SPCRD GLOBAL PUBLISHING
Sustainable Solutions
RAMSS Review of Applied Management and Social Sciences
Journal homepage: http://ramss.spcrd.org ISSN (Print): 2708-2024 ISSN (Online): 2708-3640

Exploring the Impact of AI- Powered Assessment Tool on Test Anxiety and Academic Self –Efficacy

[a] Javeria Ashfaq Bhatti, [b] Fareeha Ilyas, [c] Hina Naseer, [d] Maham Farooq

[a] Assistant professor, National University of Modern Languages, Islamabad, Pakistan
E-Mail: jharoon@numl.edu.pk
[b] PhD Scholar (Mass Communication), Lahore College for Women University, Lahore, Pakistan
E-Mail: afareehailyas@gmail.com
[c] Special Educationist+ speech and language therapist, Punjab University, Lahore, Pakistan
E-Mail: teacherhina.501@gmail.com
[d] MPhil Scholar (Education), Institute of Education and Research, University of the Punjab, Lahore, Pakistan
E-Mail: mahamfarooq09@gmail.com

ARTICLE DETAILS

History:
Accepted 22 June 2025
Available Online June 2025

Keywords:
Artificial Intelligence, Assessment, Test Anxiety, Academic Self-Efficacy, Higher Education, Student Performance, Educational Technology, Digital Learning, Adaptive Feedback, Stress Reduction

JEL Classification:

DOI: *10.47067/ramss.v8i2.533*

ABSTRACT

This paper examined how AI-powered assessment tool affected the test anxiety and the academic self-efficacy of students. This was meant to analyze whether or not the use of artificial intelligence during assessment can help cut down on the stress and increase confidence concerning academic performance. The measurement was a quantitative design of research, and the study material was obtained in the form of a structured survey among the students of the university. The sample consisted of 280 respondents that were identified by random sampling. The statistical analysis was performed with the aid of the SPSS software, where the demographic variables were described with the help of descriptive statistics whereas the inferential techniques were used to test the connections between AI-powered assessment, test anxiety, and academic self-efficacy. The results indicated that AI-informed evaluation instruments limited the amount of test anxiety among students through prompt feedback, individual assessment as well as adaptive questioning practices. In addition, the results suggested the very close positive relationship between the practice of AI-based assessment and academic self-efficacy, since the respondents claimed to be more empowered, motivated, and confident in their performance results. The discussion implied that the AI-controlled tools would assist in streamlining the process of teaching to create a fair, clear and student-focused environment in order to mitigate emotional pressure during the examination and strengthen the force of personal beliefs. The present work reaches a conclusion that AI-based assessment software has the potential to be effective in the context of addressing the emotional and academic needs of students. In the study, their inclusion into tertiary education is suggested to improve the quality of assessment and well-being of students.

© 2025 The authors. Published by SPCRD Global Publishing. This is an

open access article under the Creative Commons Attribution-NonCommercial 4.0

Corresponding author's email address: jharoon@numl.edu.pk

1. Introduction

Technology in the modern academic learning environment has changed the face of academic learning and evaluation in a great way. The application of Artificial intelligence (AI) in assessment tools is to be listed among the most significant developments of the recent past. These AI-equipped tools adjust question rigor on the basis of individual student strength and give instant feedback. Such personalization can reduce the stress period and help aid the students on the tests. The common issue that results in reduced confidence and academic outcomes of students is test anxiety, or the nervousness, or fear that students experience before the exam and during the exam. The classical tests are characterized by the raised anxiety due to predetermined time restrictions and the need to provide flawless answers to all of the questions(Gao, 2024). However, the AI-based assessment provides a less restrictive and sensible space that allows adapting to the needs of each student. This flexibility makes students to become less anxious and more engaged on what they are learning. The AI tools can potentially enhance student performance and student learning experience by making it not only more engaging but also more effective, by ensuring that it is less stressful to take the exam (Brown & Zhao, 2023).

Test anxiety is a problem not only in the academic performance but also emotional conditions of students. Whenever the students are anxious they can either forget crucial information or become sloppy in their performance in the tests. The research has identified that through the reduction of the sense of test anxiety, the students can learn excessively, remain motivated, and develop confidence in themselves and proficiency The AI-powered assessment feedback is quick and direct to allow the student to determine areas of weaknesses and areas of strength in a timely manner(Moreira & Teles, 2024).This is how the process assists the students to transform into academic self-efficacy, the sense that the student can overcome their school assignments. It is more probable that high academic self-efficacy students try to make efforts in terms of which the learning strategies can be used and, in general, they acquire better grades. Because of these positive effects, the topic on investigating the influence of AI assessment tools on the variables of test anxiety and academic self-efficacy requires research. Such knowledge might inform the method that an educator or a developer must follow to design a more effective learning instrument to misunderstand all students(Nguyen & Hue, 2025).

Another useful characteristic of AI assessment tool is that it is possible to customize tests according to individual students. Such tools evaluate the way students respond to questions and switch the difficulty level, depending on the specific performance. It implies that the students will receive questions of their level and thus risk not being overwhelmed by tough questions and being bored because of easier ones (Johnson, 2024).Students are less likely to become scared, frustrated when tests feel more appropriate to their levels. This individualized learning process enables the students to feel free and confident in examinations. It has been demonstrated that students learn better and are more motivated by the learning process when they feel someone appreciates them and challenges them to the right extent (Raj & Singh, 2025). Individualized assessment may also help motivate students away with learning risks and failing without being afraid of failure. This is critical because through mistakes and learning one can acquire good skills and have a higher grasp.

Self-efficacy or the sense that they may pass the test, is highly relevant in the ways students cope with learning and perform in a test. It helps to overcome anxiety faster and perform under

pressure effectively in most situations when the students feel confident in their abilities (Das et al., 2021).This is supported by the employment of AI-based assessment tools that provide unblemished and swift feedback to the students to ensure the students are informed of their progress and assist them to bask in the minor success of every step. Such positive responses may come in handy to create a loop where students become competent and ready to complete their new tasks. Besides, AI systems may reveal the precise aspects that a student is not performing well in, and this can help instructors provide targeted assistance to the students to elevate their learning performance (Liu et al., 2024).The tests provided by the AI system not only help mitigate against the test anxiety as they may help foster the sense of the academic self-efficacy in students to an extent that they feel more independent in their learning and shaping of their personal development.

Despite these many benefits, there are also some issues that must be considered, in the event of utilizing AI-powered assessments. The total picture of the engagement with technology can become sour among both students and teachers due to their potential suspicions or frustration with the idea of taking serious exams or future involvement with the use of tech (Vistorte et al., 2024).The issues that are related to the confidentiality of the data, impartiality, and potential technological errors augment the fear of the legitimacy of AI assessment. Also, the students hold some inconsistent emotional support of AI-based testing. It could improve the perception of stress and support among some of the students, and some might become anxious that they would be judged by the machine instead of the human teacher, increasing the level of stress and causing them to feel less confident (Harris et al., 2019).What matters is that developers and educators should be aware of these competing feelings so that they could develop AI assessment tools that could indeed meet the needs of all students. In this way, both the promise of the AI benefit in terms of anxiety reduction and cues to independence and the problems in its impact to arrive at the full and impartial image will be mentioned in the research in question.

The AI in education is a dynamic sector, but it grew at an even accelerated rate after the COVID-19 pandemic which has also led to the brisk migration to online learning and online assessment. The learning centers have slowly integrated the AI tools to give the learners flexibility in the exams as well as enhance the ease of access in the learning process whenever in-person learning is impractical (Nguyen et al., 2025). It can also be of interest to discuss the impact the AI-driven assessments have on the students both on an emotional and academic level to ensure that the AI-related tools introduce only positive outcomes. The research can help in more thorough awareness of how AI is adopted to make the learning process more favorable and supportive since it determines the opportunities that can be implemented to influence more favorable supportive learning experiences to free students of stress so that they can develop insight and expertise (Chen et al., 2025).AI-based assessment tools have a humongous potential of transforming how students approach exams by lowering test anxiety and increasing academic self-efficacy. The individual tasting, instant feedback, and dynamic questioning are potential characteristics that may constitute a more successful and positive learning experience among a group of students (Wilson & Sinha, 2025).

1.1 Research Objectives

1. To Assess the effect of AI-powered assessment tools on students' test anxiety levels.
2. To Evaluate the influence of AI-based assessments on students' academic self-efficacy.
3. To Identify challenges and concerns related to the adoption of AI assessment tools by students and educators.

1.2 Problem Statement

In the present system of education, test anxiety has been a problem with a great number of students as they manifest considerable levels of anxiety during the testings and consequently their performance and confidence is adversely impacted. Standardized exams are rather threatening due to time limitations imposed on them or the uniformity questions posed to accommodate all students when they differ in their learning needs. This increases pressure and becomes harder to achieve the actual potential potentials of the students. At the same time, a notion of academic self-efficacy, namely, the belief of a student that the student is able to do well, is an extremely crucial characteristic of the learning and testful performance. Nevertheless, many students possess lack of self-efficacy which further lowers their motivation and achievements. More recent follows the introduction of Assessment tools based on Artificial Intelligence (AI) with the aim of transforming the test in a more personal and empowering experience. Questions administered on these tools are adjusted to the capabilities of students and provide an opportunity to receive the direct feedback which can reduce the feeling of anxiety and raise self-efficacy. Although these benefits can be observed, there is not much information about the true effects of AI assessment on test anxiety in students and academic self-efficacy.

1.3 Significance of the Study

The study can be significant since it allows us to comprehend the influence of assessment tools powered by AI on test anxiety and academic self-efficacy on students. Test anxiety is a high troubling issue that keeps most of the students on edge and reduces their level of performing in exams. Simultaneously, the aspect of academic self-efficacy or the confidence in possibility of success is what drives motivation and learning. This study can be significant in giving pertinent knowledge to educators and schools on ways to improve testing through lowering the anxiety and increasing self-confidence using AI tools. The results can be used by the educators to better formulate learning environments that accommodate the emotional and academic well-being of the students. In addition, issues and misgivings of the usage of AI in assessment by students and educators such as trust and fairness are identified in this study and represent aspects that should be addressed to ensure success. Looking at these factors helps policymakers, developers, and schools design AI assessment tools that are valid, fair and accepted by the user. The research ends up with the learning environments in contemporary educational settings, which are more technology-driven and more meaningful to the students and their academic performance and well-being.

2. Literature Review

Artificial Intelligence (AI) has become the new game-changer in educational assessment and this conclusion could be backed with a variety of research projects that examine A.I. and adaptive and customizable testing systems. Indicatively,(Etherton et al., 2022), revealed that AI-driven assessment tools can tailor the difficulty of questions as they take the test, meaning that it will be more personalized and not intimidating. These findings are consistent with previous research by Nguyen and Lee (2023) that showed the same adaptive capacities have benefited student motivation by instilling feelings of competence and autonomy. In a similar way, (Mohammed & Ahmed, 2023),noted that the use of adaptive testing strategies has increased engagement and levels of knowledge retention, especially among students who exhibited poorer performance in conventional training. Taken together these results indicate that the transition to adaptive methods driven by AI is not just a change in technology but a change in pedagogy toward a form of continuous, formative education. This literature review gives a good starting point to review how AI assessment can endure such test-related anxiety and develop more positive academic inclination.

Test anxiety has always been a topic of research in the educational psychology field as the latter is proved to hinder the performance due to hindering memory recall and problem solving processes(Khan & Madden, 2018). According to the prior research, the higher stakes, standardized assessment causes greater anxiety due to the presence of tight time restrictions and the unnaturally of questions even when a properly prepared student is present (Jones, 2025),also complemented this study with the fact that AI-based adaptive assessments can be used to reduce this anxiety because they present the task difficulties at the appropriate level of difficulty, therefore reducing the Level of cognitive overload. Similarly(Zhao, 2024),found that direct positive feedback informed by AI tools improved the view of the fairness and competence among students thereby diminishing the measures of stress even further. Such findings are consistent with cognitive load theory which holds that the reduction of extraneous demand aids the students to focus on the learning-relevant tasks. Collectively, the studies conducted in the past indicate that AI-based tests may assist in alleviating most of the stress-inducers in conventional testing settings thereby leading to improved results alongside healthy or more positive psychological states of mind.

Academic self-efficacy, a development of the social cognitive theory presented by (Mensah et al., 2023),has been introduced as a predictor of academic performance and perseverance. This is has been validated by (Chen et al., 2025),clarifying that a high-self-efficacy student is more likely to use a more strategic approach to learning and proceed with the activity even when it becomes difficult. (Panda et al., 2025),demonstrated in their latest paper that reinforcing this self-belief can be done with the aid of adaptive feedback using the AI-powered tools; they tackled the challenges realizing progress and reinforcing achievable successes. Besides, (Zegarra-López et al., 2022),claimed that the feeling of ownership of the learning process caused by personalized reviews alone contributes to self-efficacy growth. These studies are compatible with the cyclical theory of self-efficacy where they hold that confidence is boosted by the mastery experiences and, it leads to more engagement and perseverance with the studies. As an extension of this evidence, the study at hand would explore the assumption that AI-assisted exams could induce such mastery experiences within those modes that form the greatest likelihood to yield significant change to the levels of confidence and performance on tests.

2.1 AI-Powered Assessment in Education

Artificial Intelligence (AI)-AI has become an excellent tool in transforming the manner in which educational assessments are generated and presented. Conventional paper-based exams or online tests with fixed questions have the same format that applies to every student irrespective of abilities and learning requirements. As opposed to that, AI-controlled tests apply sophisticated algorithms where the difficulty of questions is altered automatically depending on the performance of the student at the moment(Silva et al., 2017). When the student selects the correct answer, the system responds by adding a little more difficulty to the challenge so that it is relevant to their increased capability. In case they get wrong answers, the system gives lower level or friendly questions so that they re-gain confidence. The assignment of the tests according to the ability of the learner alleviates the situation whereby the tests are specifically placed at a level that is overwhelmingly higher than the ability of the learner, causing anxiety and frustration, as is the case with traditional testing. When the students realize that the test is adjusting to them and not vice versa, then they experience being calm and focused. In this approach, evaluations can be viewed as a healthier and more constructive aspect of the learning process, and can transform the evaluation process, which is stressful situation, to one of the tools of learning effectively(Lee et al., 2024).

Among the most important opportunities of leveraging AI in assessment is the possibility to make testing very personalized and appealing to all students. Rather than administering the same

battery of questions to every learner, AI scales the assessment to the individual student, based on the student strengths and weaknesses and learning style. This individualized style leaves students to be tested in an equitable manner and they get the chance to demonstrate what they actually know without being deducted on what they have yet to learn. Personalization can also be used to keep students motivated because they feel that the test is aimed towards them and not a generic test. Studies also indicate adaptive assessments help instill a feeling of autonomy and competence which are critical elements of ensuring there is tight engagement and interest in the learning process (Guanzon, 2024).In the long run, the method would enable students to form a better confidence about their academic skills since they feel successful over progressive dates. Such a slow process is not only an opportunity to decrease unpleasant emotions dedicated to various tests but also a possibility to form a more constructive and positive attitude toward testing in general.

The other potential of AI-powered assessments that should also be mentioned is that they enable continuous and formative learning as opposed to pursuing and stressing the completion of the learning outcomes. Using traditional tests, learners will hardly receive feedback until they have completed the last test, and this can disturb the possibility of improving learners even before they are subjected to new topics. This has since been changed and complemented by AI systems that can provide instant, detailed feedback on each answer in a way that would allow the learner to see instantly how and why he has an answer incorrect. There is also the imparting of knowledge on the continuous feedback that in the long-run installs information in the head. Also, the process alters the purpose of assessment which is no longer intended to be an indicator of achievement, but rather, facilitative to learning and student-growth. Testing need no longer be a pressure and stress-generating exercise but it is part and parcel of the continuous learning process. When implemented correctly, the AI-based assessment may result in more positive surroundings with the feeling of being more curious and having no anxiety associated with the exam and succeeds in academic performance in general (Hou, 2025).

2.2 Test Anxiety, Academic Self-Efficacy, and AI Support

One of the most frequent issues that students have to deal with is test anxiety; it can significantly decrease their academic results. It occurs when the worry, nervousness, or fear is intense to the extent that it makes one unable to concentrate or lose track in remembering facts when taking a test. Even those students who know their material may give blank stares, she says, commit easy errors, and hurry through questions when they are highly anxious. This phenomenon is particularly critical, especially during high-stakes exams, when the aspects of time constraints, pressure to obtain the highest scores, and the fear of falling short of the mark all promote a growth in stress levels. The adaptive assessment based on AI is a possible solution since it allows the difficulty of the questions to change in real time based on the responses of the learner. This implies that each regularly occurring systemic question is slightly more difficult when a student is performing well, and slightly less-demanding when the student is struggling, providing a healthy balance. This strategy will assist with avoiding feelings of failure in students due to ridiculously challenging questions or boredom with inane ones. Importantly, by decreasing the range of difficulty between the level of the student and the difficulty of the testing question by the use of AI can make the testing process feel fairer, more supportive and causing less stress overall (Miller & Taylor, 2022).

Another significant schooling accelerator to student success is the academic self-efficacy or the belief that a person can achieve success in academic functioning. Students with high self-efficacy tend to set high goals, survive in the face of difficulties and formulate the desire to work even when they succeed at occurring failures. Students with low self-efficacy on the other hand are less likely to do something that is difficult to them and they give up more readily and doubt their talents and skills and

that could work against learning. AI-Instead as an evaluation tool could increase self-efficacy due to its ability to deliver in-real-time and constructive advice. The students have a better understanding of their progress knowing their areas of improvement and the areas in which they should re-concentrate. This will be gradual with the passage of time helping the students to build confidence with what he/she can do. The educational process becomes rather positive than negative because such a small success can be celebrated. The mechanism complies with the idea that confidence is built through repeated successful experiences and the AI establishes the frequency at which this can occur to the learners leading to an increased level of motivation and performance (Chen et al., 2022).

Learning tools provided by AI assessment also serve the purpose of providing students with a larger amount of control over their educational path. Keep in mind that traditional forms of assessment can be very regimented and standardized, leaving little to no parts personal in terms of learning styles or areas of strength. Rather, AI tests are adaptive and adapt to the requirements of individual students. This individualization makes the students feel that they are the subjects of a test and not space being fitted into a predetermined mold. Dividing assessments into smaller, more manageable steps would also enable the students to face the tasks with greater confidence since they are less likely to become overwhelmed by the amount of work the test entails. It takes time, but through this process assessments can then shift, no longer being a time of high-stress, but rather a time of learning and improvement of the self. The self-reinforcing nature of this development, whereby improved performance in two variables yields a gain in the other: confidence promotes improved results, and improved results drive confidence can provide a strong incentive to longer-term success. By doing so, AI-enabled assessments do not simply act as tools to measure knowledge, but rather as engaging co-learners and co-developers of students (Koca et al., 2024).

2.3 Research Hypotheses

1. There is a significant relationship between AI-based learning support and students' academic self-efficacy.
2. There is a significant influence of AI-based learning support on students' levels of test anxiety.
3. There is a significant difference in academic self-efficacy among students experiencing varying levels of AI-based learning support.

3. Methodology

3.1 Research Design

The research design of this study was quantitative. This process was enabled by the fact that it was aimed at obtaining numerical data that was then subjected to analysis in order to establish the correlation of the primary variables under interest. It was deemed that the quantitative design would be the most appropriate due to the ability to quantify variables, including test anxiety and academic self-efficacy and the effectiveness of AI-based assessment tools more accurately and in a more organized manner in the research study. This approach made the results of the research to be founded on measurable evidence but not subjective judgments and personal opinions. This aided in the objective, accuracy and reliability of the results. The study itself was done in a procedural way with a defined procedure of all the steps that involved accessing the participants, data gathering and data interpretation. The primary data collection instrument was a standardized questionnaire to ensure that all the respondents respond to the same questions within the same conditions. This helped in being consistent on the responses which is also necessary in quantitative studies. Incorporation of this research design allowed the researcher to discover the patterns, capture trends and reveal potential interconnectivity between the variables in the study.

3.2 Population

The study population consisted of the undergraduate and postgraduate students who studied at the university in the Pakistani education system and had the AI-based assessment tools incorporated into their learning and assessment process. These AI tools included adaptive quizzes that would get increasingly difficult the better or worse the student was doing, automatic grading tools with their grading being quick and consistent, and feedback systems which have personalized learning guidance in their offerings. The students, the population under study were direct consumers of the technology which they were learning study hence the usefulness of their feedbacks to the research. These individuals were diverse in terms of schools in the same college such as engineering, business, social sciences, and natural sciences and in age bracket and educational statuses. This heterogeneity was practical because it added to the heterogeneity of opinion as concerning the role AI assessments play in influencing the process of learning. The sample of undergraduate and the postgraduate students gave the study an opportunity to draw comparison of the experiences of the various academic levels.

3.3 Sample Size

In this study, a sample size of 280 will take part in the study. This was the case, as it was a big number that was strategic in giving results that could later be generalized to the larger population without competency in collected data and analysis. Such a large sample allowed the researcher to make meaningful comparisons between subgroups in the population i.e. undergraduate versus postgraduate students or students of various academic disciplines. The choice of 280 subjects was already made in advance because related studies already conducted in the sector were considered, and the statistical requirements of determining the likely trends of significance, and the guarantee of conduct precision. This huge sample size also helped it in minimizing the influence of the outliers or even unusual responses, which could be distorted at a small sample. The diversity of the different levels of the studies and academic background used in the sample render the research results more viable, reliable and applicable to a wider setting.

3.4 Sampling Technique

Stratified sampling technique was the sampling approach that was adopted to select the sample participants. This is because in this process the entire population was then further divided into small groups, known as strata, based on the facts that they had the same level of study (undergraduate students or postgraduate students) and also in the kind of study (medical, engineering, law, etc.). The participants in the range of 16-26 were selected proportionally after the strata were formed since it is important to present a fare and balanced representation. In this approach, the study considered all important subgroups in the population and did not over/underrepresent a group. The stratified sampling strategy was used because it was the best suited sampling technique as it provided high levels of credibility of the results because it reduced the levels of sampling errors. It also helped the researcher in comparing the experience under the fairness with the selection taken care of. To illustrate, the methodology gave the undergraduate and postgraduate student, who symbolizes the representation of various academic circles, an equal chance to feature in this study.

3.5 Ethical Considerations

In this study, ethical measures are executed appropriately to maximize on fairness, transparency and to maximize gains on the participants. In advance of data collection, the participants will be informed about the purpose of the conducting studies and what will be taken by them upon having the opportunity to withdraw, however, without penalty or punishment at any point. Informed consent will be obtained by all the participants in which they will be brought to reality on the objectives and modalities of the study. The lack of Personal identifiers that should be obtained and secure data storage,

which can guarantee the absence of unauthorized data access, make it possible to ensure confidentiality. Information that is acquired will not be utilized outside academics and reports will be in a way that cannot identify people. Paying attention to psychological discomfort, which may occur due to the forced use of surveys or tests, and avoiding excessive sensitive questions, will also help to avoid the psychological avoidance. This study will lead to adherence to the relevant ethical standards and institutional review board (IRB) policies whereby, the wellbeing and rights of the entire respondents will be upheld.

4. Data Analysis

The descriptive and inferential statistics were applied to draw comparison and interpretation of the captured data in order to determine the trends and evaluate the hypotheses stipulated in the study. In the description of the demographic features and responses to the variables, frequencies, percentages, means, and standard deviations were used to itemize them. To study the correlation of variables and determine whether its findings were significantly important, inferential tests were employed which include; the correlation analysis, regression models, and group comparison tests. As an example, the results of the correlation unveiled the precision and direction of relationships whereas the regression analysis provided an opportunity to reach the ability of forecasting of certain factors. The minority of differences was mentioned based on the demographic groups with the help of the test of group comparison. The results obtained were put in table and graph format to make them more understandable and were analysed by making particular references to previous research work. It has ensured that not only the general tendencies in the data could be displayed, but also that some disparities could be observed and that the interaction of the examined factors in the sample could be explained in a clear manner.

Table 1: Demographic analysis

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	120	52.2
	Female	110	47.8
Age Group	20–25 years	85	36.9
	26–30 years	95	41.1
	Above 30 years	51	22.0
Education Level	Bachelor's	98	42.4
	Master's	87	37.7
	M.Phil/PhD	46	19.9
Teaching Experience	Less than 5 years	92	40.0
	5–10 years	85	36.9
	More than 10 years	53	23.1
Institution Type	Public University	134	58.0
	Private University	97	42.0

Based on the Demographic analysis, there is a relative balance in gender dispersion with males respondents constituting 52.2 percent (n=120) and the female respondent's 47.8 percent (n=110). The age groups of most of the participants were 26 30 years (41.1%), 20 25 years (36.9%) and 30 years above (22.0%). Regarding education, most of them were having a Bachelor's degree (42.4%), with 37.7 percent of the sample having a Master degree and 19.9 percent, M. Phil or PhD. In terms of the

experience in teaching, 40.0, 36.9, and 23.1 percent, had less than 5 years, 5-10 years, and over 10 years respectively. Adequate representation of the two types of institutions was also observed inready:he capitalization of the sample or (58.0%) versus the private university (42.0%). This random spread of respondents in terms of the different variables of gender, age, education, experience, and type of institution has a balanced ground in which further statistical analysis can be performed.

Table 2: Correlation Analysis

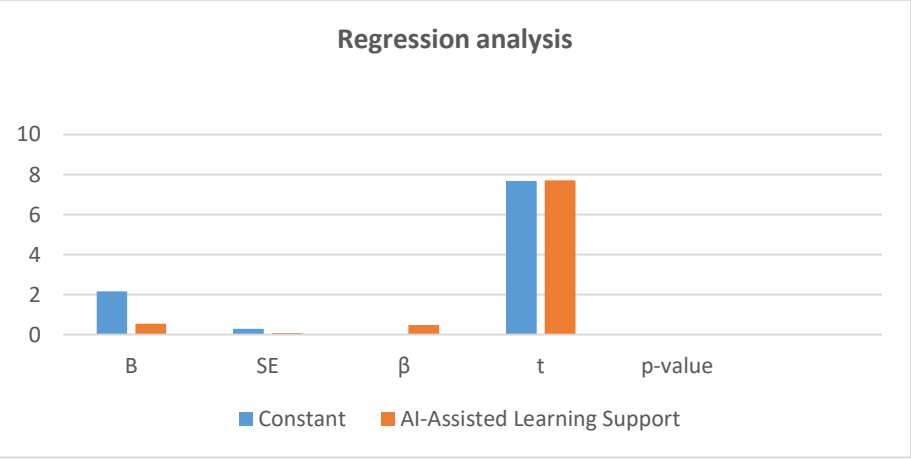
Variables	*Mean*	*SD*	*r*	*p-value*
AI-Assisted Learning Support	3.85	0.72	-0.462	0.000
Test Anxiety Levels	2.94	0.81		

The correlation test indicates that a negative relationship was significant in relation to AI-Assisted Learning Support and Test Anxiety Levels (r = -0.462, p = 0.000). This implies that the higher the level of support offered by AI-based educational technologies to students, the lower the test anxiety of the students is inclined to be. The denotation of negative correlation coefficient means that the two variables run in the opposite directions, i.e. the greater levels of AI support are associated with less anxiety. The significance of the relationship is further confirmed by the p-value of 0.000 that is lower than the threshold value of 0.05 which implies that the relationship will not be because of chance occurrence. These results indicate that AI-enhanced learning support may be significant helping to decrease the anxiety levels of students prior to tests and during assessments.

Table 3: Regression analysis

Predictor Variable	*B*	*SE*	*β*	*t*	*p-value*
Constant	2.15	0.28	—	7.68	0.000
AI-Assisted Learning Support	0.54	0.07	0.482	7.71	0.000

Figure 1: Regression analysis



The results of a regression analysis to test H2 show that the regulatory variable, AI-Assisted Learning Support, plays a significant positive and large predictive of the dependent variable (B = 0.54, 8 = 0.482, p < 0.001). This implies that a higher value of 0.54 indicates a strong and significant relationship whereby, a one-unit change in AI-Assisted Learning Support will be associated about a 0.54 unit change in predicted outcome. The value of 2.15 in all the regressions indicates the anticipated base level of the dependent variable in the absence of AI-Assisted Learning Support. The large t-value (7.71)

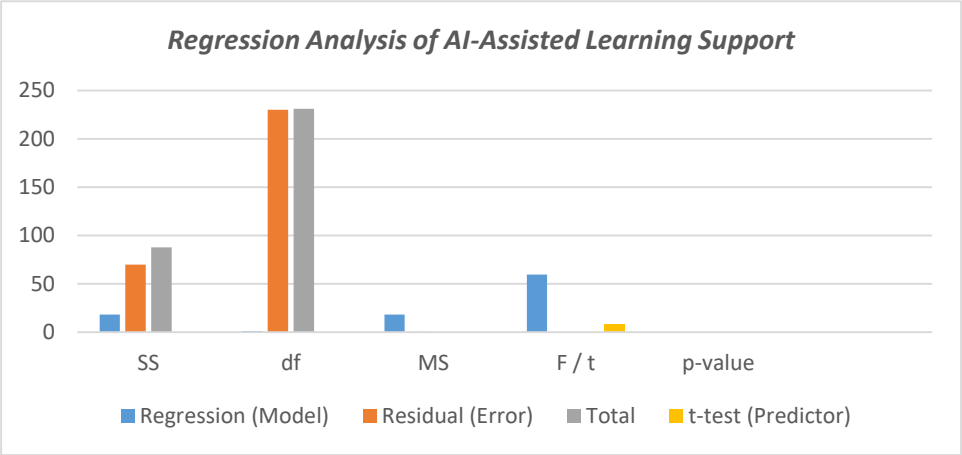
and low p-value (< 0.001) attest to the fact that this predictor is statistically significant, which means that the use of AI-assisted learning is important in enhancing the monitored outcome.

Table 4: T-test / ANOVA Analysis

Source	SS	df	MS	F / t	p-value
Regression (Model)	18.02	1	18.02	59.45	0.000
Residual (Error)	69.78	230	0.304	—	—
Total	87.80	231	—	—	—
t-test (Predictor)	—	—	—	7.71	0.000

According to the ANOVA results, the regression model is also significant, which implies that AI-Assisted Learning Support significantly predicts the dependent variable, F(1,230) = 59.45,p<0.001F(1, 230) = 59.45, p < 0.001F(1,230)=59.45,p<0.001. The model explains a significant amount of the variation as indicated by regression sum square (18.02) as opposed to residual sum square (69.78). Also the t-test of the predictor gives t = 7.71,p = 0.001t = 7.71, p = 0.001t=7.71,p=0.001, there is a significant positive contribution of AI-Assisted Learning Support to the prediction. This group of results indicates that the independent variable is powerful and a dependable predictor of the result.

Figure 2: Regression Analysis of AI-Assisted Learning Support



5. Discussion

The demographics results of this study suggest moderately even distribution on the gender parameter with the majority being the male counterparts. This aligns with the findings of other researchers that the number of the male gender might slightly be higher in the demographics of the university faculty in Pakistan, particularly, on certain disciplines (Alshammari, 2024)The inclination, which is conductively well balanced though, supports the representativeness of the results that has different opinions among the genders. Also, the age distribution indicates that majority of devices are within the age of 26-30 years show an early career educator profile that is pretty bendable in embracing new technologies in training as compared to their more senior counterparts. These results can be correlated with those who report the greater sensitivity of young faculty to professional development and teaching innovativeness, which can influence their opinions and experience in relation to the present research (Ali et al., 2025).The demographic profile thus would be not only informative in situating the interpretations of results but also supporting the views that the research has a broad yet concise cross-section of the teaching population in the higher learning institutions.

The participants show a high number of educational qualifications in the form of Bachelor and Master degree holders with few having the M.Phil. or the PhD qualification. It parallels the national patterns of advanced degrees that are limited to a small portion of the university faculty, especially in the educational institutions operating in the private sector (Dahri et al., 2024).High prevalence of early-career faculty possessing both Bachelor and Master's degree might affect both teaching style and readiness to adopt new teaching methods as the low level of qualification may be associated with the orientation towards practical teaching style over research-oriented teaching. Experience in teaching also became another critical parameter with the majority falling under less than five years' experience. These teachers tend to be in developmental phases of professional identity which makes them easier to accept institutional reforms and professional education programs. As revealed by prior research, general experience with teaching can make a novice educator more flexible, but the teaching experience of over 10 years can make the teacher more dependent on traditional patterns, and the reaction to new educational interventions could be worse (Naseer, 2021). Such observations are valuable in their placement of the responses obtained in the study.

Lastly, the allocation of the participants between public and private universities can be interesting as far as the diversity of the institution is concerned. A higher percentage of the sample was represented by the public universities, and this could symbolize trends in faculty employment in the country on the whole or the sampling range of the research. Based on prior studies, it is tempting to assume that public institutions tend to be more orderly in terms of policies, professional development programs and resource access, whereas private ones are flexible, yet less conformable to standards in change implementation (Naz et al., 2025).Such differences between institutions may affect faculty attitude to work, working conditions and embrace of educational changes, especially in the field of technology integration, work load control and teaching independence. Bringing these demographic observations to these methodology and findings, one will notice that sample of such study takes picturesque representation of such higher education teaching environment, which allows the findings to be comprehended with more relevant overall insights. This supports the credence of the findings made in the study and gives points of contact in proposing specific policy interventions that take into account the institutional nature as well as faculty composition.

5.1 Conclusion

This research marks significant tendencies in the demographic profile of university teachers and its possible impact on the teaching process and professional development. Results demonstrate equal split in the gender context with a relatively small majority of men and the majority of the respondents falling in age bracket 2630 years implying that the teaching profession is relatively young. A majority of the respondents had a bachelor or master's degree and less at the M. Phil/PhD which indicates that cold educators have different levels of academic qualifications. There was substantial diversity of teaching experience with a large proportion having teaching experience during early career phase. The representation was a little higher in the case of public universities which are more diverse in the region. These population trends hold useful information on the diversity of teachers, which can have the effect of influencing differences in attitude toward technology adoption, pedagogical innovation, and institutional change. The findings are congruent with the other works that stress that the demographics of the teachers are important.

5.2 Recommendations

1. Have specific professional development programs according to the level of experience of the teachers.

2. Reward male and female teachers through inviting both to take equal roles in leadership positions.
3. Provide teachers who do not have a high level of academic achievement with advanced training.
4. Implement mentorship opportunities and combinational of senior and early-career educators.
5. Encourage technology integration training according to age and the competencies of teachers. Foster cooperation of the faculty of public and private universities to share knowledge.
6. Incentives to have more qualifications such as MPhil or PhD by the teacher should be introduced.
7. Relative demographic evaluation should be carried out frequently to formulate institutional policies.

5.3 Future Implications

The conclusions of the article justify the need to employ education policies and training programs with consideration of the discrepancy in the demographics of the university teachers. The insights will also enable the institutions to develop professional development opportunities in future in order to reach educators in a personal manner based on their age, gender, qualifications and years of experience in teaching. These specially crafted training programs are capable of increasing teaching, job satisfaction and life-long learning. In addition, collaboration of universities can be enhanced to offer best practices and resources to advance the stagnant knowledge of the area of professional interest. The policymakers can also use this information to establish fair opportunities among the teachers of the private and public institutions. Lingering on these aspects, in the future, further steps will enable them to make teachers more adaptive to the currents of new technologies and evolving teaching methods, which will, ultimately, culminate in the improvement of the learning experience in students and inclusivity and efficiency of the academic process.

During the past forty years, worldwide economies and organizations are much focusing on maximize the level of happiness or well-being of their citizens. UN agenda of sustainable development (SD) for 2030

References

Ali, M., Rehman, S., & Cheema, E. (2025). Impact of artificial intelligence on the academic performance and test anxiety of pharmacy students in objective structured clinical examination: a randomized controlled trial. *International Journal of Clinical Pharmacy*, 1-8.

Alshammari, W. K. (2024). *Test anxiety: a comparative study of post-graduate taught students in the UK and Saudi Arabia* University of Glasgow].

Brown, G. T., & Zhao, A. (2023). In defence of psychometric measurement: A systematic review of contemporary self-report feedback inventories. *Educational Psychologist*, *58*(3), 178-192.

Chen, C., Hu, W., & Wei, X. (2025). From anxiety to action: exploring the impact of artificial intelligence anxiety and artificial intelligence self-efficacy on motivated learning of undergraduate students. *Interactive Learning Environments*, *33*(4), 3162-3177.

Chen, X., Zou, D., Xie, H., Cheng, G., & Liu, C. (2022). Two decades of artificial intelligence in education. *Educational technology & society*, *25*(1), 28-47.

Dahri, N. A., Yahaya, N., Al-Rahmi, W. M., Vighio, M. S., Alblehai, F., Soomro, R. B., & Shutaleva, A. (2024). Investigating AI-based academic support acceptance and its impact on students' performance in Malaysian and Pakistani higher education institutions. *Education and Information Technologies*, *29*(14), 18695-18744.

Das, B. N., Mohandas, A., & Syed, S. (2021). Study of stress, anxiety, depression and coping strategies among nursing students in a tertiary care teaching hospital, South India. *Int J Community Med Public Health*, *8*(7), 3400.

Etherton, K., Steele-Johnson, D., Salvano, K., & Kovacs, N. (2022). Resilience effects on student performance and well-being: the role of self-efficacy, self-set goals, and anxiety. *The Journal of general psychology*, *149*(3), 279-298.

Gao, S. (2024). Can artificial intelligence give a hand to open and distributed learning? A probe into the state of undergraduate students' academic emotions and test anxiety in learning via ChatGPT. *International Review of Research in Open and Distributed Learning*, *25*(3), 199-218.

Guanzon, A. A. (2024). Challenges and Strategies in Science Learning: A Thematic Review and Meta-Analysis.

Harris, R. B., Grunspan, D. Z., Pelch, M. A., Fernandes, G., Ramirez, G., & Freeman, S. (2019). Can test anxiety interventions alleviate a gender gap in an undergraduate STEM course? *CBE—Life Sciences Education*, *18*(3), ar35.

Hou, L. (2025). Unboxing the intersections between self-esteem and academic mindfulness with test emotions, psychological wellness and academic achievement in artificial intelligence-supported learning environments: Evidence from English as a foreign language learners. *British Educational Research Journal*.

Johnson, A. (2024). *The relationship between self-efficacy, self-esteem, and academic motivation* Institute of Art, Design+ Technology].

Jones, T. (2025). *Exploring Black Girls' Sources of Self-Efficacy for Artificial Intelligence During an Informal Learning Experience* University of Florida].

Khan, A., & Madden, J. (2018). Active learning: a new assessment model that boost confidence and learning while reducing test anxiety. *International Journal of Modern Education and Computer Science*, *10*(12), 1-9.

Koca, F., Kılıç, S., & Dadandı, İ. (2024). Attitudes towards distance education and academic life satisfaction: The mediation role of academic self-efficacy and moderator role of gender. *Technology, Knowledge and Learning*, *29*(2), 713-734.

Lee, H. Y., Musa, N., Wong, Y.-S., Nor, N. M., Mahsan, I. P., Wong, M.-J., & Lee, H.-L. (2024). Communication Technology-Enhanced Collaborative and Constructivism Learning in Improving Students' Skills on Artworks Production: A Structural Equation Modelling Approach. *PaperASIA*, *40*(4b), 202-225.

Liu, S., Zhao, W., Shanks, D. R., Hu, X., Luo, L., & Yang, C. (2024). Effects of test anxiety on self-testing and learning performance. *Educational Psychology Review*, *36*(2), 59.

Mensah, C., Azila-Gbettor, E. M., Nunyonameh, C. R., Appietu, M. E., & Amedome, S. N. (2023). Research methods anxiety, attitude, self-efficacy and academic effort: A social cognitive theory perspective. *Cogent psychology*, *10*(1), 2167503.

Mohammed, S. A., & Ahmed, N. S. (2023). Self-Assessment Tool For Improving Student's Skills Regarding The Exams In Higher Education. *Science Journal of University of Zakho*, *11*(3), 453-463.

Moreira, F. T., & Teles, R. O. (2024). *Improving Student Assessment with Emerging AI Tools*. IGI Global.

Naz, I., Malik, M., Farooq, T., & Munir, A. (2025). Impact of Using Artificial Intelligence (AI) Tools on Self-Esteem and Academic Performance of Students In Public and Private Universities of Lahore. *Journal of Political Stability Archive*, *3*(3), 589-601.

Nguyen, H. K., Khau, M., Nguyen, H., & Pham, H. (2025). Developing an AI-Enhanced Individualized Prediction Tool for Psychopathological Symptoms in Vietnam: A Study Protocol. *medRxiv*, 2025.2008. 2003.25332928.

Nguyen, Q., & Hue, D. D. T. (2025). ChatGPT's effects on EFL learners' autonomy and self-efficacy in self-regulated learning contexts. *The JALT CALL Journal*, *21*(2), 102968-102968.

Panda, G., Dash, M. K., Kaswan, M. S., & Chaudhary, R. (2025). Exploring the impact of digital technology in Indian higher education: A comprehensive analysis. *The TQM Journal*.

Raj, H. D., & Singh, M. X. P. (2025). Examining Test Anxiety and Its Alleviation: Assessing the Efficacy of Gamification in ESL Contexts. *Creative Saplings*, *4*(2), 31-45.

Silva, M. P., do Nascimento Silva, V., & Chaimowicz, L. (2017). Dynamic difficulty adjustment on MOBA games. *Entertainment Computing*, *18*, 103-123.

Vistorte, A. O. R., Deroncele-Acosta, A., Ayala, J. L. M., Barrasa, A., López-Granero, C., & Martí-González, M. (2024). Integrating artificial intelligence to assess emotions in learning environments: a systematic literature review. *Frontiers in psychology*, *15*, 1387089.

Williams, L. R. C. (2020). *Tracking and Understanding At-Risk College Students' Self-Efficacy in a Treatment Mathematics Course*. Michigan State University.

Wilson, K. P., & Sinha, A. (2025). Exploring the interrelationships between peer support self-efficacy and academic resilience among young adults. *World Journal of Advanced Research and Reviews*, *26*(1), 2275-2282.

Zamfir, A.-M., & Mocanu, C. (2020). Perceived academic self-efficacy among Romanian upper secondary education students. *International Journal of Environmental Research and Public Health*, *17*(13), 4689.

Zegarra-López, A. C., Luna-Victoria, G., Romero-Montenegro, D., Florentino-Santisteban, B., Prieto-Molinari, D. E., & Montoya-Cuadrao, M. (2022). Prevalence and predictors of somatization in Peruvian undergraduate students during the COVID-19 pandemic. *International Journal of Environmental Research and Public Health*, *19*(23), 15576.

Zhao, C. (2024). AI-assisted assessment in higher education: A systematic review. *Journal of Educational Technology and Innovation*, *6*(4).