about Gen AL should center on how to use these tools instead of whether to use them. This is because many teachers are already using AI to aid formative assessment in various educational settings (Gerard & Linn, 2016; Lee et al., 2021).

To persuade instructors and professors who doubt the validity of using Gen AI in student assessment in higher education, it is essential to examine the factors that may influence their decisions. Therefore, the purpose of this study is to explore the factors that influence higher education instructors' use of Gen AI in assessing students from their perspective.

2. Research problems

The rapid advancement of Gen AI technologies has sparked considerable interest among educators regarding their potential applications in tertiary education, especially in student assessments. However, the adoption of Gen AI tools in educational assessments is fraught with challenges and controversies. Critics worry that the use of artificial intelligence (AI) in assessments may jeopardize academic integrity, leading to increased instances of plagiarism and reducing the reliability of assessment outcomes (Swiecki et al., 2022; Chan, 2023). Furthermore, there are concerns that reliance on Gen AI could impair students' writing and critical thinking skills, and degrade the quality of instruction and learning outcomes (Warschauer et al., 2023; Chan & Lee, 2023).

Despite these concerns, proponents highlight the benefits of Gen AI, such as enhanced student engagement, timely feedback, and reduced instructor workload, which can make learning more accessible and personalized (Mate & Weidenhofer, 2021; Celik et al.). Given these opposing viewpoints, it is vital to explore the factors impacting the acceptability and usage of Gen AI tools in higher education from the perspective of educators. This study seeks to fill this gap by investigating the constructs that influence the acceptance of Gen AI for student evaluation, providing insights that might assist define policies and approaches for effective implementation of AI in schools and universities.

2.1. Research purpose

The goal of this study is to investigate the constructs that may influence the use of Gen AI in assessing students in university settings, as seen through the viewpoints of early adopter educators in higher education institutions. Moreover, this study provides a structural relationship between these constructs by using PLS-SEM analysis of the retrieved data from the potential participants.

2.2. Contribution of the study

This study makes a significant contribution to the field of educational technology by empirically examining the factors influencing the adoption of Gen AI tools for students' assessment in higher education. Utilizing the Unified Theory of Acceptance and Use of Technology (UTAUT) model, the research validates the critical roles of performance expectancy, effort expectancy, social influence, and hedonic motivation in shaping educators' behavioral intentions and actual usage of Gen AI. By highlighting the moderating effect of professors' experience, the study provides nuanced insights into how familiarity with technology impacts its adoption.

Moreover, the research addresses both the benefits and challenges of integrating Gen AI, offering practical implications for educators, institutions, and policymakers to enhance the effective and ethical use of AI in educational assessments. These findings lay the groundwork for future studies to explore long-term impacts, diverse contexts, and the development of robust frameworks for the ethical use of Gen AI in education.

3. Literature review

Writing exams and assessments for students is an integral part of the teacher's job. It is often a boring, time-consuming, and tiresome process that requires follow-up work that involves correcting these tests and monitoring and checking students' grades. With the development of AI techniques, it has become possible to rely on generative multiple-choice question tools to complete all that tedious work. Recent studies show that AI is

transforming how students are assessed, making the process more personalized, efficient, and effective (Hooda et al., 2022; Braiki et al., 2020; Chen et al., 2020; Gardner et al., 2021; González-Calatayud et al., 2021; Talan & Kalinkara, 2023).

3.1. Assessment in tertiary education

In tertiary education, assessment and feedback serve as pivotal elements of education, influencing a diverse array of stakeholders, including students, faculty, and administrative personnel. Assessment and feedback not only augment students' grading proficiency, motivational engagement, and academic performance but also facilitate enhanced learning trajectories (Gamage et al., 2023; Heywood, 2000; Pereira et al., 2016; Umar & Majeed, 2018). Many studies highlight the transformative impact of assessment on the pedagogical outcomes of students within tertiary educational settings. Assessment and feedback have moved beyond a student-centered focus to encompass elements such as curricular frameworks, pedagogical methodologies, and administrative mechanisms. These assessments are critical to elevating student academic outcomes and are integral to their subsequent academic and professional achievements (Umar & Majeed, 2018).

Diagnostic, formative, summative, and electronic assessments are among the assessment types used in higher education, with self-evaluation and peer assessment being common as well. The proper assessment type is determined by the course's specific educational objectives and expected learning outcomes. Formative assessments, or "assessment for learning," are implemented throughout the educational process, whereas summative assessments, or "assessment of learning," are typically administered at the culmination of educational activities (Jacoby et al., 2013; Svensäter & Rohlin, 2023).

Traditionally, evaluations in higher education have generally focused on the retention and application of knowledge within narrowly defined contexts, typically measured through conventional examinations and academic tasks like term paper composition. These assessment methodologies are fundamental to instructional strategies that furnish feedback, thereby allowing both students and educators to refine ongoing teaching and learning processes to better achieve intended instructional outcomes. Moreover, educators are increasingly adopting cognitive analytics as a foundation for robust e-learning evaluations, thereby enabling learners to substantially improve their academic performance (Chen et al., 2023)

Assessment involves collecting and analyzing students' exams and work according to a certain criterion and rubric so as to make judgments. Assessment or evaluation is an essential component of education, closely linked to learning, teaching, and curriculum, and plays a critical role in generating successful learning outcomes and increasing student satisfaction. In many Arab nations where students care about passing their tests that are centered on memorization and rote learning, assessment is the most essential aspect of their study (Hamamra et al., 2021). Because assessment is so important in education, many studies have looked into the characteristics of assessments, including both summative and formative assessments, and how they affect students' learning performance, motivation, and learning quality (Holmes, 2018; Sharma et al., 2016). Moreover, research on peer and self-assessment has highlighted that these methods enhance students' skills, their participation, and eventually their academic excellence.

Summative evaluation analyzes students at the end of a course by summarizing both their learning and teaching experiences. This assessment method provides critical feedback on student achievements during the course, using grades, projects, term papers, and standardized tests (Mahshanian et al., 2019). The advantages of summative assessment include (1) assisting instructors in minimizing errors, (2) enhancing their ability to correct mistakes, (3) offering dependable data such as grades and mid-term marks for accountability purposes among various stakeholders, including learners, teachers, and administrators in higher education, and (4) aiding in the development of educational strategies such

as curriculum or funding departments (Kincal & Ozan &, 2018). Traditionally, higher education institutions have relied on summative assessments to gauge student learning outcomes (Fischer et al., 2024).

The integration of generative AI tools into higher education assessment practices has sparked discussions on adapting traditional assessment strategies. Educators and students have different attitudes toward the use of AI in assessments, with educators favoring tailored assessments that promote critical thinking and questioning. In contrast, students expressed concerns about the potential lack of creativity (Smolansky et al., 2023). Studies have shown that AI-generated content, such as that from GPT-4, poses challenging situations in detecting academic misconduct, highlighting the need for improved AI detection tools and enhanced awareness amongst faculty and students (Mills et al., 2023; Tenakwah et al., 2023). To address these challenges, there is a call for adjustments in assessment strategies to enhance resistance against AI tools, the incorporation of AI-inclusive assessments, and the implementation of comprehensive training programs for both faculty and students (Perkins et al., 2023).

Assessment is a vital method in education, providing valuable statistical information for students, parents, educators, and policymakers to track progress, regulate efforts, and make knowledgeable decisions (Magdalena et al., 2023; Sievertsen, 2022). It is crucial for making choices based on data, demonstrating worth, and highlighting the impact on student achievement (Lundquist & Kelly, 2022). Nevertheless, challenges such as inadequate data accuracy and contested data might impede the assessment process. Assessment provides information to students, parents, educators, and schools on the progress of learning, which helps guide study efforts and course choices (Sievertsen, 2022). Assessment in college and university settings promotes learning and generates formal records of achievement by utilizing grading frameworks such as norm-referenced and criterion-referenced (Allen, 1992; Sarkar, 2012). The development of assessment systems, legislation, and policies in education, as well as the incorporation of international assessment systems, highlights the significance of assessment in enhancing the quality and outcomes of education. Effective assessment design is essential for impacting students' future lives and professional careers (Allen, 1992).

This sentence is confusing OL something is missing

AI tools offer significant advantages in educational assessment. They help students monitor their learning AI tools offer significant advantages in educational assessment. They help students monitor their learning progress and prepare for tests, while also enabling teachers to efficiently create, correct, and give feedback on assessments. There is apprehension that AI may undermine traditional forms of evaluation, like essay writing, because AI tools can generate high-quality written content that performs well in standardized settings (Hamamra et al. 2024). To mitigate these concerns, students could be tasked with correcting or improving texts generated by AI, which not only tests their understanding but also engages them in critical thinking. These methods guarantee that AI instruments are employed to supplement, not to replace, the teaching process. It is also critical to understand the limitations of AI, which include the potential for "hallucinations" and erroneous information to be produced. Instructors must create exams that not only make good use of AI, but also push students to think critically and use their knowledge in novel ways. This is especially important in fields like language and literature courses, where the content is subjective and creative.

3.2. Evolution of AI in education

Artificial Intelligence (AI) has significantly changed education since it was first developed in 1956 (Sanabria-Navarro et al., 2023). It offers tailored solutions to enhance student learning, while improper usage might have detrimental effects (You et al., 2023). While many contend that artificial intelligence (AI) has the potential to replace human educators, others maintain that human educators are irreplaceable because to their unique qualities, such as creativity and critical thinking (Chan & Tsi, 2023). Therefore, it is essen-

tial to integrate AI effectively without seeing it as a substitute for providing a comprehensive learning experience (McCalla, 2023). Moturu & Nethi (2023) argued that AI applications are increasingly essential in education, aiming to personalize learning experiences, make them effective, focus on output, promote integration, and foster long-term retention. The integration of AI in education is directly linked to advancements in educational methodologies, underscoring the importance of AI-based e-learning applications in revolutionizing the educational environment.

Significant progress has been made in student-facing systems, personalized adaptive learning, automatic grading, and teacher feedback thanks to AI in education over the last 30 years. The integration of AI with cutting-edge technologies like the Internet of Things and immersive technology is essential to the future of AI in education (Tan, 2023). Undergraduate nursing education currently incorporates artificial intelligence simulations (Lebo & Brown, 2024). By using this technology, students will have the opportunity to engage with a virtual patient that is constantly changing as they advance through the curriculum, beginning with essential skills.

3.3. Using AI in student's assessment

Many academics have noted that the COVID-19 epidemic has greatly increased the acceptance of asynchronous and remote learning approaches (Lockee, 2021). Such approaches are at the forefront of the ongoing digital revolution in education (Khlaif, Mousa, et al., 2023). . Artificial intelligence has resulted in the creation of innovative tools with the capability to revolutionize various aspects. A notable example is GPT-3, which has demonstrated its ability to create educational materials, debug software, and compose detailed texts that rival the quality of human writing (Sharples, 2022).

The definition of AI varies depending on the context, but it generally refers to machines' ability to execute tasks that would normally need human intelligence. Some scholars define it as the intelligence demonstrated by computers and programs to mirror human mental capacities and work habits, such as the ability to learn, infer, and react to unprogrammed conditions. Furthermore, it is the name of an academic discipline that studies how to develop programs and computers that are capable of exhibiting intelligent behavior.

Education is not an exception to the growing presence of AI in many spheres of society. AI in education started in 1960 when computers were brought into classrooms to handle administrative duties including scheduling, record-keeping, and evaluation (Doroudi, 2023). It has been improved over many years to help teachers assess students and determine their strengths and weaknesses more effectively. With the tremendous development brought about by the Internet, educational chatbots that support artificial intelligence have recently emerged. They can simulate learners and answer all their queries. This resulted in the development of individualized learning algorithms that are tailored to the needs of each individual learner.

Artificial Intelligence contributed to minimizing the administrative burdens on the educational system. It helped in creating tables and records and therefore improved the process of distributing tasks. This can develop the curriculum and provide academic content for learners in accordance with their needs and capabilities. It also prepares tests and corrects questions, as in most universities that adopt distance learning, where the learner answers random questions from a bank of questions covering all aspects of the subject, whether the questions are multiple-choice or essay questions. In addition, learners can also have access to recorded lectures of their courses at any time and with the least effort. This also comes with instant translations that the learner can use in any language to avoid difficulties in receiving and understanding the information. All these advantages have contributed to creating a more advanced educational system where the learner does not feel overwhelmed and tired, leading to higher levels of productivity. In general, AI can transform education into a more effective and interesting experience in the future.

The transition from traditional, in-class education to an online mode of learning has sparked concerns regarding student evaluation, which remains a core aspect of e-learning. Previously, in-class evaluations were conducted using conventional methods such as paper-based exams, which required extensive effort and time from educators to prepare, administer, correct, and archive. These traditional methods often fell short of achieving educational objectives, particularly those involving technology. In contrast, the modern digital era, with its advancements in Gen AI technologies, has enhanced the educational process for both teachers and students. While AI tools have significantly aided in meeting diverse educational needs, it is crucial to view them as supplements rather than replacements.

3.4. The potential of Gen AI in assessment

Assessing knowledge stands as a crucial component of the educational journey, offering quantifiable insights into the knowledge acquired by learners. It highlights areas needing improvement, thereby facilitating positive reinforcement, and motivating students to excel further. Technological advancements have revolutionized not just dynamic teaching and learning methodologies but also the conventional approach to examinations. Traditional pen-and-paper tests are increasingly giving way to automated online assessments, which are more inclusive, accessible, and precise. Furthermore, these automated examinations encapsulate the refined best practices in evaluation and testing that have evolved over time.

3.5. The factors influencing the usage of Gen AI in students' assessment

Scholars have pinpointed assessment as a key domain where AI and related technological advancements hold substantial promise for educational innovation (Swiecki et al., 2022; Zhai & Nehm, 2023). Nonetheless, the broad adoption of AI is not without its challenges, introducing both practical and ethical issues that must be addressed (Khlaif et al., 2023).

Student perceptions considerably influence the usage of Gen AI in assessments in higher education. Students have a positive opinion regarding Gen AI, recognizing its potential for individualized learning support, writing aid, and research capabilities (Smolansky et al., 2023). Furthermore, the intention to use Gen AI correlates positively with perceived value and negatively with perceived cost. Concerns regarding accuracy, privacy, ethical issues, personal growth, and societal values also influence students' desire to use Gen AI tools (Chan & Hu, 2023; Chan & Zhou, 2023). Educators and policymakers must evaluate these elements in order to appropriately customize Gen AI technologies, address student concerns, and promote responsible assessment integration, thereby improving teaching and learning experiences in tertiary education (Bulut & Wongvorachan, 2022).

3.6. Proposed model of the study

Based on the discussion in the previous sections and the framework of this study UTAUT2, the researchers developed the proposed model (figure 1).

You need a more detailed description of the relations between construct of the proposed model and about Moderator construct (ExP).

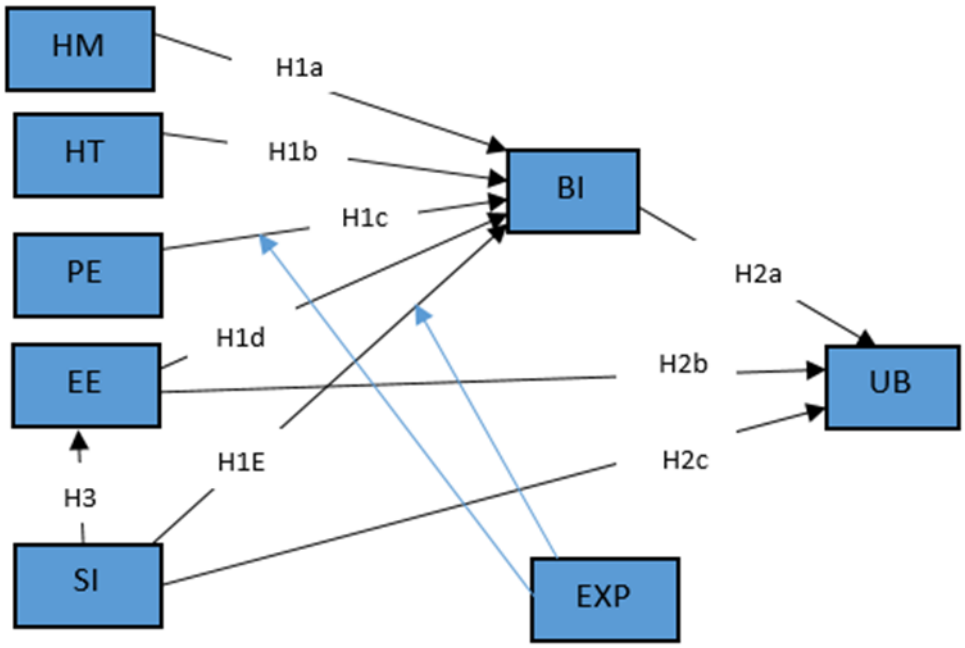


Figure 1. Proposed model.

3.6. Context of the study

The current study was carried out in a number of Middle Eastern higher education institutions. We recruited participants who were early adopters of using Gen AI in teaching. A snowball technique was used to recruit the potential participants for this study based on predefined conditions, including using different Gen AI applications for teaching, using these tools frequently in his/her courses, and using these tools in assessing student work/assignments. Therefore, the present investigation focuses on the following research questions:

RQ1: How do teachers in higher education institutions use Gen AI to assess their students' performance?

RQ2: What are the factors that drive instructors to use Gen AI in assessing students' performance in higher education institutions from teachers' perspectives?

RQ3: What is the relationship among these drives to use Gen AI in assessing students' performance?

This is missing in Abstract

4. Methodology

4.1. Participants

The participants of this study were faculty members who were teaching in higher education institutions in in the Middle East. We devised a set of criteria for recruiting participants to ensure that our study includes a broad and relevant group of participants from various universities, which will enrich the insights and increase the application of the study's findings. Participants in the current study had to be instructors in a higher education institution, have experience and familiarity with Gen AI tools, have used AI tools in teaching their courses, be early adopters of Gen AI technology, come from various fields and universities, and have attended professional development workshops on integrating Gen AI applications into teaching settings. Based on the proposed criteria, the total participants in the current study were 358 instructors (47.2% female and 52.8% male). The participants from the social sciences were 34% of the total participants, the natural and engineering sciences were 41%, and the medical sciences were 25%.

4.2. *Open-ended questions data analysis*

We consider participants' responses to the open-ended questions as qualitative data, which we utilized to address the first and second research questions. To address the first question, we conducted an inductive thematic analysis, following the six-step methodology proposed by Braun and Clarke (2006). This process involved conducting and recording 10.5 hours of interviews. Prior to analysis, we cleaned and organized the responses. Qualitative data analysis during this phase was guided by the six phases of thematic analysis outlined by Braun and Clarke (2006) (Figure 2).

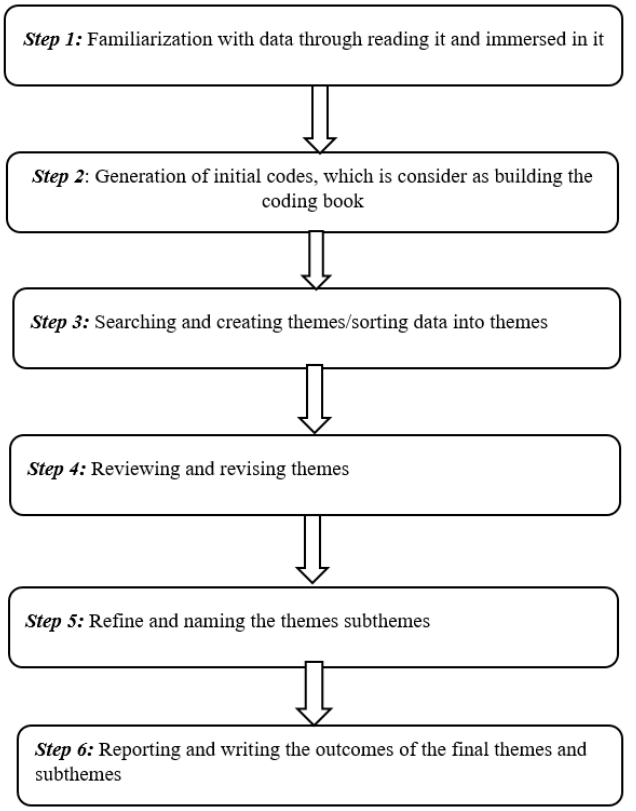


Figure 2. The six steps that guided the qualitative data analysis process.

4.3. *Translation Process*

Because the survey items and participants' responses to the open-ended questions were in Arabic, the researchers employed a conceptual equivalence translation method combined with a back-translation approach to ensure the accuracy and reliability of the translated themes and survey items. Initially, the survey items, quotations, and themes were translated from Arabic to English by a first translator. The researchers then meticulously reviewed these translations to identify and correct any errors or technical inaccuracies. This review process was crucial for addressing potential misunderstandings related to technical concepts, ensuring that the translated content faithfully represented the original material.

Following this initial translation, the researchers implemented the back-translation technique. The English version of the quotations, themes, and survey items were given to a second translator who was not privy to the original Arabic content. This second translator then translated the English text back into Arabic. The purpose of this step was to evaluate the consistency and conceptual equivalence between the original Arabic text and the back-translated version.

Upon receiving the back-translated Arabic version, the researchers conducted a detailed comparison with the original data and survey items. This comparison focused on

ensuring that the meaning and concepts conveyed in the translations aligned with the original content. The results showed a high degree of agreement, with a 93% match between the translated and original versions. This high level of similarity indicated that the translations were conceptually equivalent and accurately reflected the intended meaning of the survey items.

Due to time constraints and the substantial agreement observed between the translations, the researchers decided not to convene a panel of translation experts for further validation. The rigorous review and back-translation processes were deemed sufficient to ensure the quality and accuracy of the translations, allowing the researchers to proceed with confidence in the reliability of the translated survey items.

4.4. *Research instrument*

A quantitative approach was used to achieve the purpose of this study by using a self-administered online survey. The research tool was composed of closed-ended questions based of Likert scale and open-ended questions. The researchers developed a survey (See Appendix A) based on the findings of previous studies.

We developed a survey based on the findings of previous studies and the UTAUT model with slight changes to meet the context of this study. The selected items were adopted from previous studies used to develop the survey (See Table1).

Table 1. Measurement scale.

Construct	Item	Items	Source
Performance expectancy	PE1	"I believe that Gen AI is useful in assessing students assignments"	(Venkatesh et al., 2012)
	PE2	"Using Gen AI increases my chances to evaluate my students assignments professionally"	
	PE3	"Using Gen AI helps students get tasks and projects done faster"	
	PE4	"Using Gen AI increases students' productivity in their assignments"	
Effort expectancy	EE1	"Learning how to use Gen AI in assessment is easy for me"	Venkatesh et al. (2003)
	EE2	"My interaction with Gen AI is clear and understandable"	
	EE3	"I find Gen AI easy to design rubrics for assessing my students' projects"	
	EE4	"It is easy for me to become skillful at using Gen AI in "	
Social influence	SI1	"People who are important to me think I should Gen AI in assessment"	Kandoth, & Shekhar (2022)
	SI2	"People who influence my behavior believe that I should use Gen AI"	
	SI3	"People whose opinions I value prefer me to use Gen AI for students assessment"	
Facilitating conditions	FC1	"I have the resources necessary to use Gen AI in assessing my students"	(Venkatesh et al., 2012)
	FC2	"I have the knowledge necessary to use Gen AI for students' assessment"	
	FC3	"Gen AI is compatible with technologies I use in teaching"	

	FC4	"I can get help from others when I have difficulties using Gen AI"	
Hedonic motivation	HM1	"Using Gen AI for assessment is fun"	(Venkatesh et al., 2012)
	HM2	"Using Gen AI for assessment is enjoyable"	
	HM3	"Using Gen AI for assessment is very entertaining"	
Price value	PV1	"Gen AI is reasonably priced"	Gansser et al., 2019
	PV2	"Gen AI is good value for the money"	
	PV3	"At the current price, Gen AI provides a good value"	
Habit	HT1	"The use of Gen AI for students' assessment has become a habit for me"	(Venkatesh et al., 2012)
	HT2	"I am addicted to using Gen AI in teaching and assessment"	
	HT3	"I must use Gen AI for students' assessment"	
	HT4	"Using Gen AI for assessment has become natural for me"	
Behavioral Intention	BI1	"I intend to continue using Gen AI for assessment in the future"	(Venkatesh et al., 2012)
	BI2	"I will always try to use Gen AI in my teaching and assessment"	
	BI3	"I plan to continue to use Gen AI for assessment frequently"	
Personal innovativeness	PI1	"I like experimenting with new information technologies"	(Agarwal & Prasad, 1998; (Floruss & Vahlpahl, 2020)
	PI2	"If I heard about a new information technology, I would look for ways to experiment with it"	
	PI3	"Among my family/friends, I am usually the first to try out new information technologies"	
	PI4	"In general, I do not hesitate to try out new information technologies"	
Use Behavior	UB1	"Please choose your usage frequency for Gen AI: 1. Never; 2. Once a month; 3. Several times a month; 4. Once a week; 5. Several times a week; 6. Once a day; 7. Several times a day"	(Venkatesh et al., 2012)

5. Results

5.1. RQ1: How faculty members in higher education institutions use Gen AI for assessing students' performance?

In their responses the participants focused on two main themes. The first one was about their procedures to get high quality assignments and assessment through their dialogue with Gen AI and the second theme was about strategies to use Gen AI in assessing students performance. Below more description about these findings:

5.1.1. Procedures for using Gen AI to generate assignments and ways to assess students

Based on the analysis of participants' responses to open-ended questions, various procedures were identified for obtaining high-quality outputs from Generative AI (Gen AI) applications in generating assignments and assessing students' performance. The participants described a range of approaches, which were not uniform across the board. Each participant utilized a different set of steps to achieve their goals, indicating the diversity in strategies and techniques employed.

The researchers organized and synthesized these varied approaches into a cohesive flowchart (see Figure 3). This flowchart serves as a guide, outlining the essential steps that educators can follow to optimize the use of Gen AI applications in their teaching practices. The process begins with a deep understanding of the context in which the AI will be used, followed by the careful crafting of prompts to generate relevant and high-quality responses. Participants emphasized the importance of revising and iterating on these prompts to to continually improve the quality of the generated outputs.

Moreover, the evaluation of responses was a critical step, involving assessing the quality and relevance of the AI-generated content. This process includes determining the effectiveness of the AI in meeting the educational objectives and adjusting the prompts or approaches as necessary. The flowchart highlights the iterative nature of this process, encouraging educators to continually refine their methods.

Finally, the participants' approaches culminated in the practical application of the generated content, whether for assignments or assessments. The use of Gen AI applications in this context requires not only technical proficiency but also a nuanced understanding of how to integrate these tools into pedagogical practices effectively. The resulting flowchart provides a valuable resource for educators and researchers, offering a structured framework to harness the potential of Gen AI in educational settings.

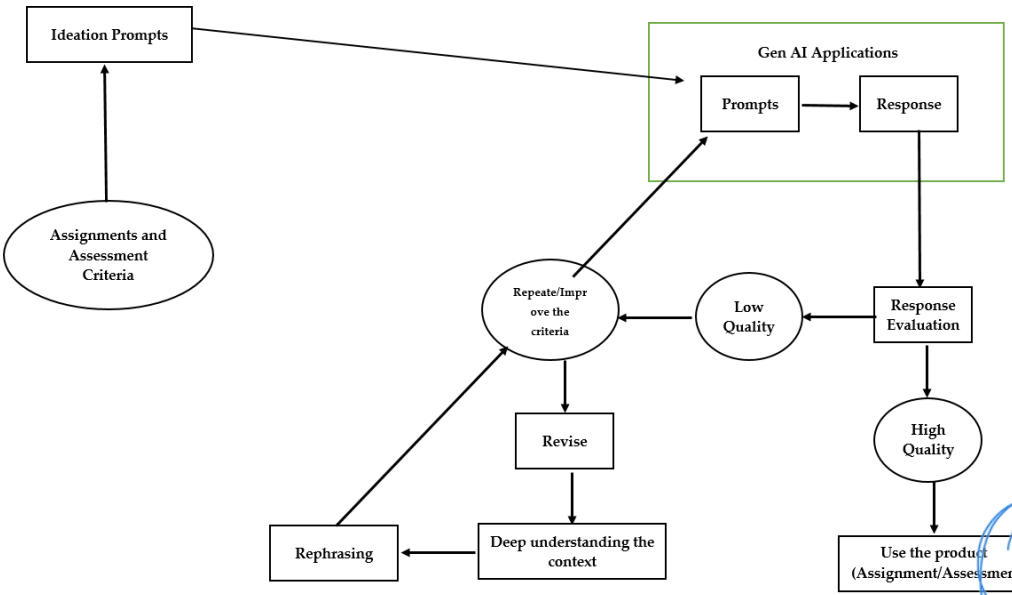


Figure 3. Flowchart of procedures as reported by the participants.

The participants in this study identified various strategies for integrating Gen AI into their assessment practices. Their responses varied based on their teaching fields, experience with technology, and institutional policies on using Gen AI. The strategies they shared reflect their understanding of Gen AI's capabilities and how to incorporate them into their assessments to promote fair, authentic, and inclusive practices.

5.1.2. Categorizing assignments in the Gen AI Era

The researchers categorized the responses of the participants in terms of the type of assignments into three themes, including assignments without Gen AI, Gen AI assisted assignments, and Gen AI empowered assignments. These types of assignments emerged based on the development of Gen AI in teaching and learning, as reported by most of the responses of the participants.

5.1.3. Assignments without Gen AI

In this type of assessment, as described by the responses of the participants, students were not allowed to use any type of Gen AI applications. Some of the assessment tools are in-person exams, oral exams, practical applications, and final presentations. A Professor in nursing said that "In the course description, I informed my students where they can use Gen AI and where they cannot use it. So already they know in exams and oral presentations they are not allowed to use it".

5.1.4. Gen AI assisted assignments

The second type of assignment is using Gen AI as an assistant for students. Students can use it to generate ideas for their assignments and teamwork projects and can use it for brainstorming but must write the final text themselves. This type of assignment is to develop their skills and critical thinking, especially while critiquing the ideas generated by the Gen AI applications. A professor in computer engineering wrote that "allowing students to use ChatGPT or any generated application enhances the learning ethics of AI and its literacy. My students were not allowed to copy and paste the ideas; I requested that they critique and develop the materials, and also include the generated text as an appendix in the final project."

In addition, some faculty members reported using these tools to generate assignments for their students. An assistant professor in social sciences emphasized that, "I used generative AI to create project-based assignments, saving time by providing the tool with criteria and the final outcome".

5.1.5. Gen AI empowered assignments

In this type of assignment, as reported by the participants in their responses to the open-ended questions, students were allowed to create everything in their assignments, focusing on critical thinking and problem solving. All students had to write a reflection paper about their project and their experience with Gen AI in completing the assignments. An IT professor wrote that "students are allowed to fully integrate Gen AI into their assignments, but they are also required to write a reflection paper on their experience using it." Another professor in humanities wrote that "using Gen AI to empower students in the assignment will make them lazy and depend on it in the future. I do not like to use it in this way; my idea is that educators use it only for assessment, teaching, and scientific research."

5.1.6. Utilizing Gen AI in assessing students' performance

The majority of the participants in this study confirmed in their responses to the open-ended question that they use different Gen AI applications to generate various types of exam questions, such as false/true questions, multiple questions, and short essay questions. For example, a professor Biology said: "I used ChatGPT-4 to generate multiple-

choice questions for my courses and shared the presentations online, making slight changes to the generated questions. Students were not allowed to use any Gen AI during the exam".

Some participants mentioned challenges such as accuracy and redundancy in AI-generated questions. "When I use Gemini to generate multiple-choice and true/false questions, I notice high similarity in questions. These tools are not professional enough to generate exams," wrote an assistant professor in IT.

5.1.7. Utilizing Gen AI for assignments and rubric design

Many participants used Gen AI tools to design assignments and create grading rubrics, aiming to ensure fairness and accurately assess students' knowledge and skills. A professor in computer engineering noted that "I used these tools to generate ideas for my assignments to ensure fairness and make sure my students complete the assignment without Gen AI assistance".

5.1.8. Grading handwritten assignments

Some participants reported using ChatGPT-4 for grading-handwritten assignments. They defined criteria for assessing students' work and reviewed AI-generated feedback to ensure its suitability. "I used ChatGPT-4 to grade students' work and provide feedback, usually reviewing and modifying the feedback", said a faculty member in educational sciences. Another mentioned that tools like "GradeScope" combined with ChatGPT can save time and effort, especially during the busy end-of-semester grading period".

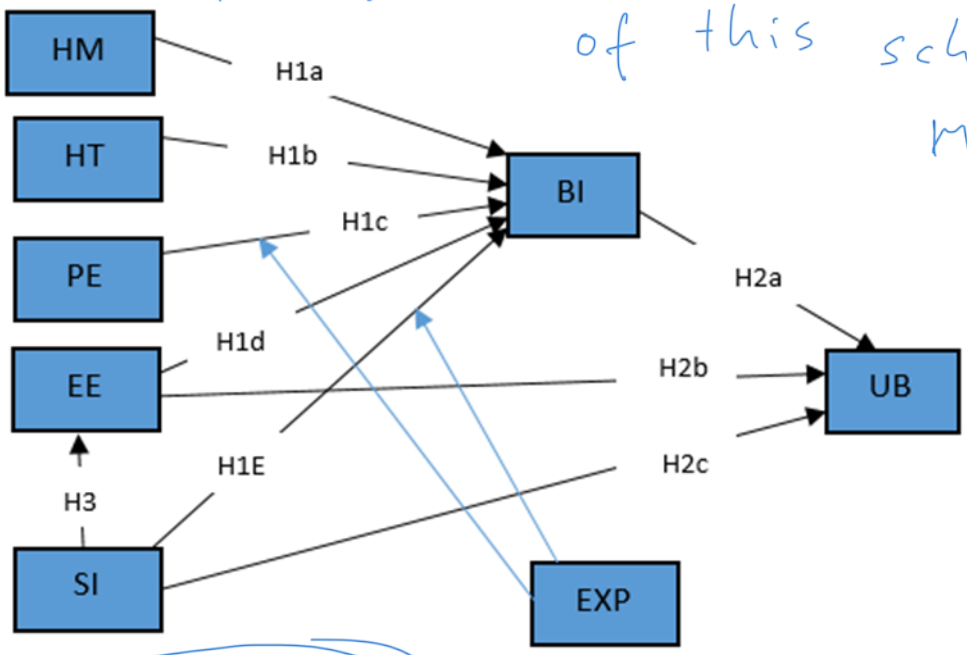
5.1.9. Generating varied assignments

Participants highlighted the power of Gen AI to create diverse assignments, including images, text, and videos. "I used it to generate assignments with audio, video, and images. You just need to know how to use it to generate assignments based on your teaching style", explained an assistant professor in electronics.

5.2. RQ2: What are the factors that drive instructors to use Gen AI in assessing students' performance in higher education institutions from teachers' perspectives?

The researchers utilized both qualitative and quantitative data to address the second question in this study, which aimed to explore the factors influencing educators' adoption of Gen AI for assessing students' academic performance. The analysis of the open-ended responses revealed several factors affecting educators' use of Gen AI in assessment, including institutional policies, Gen AI application features, pricing considerations, and integration with learning management systems (LMS). Furthermore, the researchers identified the main survey themes as additional factors that could influence the adoption of Gen AI in student assessment.

5.2.1. Smart PLS analysis / PLS-SEM Analysis?



5.2.2.

~~**Figure 1.** Proposed model.~~

~~4.3.~~ *Model estimation*

We assessed the reflectively specified constructs by analyzing the indicator loadings (Table 2). An indicator loading greater than 0.7 indicates an acceptable level of item reliability.

Validity and construct reliability are established as part of the measurement model assessment. Composite reliability (CR) and Cronbach's alpha were utilized to establish construct reliability. Table 3 displays the participants sample's construct reliability and convergent validity. For every construct, the Cronbach alpha values and CR exceeded the suggested threshold of 0.7 (Hair et al., 2022). Convergent validity is supported by the constructs' Average Variance Extracted (AVE), which was more than 0.5 (Sarstedt et al., 2022). The Goodness of Fit (GoF) for the overall hypothesized model was 0.69, confirming that the model met Heseler & Sarstedt's (2013) global criteria of 0.3.

Table 2. Item loadings.

Construct	Item	loading
Behavioral intention	BI1	0.96
	BI2	0.96
	BI3	0.97
Effort expectancy	EE1	0.96
	EE2	0.95
	EE3	0.96
	EE4	0.96
Hedonic motivation	HM1	0.97
	HM2	0.97

	HM3	0.98
	HT1	0.93
	HT2	0.9
Habit	HT3	0.92
	HT4	0.95
	PE1	0.96
	PE2	0.97
Performance expectancy	PE3	0.97
	PE4	0.95
	SI1	0.95
Social influence	SI2	0.93
	SI3	0.94
Use behavior	UB	

Table 3. Reliability and convergent validity.

Construct	Cronbach's α	CR	AVE
Behavioral intention (BI)	0.96	0.96	0.92
Effort expectancy (EE)	0.97	0.97	0.92
Hedonic motivation (HM)	0.97	0.97	0.95
Habit (HT)	0.95	0.96	0.86
Performance expectancy (PE)	0.97	0.97	0.93
Social influence (SI)	0.94	0.94	0.88

To assess the discriminant validity of PLS-SEM, we use the Fronell-Larcker criterion and HTMT. Fronell-Larcker states that a construct's square root of the average variance it extracts must be larger than the correlation it has with any other construct. Fornell, C., & Larcker, D. F. (1981). Henseler et al.'s (2015) heterotrait-monotrait (HTMT) ratio of correlations technique was used. It is recommended to use the HTMT threshold of 0.90 when constructs are conceptually comparable. A lower requirement of 0.85 is suggested by Heseler et al. (2015) for more distinct entities. Because every value in Table 4 is below the 0.85 threshold, discriminant validity is maintained.

Table 4. Discriminant validity using the criterion by Fornell & Larcker and Heterotrait-Monotrait Method (HTMT).

Construct	BI	EE	HM	HT	PE	SI
BI	0.96	0.89	0.89	0.82	0.9	0.85
EE	0.85	0.96	0.83	0.82	0.84	0.83
HM	0.86	0.83	0.97	0.78	0.88	0.81
HT	0.85	0.85	0.81	0.93	0.74	0.79
PE	0.85	0.84	0.84	0.77	0.96	0.81
SI	0.84	0.85	0.85	0.83	0.85	0.94

Diagonal and italicized elements are the square roots of the AVE (average variance extracted). Above the diagonal, the elements are the correlations between the constructs. Below the diagonal are the HTMT values.

Examining the proposed relationships was the next stage of our investigation. Direct relationships were examined first. Table 5 and Figure 2 present the analysis's results in detail.

Table 5. Direct relationships.

Hypotheses	Path	*B*	*t*	*P*	Result
H2a	BI -> UB	0.99	30.83	0.00	supported
H1d	EE -> BI	0.19	3.92	0.00	supported
H2b	EE -> UB	-0.14	3.72	0.00	supported
H1a	HM -> BI	0.14	2.49	0.01	supported
H1b	HT -> BI	0.07	2.02	0.04	supported
H1c	PE -> BI	0.3	6.83	0.00	supported
H1e	SI -> BI	0.26	4.73	0.00	supported
H2c	SI -> UB	0.11	3.51	0.00	supported
H3	SI -> EE	0.83	40.7	0.00	supported

Table 6 compares the initial result of the bootstrap-based test for the exact overall model fit (i.e., d_ULS and d_G) with the confidence interval derived from the sampling distribution. The initial value ought to be included in the confidence interval. Therefore, to show that the model has a "good fit," the upper bound of the confidence interval needs to be greater than the initial value of the d_ULS and d_G fit requirements. Select the confidence interval so that the 95% or 99% point represents the upper bound (Schuberth et al., 2022). Moreover, satisfactory fitting is indicated by an SRMR value of 0.05, which is less than 0.08 (Hu and Bentler, 1999).

Table 6. Goodness of fit.

_	_	Original sample (O)	Sample mean (M)	95%	99%
SRMR	Saturated model	0.05			
d_ULS	Saturated model	0.3	0.15	0.21	0.44
	Estimated model	0.71	0.43	0.69	0.87
d_G	Saturated model	0.6	0.45	0.57	0.64
_	Estimated model	0.72	0.46	0.59	0.76

Results revealed that all hypotheses were supported as shown in Figure 4 with positive coefficients except H2b: EE -> UB effort expectancy → use behaviour (β = -0.14, t = 3.72, p = 0.00) was found to be significant with a negative coefficient. model explanatory power is assessed. The study's endogenous variables have R2 values of 0.52 for effort expectancy, 0.87 for behavioral intention, and 0.89 for use behavior. The R2 values range from substantial to very good (Hair et al., 2013). We evaluated predictive relevance by utilizing the Q2 value. The endogenous constructs' Q2 values varied between 0.69 and 0.89. According to Hair et al. (2013), the study's Q2 values can be characterized as high.

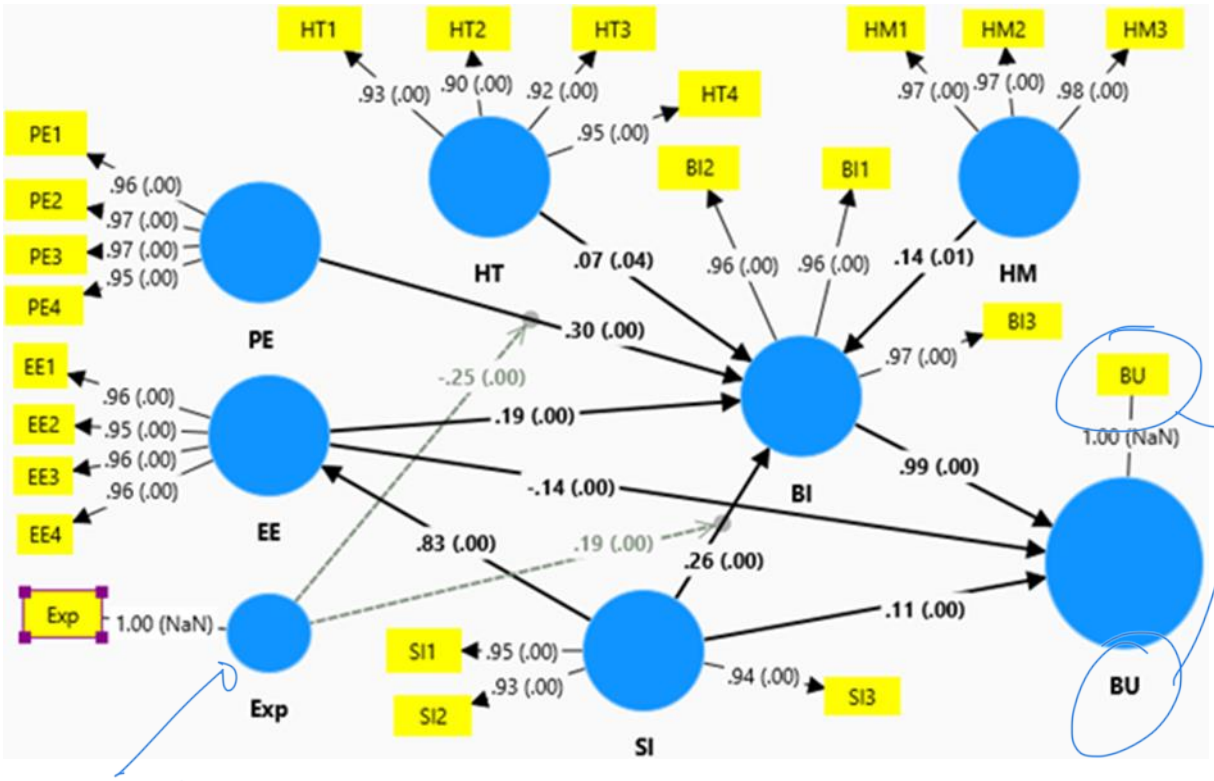


Figure 4. Path result with (Factor loadings, P) for outer model and (β, p) for inner model.

RQ#3: What is the relationship among these drives to use Gen AI in assessing students' performance?

The researchers answered the third question which was about the relationship among the factors that guided the adoption and acceptance of Gen AI in assessing students' performance using Smart PLS. Therefore, results~~Results~~ for the analysis of the mediated relationships are presented in Table 5. revealed a significant mediating role of behavioral intention between use behavior and effort expectancy (β =.19, t = 3.79, p =.00), hedonic motivation (β = 0.14, t = 2.49, p =0.01), habit (β =.07, t = 2.04, p <.04), performance expectancy (β =.29, t = 6.64, p =.00), and social influence (β =.25, t = 4.71, p =.00). Effort expectancy also mediated significantly between use behavior and social influence (β = -.12, t = 3.73, p =.00) and between social influence and behavioral intention (β =.16, t = 3.89, p =.00). Effort expectancy and behavioral intention together mediated significantly between social influence and use behavior (β =.15, t = 3.78, p =.00).

Table 6. Mediation analysis.

Path	*B*	*t*	*P*
EE -> BI -> UB	0.19	3.79	0.00
HM -> BI -> UB	0.14	2.49	0.01
SI -> EE -> BI	0.16	3.89	0.00
HT -> BI -> UB	0.07	2.04	0.04
SI -> EE -> UB	-0.12	3.73	0.00
PE -> BI -> UB	0.29	6.64	0.00
SI -> BI -> UB	0.25	4.71	0.00
SI -> EE -> BI -> UB	0.15	3.78	0.00

There was a significant moderate relationship between performance expectancy and behavioral intention with a positive coefficient (β = .19, t = 4.30, p = .00), indicating that

professors' experience strengthens the relation PE -> BI. The R^2 change in behavioral intention was 0.02, and f^2 = .153. Additionally, there was a negative moderate relationship between social influence and behavioral intention (β = -.25, t = 5.17, p = .00), suggesting that professors' experience weakens the relation SI -> BI. The R^2 change in behavioral intention was 0.03, and f^2 = .31. Professors' experience had a medium effect size (Cohen, 1988), as shown in Table 6.

Table 7. Moderation analysis.

Path	*β*	*T*	*P*	*R2*	*f2*
Exp x PE -> BI	.19	4.30	.00	0.02	0.153
Exp x SI -> BI	-.25	5.17	.00	0.04	0.304

f2is (>=0.02 is small; >= 0.15 is medium;>= 0.35 is large).

5. Discussion

The findings of this study highlight the complex landscape of using Gen AI in the assessment of students in higher education. The results underscore both the potential benefits and challenges associated with integrating this new technology, providing valuable insights for educators, policymakers, and academic institutions. Moreover, participants reported different procedures used to improve the quality of assignments and assessment methods. Implementing new assessment methods with varied assignments in the era of AI can enhance the empowerment of learning and assessment procedures through Gen AI.

5.1. Potential Benefits

One of the key advantages of Gen AI in education is its ability to provide immediate and detailed feedback to students, which can enhance learning outcomes and reduce the workload for educators (Celik et al., 2023). The high composite reliability (CR) and average variance extracted (AVE) values in the measurement model indicate that the constructs were well-measured and reliable, supporting the robustness of the findings. In addition, the study revealed significant positive relationships between several constructs and the use of Gen AI in assessments. Performance expectancy, effort expectancy, hedonic motivation, habit, and social influence all positively influenced behavioral intention to use Gen AI, which in turn positively influenced actual use behavior. These findings align with previous research emphasizing the usefulness and efficiency of Gen AI tools in educational settings (Mate & Weidenhofer, 2021; Moorhouse et al., 2023).

~~*One of the key advantages of Gen AI in education is its ability to provide immediate and detailed feedback to students, which can enhance learning outcomes and reduce the workload for educators (Celik et al., 2023). The high composite reliability (CR) and average variance extracted (AVE) values in the measurement model indicate that the constructs were well-measured and reliable, supporting the robustness of the findings.*~~

5.2. Challenges and Concerns

Despite these benefits, the study also identified significant challenges. Effort expectancy negatively impacted use behavior, suggesting that the ease of use of Gen AI tools might not always translate into actual usage. This outcome emphasizes the importance of thorough training and assistance for educators in effectively integrating these tools into their teaching practices (Swiecki et al., 2022). Additionally, concerns about academic integrity and the potential for AI-generated content to undermine traditional assessment methods were prevalent among participants. This result is consistent with previous research that emphasizes the need for improved AI detection tools and awareness programs to reduce the dangers of plagiarism and academic dishonesty (Mills et al., 2023; Tenakwah et al., 2023).

5.3. Moderating Role of Experience

The study also found that professors' experience mediated the relationship between performance expectancy, social influence, and behavioral intention. Experienced educators were more likely to see the benefits of Gen AI tools, suggesting that familiarity and comfort with technology play crucial roles in its adoption. This finding suggests that targeted professional development and continuous learning opportunities are essential to foster positive attitudes towards Gen AI in education (Chan & Tsi, 2023).

5.4. Implications

The study's findings have many implications for practice and policy. First, robust frameworks for the use of AI in evaluations must be developed in order to address concerns about academic integrity. This entails formulating clear guidelines and educating teachers and students on ethical application of AI tools (Perkins et al., 2023). Secondly, higher education institutions should allocate resources to professional development programs aimed at improving educators' digital skills, especially in utilizing Gen AI tools. By fostering a supportive environment, institutions can encourage the effective integration of these technologies, thereby enhancing teaching and learning outcomes (Lundquist & Kelly, 2022).

Finally, policymakers should take into account the various factors that impact the adoption of Gen AI in education, such as effort expectancy, performance expectancy, and social influence. By understanding these factors, strategies can be developed to promote the adoption of AI tools, ensuring they are used to enhance, rather than replace, traditional educational practices (Chan & Hu, 2023).

5.4.1. Theoretical Implications

The study adds to the expanding body of literature on the integration of Gen AI in higher education by giving empirical evidence on the factors that influence its use for student evaluations. Using the UTAUT model, this study validates the role of performance expectancy, effort expectancy, social influence, and hedonic motivation in altering instructors' behavioral intentions and actual usage of Gen AI tools. The constructs utilized in this study were very reliable and valid, reaffirming the UTAUT model's robustness in the context of educational technology adoption.

Furthermore, the study contributes to a better understanding of how instructors' experience moderate the relationship between performance expectancy, social influence, and behavioral intention. This finding highlights the importance of considering user experience when investigating technology adoption, suggesting that experienced educators are more likely to perceive the benefits and integrate Gen AI tools into their teaching practices effectively.

5.4.2. Practical Implications For Educators and Institutions

Professional Development and Training: The negative impact of effort expectancy on use behavior underscores the need for comprehensive training programs. Educators should be given continuous professional development opportunities to improve their digital competencies and facilitate the integration of Gen AI tools into their assessment methods. Training should include both the technical aspects of using these technologies and their educational applications.

Addressing Academic Integrity: Concerns about academic dishonesty and plagiarism require the creation of rigorous standards and norms for the ethical application of Gen AI in evaluations. Institutions should implement policies that promote academic integrity and provide tools to detect and mitigate the misuse of AI-generated content. Educators should be trained to recognize AI-generated work and incorporate strategies that encourage original student contributions.

Enhanced Support Systems: Facilitating conditions, such as access to resources and support, are critical to the adoption of Gen AI solutions. Institutions should provide educators with the required technological infrastructure and support services. Peer support networks and collaborative platforms can also help educators share best practices and troubleshoot common issues.

5.4.3. For Policymakers

Policy Development: Clear guidelines and standards for the use of Gen AI in educational assessments should be devised by policymakers. These regulations should address ethical concerns, data protection, and the equitable application of AI tools in various educational settings. By establishing a regulatory framework, policymakers can help mitigate the risks associated with Gen AI and promote its responsible use.

Incentives for Adoption: To encourage the adoption of Gen AI tools, policymakers can provide incentives such as grants, funding for technology integration projects, and recognition programs for innovative teaching practices. These incentives can encourage instructors to try out and accept new technology, thereby improving educational quality.

Research and Development: Continued research into the effects of Gen AI on educational outcomes is critical. Policymakers should encourage research projects that look into the long-term effects of AI integration in education, identify best practices, and create new tools and methodologies. Collaborative efforts between academia, industry, and government can drive innovation and ensure that AI tools are aligned with educational goals.

5.5. Limitations

Generalizability: While the study included a large number of participants from Middle Eastern higher education institutions, the results may not be applicable in other educational contexts. The cultural, technological, and educational differences across regions may have influenced participants' adoption and successful integration of Gen AI tools.

Self-Reported Data: The study relied on self-reported data from participants, which is susceptible to biases such as social desirability and recollection bias. Participants may have inflated or understated their use and perceptions of Gen AI tools, potentially impacting the results' accuracy.

Cross-Sectional Design: The study used a cross-sectional approach, collecting data at a single point in time. This technique limits the ability to infer causality or track changes in perceptions and behaviors over time. Longitudinal studies would be more effective in understanding the evolution of educators' attitudes and the long-term impacts of Gen AI integration.

Focus on Early Adopters: The study focused on early adopters of Gen AI tools, who may have more positive perceptions and experiences compared to the general population of educators. This could lead to an overestimation of the benefits and an underestimation of the challenges associated with Gen AI adoption.

Technological Variability: The study did not account for the variability in the types and functionalities of Gen AI tools used by participants. Different tools may have varying levels of effectiveness and user-friendliness, influencing educators' perceptions and experiences.

5.6. Future Research

Longitudinal Studies: Future studies should use longitudinal designs to track changes in educators' perceptions, attitudes, and use of Gen AI tools over time. This would provide further insights into the long-term effects of Gen AI on educational assessment and learning outcomes.

Comparative Studies: Conducting comparative studies across different regions, educational levels, and cultural contexts can help identify universal and context-specific factors influencing Gen AI adoption. This would enhance the generalizability of the findings and inform tailored implementation strategies.

Exploring Diverse Populations: Future studies should include a broader range of individuals, including those who are skeptical or neutral about Gen AI techniques. Understanding barriers and facilitators for different groups can provide a more complete picture of the problems and potential for integrating Gen AI into education.

Impact on Student Learning: While the current study focused on instructors' perceptions, future research should investigate the influence of Gen AI tools on student learning results, engagement, and satisfaction. Investigating students' opinions and experiences using AI-driven evaluations can provide useful insights about the instruments' effectiveness.

Technological Advancements: As Gen AI technologies continue to evolve, future research should examine the latest advancements and their implications for educational assessment. Studies should investigate the integration of emerging technologies, such as immersive VR and adaptive learning systems, with Gen AI tools to enhance educational experiences.

Ethical and Policy Considerations: Further research is needed to investigate the ethical implications of utilizing Gen AI in education, including concerns about data privacy, academic integrity, and the possibility of AI bias. Developing comprehensive ethical rules and policies will be critical to the responsible use of Gen AI capabilities.

Training and Support: Investigating the effectiveness of different training and support programs for educators using Gen AI tools can provide insights into best practices for professional development. Future research should explore the most effective ways to build educators' digital competencies and confidence in using AI-driven technologies.

By addressing these limitations and exploring the recommended future research topics, scholars can contribute to a more comprehensive understanding of Gen AI integration in educational evaluations, as well as its potential to improve higher education teaching and learning.

6. Conclusion

This study offers a thorough understanding of the factors influencing the use of Generative Artificial Intelligence (Gen AI) in student assessments in higher education. Although there are evident benefits, such as increased efficiency and personalized feedback, challenges related to ease of use and academic integrity need to be addressed. By leveraging these insights, educational institutions and policymakers can develop strategies to effectively integrate Gen AI, thereby enhancing both teaching practices and student learning experiences.

Supplementary Materials:.

Author Contributions:.

Funding:.

Institutional Review Board Statement: The authors of this study got approve from the (Institutional Review Board (IRB) committee at XXX. The IRB approval reference is Intr. Jan.2024/43.

Informed Consent Statement: Informed consent was obtained from all of the participants to participate in the study.

Data Availability Statement:.

Acknowledgments:.

Conflicts of Interest: The authors declare that there is no conflict of interest.

References

1. Allen, N. (1992). Assessment in Higher Education. *The Reference Librarian*, *17*(38), 57–68. https://doi.org/10.1300/j120v17n38_08
2. Braiki, B. A., Harous, S., Zaki, N., & Alnajjar, F. (2020). Artificial intelligence in education and assessment methods. *Bulletin of Electrical Engineering and Informatics*, *9*(5), 1998–2007. https://doi.org/10.11591/eei.v9i5.1984
3. Bulut, O., & Wongvorachan, T. (2022). Feedback Generation through Artificial Intelligence. *The Open/Technology in Education, Society, and Scholarship Association Conference*, *2*(1), 1–9. https://doi.org/10.18357/otessac.2022.2.1.125
4. Casal, J. E., & Kessler, M. (2023). Can linguists distinguish between ChatGPT/AI and human writing?: A study of research ethics and academic publishing. *Research Methods in Applied Linguistics*, *2*(3), 100068. https://doi.org/10.1016/j.rmal.2023.100068
5. Celik, I., Dindar, M., Muukkonen, H., & Järvelä, S. (2022). The Promises and Challenges of Artificial Intelligence for Teachers: a Systematic Review of Research. *TechTrends*, *66*(4). Springer. https://doi.org/10.1007/s11528-022-00715-y
6. Chan, C. (2023). A comprehensive AI policy education framework for university teaching and learning. *International Journal of Educational Technology in Higher Education*, *20*(1). https://doi.org/10.1186/s41239-023-00408-3
7. Chan, C. K. Y., & Tsi, L. H. Y. (2023, May 1). *The AI Revolution in Education: Will AI Replace or Assist Teachers in Higher Education?* ArXiv.org. https://doi.org/10.48550/arXiv.2305.01185
8. Chan, C. K. Y., & Zhou, W. (2023, May 1). *Deconstructing Student Perceptions of Generative AI (GenAI) through an Expectancy Value Theory (EVT)-based Instrument*. ArXiv.org. https://doi.org/10.48550/arXiv.2305.01186
9. Chan, C., & Hu, W. (2023). Students' Voices on Generative AI: Perceptions, Benefits, and Challenges in Higher Education. *International Journal of Educational Technology in Higher Education*, *20*(43). https://doi.org/10.48550/arxiv.2305.00290
10. Chan, C., & Lee, K. (2023). The AI generation gap: Are gen Z students more interested in adopting generative AI such as ChatGPT in teaching and learning than their Gen X and millennial generation teachers? *Smart Learning Environments*, *10*(1). https://doi.org/10.1186/s40561-023-00269-3
11. Chen, D. W., Jeng, A., Sun, S., & Kaptur, B. (2023). Use of technology-based assessments: a systematic review covering over 30 countries. *Assessment in Education: Principles, Policy & Practice*, 1–33. https://doi.org/10.1080/0969594x.2023.2270181
12. Chen, L., Chen, P., & Lin, Z. (2020). Artificial Intelligence in Education: a Review. *IEEE Access*, *8*, 75264–75278. https://doi.org/10.1109/ACCESS.2020.2988510
13. Chiu, T. (2023). The Impact of Generative AI (GenAI) on practices, Policies and Research Direction in education: a Case of ChatGPT and Midjourney. *Interactive Learning Environments*, 1–17. https://doi.org/10.1080/10494820.2023.2253861
14. Doroudi, S. (2022). The Intertwined Histories of Artificial Intelligence and Education. *International Journal of Artificial Intelligence in Education*, *33*, 885–928. https://doi.org/10.1007/s40593-022-00313-2
15. Fischer, J., Bearman, M., Boud, D., & Tai, J. (2023). How does assessment drive learning? A focus on students' development of evaluative judgement. *Assessment & Evaluation in Higher Education*, *49*(2), 1–13. https://doi.org/10.1080/02602938.2023.2206986
16. Floruss, J., Vahlpahl, N., 2020. Artificial Intelligence in Healthcare: Acceptance of AI-based Support Systems by Healthcare Professionals [onkoping University].
17. Gamage, K. A. A., Dehideniya, S. C. P., Xu, Z., & Tang, X. (2023). ChatGPT and higher education assessments: More opportunities than concerns? *Journal of Applied Learning & Teaching*, *6*(2). https://doi.org/10.37074/jalt.2023.6.2.32
18. Gansser, O. A., & Reich, C. S. (2021). A new acceptance model for artificial intelligence with extensions to UTAUT2: An empirical study in three segments of application. *Technology in Society*, *65*, 101535
19. Gardner, J., O'Leary, M., & Yuan, L. (2021). Artificial intelligence in educational assessment: "Breakthrough? Or buncombe and ballyhoo?" *Journal of Computer Assisted Learning*, *37*(5), 1207–1216. https://doi.org/10.1111/jcal.12577
20. Gerard, L. F., & Linn, M. C. (2016). Using Automated Scores of Student Essays to Support Teacher Guidance in Classroom Inquiry. *Journal of Science Teacher Education*, *27*(1), 111–129. https://doi.org/10.1007/s10972-016-9455-6
21. González-Calatayud, V., Prendes-Espinosa, P., & Roig-Vila, R. (2021). Artificial Intelligence for Student Assessment: A Systematic Review. *Applied Sciences*, *11*(12), 5467. https://doi.org/10.3390/app11125467
22. Hamamra, B., Alawi, N., & Daragmeh, A. K. (2021). Covid-19 and the decolonisation of education in Palestinian universities. *Educational Philosophy and Theory*, *53*(14), 1–15. https://doi.org/10.1080/00131857.2020.1865921
23. Hamamra, B., Mayaleh, A., & Khlaif, Z. N. (2024). Between tech and text: the use of generative AI in Palestinian universities - a ChatGPT case study. *Cogent Education*, *11*(1). https://doi.org/10.1080/2331186X.2024.2380622
24. Heywood, J. (2000). *Assessment in higher education* (Vol. 56). Jessica Kingsley Publishers.
25. Holmes, N. (2017). Engaging with assessment: Increasing student engagement through continuous assessment. *Active Learning in Higher Education*, *19*(1), 23–34. https://doi.org/10.1177/1469787417723230
26. Hooda, M., Rana, C., Dahiya, O., Rizwan, A., & Hossain, M. S. (2022). Artificial Intelligence for Assessment and Feedback to Enhance Student Success in Higher Education. *Mathematical Problems in Engineering*, *2022*(5215722), 1–19. https://doi.org/10.1155/2022/5215722
27. Jacoby, J. C., Heugh, S., Bax, C., & Branford-White, C. (2013). Enhancing learning through formative assessment. *Innovations in Education and Teaching International*, *51*(1), 72–83. https://doi.org/10.1080/14703297.2013.771970

28. Khlaif, Z. N., Mousa, A., Hattab, M. K., Itmazi, J., Hassan, A. A., Sanmugam, M., & Ayyoub, A. (2023). The Potential and Concerns of Using AI in Scientific Research: ChatGPT Performance Evaluation. *JMIR Medical Education*, *9*(1), e47049. https://doi.org/10.2196/47049
29. Khlaif, Z. N., Sanmugam, M., Hattab, M. K., Bensalem, E., Ayyoub, A. A., Sharma, R. C., Joma, A., Itmazi, J., Najmi, A. H., Ahmed, M. A., Jawad, A. A., Ramadan, M., & Bsharat, T. R. K. (2023). Mobile technology features and technostress in mandatory online teaching during the COVID-19 crisis. *Heliyon*, *9*(8), e19069–e19069. https://doi.org/10.1016/j.heliyon.2023.e19069
30. Kandoth, S., & Shekhar, S. K. (2022, September). Social influence and intention to use AI: the role of personal innovativeness and perceived trust using the parallel mediation model. In *Forum Scientiae Oeconomia* (Vol. 10, No. 3, pp. 131-150)
31. Kıncal, R. Y., & Ozan, C. (2018). Effects of Formative Assessment on Prospective Teachers' Achievement, Attitude and Self-Regulation Skills. *International Journal of Progressive Education*, *14*(2), 77–92. https://doi.org/10.29329/ijpe.2018.139.6
32. Kohnke, L., Moorhouse, B. L., & Zou, D. (2023). ChatGPT for Language Teaching and Learning. *RELC Journal*, *54*(2), 003368822311628. https://doi.org/10.1177/00336882231162868
33. Lebo, C., & Brown, N. (2024). Integrating Artificial Intelligence (AI) Simulations Into Undergraduate Nursing Education. *Nursing Education Perspectives*, *45*(1), 55–56. https://doi.org/10.1097/01.nep.0000000000001081
34. Lee, H.-S., Gweon, G.-H., Lord, T., Paessel, N., Pallant, A., & Pryputniewicz, S. (2021). Machine Learning-Enabled Automated Feedback: Supporting Students' Revision of Scientific Arguments Based on Data Drawn from Simulation. *Journal of Science Education and Technology*, *30*(2), 168–192. https://doi.org/10.1007/s10956-020-09889-7
35. Lockee, B. B. (2020). Shifting digital, shifting context: (re)considering teacher professional development for online and blended learning in the COVID-19 era. *Educational Technology Research and Development*. https://doi.org/10.1007/s11423-020-09836-8
36. Lundquist, A. E., & Kelly, C. (2022). Assessment: Using data to support graduate student success and program effectiveness. In V. A. Shepard & A. L. Perry (Eds.), *A Practitioner's Guide to Supporting Graduate and Professional Students* (pp. 185–208). Routledge. https://doi.org/10.4324/9781003121671
37. Magdalena, I., Aan Nurchayati, & Rara Mustikawati. (2023). Kompetensi Pengetahuan dan Teknik Penilaian dalam Evaluasi Pembelajaran di Sekolah Dasar. *TSAQOFAH*, *3*(5), 794–801. https://doi.org/10.58578/tsaqofah.v3i5.1375
38. Mahshanian, A., Shoghi, R., & Bahrami, M. (2019). Investigating the Differential Effects of Formative and Summative Assessment on EFL Learners' End-of-term Achievement. *Journal of Language Teaching and Research*, *10*(5), 1055. https://doi.org/10.17507/jltr.1005.19
39. Mate, K., & Weidenhofer, J. (2021). Considerations and strategies for effective online assessment with a focus on the biomedical sciences. *FASEB BioAdvances*, *4*(1), 9–21. https://doi.org/10.1096/fba.2021-00075
40. McCalla, G. (2023). The history of artificial intelligence in education–the first quarter century. In B. du Boulay, A. Mitrovic, & K. Yacef (Eds.), *Handbook of Artificial Intelligence in Education* (pp. 10–29). Edward Elgar Publishing. https://doi.org/10.4337/9781800375413.00010
41. Mills, A., Bali, M., & Eaton, L. (2023). How do we respond to generative AI in education? Open educational practices give us a framework for an ongoing process. *Journal of Applied Learning and Teaching*, *6*(1), 16–30. https://doi.org/10.37074/jalt.2023.6.1.34
42. Moorhouse, B. L., Yeo, M. A., & Wan, Y. (2023). Generative AI tools and assessment: Guidelines of the world's top-ranking universities. *Computers and Education Open*, *5*, 100151. https://doi.org/10.1016/j.caeo.2023.100151
43. Moturu, V. R., & Nethi, S. D. (2023). Artificial Intelligence in Education. In M. A. Chaurasia & CF. Juang (Eds.), *Emerging IT/ICT and AI Technologies Affecting Society* (pp. 233–244). Springer. https://doi.org/10.1007/978-981-19-2940-3_16
44. Nicolae Moroianu, Silvia-Elena Iacob, & Alexandra Maria Constantin. (2023). Artificial Intelligence in Education: a Systematic Review. *Sciendo EBooks*, 906–921. https://doi.org/10.2478/9788367405546-084
45. Pereira, D., Flores, M. A., & Niklasson, L. (2016). Assessment revisited: a review of research inAssessment and Evaluation in Higher Education. *Assessment & Evaluation in Higher Education*, *41*(7), 1008–1032. https://doi.org/10.1080/02602938.2015.1055233
46. Perkins, M., Roe, J., Postma, D., McGaughran, J., & Hickerson, D. (2023). *Game of Tones: Faculty detection of GPT-4 generated content in university assessments*. https://doi.org/10.48550/arxiv.2305.18081
47. Sanabria-Navarro, J.-R., Silveira-Pérez, Y., Pérez-Bravo, D.-D., & de-Jesús-Cortina-Núñez, M. (2023). Incidences of artificial intelligence in contemporary education. *Comunicar: Media Education Research Journal*, *31*(77), 93–103. https://doi.org/10.3916/c77-2023-08
48. Sarkar, T. K. (2012). Assessment in Education in India. *A-EDUC JOURNAL*, *9*(2), 1–37. chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://law.nwu.ac.za/sites/law.nwu.ac.za/files/files/p-saeduc/New_Folder_1/1_Assessment%20in%20Education%20in%20India.pdf
49. Sharma, R., Jain, A., Gupta, N., Garg, S., Batta, M., & Dhir, S. (2016). Impact of self-assessment by students on their learning. *International Journal of Applied and Basic Medical Research*, *6*(3), 226. https://doi.org/10.4103/2229-516x.186961
50. Sharples, M. (2022). Automated Essay Writing: An AIED Opinion. *International Journal of Artificial Intelligence in Education*, *32*, 1119–1126. https://doi.org/10.1007/s40593-022-00300-7
51. Sievertsen, H. H. (2022). Assessments in Education. *ArXiv (Cornell University)*, 1–44. https://doi.org/10.48550/arxiv.2208.05826
52. Smolansky, A., Cram, A., Raduescu, C., Sandris Zeivots, Huber, E., & Kizilcec, R. F. (2023). Educator and Student Perspectives on the Impact of Generative AI on Assessments in Higher Education. *Educator and Student Perspectives on the Impact of Generative AI on Assessments in Higher Education*, *27*(1), 149–157. https://doi.org/10.1145/3573051.3596191

53. Swiecki, Z., Khosravi, H., Chen, G., Martinez-Maldonado, R., Lodge, J. M., Milligan, S., Selwyn, N., & Gašević, D. (2022). Assessment in the age of artificial intelligence. *Computers and Education: Artificial Intelligence*, *3*(3), 100075. https://doi.org/10.1016/j.caeai.2022.100075
54. Talan , T., & Kalinkara, Y. (2023). The Role of Artificial Intelligence in Higher Education: ChatGPT Assessment for Anatomy Course. *Uluslararası Yönetim Bilişim Sistemleri ve Bilgisayar Bilimleri Dergisi*, *7*(1). https://doi.org/10.33461/uybisbbd.1244777
55. Tan, S. (2013). Harnessing Artificial Intelligence for Innovation in Education. In *Learning Intelligence: Innovative and Digital Transformative Learning Strategies* (pp. 335–363). Springer. https://link.springer.com/chapter/10.1007/978-981-19-9201-8_8
56. Tenakwah, E. S., Boadu, G., Tenakwah, E. J., Parzakonis, M., Brady, M., Kansiime, P., Said, S., Ayilu, R. K., Radavoi, C. N., & Berman, A. L. (2023). Generative AI and Higher Education Assessments: A Competency-Based Analysis. *Research Square (Research Square)*. https://doi.org/10.21203/rs.3.rs-2968456/v2
57. Umar, A. M. A.-T. (2018). The Impact of Assessment for Learning on Students' Achievement in English for Specific Purposes A Case Study of Pre-Medical Students at Khartoum University: Sudan. *English Language Teaching*, *11*(2), 15. https://doi.org/10.5539/elt.v11n2p15
58. Warschauer, M., Tseng, W., Yim, S., Webster, T., Jacob, S., Du, Q., & Tate, T. (2023). The Affordances and Contradictions of AI-Generated Text for Second Language Writers. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4404380
59. You, Y., Chen, Y., You, Y., Zhang, Q., & Cao, Q. (2023). Evolutionary Game Analysis of Artificial Intelligence Such as the Generative Pre-Trained Transformer in Future Education. *Sustainability*, *15*(12), 9355–9355. https://doi.org/10.3390/su15129355
60. Zhai, X., & Nehm, R. H. (2023). AI and formative assessment: The train has left the station. *Journal of Research in Science Teaching*, *60*(6), 1390–1398. https://doi.org/10.1002/tea.21885

Appendix A

Appendix A

Gender: Male Female
Teaching experience:
Teaching experience with ICT:

Items	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
"I believe that Gen AI is useful in assessing students assignments"					
"Using Gen AI increases my chances to evaluate my students assignments professionally"					
"Using Gen AI helps students get tasks and projects done faster"					
"Using Gen AI increases students' productivity in their assignments"					
"Learning how to use Gen AI in assessment is easy for me"					
"My interaction with Gen AI is clear and understandable"					
"I find Gen AI easy to design rubrics for assessing my students' projects"					
"It is easy for me to become skillful at using Gen AI in "					
"People who are important to me think I should Gen AI in assessment"					
"People who influence my behavior believe that I should use Gen AI"					
"People whose opinions I value prefer me to use Gen AI for students assessment"					
"I have the resources necessary to use Gen AI in assessing my students"					
"I have the knowledge necessary to use Gen AI for students' assessment"					
"Gen AI is compatible with technologies I use in teaching"					
"I can get help from others when I have difficulties using Gen AI"					
"Using Gen AI for assessment is fun"					
"Using Gen AI for assessment is enjoyable"					
"Using Gen AI for assessment is very entertaining"					
"Gen AI is reasonably priced"					
"Gen AI is good value for the money"					
"At the current price, Gen AI provides a good value"					
"The use of Gen AI for students' assessment has become a habit for me"					
"I am addicted to using Gen AI in teaching and assessment"					
"I must use Gen AI for students' assessment"					
"Using Gen AI for assessment has become natural for me"					
"I intend to continue using Gen AI for assessment in the future"					
"I will always try to use Gen AI in my teaching and assessment"					
"I plan to continue to use Gen AI for assessment frequently"					
"I like experimenting with new information technologies"					
"If I heard about a new information technology, I would look for ways to experiment with it"					
"Among my family/friends, I am usually the first to try out new information technologies"					
"In general, I do not hesitate to try out new information technologies"					
"Please choose your usage frequency for Gen AI:					

1. Never; 2. Once a month; 3. Several times a month; 4. Once a week; 5. Several times a week; 6. Once a day; 7. Several times a day"					

Based on your experience, please answere the following open questions"

Can you describe your experience with using Generative aI tools for students assessment in your courses?

How do you use Gen AI tools in your teaching and assessing your students (please write the Gen AI tools you experience