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Impact of Technology-Integrated Innovative Assessment Methods on Chinese Tertiary Students' Academic Achievement

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Abstract: In today's global shift towards formative assessment, technology-integrated innovative assessment methods have become the call of the day. This is especially true in a majority of the post-pandemic online teaching and learning environments that are supported by innovative information and communications technology (ICT) solutions. The main aim of this study was to assess the impact of technology-integrated innovative assessment methods on 70 Chinese tertiary students' academic achievement in a private university located in Shanghai, China. The study involved two stages, i.e., an experimental research design and a survey design. In the experimental design, assessment tasks in the experimental group were based on technology-integrated innovative assessment methods, whilst the control group was assessed based on traditional-based assessment methods. For the survey, data was collected using a survey questionnaire wherein the data analysis employed mean and standard deviation and Partial least squares (PLS). The experimental results revealed that students belonging to the experimental group performed academically better than the control group's students in the end-of-module examination. Furthermore, findings from the survey showed that technology acceptance, platform usability, and assessment convenience moderately influenced performance expectancy. Besides, while higher cumulative grade point average (CGPA) levels correlated with a stronger relationship between assessment convenience and performance expectancy, lower CGPA levels correlated with a stronger relationship between technology acceptance and performance expectancy. The findings in this study imply that educators must embrace and integrate technology-integrated innovative assessment methods to enhance educational quality, which is in line with SDG 4, with an ultimate aim to optimize student learning experiences in an increasingly technology-driven educational environment.

Keywords: Academic Performance, Assessment Methods, Experimental Design, Technology-Integrated Innovative Assessment, Technology Factors

1. Introduction

In 2020, the COVID-19 pandemic led to the closure of schools in over 190 countries, impacting almost 1.6 billion students (UN, 2020). Although the majority of schools have reopened globally, many universities' instruction methods have changed from traditional face-to-face classroom lectures to online lectures, which has also seen a change in assessment methods. A similar situation prevailed in Shanghai, China. Due to the pandemic, students who attended classes during the spring semesters of the year 2020 and 2022 in Shanghai utilized online teaching and assessment.

Assessment is a procedure that systematically plans, selects, collects, designs, and reviews information about students' performance to improve academic programs (Palomba & Banta, 1999). An assessment, which assesses if and how well the learning objectives have been fulfilled, is an essential component of the learning process (Kiryakova, 2021). Online assessment has become a vital education component, particularly considering the COVID-19 epidemic. Since the onset of the COVID-19 pandemic, there has been a demand for higher education institutions (HEI) to implement online teaching and testing strategies (Rahmani, 2021). Not much research has looked into the development of online assessment programs, focusing on different fields and educational levels (Adri et al., 2021).

Assessment methods, which refer to the techniques employed by educators to gauge student progress and inform their instructional planning (Indeed Editorial Team, 2023), are equally important as teaching strategies. Traditional assessments are usually paper-based, conducted in a controlled environment, such as a classroom or examination hall, and often time-limited. By contrast, innovative assessment is the result of combining several approaches and strategies to raise the quality of students' learning. Furthermore, modern information and communication technologies (ICT) enable learning in a digital environment with the ability to diversify, enhance, and expand traditional evaluation methodologies (Kiryakova, 2021). Many commercial online assessment platforms are widely used in virtual classrooms, like WhatsApp Group, Microsoft Teams, Zoom, and Google Classroom (Wijayati et al., 2022). Additionally, numerous universities have used customized online assessment systems or platforms to accommodate multiple requirements.

This two-stage research design first uses the experimental design followed by the survey design to compare the academic performance of students using the technology-integrated innovative assessment versus the traditional paper-based assessment. In the first stage, the experimental design was conducted by analyzing test scores between the two groups. In the second stage, the survey examined the relationships between technology acceptance, platform usability, assessment convenience, performance expectations, and student's cumulative grade point average (CGPA). The goal was to provide insights into the benefits and drawbacks of paper-based versus ICT-based assessments. Its three-pronged objective was to provide practical approaches to integrate technology into online education. The following three research objectives are :

- RO1: To compare tertiary students' academic performance and determine if there is any significant difference in test scores among students using traditional paper-based and ICT-based assessments.
- RO2: To examine the relationship between technology acceptance (TA), platform usability (PU), assessment convenience (AC), and performance expectation (PE).
- RO3: To assess if the student's cumulative grade point average (CGPA) level moderates the relationships between technology acceptance (TA), platform usability (PU), assessment convenience (AC), and performance expectations (PE).

2. Literature Review

Educational assessment is grounded in empirical research that explores how people learn and how learning can be effectively measured. This research provides valuable insights into the cognitive processes involved in learning and informs the development of various assessment methods. These methods are rigorously tested in experimental contexts, allowing researchers to refine and validate specific assessment techniques.

2.1 Types of Assessment

2.1.1 Process Assessment (PA)

Process assessment is a form of evaluation that focuses on the use of specific strategies and methods to evaluate and explain the learning process of the students as well as supporting students in educational activities to help them acquire the capacity for self-awareness, self-development, and self-improvement (Zhang & Shao, 2017). It also aims to provide students with feedback on their learning processes and to help them develop strategies to improve their performance (Bess, 2004). In detail, it refers to the comprehensive assessment of each phase that includes tests, homework assignments, online performance, etc., evaluating and measuring the outcomes or results and the processes used to complete a task or activity.

2.1.2 End of Module Assessment (EMA)

End-of-module assessments have been used in educational settings for many years to evaluate students' learning and understanding of the material covered in a specific module or course. Richardson (2015), who introduced the use of EMAs, discussed various academic arguments for the increased use of coursework in end-of-module assessment and examined the impact of this trend on student grades and degree classification. The EMA comprehensively evaluates the knowledge and skills acquired throughout a module or course. It is designed to assess the understanding, application, and mastery of the subject matter covered in the module. The assessment typically consists of tasks, tests, or projects that allow students to demonstrate their proficiency in the module's learning outcomes. The purpose of the EMA is to provide feedback on students' learning progress, identify areas of strength and weakness, and determine the level of achievement of the module objectives. It helps instructors evaluate the effectiveness of their teaching methods and curriculum and guide future instructional decisions.

2.1.3 Computer Assisted Assessment (CAA)

Computer-assisted assessment (CAA) has been rapidly developed and widely used over the last decades in colleges and universities. It provides educational and technical solutions that include simulations and multimedia-based questions that are not applicable to paper-based assessments (Bull & McKenna, 2004). Objective questions (e.g., multiple-choice, true/false, or numeric answers) that need a predetermined answer are the most common format in CAA. Other examination questions (such as essay, matching, image drag and drop, etc.) are also applicable in CAA.

2.2 Conceptual Framework & Proposed Hypotheses

A conceptual framework is depicted as a set of broad ideas and principles drawn from relevant fields of inquiry and used to build a subsequent presentation (Reichel & Ramey, 1987). A conceptual framework can organize and integrate existing research on the effects of different assessment methods by showing how different studies link to each other and what gaps in knowledge remain.

Figure 1 illustrates the current composition of the conceptual framework, which includes the dependent variable of performance expectancy, the moderating variable of the CGPA level, and three independent variables focusing on technological influences. After a comprehensive systematic literature review, technology acceptance (TA), platform usability (PU), and assessment convenience (AC) were selected as independent variables.

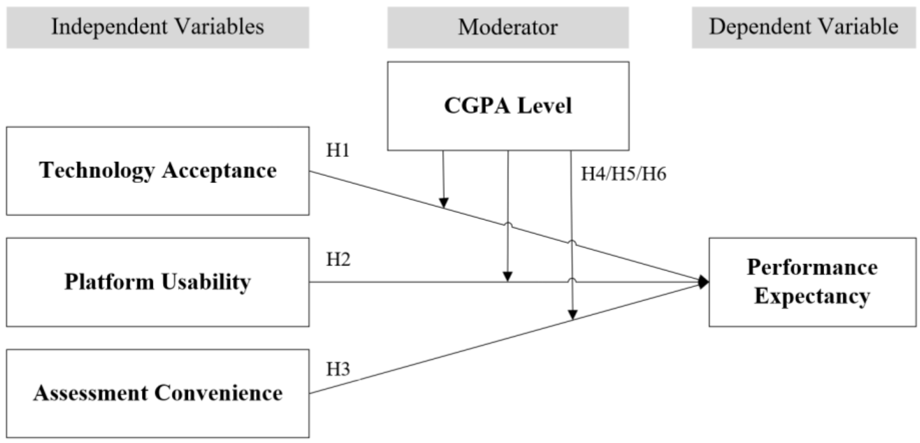


Fig. 1 Conceptual Framework

2.2.1 Performance Expectation (PE)

Geiger and Cooper (1995) found that college students' GPAs could be predicted from performance expectancy measures. Another study using online course platforms by college students found that performance expectancy is a significant intermediate factor (Chen et al., 2021). Furthermore, Performance Expectancy (PE) can be described as the extent to which students perceive that using new technologies will help them perform better with their academic results (Onaolapo & Oyewole, 2018). Performance Expectancy (PE) focuses on users' expectations regarding the impact of many technological factors on their academic performance. Questions for Performance Expectancy (PE) were also selected and altered from a published journal article (Tan, 2013).

2.2.2 Technology Acceptance (TA)

The original Technology Readiness Index (TRI), introduced by Parasuraman in 2000, has been a cornerstone in understanding users' openness to technology. Moreover, an updated and streamlined Technology Readiness Index - TRI 2.0 - building on Parasuraman and Colby's model in 2015 is the key driver of technology adoption readiness (Parasuraman & Colby, 2015). Technology Acceptance reflects individuals' willingness to adopt and use technology. The connection between these two constructs is pivotal. In this context, we propose the first hypothesis:

H1: There is a positive relationship between Technology Acceptance (TA) and Performance Expectation (PE).

2.2.3 Platform Usability (PU)

Platform usability in the context of ICT-based assessment usually refers to the ease of use and effectiveness. These resources can include websites, learning management systems, simulation programs, etc. (Estrada-Molina et al., 2022). Platform Usability (PU) related questions were based on indicators from Chen et al. (2020) and revised according to this research setting. This part aims to establish an effective but non-redundant index system to study the relationship between Platform Usability (PU) and Performance Expectation (PE). We propose the second hypothesis:

H2: There is a positive relationship between Platform Usability (PU) and Performance Expectation (PE).

2.2.4 Assessment Convenience (AC)

Assessment convenience (AC) refers to the perceived level of convenience and ease of use associated with an assessment method or platform. More convenient assessment processes, such as computer-based assessment, can provide rapid feedback, contributing to students' learning (Sundre &

Thelk, 2010). Questions for Assessment Convenience were adopted and modified according to Tan's (2013) journal article. Thus, we propose the third hypothesis:

H3: There is a positive relationship between Assessment Convenience (AC) and Performance Expectation (PE).

2.2.5 The CGPA Level as a Moderator

In this study, the moderating variable uses different CGPA levels to determine whether it affects the strength or direction of the relationship between two other variables. Three hypotheses were proposed :

H4: Different CGPA levels positively moderate the relationship between Technology Acceptance (TA) and Performance Expectation (PE).

H5: Different CGPA levels positively moderate the relationship between Platform Usability (PU) and Performance Expectation (PE).

H6: Different CGPA levels positively moderate the relationship between Assessment convenience (AC) and Performance Expectation (PE).

3. Methodology

3.1 Research Design

This study utilized an experimental study involving one control and one experimental group of 70 Chinese tertiary students. Data were collected based on semester-end assessment performance scores and a survey questionnaire. The study setting was a private university in Shanghai, China. It involved one selected faculty that offers a four-year software engineering program. The foundational course, Principles of Database, was selected for this experimental study. It involved a group of 70 Semester Five (5) tertiary students in the selected undergraduate foundational course. The experiment was conducted over a duration of six (6) weeks.

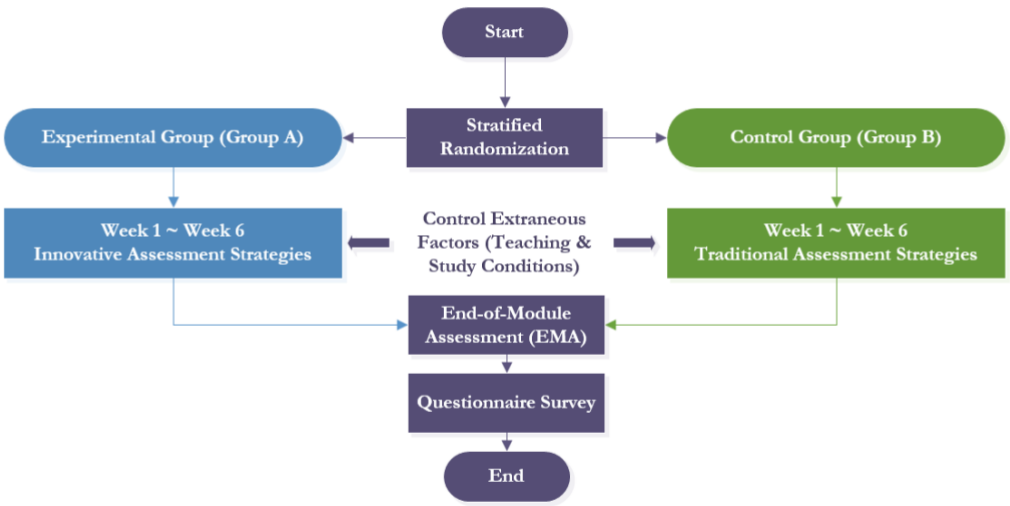


Fig. 2 Research Design Workflow

Given above in Figure 2 is the workflow of how the experimental study was conducted. Based on stratified random sampling, all 70 students were divided into two groups, namely Group A and Group B. Group A, the experimental group, comprised 35 students, and their assessment tasks throughout the semester were based on technology-integrated innovative formative assessment methods. On the other hand, Group B, the control group, comprised 35 students, and they were assessed based on the traditional paper and pen assessment methods. The contents of the assessment tasks included the following subject topics, namely relational database, structured query language, and database integrity. These topics were deemed suitable for standardized online technology-integrated assessment tasks, and they utilized structured query language alongside database integrity.

At this juncture, it is worth mentioning that an independent third-party tutor conducted all the manual subjective score markings of all the similar tests and assignments taken by the two groups of students. All the extraneous factors, including teaching methods and study conditions, were controlled.

At the end of the six weeks, all respondents were required to sit for the end-of-module Assessment (EMA), which was aimed at examining the course learning outcomes. This was followed by the administration of the survey questionnaire, which comprised closed-ended questions (also called restricted questions) with multiple-choice options.

3.2 Participants and Sampling

A total of seventy (70) participants undertaking the software engineering course at a private university in Shanghai, China, were selected to participate in this study. The respondents' levels of information technology skills were intermediate, and their ages were between 18 and 24 years old. Two equal groups, the control group and the experiment group, of the target participants were chosen using stratified random sampling to mitigate the students' learning capacity bias, measured by Cumulative Grade Point Average (CGPA). A random sample was then selected from each stratum. Furthermore, disproportionate stratified sampling, a technique where the sample size selected from each stratum was not in proportion to the relative size of that stratum, was introduced (Oxford Reference, 2023) (Hassan, 2024). Students' CGPAs of computer-specialized courses were used as the characteristic of a disproportionate stratified sample in this research. Three strata (1.0-2.0 as Low, 2.0-3.0 as Medium, and 3.0-4.0 as High) were generated according to regulations on educational administration. Finally, tests of normality and independent sample tests were done.

3.3 Experimental Design

Respondents from the experimental and control groups were required to take six formative and one summative assessment tasks. The assessment task involved three process assessments, three continuous assignments, and one end-of-module assessment (EMA) (See Figure 3).

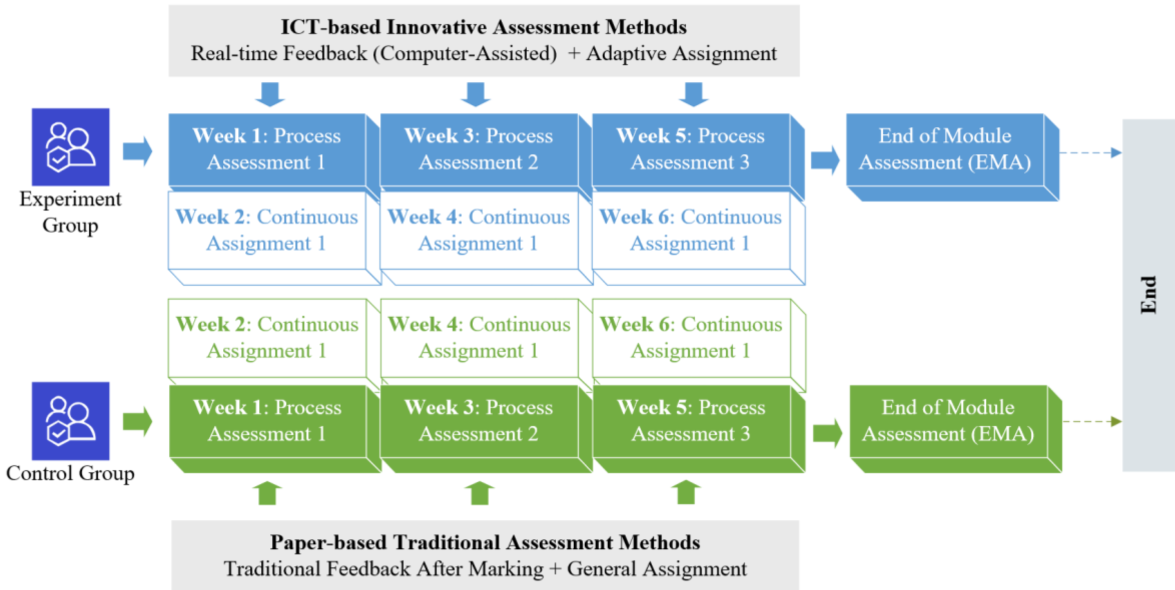


Fig. 3 Structure Diagram of the Experiment

All the assessments, excluding continuous assignments, used the same questions and scoring standards. The main difference was that the respondents from the experimental group responded to ICT-based innovative assessment tasks for process assessments. In contrast, the control group took the traditional paper-based assessment tasks during the process assessment period.

3.3.1 Technology-integrated Innovative Assessment Methods

Technology or ICT-based innovative process assessment methods implemented computer-assisted automatic grading and real-time feedback for quick reviewing and self-study for self-improvement. Following these process assessments, adaptive or customized continuous assignments (Rushkin et al., 2017) with similar knowledge points were distributed to respondents in the experimental group. Furthermore, differentiated assessment tasks were given to all respondents where the criteria were as follows: Students achieving 80% or more in process assessment were allocated High-Difficulty (HD) assignments, while those achieving less than 80% were given Low-Difficulty (LD) assignments. The grade rating (A, B, C, D, or E) was used to evaluate the formative assignments.

3.3.2 Traditional Assessment Methods

In contrast to innovative strategies, traditional paper-based assessment tasks were conducted in the control group. This included traditional manual marking by lecturers and corrections upon receiving feedback on their assessment tasks. A unified paper-based continuous assignment based on the process assessment task was delivered to all respondents in the control group. After the manual marking of the assignments, the allocation of the grade rating (A, B, C, D, or E) was also conducted.

3.4 Instruments & Measurement Development

Instruments were used to implement the experimental process, collect the outcomes, and analyze the results. It was crucial to guarantee that all the tools utilized in the study were accurate, dependable, and suitable for the research goals. The next section discusses the platforms, tools, and materials used for this study:

3.4.1 ICT-based Online Assessment Platform (U+ Platform)

The experimental group of students was assigned to technology-integrated innovative assessment tasks conducted on an ICT-based innovative assessment platform referred to as the U+ Emerging Engineering Education Cloud Platform (Abbreviated to U+ Platform). The U+ Platform is an integrated teaching and assessment platform spanning four years of undergraduate talent cultivation. It was independently developed by Qingruan Innovative Science and Technology Group Co., Ltd., with big data and artificial intelligence as its core technologies. The U+ Platform is equipped with high-quality, flexible, and highly reusable course content, actively exploring an online and offline combined model, providing a comprehensive "platform + content + service" solution. In this research, the U+ Platform is simple to use, safe, and can offer various assessment activities (e.g., quizzes, exams, and assignments) and functions (e.g., online examination, automatic grading, etc).

3.4.2 Traditional Assessment Materials

The control group of students was, however, exposed to the traditional teaching and learning processes, and their assessment tasks involved paper-an-pen tests, exams, and assignments. This classic traditional assessment form has long been used to evaluate student achievement. Paper-and-pencil examinations require students to answer questions in writing in a standardized testing environment where the test papers, administration processes, and scoring criteria are the same for each examinee (Berry, 2008).

3.4.3 Academic Records

Academic transcripts and academic records are formal collections of a student's academic history. They typically include courses taken, units, grades, and completed degrees, minors, or specializations. This study used respondents' academic records for final data analysis. In university, academic records, such as students' grades, homework marks, and CGPAs, are usually used to provide data on students' academic performance.

3.4.4 Measurement

The questionnaire design was based on the conceptual framework of this study, as shown in Fig 1. A 5-point Likert scale was used to explore the associations among the research variables. The scale ranged from a score of 1 to 5, wherein 1=strongly disagree, 2=disagree, 3=neither agree nor disagree, 4=agree, and 5=strongly agree.

The survey questionnaire comprised the following constructs: Technology Acceptance (TA), Platform Usability (PU), Assessment Convenience (AC), and Performance Expectancy (PE). All the survey questions were adapted and revised from published journal articles. Questions relating to Technology Acceptance (TA) were suggested by Parasuraman and Colby (2015). Platform Usability (PU) related questions were based on indicators from Chen et al. (2020) and revised according to this research setting. Questions for Assessment Convenience (AC) and Performance Expectancy (PE) were adapted and modified according to Tan's (2013) journal article.

3.5 Data Collection

Experimental-related data in this research is quantitative data expressed in numbers and graphs and analyzed through statistical methods. The data collection stages were divided into 5 parts (Bhandari, 2020). First, academic records used for stratified random sampling were collected via the administration process. Then, all the participants were divided into 2 groups of 35 people. After that, the experiment began. Three process assessments and three continuous assignments' results were collected using two methods: one ICT-based and one paper-based. After this, the EMA assessment results were collected for further study. In the last phase, the student's questionnaire data was collected through the Questionnaire Collection platform.

3.6 Data Analysis

The collected data were preprocessed, analyzed, and tabulated for the experimental part using IBM© SPSS© Statistic Version 27. The normal distribution of the collected data was examined by Shapiro-Wilk tests, which is appropriate for small sample sizes (< 50 samples) (Hanusz & Tarasińska, 2015). The reliability and validity analysis of the questionnaire data was carried out. The next step was to compute the descriptive and inferential statistics. The Independent Samples t-test was done to compare the assessment mean scores between the control group and the experimental group.

For the questionnaire part, SmartPLS© was introduced for data processing after the data preparation and model specification were done. After the latent variables and their indicators and the relationships between the latent variables were defined, measurement model analysis checking the factor loadings, composite reliability, average variance extracted (AVE), and discriminant validity were applied. Finally, structural model analysis involves checking the path coefficients, R-squared values, and the significance of the path coefficients. Berkowitz and Stern (2018) have used the structural equation model (SEM) to analyze the effect of ability on academic performance.

4. Results and Findings

This section presents the key findings of the study, organized according to the three research objectives. The analysis began by comparing tertiary students' academic performance and highlighting significant differences in test scores. Subsequently, the relationships between technology acceptance, platform usability, assessment convenience, and performance expectation were explored. Finally, the study examined how students' CGPA levels moderate these relationships.

4.1 Comparison of Tertiary Students' Academic Performance

Addressing the aim of RO1, this section presented an analysis of tertiary students' academic performance, comparing traditional paper-based and ICT-based assessment methods. The analysis was structured into three key components: the results of stratified sampling, an examination of Process Assessment (PA) and Continuous Assignment (CA) outcomes, and an evaluation of End of Module Assessment (EMA) results.

4.1.1 Sampling Results

The experimental group and control group were divided into 3 strata, namely (1.0-2.0 as Low, 2.0-3.0 as Medium, and 3.0-4.0 as High) as guided by the university educational regulations. These stratification criteria were based on the CGPA defined in the university's educational policies.

The mean CGPA of the experimental group was fixed at 2.65±0.47, and the control group was 2.59±0.48 (See Table 1). From the visualization of data distribution using a violin diagram with a box plot, the general distribution of the two groups was found to be similar (See Figure 4).

Table 1. Distribution of CGPA between the experimental and control groups

	Experimental Group				Control Group			
	Count	Ratio (%)	Mean	SD	Count	Ratio (%)	Mean	SD
stratum 1*	3	8.57	1.85	0.13	3	8.57	1.78	0.19
stratum 2**	25	71.43	2.55	0.26	25	71.43	2.51	0.31
stratum 3***	7	20.00	3.34	0.28	7	20.00	3.25	0.18
Total	35	100.00	2.65	0.47	35	100.00	2.59	0.48

*Individual CGPA from 1.0 to 2.0 (Low-CGPA Stratum)
** Individual CGPA from 2.0 to 3.0 (Medium-CGPA Stratum)
*** Individual CGPA from 3.0 to 4.0 (High-CGPA Stratum)

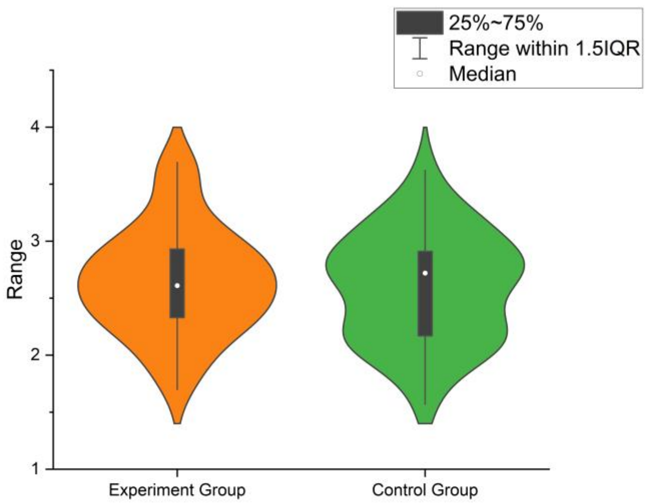


Fig. 4 Violin Diagram with Box Plot of CGPA

Both visualization of data and Tests of Normality were used to determine whether the given data set follows a normal distribution. Table 2 shows the results of the two tests of normality conducted, namely Kolmogorov-Smirnov and Shapiro-Wilk. The Shapiro-Wilk test is more appropriate for small sample sizes (<50 samples), and it tested the null hypothesis that the data was normally distributed. Both the experimental group and control group had a Shapiro-Wilk test statistic of 0.981, which was not significant at the 0.05 level. Overall, at the significance level of α=0.05, with P>0.05, it indicates that the experimental and control groups' data follows a normal distribution.

Table 2. Tests of Normality

	Kolmogorov-Smirnova			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Experiment Group	0.070	35	.200*	0.981	35	0.787
Control Group	0.118	35	.200*	0.981	35	0.789

* This is a lower bound of the true significance.

To ensure that both classes had similar academic levels of students, an independent sample t-test was done to compare the means of the two independent groups to determine whether there was a significant difference between them. The hypothesis suggests a substantial difference between the means of the two groups. Table 3 shows the results of Levene's test, which shows that the variances were equal (F=0.277, P=0.6). The t-test results show that t=0.493, P>0.05, indicating no statistically significant difference between the mean CGPA of the experimental group and the control group.

In conclusion, the division between the experimental and control groups was confirmed to be non-biased and reasonable.

Table 3. Independent Sample t-Test

	Levene's Test for Equality of Variances		t-test for Equality of Means				
	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
Equal variances assumed	0.277	0.600	0.493	68	0.624	0.056	0.114
Equal variances not assumed			0.493	67.972	0.624	0.056	0.114

4.1.2 Experimental Results

The results of innovative methods, made possible by information and communication technology, differed from those of conventional methods. Ozerbas and Erdogan (2016) demonstrated that students in the experimental group who learned in a digital classroom achieved academically better than students in the control group who did not use any digital technology. In contrast to this, the results of Ladyshewsky (2015) showed that the average test scores did not rise with time, and the average test scores for the online exam did not differ substantially from the average test scores for the in-person test. This study's confirmation of this tendency supported the notion that supporting innovative designs might affect students' academic achievement. The study's findings indicated a positive relationship between the use of innovative assessments and academic achievement and that ICT shaped this relationship. These findings conformed to the study by Ozerbas and Erdogan (2016).

4.1.3 Process Assessment (PA) & Continuous Assignment (CA) Results

It is a crucial metric for monitoring the student's academic process achievement using three consecutive PA results. The simple mean scores of PA results were used to gauge the process achievement, as shown in Figure 5. The score difference between the experimental group (77.89) and the control group (76.74) was not significant in the first PA. As the experiment progressed, the difference in scores between the experimental and control groups expanded. More precisely, the second PA's mean score for the experimental group is 6.4 points higher than the control group. Similarly, the mean score for the experimental group in the third PA is 6.25 points greater than that of the control group. As the experiment unfolded, the scores of the experimental group exhibited a more pronounced increase compared to the control group.

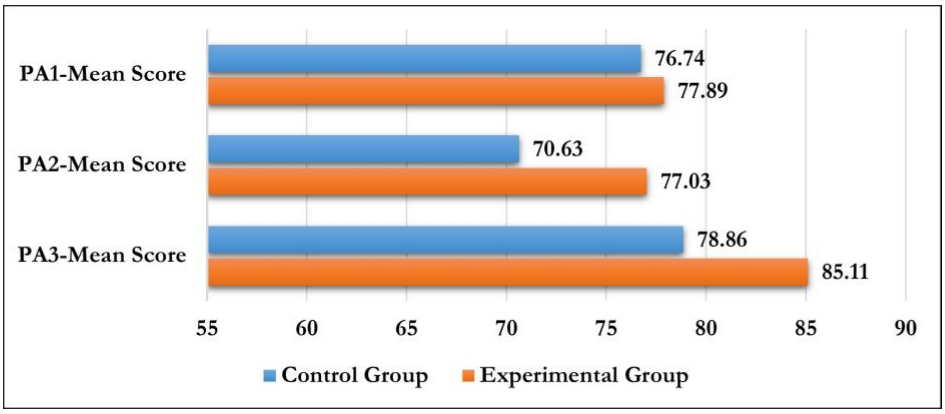


Fig. 5 Process Assessment (PA) Results

Continuous Assignment (CA) is a crucial indicator for monitoring students' academic progress. Conducted shortly after the PA, the experimental group received adaptive CA based on PA results. An external tutor designed and graded CA questions of varying difficulty levels to ensure authenticity and validity. For clarity in visual analysis, grades A, B, C, D, and E were categorized into two sets: (1) Equal or Above Merit (A and B) and (2) Equal or Below Average (C, D, and E).

Figure 6 highlights the high percentage of equal or above merit grades in the experimental group. Initially, the disparity between high and low grades was minimal, as seen in the first CA. However, as the course progressed, both high-difficulty and low-difficulty sub-groups in the experimental group showed better academic performance compared to the control group. In the third CA, the equal or above merit rates peaked at 85.7% for the high-difficulty sub-group and 76.2% for the low-difficulty sub-group. Notably, the second CA's high-difficulty sub-group saw a low percentage of merit grades due to the difficulty of the assignment questions.

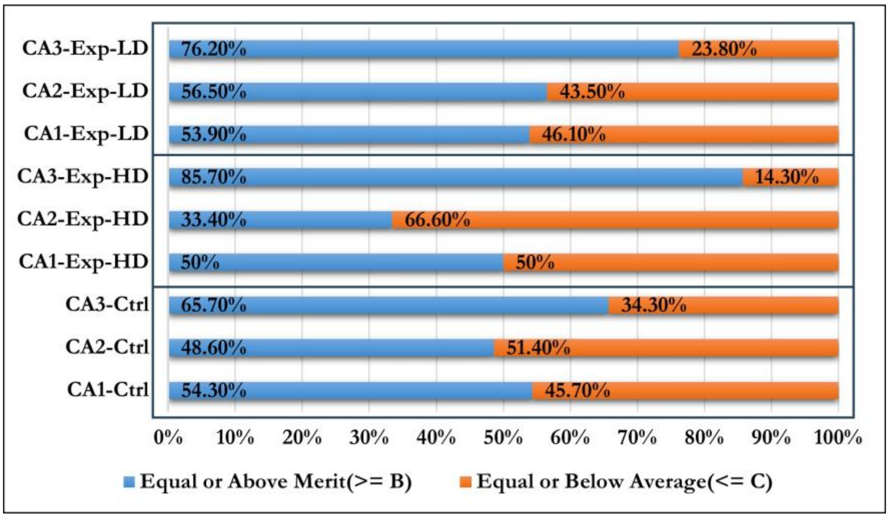


Fig. 6 Continuous Assignment (CA) Results

4.1.4 End of Module Assessment (EMA) Result

The analysis aimed to determine whether the data collected from the two groups of EMA and Final Exam results followed a normal distribution, which is a fundamental assumption for many statistical tests. The Shapiro-Wilk test was more appropriate for this research's small sample sizes (<50 samples) and was used to test whether the data were normally distributed. Table 4 reported that the EMA's experiment group and the control group had the Shapiro-Wilk test statistic of 0.126 and 0.144, which were not significant at the 0.05 level, indicating that the data from the experiment group and the control group were assumed to follow a normal distribution.

Table 4. Independent Sample Test

	Group	Kolmogorov-Smirnova			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
EMA	Exp	.100	35	.200*	.951	35	.126
	Ctrl	.102	35	.200*	.953	35	.144

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

The mean score is an essential indicator for the analysis of data. Table 5 shows the statistics for two groups: the experimental group (Exp) and the control group (Ctrl) for the End-of-Module Assessment (EMA). The group of students who were exposed to the ICT-based innovative assessment strategy demonstrated significantly higher academic performance in EMA (M = 66.8, SD = 11.2) compared to the group of students who underwent the traditional assessment strategy in EMA (M = 59.2, SD = 14.1).

Table 5. Results of Academic Performance Between Two Groups

	Group	N	Mean	Std. Deviation	Std. Error Mean
EMA	Exp	35	66.80	11.219	1.896
	Ctrl	35	59.17	14.062	2.377

The independent samples t-test results in Table 6 reveal a significant difference in academic performance between the two groups. The t-value was significant at the 0.05 level for EMA (t = 2.5, p = 0.015), indicating a statistically significant difference. These findings suggested that the innovative assessment strategy positively impacted student's academic performance, leading to higher scores compared to the traditional approach.

Table 6. Independent Samples t-Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Diff	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Diff	Std. Error Diff	Lower	Upper
EMA	Equal variances assumed	2.425	.124	2.509	68	.015	7.629	3.041	1.561	13.696
	Equal variances not assumed			2.509	64.804	.015	7.629	3.041	1.556	13.702

4.2 Relationship between Technology Acceptance (TA), Platform Usability (PU), Assessment Convenience (AC), and Performance Expectation (PE).

In direct alignment with Research Objective 2 (RO2), this section examines the variables' interrelationships. The analysis is structured into two key components: Reliability and Validity Results, which establish the robustness of the measurement model, and Path Modelling Results, which reveal the strength and significance of the relationships between these constructs.

4.2.1 Reliability and Validity Results

The first step checked on the reliability and validity of the data. In this case, Cronbach's alpha coefficient of 0.846 (See Table 7) indicates that the questionnaire has high internal consistency in measuring the target concept or attribute.

Table 7. Cronbach's α Coefficients

Cronbach's α	Standardized Cronbach's α	Items	Sample Size
0.846	0.844	18	70

The data in Table 8 shows the reliability and validity of the different constructs, which correlated with the differences observed in the study. In the construct assessment, some constructs showed high internal consistency and validity, while others were slightly lower. For TA (Technology Acceptance), Cronbach's alpha and rho A coefficients were at acceptable levels (0.708 and 0.709). However, the AVE (0.402) was relatively low, implying that there is room for improvement in the validity of the construct. Although the Average Variance Extracted (AVE) should be higher than 0.5, we can accept 0.4. Fornell and Larcker said that if AVE is less than 0.5 but composite reliability is higher than 0.6, the convergent validity of the construct is still adequate (Fornell & Larcker, 1981).

In contrast, the PU (Platform Usability) and PE (Performance Expectations) constructs showed high reliability and validity. The PU had a high Cronbach's alpha (0.756) and rho_A (0.794) and a high AVE (0.579), while the PE showed very high reliability and validity (Cronbach's Alpha 0.868 and rho_A 0.878, AVE 0.715). Finally, the AC (Assessment Convenience) construct also had acceptable levels of reliability and validity.

Table 8. Construct Reliability and Validity

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
TA	0.708	0.709	0.800	0.402
PU	0.756	0.794	0.845	0.579
AC	0.728	0.752	0.830	0.554
PE	0.868	0.878	0.909	0.715

These results suggest that the constructs' reliability and validity were acceptable.

In Table 9, the KMO value (Kaiser-Meyer-Olkin value) assessed the applicability of the factor analysis, which usually ranges between 0 and 1. In this case, the KMO value is 0.70, which was moderate. Bartlett's test of sphericity was used to test whether the observed correlation matrix is significantly different from the unit matrix (complete independence). In this case, as shown in Table 9, it was noted that there is a significant difference between the observed correlation matrix and the unit matrix at a 1% level of significance. These results provide important statistical information for further exploration and validation of the applicability of factor analysis.

Table 9. KMO test and Bartlett's test

KMO Value		0.70
	chi-square (Approx.)	521.72
Bartlett's test of sphericity	df	153
	P	0.000***

*** Representing a 1 % level of significance respectively
** Representing a 5 % level of significance respectively
* Representing a 10 % level of significance respectively

4.2.2 Path Modelling Results

Partial least squares (PLS) path modeling, a variance-based structural equation modeling technique commonly used in observational and experimental research (Henseler et al., 2016), was applied in this study. The process usually contains the following steps: Model Specification, Identification, Estimation, Testing, and Modification. Figure 7 shows the PLS results after applying Bootstrapping and PLS Algorithm functions. In this educational research, with a sample size of 70, a p-value threshold of 0.1 was adopted. This slightly more lenient significance level is appropriate for an exploratory study with a relatively small sample, allowing for detecting potentially meaningful effects that might be overlooked with a stricter threshold.

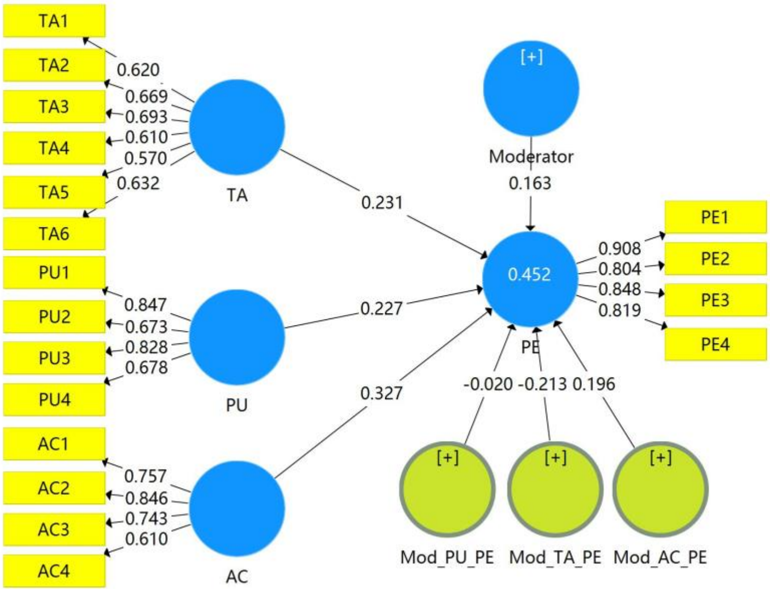


Fig. 7 Partial Least Squares (PLS) Path Modelling

In Table 10, path coefficients were analyzed. Path coefficients are the results of the PLS algorithm, representing the size of the relationship between two latent constructs.

Table 10. Path Coefficients

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
TA -> PE	0.231	0.269	0.105	2.194	0.028
PU -> PE	0.227	0.239	0.105	2.167	0.030
AC -> PE	0.327	0.324	0.124	2.639	0.008

TA -> PE: The p-value of significance is 0.028 ($p < 0.1$). Hence, hypothesis one (H1) is accepted, which means there is a positive relationship between Technology Acceptance (TA) and Performance Expectation (PE). This path is valid, and its impact coefficient is 0.231.

PU -> PE: The p-value of significance is 0.03 ($p < 0.1$). Hence, hypothesis two (H2) is accepted, which means there is a positive relationship between Platform Usability (PU) and Performance Expectation (PE). This path is valid, and its impact coefficient is 0.227.

AC -> PE: The p-value of significance is 0.008 ($p < 0.1$). Hence, hypothesis three (H3) is accepted, which means there is a positive relationship between Assessment Convenience (AC) and Performance Expectation (PE). This path is valid, and its impact coefficient is 0.327.

The variance in the endogenous variable is explained by the exogenous variable(s) using R Square statistics. Falk and Miller (1992) recommended that R square values be equal to or greater than 0.10 for the variance explained by a particular endogenous construct to be deemed adequate. In scholarly research, Hair et al. (2013) suggest that R square values of 0.75, 0.50, or 0.25 for endogenous latent variables can be described as substantial, moderate, or weak. According to these criteria, the R square is 0.452 (See Table 11), meaning that the PE influenced by TA, PU, and AC has an R-square value of 0.452. In other words, the 45.2% change in PE could be explained moderately by TA, PU, and AC.

Table 11. R-Square Result

	R Square	R Square Adjusted
PE	0.452	0.390

4.3 Moderating Effect on Performance Expectation (PE).

In fulfillment of Research Objective 3 (RO3), this section investigates the moderating effect of students' cumulative grade point average (CGPA) levels on the relationships between independent variables and the dependent variable.

4.3.1 Path Modelling Results

Table 12 shows the path coefficients of moderators after analysis. These coefficients quantify the strength and direction of the relationships between the moderating variables and the outcome construct.

Mod_TA_PE -> PE: The p-value of significance is 0.074 ($p < 0.1$). Hence, hypothesis four (H4) is accepted. Different CGPA levels can moderate the relationship between Technology Acceptance (TA) and Performance Expectation (PE). This path is valid, and its impact coefficient is -0.213.

Mod_PU_PE -> PE: The p-value of significance is 0.858 ($p > 0.1$). Hence, hypothesis five (H5) is rejected. Different CGPA levels cannot moderate the relationship between Platform Usability (PU) and Performance Expectation (PE). This path is invalid.

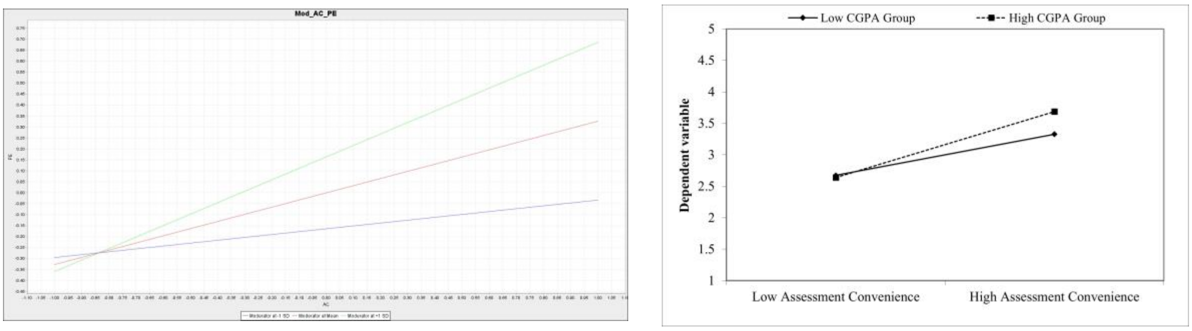
Mod_AC_PE -> PE: The p-value of significance is 0.08 ($p < 0.1$). Hence, hypothesis six (H6) is accepted. Different CGPA levels moderate the relationship between Assessment convenience (AC) and Performance Expectation (PE). This path is valid, and its impact coefficient is 0.196.

Table 12. Path Coefficients of Moderating Effects

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Mod_TA_PE -> PE	-0.213	-0.185	0.119	1.787	0.074
Mod_PU_PE -> PE	-0.020	-0.004	0.111	0.179	0.858
Mod_AC_PE -> PE	0.196	0.173	0.112	1.748	0.080

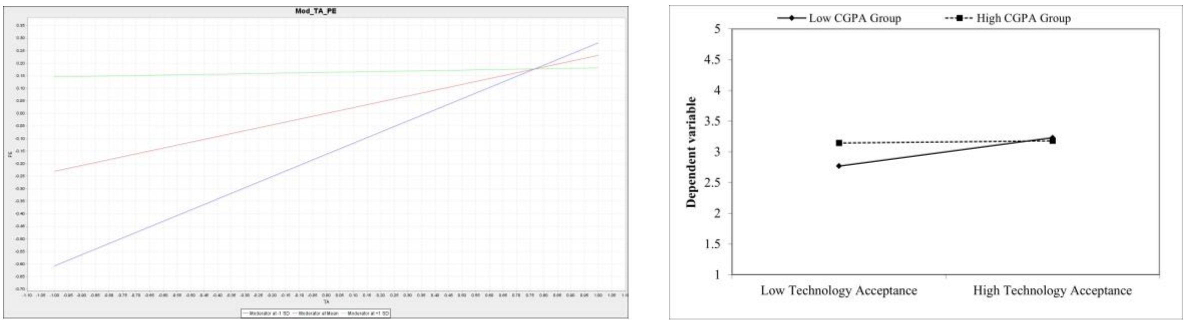
4.3.2 Slope Analysis Results

Slope analysis of SmartPLS is usually used in moderation analysis. In a simple slope plot, the slope of the line shows the effect of the predictor variable on the dependent variable at a given moderator value. It demonstrates how the relationship between two variables changes depending on the moderator value. (Ringle et al. 2022).



(**a**) (**b**)

Fig. 8 Slope Analysis for Mod_AC_PE relationship.
(a) Original output from SmartPLS; (b) Visual representation of moderation effect.



(**a**) (**b**)

Fig. 9 Slope Analysis for Mod_TA_PE relationship.
(a) Original output from SmartPLS; (b) Visual representation of moderation effect.

In Figure 8, higher CGPA levels entailed a stronger relationship between AC and PE, while lower levels of CGPA levels led to a weaker relationship between AC and PE. The graph showed a steeper and positive gradient in the High CGPA group than in the Low CGPA group. By contrast, in Figure 9, higher CGPA levels entailed a weaker relationship between TA and PE, while lower levels of CGPA levels led to a stronger relationship between TA and PE. The graph showed a steeper and positive gradient in the Low CGPA group than in the High CGPA group.

5. Conclusion

The findings from the experiment and questionnaire survey indicate that all three research objectives (ROs) were achieved:

Using ICT-based assessment methods has a positive relationship with students' academic performance compared to traditional assessment methods. Specifically, students exposed to the ICT-based innovative assessment strategy demonstrated significantly higher academic performance than students who underwent the traditional assessment method. This significant difference in test scores underscores the effectiveness of integrating technology in assessments.

There was a significant positive relationship between technology acceptance (TA) and performance expectations (PE). As technology acceptance increased, performance expectations also increased. Similarly, there was a significant positive relationship between platform usability (PU) and performance expectations, indicating that as platform usability increased, so did performance expectations. Additionally, a significant positive relationship was observed between assessment convenience (AC) and performance expectations, suggesting that increased assessment convenience also led to higher performance expectations.

Different CGPA levels moderated the relationship between technology acceptance (TA), assessment convenience (AC), and performance expectations (PE). However, CGPA did not significantly moderate the relationship between platform usability (PU) and performance expectations. Specifically, a stronger association between assessment convenience and performance expectations was observed for students with higher CGPA levels. Conversely, a stronger association between technology acceptance and performance expectations was noted for students with lower CGPA levels.

The study demonstrates that innovative ICT-based assessment methods, when successfully implemented and yielded, bring meaningful results in evaluating tertiary students' academic performance. Data from the experimental group demonstrated that students well-received the integration of technology. Statistical outcomes revealed that the experimental group had a more favorable growth curve than the control group. Survey results indicated high ratings for technology acceptance (TA). Analysis showed that technology acceptance (TA), platform usability (PU), and assessment convenience (AC) significantly positively affect performance expectations (PE). For students with higher CGPA, assessment convenience is more important for boosting performance expectations. In comparison, for students with lower CGPA, greater acceptance and use of technology compensate for decreased assessment convenience in terms of performance expectations.

6. Limitations

Two limitations were noted despite the study's contributions to fully comprehending the research findings. Firstly, the sample size for the experimental design was limited. The study's limitation to one private institution in Shanghai may restrict the applicability of the findings to other educational environments. A more considerable and more representative sample might improve the results' external validity. Secondly, there were time constraints. Since the study was completed in one semester, the scope and depth of data collection might have been constrained. A more extended research period would have clarified the long-term effects of implementing innovative assessments.

7. Recommendation

Implementing an innovative ICT-based assessment method for undergraduates in a private university in Shanghai has been experimentally shown to be an effective higher education method. These findings significantly contribute to the field of online education. Education practitioners should integrate more ICT-based tools and assessment platforms into student assessment processes. To maximize the advantages of ICT-based assessments, it is recommended that training and assistance be offered to enhance students' willingness and ease in adopting technology. Implementing ICT-based innovative assessment methods can improve online assessment effectiveness, guide educational institutions in developing assessment methods, and support the development of national policies. This aligns with Sustainable Development Goal 4, which emphasizes quality education.

Overall, this study demonstrates the promise of using Technology-Integrated Innovative Assessment Methods or ICT to transform student assessment, thereby enhancing individual and societal learning. Further research and intelligent implementation focused on improving student experiences are essential as education becomes increasingly technology-driven.

8. Co-Author Contribution

The authors affirmed that there is no conflict of interest in this article. Author 1 played a vital role in conceptualizing and executing the overall research, including data collection, analysis, interpretation, and manuscript preparation. Author 2 made significant contributions to formulating

research questions and objectives, along with conducting comprehensive data analysis. Author 3 contributed substantially to the manuscript revision and development of the literature review. Author 4 was instrumental in the data collection and analysis processes. Author 5 made valuable contributions through questionnaire design and data interpretation. Author 6 provided the general research direction, established methodological procedures, and supervised the experimental process throughout the study.

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Appendix A Questionnaire

Table A.1. Constructs & Measurement Items

Construct	Measurement Items
Demographics	1. Gender: [ ] Male [ ] Female 2. Grade: [ ] First Year [ ] Second Year [ ] Third Year [ ] Fourth Year 3. Year of Birth: [ ] 2001 [ ] 2002 [ ] 2003 [ ] 2004 [ ] 2005 [ ] Other (Year:)
Technology Acceptance (TA)	TA1: New technologies contribute to a better quality of study life. TA2: Technology makes me more productive in my personal study life TA3: Technology gives people more freedom to study where they please. TA4: I feel confident that technology-based systems will follow through with what I instruct them to do TA5: Products and services that use the newest technologies are much more convenient to use TA6: Technology gives me more freedom of mobility.
Platform Usability (PU)	PU1: The navigation system of the online assessment platform you use is clear, without confusion, and the page is easy to browse. PU2: The online assessment platform you use can accurately record your assessment information and assessment content. PU3: The existing functions of the online assessment platform can meet your learning and assessment needs. PU4: Overall, you are very satisfied with the online assessment platform.
Assessment Convenience (AC)	AC1: ICT-based assessment would probably be easy to use. AC2: ICT-based assessment should be easy for me. AC3: ICT-based assessment should facilitate test completion. AC4: Using ICT-based assessment is understandable.
Performance Expectancy (PE)	PE1: I believe that taking an ICT-based assessment could improve my academic results of end-of-module (EMA). PE2: I think that taking an ICT-based assessment could improve my academic performance in the final examination. PE3: The ICT-based assessment could accelerate my academic performance.

PE4: ICT-based assessment could be beneficial to my learning activities.

Appendix B Statistical Results of Questionnaire

Table B.1. Statistical Results of Technology Acceptance (TA) Related Questions

Items	SA	A	N	D	SD	Mean	Std Dev
TA1	28 40%	31 44.30%	8 11.40%	3 4.30%	0 0.00%	4.20	0.809
TA2	21 30%	26 37.10%	20 28.60%	3 4.30%	0 0.00%	3.93	0.873
TA3	22 31.40%	25 35.70%	17 24.30%	5 7.10%	1 1.40%	3.89	0.986
TA4	8 11.40%	27 38.60%	30 42.90%	5 7.10%	0 0.00%	3.54	0.793
TA5	17 24.30%	39 55.70%	11 15.70%	3 4.30%	0 0.00%	4.00	0.761
TA6	24 34.30%	28 40%	15 21.40%	2 2.90%	1 1.40%	4.03	0.900

Key: SA=Strongly Agree-5, A=Agree-4, N=Neither Agree nor Disagree-3, D=Disagree-2, SD=Strongly Disagree-1

Table B.2. Statistical Results of Platform Usability (PU) Related Questions

Items	SA	A	N	D	SD	Mean	Std Dev
PU1	21 30%	33 47.10%	14 20%	1 1.40%	1 1.40%	4.03	0.834
PU2	18 25.70%	23 32.90%	20 28.60%	5 7.10%	4 5.70%	3.66	1.115
PU3	12 17.10%	20 28.60%	20 28.60%	17 24.30%	1 1.40%	3.56	1.077
PU4	37 52.90%	23 32.90%	10 14.30%	0 0.00%	0 0.00%	3.39	0.728

Key: SA=Strongly Agree-5, A=Agree-4, N=Neither Agree nor Disagree-3, D=Disagree-2, SD=Strongly Disagree-1

Table B.3. Statistical Results of Assessment Convenience (AC) Related Questions

Items	SA	A	N	D	SD	Mean	Std Dev
AC1	21 30%	25 35.70%	18 25.70%	5 7.10%	1 1.40%	3.86	0.982
AC2	20 28.60%	19 27.10%	22 31.40%	8 11.40%	1 1.40%	3.70	1.054
AC3	23 32.90%	28 40%	14 20%	4 5.70%	1 1.40%	3.97	0.947
AC4	27	26	14	3	0	4.10	0.871

	38.60%	37.10%	20%	4.30%	0.00%		

Key: SA=Strongly Agree-5, A=Agree-4, N=Neither Agree nor Disagree-3, D=Disagree-2, SD=Strongly Disagree-1

Table B.4. Statistical Results of Performance Expectancy (PE) Related Questions

Items	SA	A	N	D	SD	Mean	Std Dev
PE1	15	28	18	7	2	3.67	1.018
	21.40%	40%	25.70%	10%	2.90%		
PE2	16	24	16	11	3	3.56	1.137
	22.90%	34.30%	22.90%	15.70%	4.30%		
PE3	14	31	20	2	3	3.73	0.962
	20%	44.30%	28.60%	2.90%	4.30%		
PE4	19	23	21	6	1	3.76	0.999
	27.10%	32.90%	30%	8.60%	1.40%		

Key: SA=Strongly Agree-5, A=Agree-4, N=Neither Agree nor Disagree-3, D=Disagree-2, SD=Strongly Disagree-1