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Role of technology attitude and online platform effectiveness in shaping learning outcomes among competitive examination aspirants in India

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Abstract

In India, competitive examinations play a crucial role in shaping students' academic and career trajectories, leading to increased reliance on online learning platforms. Despite this shift, limited research has examined how platform effectiveness and learners' attitudes towards technology jointly influence learning outcomes in this context. Grounded in the Technology Acceptance Model (TAM), this study investigates the role of technology attitude and online platform effectiveness in shaping learning outcomes among competitive examination aspirants. A descriptive and correlational research design was adopted, and data were collected from 384 aspirants using a structured and validated questionnaire. The data were analysed using t-tests, ANOVA, regression, and structural equation modelling (SPSS 26 and AMOS 23). The findings reveal that the effectiveness of online platforms—particularly innovation, infrastructure, and learning flexibility—significantly enhances learning outcomes. Additionally, attitude towards technology plays a mediating role in this relationship. Demographic differences were also observed, indicating variations in perceptions across gender, age, and educational background. The study contributes to the literature by providing a theoretically grounded understanding of EdTech effectiveness and its impact on learning outcomes in the competitive examination context. The findings offer practical implications for educators and platform developers to design more learner-centric and effective digital learning environments. Future research may explore longitudinal effects and behavioural outcomes of technology adoption.

Keywords Technology acceptance, EdTech effectiveness, Online learning outcome, Competitive examination aspirants, Technology usage

1 Introduction

Competitive examinations are a central pathway to higher education and public sector employment in India, leading to intense competition among millions of aspirants each year. In response, the preparation ecosystem has rapidly shifted from traditional

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coaching to technology-enabled learning, supported by increased internet penetration, policy initiatives such as the National Education Policy [38], and the expansion of the EdTech sector [15, 30]. Online platforms now offer flexible, accessible, and personalized learning opportunities, making them particularly relevant for aspirants across diverse geographic and socio-economic contexts.

Prior research indicates that digital learning environments can enhance learner engagement, motivation, and academic performance [24, 52]. However, the effectiveness of such platforms in consistently improving learning outcomes remains mixed. While some learners benefit significantly, others do not experience comparable gains, suggesting that the impact of EdTech is contingent on both platform-related and learner-related factors.

The Technology Acceptance Model (TAM) provides a useful theoretical lens to understand this phenomenon. TAM posits that perceived usefulness and perceived ease of use influence users' attitudes towards technology, which subsequently affect behavioural outcomes [18, 56]. In e-learning contexts, studies have confirmed that positive attitudes towards technology significantly influence adoption and engagement [1]. However, most TAM-based studies primarily focus on technology adoption and behavioural intention, rather than actual learning outcomes, limiting their applicability in performance-oriented contexts such as competitive examinations.

A critical review of the literature highlights three key gaps. First, existing studies predominantly emphasise technology acceptance rather than examining how technology use translates into measurable learning outcomes [1]. Second, prior research often analyses platform characteristics (e.g., system quality, accessibility) and learner attitudes independently, with limited integration of these constructs within a unified framework [24]. Third, there is a scarcity of studies focusing specifically on competitive examination aspirants, whose learning requirements differ significantly from general higher education due to the need for sustained practice, conceptual clarity, and performance-driven preparation.

Addressing these gaps, the present study adopts a TAM-based framework to examine how online platform effectiveness influences learning outcomes both directly and indirectly through learners' attitudes towards technology usage in the context of competitive examination aspirants in India. By integrating platform and behavioural dimensions and shifting the focus from adoption to outcomes, the study extends existing literature both theoretically and contextually.

Accordingly, the study is guided by the following research questions:

RQ1: How does the effectiveness of online platforms influence learning outcomes among competitive examination aspirants?

RQ2: What is the impact of learners' attitudes towards technology usage on learning outcomes?

RQ3: Does attitude towards technology mediate the relationship between platform effectiveness and learning outcomes?

RQ4: Do demographic factors influence aspirants' perceptions of platform effectiveness, attitude, and learning outcomes?

The objectives of the study are:

1. To examine the effect of online platform effectiveness on learning outcomes;
2. To analyse the role of attitude towards technology usage in shaping learning outcomes;

3. To investigate the mediating role of attitude between platform effectiveness and learning outcomes; and
4. To assess demographic differences in EdTech usage among aspirants.

This study contributes by providing a theoretically grounded and context-specific explanation of how EdTech platforms can be leveraged to enhance learning outcomes in competitive examination settings.

2 Theoretical framework and hypotheses development

The rapid expansion of digital learning environments has fundamentally reshaped educational practices, particularly in high-stakes contexts such as competitive examination preparation. Despite the growing body of literature on e-learning and educational technology, existing studies remain largely fragmented and descriptive, focusing on isolated dimensions such as infrastructure, accessibility, or learner engagement without integrating them into a coherent theoretical explanation of learning outcomes. This limitation is particularly evident in the context of competitive examinations, where learning is performance-oriented and requires sustained engagement, conceptual clarity, and strategic preparation. To address this gap, the present study adopts the Technology Acceptance Model (TAM), originally proposed by Davis [18], as its theoretical foundation and extends it to explain learning outcomes in digital learning environments.

TAM posits that perceived usefulness and perceived ease of use are the primary determinants of users' attitudes toward technology, which subsequently influence behavioural intention and actual usage. While the model has been widely validated in educational settings [1, 56], its application has predominantly focused on explaining technology adoption rather than performance outcomes. This creates a critical theoretical limitation, as the ultimate objective of educational technology is not merely to facilitate usage but to enhance learning effectiveness. Moreover, prior studies often treat technological attributes and learner perceptions as independent constructs, resulting in fragmented insights that fail to capture the complexity of digital learning environments. This issue becomes more pronounced in competitive examination contexts, where learning outcomes depend not only on access to technology but also on the effectiveness of its use and the learners' psychological orientation toward it.

In addition to technological and behavioural dimensions, demographic characteristics have been recognized as influencing technology usage and learning experiences. The Unified Theory of Acceptance and Use of Technology (UTAUT) highlights the role of age, gender, and educational background as important contextual factors [56]. Empirical findings, however, remain inconsistent. While some studies report significant demographic differences in e-learning adoption and usage [6, 48], others suggest that such differences are diminishing in increasingly digital learning environments. A critical limitation of prior research is the inconsistent positioning of demographic variables, which are often treated as core explanatory constructs rather than contextual influences. This creates theoretical ambiguity and weakens model clarity. In the present study, demographic factors are conceptualized as control variables that influence learners' perceptions of platform effectiveness, their attitudes toward technology, and learning outcomes, without forming part of the core theoretical mechanism. This positioning aligns with extended TAM and UTAUT perspectives, ensuring conceptual clarity while accounting for contextual variability. Based on this reasoning, it is hypothesized that:

H1: Demographic factors significantly influence aspirants' perceptions of platform effectiveness, attitude toward technology usage, and learning outcomes.

The effectiveness of online platforms has been widely discussed as a determinant of learning success, yet empirical evidence presents mixed and often contradictory findings. On one hand, studies by [2, 3] argue that structured digital platforms enhance knowledge acquisition and retention through interactive content and organized learning pathways. Similarly, [24] demonstrate that flexibility and interactivity significantly improve student performance and satisfaction. On the other hand, contrasting evidence suggests that access to digital tools alone does not guarantee improved learning outcomes, particularly when learners lack motivation, discipline, or effective learning strategies [27]. These inconsistencies indicate that platform effectiveness cannot be understood as a unidimensional construct and must instead be examined as a multidimensional phenomenon.

Existing frameworks such as the The DeLone and McLean Model of Information Systems Success: A Ten-Year Update [55] information systems success model conceptualize system effectiveness through dimensions such as system quality, information quality, and service quality. However, these frameworks do not fully capture the pedagogical and experiential aspects of online learning. More recent studies emphasize learner-centric attributes such as personalization, engagement, and flexibility [51], yet these dimensions are often examined independently rather than within a unified theoretical structure. Addressing this limitation, the present study conceptualizes platform effectiveness through innovation, infrastructure, learning flexibility, and learner experience. Importantly, these dimensions are not merely derived from empirical observations but are theoretically aligned with TAM, where innovation and infrastructure represent perceived usefulness, and learning flexibility and learner experience reflect perceived ease of use. This theoretical alignment strengthens construct validity and ensures that the model is grounded in established theory rather than being purely data-driven.

From a TAM perspective, perceived usefulness directly influences performance outcomes. When learners perceive online platforms as effective in enhancing their understanding, facilitating revision, and improving exam readiness, they are more likely to achieve better learning outcomes. However, prior research has not sufficiently examined this relationship in the context of competitive examination preparation, where performance pressure, syllabus complexity, and time constraints significantly influence learning behaviour. Most existing studies are conducted in general higher education settings, thereby limiting their applicability to competitive exam environments. This contextual gap highlights the need for a focused investigation that considers the unique characteristics of competitive examination preparation. Accordingly, it is proposed that:

H2.1: Effectiveness of online platforms positively influences learning outcomes among competitive examination aspirants.

Beyond its direct influence, TAM suggests that the impact of system characteristics on outcomes is mediated through users' attitudes toward technology. Perceived usefulness and perceived ease of use shape individuals' attitudes, which in turn influence their engagement and behaviour [18]. Empirical studies support this relationship, demonstrating that platform usability, accessibility, and interactivity significantly influence learners' attitudes toward technology usage [34, 39]. Pal and Vanijja [42] further argue that system effectiveness enhances user satisfaction and fosters positive perceptions of

technology. However, a critical limitation of existing literature is that attitude is often treated as an outcome variable rather than as a mediating mechanism linking platform characteristics to learning outcomes. This weakens theoretical integration and limits explanatory power.

In competitive examination contexts, where sustained engagement, motivation, and disciplined study behaviour are essential, learners' attitudes toward technology play a pivotal role in shaping their learning experiences. A positive attitude toward online platforms enhances engagement, increases time spent on learning activities, and improves the effectiveness of preparation. Conversely, negative attitudes may reduce engagement and limit the benefits of even highly effective platforms. By incorporating attitude as a mediating variable, the present study provides a more comprehensive explanation of how platform effectiveness translates into improved learning outcomes. This leads to the proposition that:

H2.2: Effectiveness of online platforms positively influences aspirants' attitudes toward technology usage.

While TAM establishes the importance of attitude in shaping behavioural outcomes, its role in influencing learning outcomes remains underexplored. Existing studies primarily focus on direct relationships and often neglect the mediating mechanisms through which technology impacts performance. Venkatesh and Davis [56] emphasize that attitude plays a central role in determining how effectively individuals utilize technology, which in turn affects outcomes. In educational contexts, positive attitudes toward technology have been associated with higher engagement, improved persistence, and better academic performance [1]. However, most studies rely on simple analytical techniques and do not explicitly test mediation effects using advanced methods such as Structural Equation Modelling (SEM).

By explicitly incorporating attitude as a mediating construct, the present study addresses this gap and provides a deeper understanding of the causal relationships between platform effectiveness and learning outcomes. This approach not only aligns with TAM but also extends it by linking system characteristics to performance outcomes through psychological processes. Accordingly, it is hypothesized that:

H3: Attitude toward technology usage mediates the relationship between online platform effectiveness and learning outcomes.

A critical synthesis of the literature reveals several gaps that justify the present study. First, there is a predominant focus on technology adoption rather than learning outcomes, limiting the relevance of existing models in performance-oriented contexts. Second, prior studies lack integration between platform effectiveness and learner attitudes, resulting in fragmented insights. Third, the mediating role of attitude remains underexplored, particularly in studies employing robust analytical techniques. Fourth, there is limited research focusing specifically on competitive examination aspirants, whose learning requirements differ significantly from general academic settings. These gaps highlight the need for a theoretically grounded and empirically robust framework that integrates platform effectiveness, attitude, and learning outcomes.

To address these gaps, the present study employs Structural Equation Modelling (SEM), which is widely recognized as a powerful technique for testing complex relationships among latent constructs [25]. SEM allows for the simultaneous examination of direct and indirect effects, making it particularly suitable for testing mediation models.

Additionally, it enables the validation of measurement models and structural relationships within a unified analytical framework. The use of SEM therefore enhances both the theoretical rigor and empirical robustness of the study, ensuring that the proposed relationships are tested in a comprehensive and statistically sound manner.

Figure 1 demonstrates the Conceptual Model depicting the influence of effectiveness of online platform (Independent Variable) on online learning outcome (Dependent Variable) through the mediation of attitude towards technology usage (mediating variable). It also depicts the influence of demographic factors.

3 Methodology

3.1 Research type

The current study used a descriptive and correlational research design to explore the relationship between the attitudes of the participants towards technology, the effectiveness of technology usage in enhancing online learning outcomes, as well as to describe the participant characteristics and examine the variables based on the objectives. The study used a logical methodology, creating and testing hypotheses. Using a standardised questionnaire, the study incorporated quantitative research approach that is measurable and statistically provable to draw a meaningful inference. It is significant to highlight that this study is empirical in nature because it is based mostly on survey information gathered from candidates studying for competitive examinations utilising e-learning/online platforms.

3.2 Sampling procedure and data collection

The target population of the study comprised individuals aged 18 years and above who were actively preparing for competitive examinations using online or EdTech platforms. Given the absence of a clearly defined sampling frame, a non-probability purposive sampling technique was employed to ensure that only relevant respondents (i.e., active aspirants using online platforms) were included in the study [20]. The minimum sample

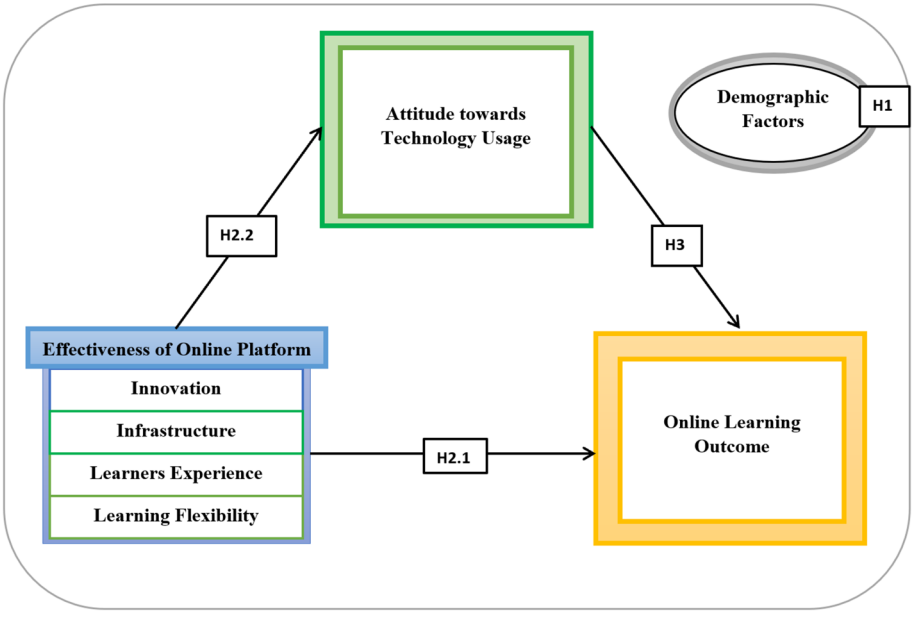

Fig. 1 Conceptual model. Developed by the Authors

size was determined using the standard formula for an infinite population: SS = (Z^2 × p × (1 − p)) / C^2 [16], where Z = 1.96 at a 95% confidence level, p = 0.5, and margin of error (C) = 0.05. The calculated sample size was 384, which satisfies the recommended threshold for social science research. Data were collected through an online structured questionnaire distributed via academic networks and aspirant communities. A total of 400 responses were received, of which 384 were retained after removing incomplete or inconsistent responses, ensuring data quality and reliability.

3.3 Instrument development procedure

The data were collected using a structured questionnaire comprising three core constructs: effectiveness of online platforms, attitude towards technology usage, and online learning outcomes. Although existing validated scales were available, the present study adapted and contextualized these measures to suit the specific setting of competitive examination aspirants. Items measuring the effectiveness of online platforms were adapted from Goh and Blake [22] and further refined based on literature and contextual relevance. Attitude towards technology usage was adapted from Rosen et al. [49] and Şahin et al. [50], while online learning outcomes were derived from Panigrahi et al. [43], Nguyen [41], and Hsu et al. [28]. In addition to scale adaptation, minor modifications were made to ensure clarity, relevance, and contextual appropriateness for competitive examination preparation. To ensure content validity, the questionnaire was reviewed by academic experts and subject specialists. A pilot study was conducted with 30 respondents to assess clarity, reliability, and item relevance. Based on feedback, ambiguous items were revised and refined. Subsequently, Exploratory Factor Analysis (EFA) was employed to identify underlying factor structures, followed by Confirmatory Factor Analysis (CFA) to validate the measurement model. Reliability was assessed using Cronbach's alpha and composite reliability, while validity was established through convergent and discriminant validity measures [21, 25]. All values met the recommended thresholds, confirming the robustness and suitability of the measurement instrument (see Table 3).

3.4 EFA

The practicality of variables in a research model must be determined in accordance with specific criteria, claim Hair et al. [25]. These criteria include conducting a Kaiser–Meyer–Olkin (KMO) test with a result greater than 0.5 and a significance level of less than 0.005. Additionally, only factors with an eigenvalue of 1 or higher and a total variance explained of at least 50% should be retained. Important factor loadings must be equal to or more than 0.5,otherwise, they should be eliminated [10]. Separate exploratory factor analysis (EFA) tests were run on the independent variable i.e. effectiveness of online platform as it had numerous items to account for the study model's complexity. Subsequently, a comprehensive EFA test was performed using the selected items. As the measurements for effective online platforms were taken from Goh and Blake [22] by modifying it as per the observation, subject expert and study group, EFA was run. The KMO value of 0.933 indicated that the factor analysis conducted on the data is reliable and valid. The significance value being less than 0.01 suggests that the results are statistically significant at a 99% confidence level. The high chi-square value of 12,826.104 obtained from Bartlett's test of Sphericity specifies that the variables have been

appropriately factored. As a result, a total of 4 factors were derived from 36 effectiveness of online platform indicators, which were developed based on the relevant existing research. These factors were categorized as innovation, infrastructure, learners' experience, and learning flexibility. The first factor consisted of 9 variables, followed by 7, 8, 12 variables, respectively. The analysis resulted in four factors that accounted for a total variance of 61.628%. The principal component analysis revealed that the factor loadings ranged from 0.555 to 0.796. Importantly, all the factor loadings exceeded the threshold of 0.5 [8], indicating the retention of the above indicators as significant factors.

3.5 Confirmatory factor analysis

The measurement models were evaluated using IBM SPSS Analysis of Moment Structures (AMOS) 24 for goodness of fit, composite reliability, convergent and discriminant validity. Confirmatory Factor Analysis is a technique for confirming items or factors that accurately reflect created factors [9, 17]. Confirmatory factor analysis revealed that all items properly fit the constructs they represent (loading greater than 0.5). Later, fit indices are produced to determine the model's overall fit. The model's goodness of fit was adequate, as stated by Hair et al. [25, 26], Hu and Bentler [29], and Byrne [11, 12] (χ^2/df = 1.706; GFI = 0.903; AGFI = 0.901; CFI = 0.958; NFI = 0.911; RMSEA = 0.046). Moreover, study tested reliability and validity (see Table 1).

Further, the study analysed the convergent validity of the constructs. The standardized factor loadings were initially assessed, and the findings showed that all the items representing the constructs loaded into the constructs, above the required criterion of 0.50 as recommended by Hair et al. [25]. As indicated in Table 3, the average variance extracted (AVE) of the research constructs exceeded the recommended cut-off i.e. 0.5 by Hair et al. [25].

In support of this, the composite reliability and Chronbach Alpha estimations were likewise in accordance with the guideline, with all exceeding 0.70 as recommended by Hair et al. [25], indicating convergent validity and reliability of the scale constructs. Moreover, descriminant validity was tested using Fornell Larker Criteria. The square root of AVE found to be higher than the respective inter correlation between the inter constructs indicating that the variables have discriminant validity. As a result, the measuring model demonstrated excellent construct validity and psychometric qualities (see Table 2).

3.6 Assumption fullfillment

In this study, the normality of the data was assessed using two different methods. Firstly, a graphical approach was employed, which involved visually inspecting the distribution of the data through histograms and box plots. The analysis's findings indicated that the data had a normal distribution.

Second, statistical tests for skewness and kurtosis were carried out numerically with SPSS 23. The skewness and kurtosis values that were obtained fell inside the permissible threshold ranges of 2 and 7, respectively. These findings support the notion that the data followed a normal distribution.

Two software applications, SPSS 26 and SPSS AMOS 23, were used to analyse the data that had been gathered. To analyse the suggested conceptual model using structural equation modelling (SEM), SPSS AMOS was employed particularly. Additionally, a

Table 1 Descriptive statistics

Construct	Items	λ	Authors	Mean
Effectiveness of online platform			Goh and Blake [22], observation and opinion of subject experts	3.7334
Innovation				
Enables real time question and answer	IN1	0.758		
Ensures user-friendly learning	IN2	0.735		
Develops innovative learning lifecycles	IN3	0.712		
Offers free and premium based courses	IN4	0.702		
Enables well-versed technology utilization	IN5	0.700		
Helps to gain ample amount of knowledge on the same topic from different perspectives	IN6	0.681		
Ensures anytime and anywhere learning access	IN7	0.616		
Creates a technology-driven method that bases the entire teaching–learning process	IN8	0.787		
Infrastructure			Goh and Blake [22], observation and opinion of subject experts	3.4234
Easily accessible through mobile/computer/laptop	IF1	0.765		
Ensures low data consumption	IF2	0.729		
Ensures smooth online learning even using 4G/3G network	IF3	0.709		
It is easy to get connected to tutor	IF4	0.684		
Provides exposure to professional educators virtually	IF5	0.685		
It enables easy access to information and systems so that the information might be used in novel and inventive manners	IF6	0.669		
All learning materials are available for download	IF7	0.623		
Learners experience			Goh and Blake [22], observation and opinion of subject experts	3.5020
Encourage students' participation by having interaction during the class	LE1	0.750		
Quality contents are delivered	LE2	0.745		
Content aggregation and delivery are good and understandable to the great extent	LE3	0.687		
Online lectures go beyond geographic boundaries which help to gain more knowledge on the subject	LE4	0.679		
Highly qualified teachers and professors are available over the platform	LE5	0.647		
Sessions arranged by inviting industry mentors are useful to get the insights	LE6	0.634		
Provide more learning materials for further reference	LE7	0.544		
Virtual classes cover more information than physical coaching centre	LE8	0.545		
Learning flexibility			Goh and Blake [22], observation and opinion of subject experts	3.4948
Provides a comfortable learning environment	LF1	0.750		
Ensures 24 × 7 access to guidance and lectures	LF2	0.739		
More engagement with scheduled classes	LF3	0.734		
Frequently quizzes and online tests are arranged	LF4	0.738		
Access to live classes	LF5	0.701		
Interactive classes are held for quick doubt resolution	LF6	0.705		
Making an effective strategy with a day-by-day study schedule	LF7	0.679		
If any live session missed, the recordings of the session made available	LF8	0.681		
Help to learn anytime and anywhere	LF9	0.661		
Quick response received on any enquiry with the concerned teacher	LF10	0.652		
Provides a customised learning route depending on the learner's strengths and shortcomings as determined by learning analytics	LF11	0.634		
Provides all the Study Material for preparation	LF12	0.545		

Table 1 (continued)

Construct	Items	λ	Authors	Mean
Attitude towards usage technology			Rosen et al. [49], Şahin et al. [50], observation and opinion of subject experts	3.6141
I have no difficulty adopting new technology	AT1	0.711		
I relate well to technology and machines	AT2	0.779		
I feel as up-to-date on technology as my peers	AT3	0.812		
I enjoy learning new computer programs and hearing about new technologies	AT4	0.733		
I find most technology easy to learn	AT5	0.719		
Technology is very friendly	AT6	0.791		
Online learning outcome			Panigrahi et al. [43], Nguyen [41], Hsu et al. [28], observation and opinion of subject experts	3.6344
Enhanced my knowledge on the subject	OL1	0.810		
Improved my IQ level	OL2	0.777		
Helped to understand the concepts in simple way	OL3	0.708		
Learned contents are easily recallable	OL4	0.805		
Promoted better learning skill in me	OL5	0.775		
Able to face the exams boldly	OL6	0.811		
Enhance the quality of learning	OL7	0.760		
Quick clearance of doubts makes concepts understandable	OL8	0.711		
Easy to refer the recorded videos whenever required	OL9	0.723		
Made revision easy	OL10	0.691		
Frequent feedback on the progress helped to improve in all the stages of exam preparation	OL11	0.779		
Time management tactics are learned through online teachers	OL12	0.716		
Improved my confidence level	OL13	0.801		

Source Computed using SPSS and AMOS

Table 2 Reliability and validity

Variable	Reliability		Validity			
	Composite reliability	Cronbach alpha	AVE	Effectiveness of online platform	Attitude towards technology	Online learning outcome
Effectiveness of online platform	0.943	0.942	0.690	**0.831**		
Attitude towards technology	0.884	0.883	0.575	0.708	**0.759**	
Online learning outcome	0.921	0.920	0.578	0.666	0.691	**0.760**

Source Computed using SPSS and AMOS

one-way ANOVA, independent sample t-test, and one sample t-test were used to explain the data and investigate any potential demographic impacts on the model's constituent parts. Moreover, regression analysis has also been carried out, which demanded the fulfilment of multicollinearity assumptions. Multicollinearity refers to a situation where there is a strong correlation between multiple independent variables, which can hinder achieving a normal distribution. To assess the presence of multicollinearity, the table below presents the tolerance and Variance Inflation Factor (VIF) values. The study used a multi-collinearity test to assess instrument consistency. According to Miles [37], the VIF statistics, which indicate collinearity, were below the threshold of 5. Higher VIF values indicate that the variance of the predicted regression coefficients is overstated, resulting in less precise and unstable estimations. As a result, the dataset is deemed suitable for conducting multiple regression analysis, as it is free from the issues caused by multicollinearity. In the current study, the levene test was utilized to assess data homogeneity. The null hypothesis assumes that the variances are equal. As per the study results, the

levene statistic for all constructions is larger than 0.5, with a significance level greater than 0.05. Thus, the null hypothesis is accepted, and the variances are found to be equal. Hence, aspirant's are homogeneous.

3.7 Common method bias assessment

Since the data were collected using a single self-reported questionnaire, the potential for common method bias (CMB) was assessed. Harman's single-factor test was conducted by loading all measurement items into an unrotated factor solution. The results indicated that the first factor accounted for less than 50% of the total variance, suggesting that common method bias is not a significant concern [45].

Additionally, variance inflation factor (VIF) values were examined, and all values were found to be below the threshold of 3.3, further confirming the absence of serious common method bias issues [33].

4 Results

4.1 Aspirant's profile

Understanding the profile of the collected sample is vital for further analysis. The sample description entails respondents' gender, age, marital status, qualification and region. This will assist us comprehend the diversity of research aspirants. Overall, 384 responses were collected from the population. Out of 384 respondents, most (62.5%) of them were female and 37.5% were male. Moreover, 94.5% of the respondents preparing for the competitive examination belong to 20–40 years. As far as respondents' marital status is concerned, majority (73.7%) of the samples were unmarried and remaining 26.3% were married. 78% of the aspirants were post graduates and 18% of them were undergraduates. Furthermore, 42.7% of them reside in urban area followed by rural (32.8%) and semi urban area (24.5%). The research shows that the frequency of aspirants is distributed evenly across demographic and educational characteristics.

4.1.1 Edtech profile (competitive examination profile of the aspirants)

When the aspirants were asked about the competitive exams they have attempted, 27% of them stated they have attempted CPT and remaining appeared for NET (10%), PGCET (10%), both NET & KSET (7%), IBPS (7%), MAT (7%), Bank, post office, NET, SLET (4%), Bank, Assistant Professor, SSC and PhD entrance (4%), sports certification (4%), only K-Set (4%), NET, KSET, RBI Assistant, EPF, KPSC (4%), NET, KSET, SBI PO, IBPS (4%) and UGC- NET and SSC exam (4%).

4.1.1.1 Descriptive statistics The mean scores for innovation (M = 3.7334), infrastructure (M = 3.4234), learning flexibility (M = 3.5020), learner experience (M = 3.4948), attitude towards technology usage (M = 3.6142), and online learning outcome (M = 3.6344) were above the test value of 3, indicating statistically significant positive perceptions (see Table 2).

5 Hypothesis testing and structural equation modelling

5.1 Influence of demographic factors on EdTech usage

5.1.1 Gender (t-test)

There was no significant difference between male and female respondents in terms of online learning outcomes (t = – 1.468, p = 0.143) and attitude towards technology usage (t = – 0.300, p = 0.764). However, a significant difference was observed in perceptions of platform effectiveness (t = – 2.400, p = 0.017).

5.1.2 Age (ANOVA)

Significant differences were observed across age groups for online learning outcomes (F = 27.023, p < 0.001), platform effectiveness (F = 23.473, p < 0.001), and attitude towards technology usage (F = 23.423, p < 0.001).

5.1.3 Marital status (t-test)

No significant differences were observed for online learning outcomes (t = 0.865, p = 0.388), platform effectiveness (t = – 0.032, p = 0.974), or attitude (t = – 0.186, p = 0.853).

5.1.4 Educational qualification (ANOVA)

Significant differences were found across qualification groups for online learning outcomes (F = 9.042, p < 0.001), platform effectiveness (F = 9.105, p < 0.001), and attitude (F = 14.338, p < 0.001).

5.1.5 Region (ANOVA)

Significant differences were observed across regions for online learning outcomes (F = 23.935, p < 0.001), platform effectiveness (F = 30.181, p < 0.001), and attitude (F = 25.691, p < 0.001).

5.2 Multiple regressions

The efficacy of an online learning platform is reflected in its innovation, infrastructure, learning flexibility, and learning experience. In order to test the H2, multiple regression analysis has been implemented which tests the contribution of effective online platforms on aspirants' online learning outcome with respect to their preparation for competitive exams (see Table 3).

Table 3 Multiple regression results

Model 2.1	Beta	t-value	Sig	R	R^2	Adjusted R^2	F	p
H 2.1: Effectiveness of online platform is crucial in enhancing online learning outcome								
Innovation	0.201	4.378	0.000	0.825	0.681	0.677	201.978	0.000***
Infrastructure	0.171	3.932	0.000					
Learning Flexibility	0.318	7.073	0.000					
Learners Experience	0.253	5.039	0.000					
H2.2: Effectiveness of online platform is crucial in improving their attitude towards technology usage								
Innovation	0.135	2.571	0.011	0.764	0.584	0.580	132.968	0.000***
Infrastructure	0.135	2.720	0.007					
Learning Flexibility	0.461	9.000	0.000					
Learners Experience	0.129	2.253	0.025					

*** indicates highly significant

Source Computed using SPSS and AMOS

The regression results are presented in Table 3. For online learning outcomes (Model 2.1), learning flexibility (β = 0.318, $p < 0.001$), learner experience (β = 0.253, $p < 0.001$), innovation (β = 0.201, $p < 0.001$), and infrastructure (β = 0.171, $p < 0.001$) were found to be significant predictors. The model was statistically significant (F = 201.978, $p < 0.001$, $R^2 = 0.681$).

For attitude towards technology usage (Model 2.2), learning flexibility (β = 0.461, $p < 0.001$), innovation (β = 0.135, $p = 0.011$), infrastructure (β = 0.135, $p = 0.007$), and learner experience (β = 0.129, $p = 0.025$) were significant predictors. The model was statistically significant (F = 132.968, $p < 0.001$, $R^2 = 0.584$).

Therefore, it is proved that effectiveness of online platforms is crucial in enhancing online learning outcomes and improving their attitude towards technology usage.

5.3 Structural equation modelling

To test the proposed theoretical model and examine the mediating role of attitude towards technology usage, Structural Equation Modelling (SEM) was employed using AMOS. SEM enables simultaneous estimation of multiple relationships and is particularly suitable for testing mediation effects among latent constructs [25, 32].

Mediation analysis was conducted using the bootstrapping approach, which is widely recommended for assessing indirect effects due to its higher statistical power and fewer assumptions compared to traditional methods [46]. A bootstrap sample of 5000 resamples was generated to estimate the significance of indirect effects.

The structural model results (see Table 4 and Fig. 2) indicate that effectiveness of online platforms has a significant direct effect on attitude towards technology usage (β = 0.746, $p < 0.001$) and on online learning outcomes (β = 0.552, $p < 0.001$). Additionally, attitude towards technology usage has a significant effect on online learning outcomes (β = 0.363, $p < 0.001$).

The indirect effect of platform effectiveness on learning outcomes through attitude was also found to be significant (β = 0.271, $p < 0.001$), based on bootstrapped confidence intervals. Since both direct and indirect effects are significant, the results indicate partial mediation (see Table 5).

The total effect of platform effectiveness on learning outcomes (β = 0.823) reflects the combined influence of both direct and indirect paths. These findings confirm that while platform effectiveness directly enhances learning outcomes, it also exerts an additional influence through shaping learners' attitudes towards technology usage.

The regression results provide preliminary support for the proposed relationships. However, to simultaneously examine direct and indirect effects within a unified framework, Structural Equation Modelling (SEM) was employed. In this study, the direct

Table 4 Mediation of attitude between effectiveness of online platform and online learning outcome

H	Hypotheses	Estimate	S.E	C.R	*P*	Label
H3.1	Effectiveness of online platform significantly alters aspirants attitude towards technology	0.746	0.043	21.955	0.000***	Accepted
H3.2	Effectiveness of online platform remarkably contributes to the online learning outcome	0.552	0.046	13.958	0.000***	Accepted
H3.3	Online learning outcome is significantly determined by aspirants' attitude towards technology	0.363	0.037	9.170	0.000***	Accepted

*** indicates highly significant

Source Computed using AMOS

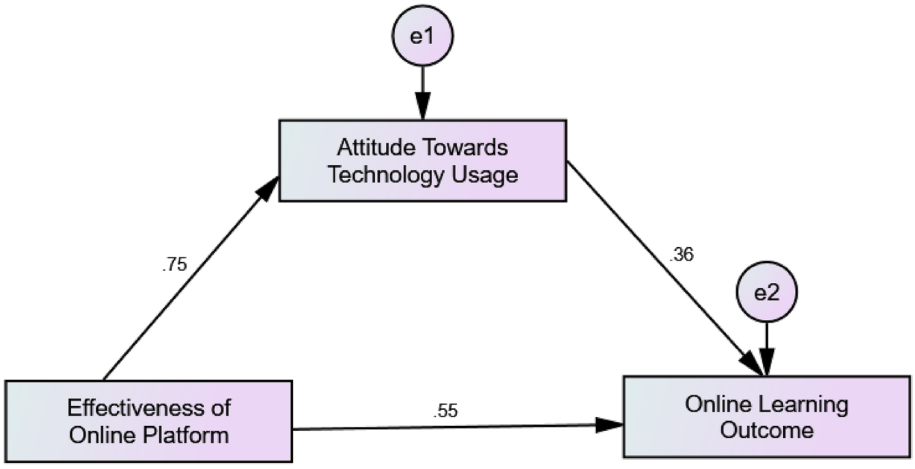

Fig. 2 Mediation of attitude between effectiveness of online platform and online learning outcome.*Source* Computed using AMOS

Table 5 Mediation result

Effect	Standardized estimation (SE)	*P*-value	Results
Effect (final)	0.823	0.000**	Statistically significant
Effect (direct)	0.552	0.000**	Statistically significant
Effect (indirect)	0.271	0.000**	Statistically significant

*** indicates highly significant

Source Computed using AMOS

effect refers to the influence of platform effectiveness on learning outcomes without mediation, while the indirect effect captures the influence transmitted through attitude towards technology usage. The presence of both significant direct and indirect effects indicates that attitude partially mediates this relationship.

6 Discussion

The research findings show that online platforms have brought greater convenience and flexibility in learning among learners for competitive exams, where proper educational resources are easily accessible. The findings show that learners have welcomed online platforms for allowing them to study at their own pace and convenience, a factor that agrees with earlier studies done by Jones and Sharma, [31], Simamora [53] and Xie et al., [57]. Further research also confirms that recorded lectures and digital resources make it easy to refer to and learn repeatedly, and thus improve understanding [3, 23]. This current study also identifies that despite such gains, a few challenges posed by this mode stand out clearly, such as the inability to provide personalized feedback and interaction with students. Further linking to the findings from Adnan [4] and Rahiem [47], it was observed during the pandemic that there was limited engagement.

The findings show significant demographic differences in perceptions about the use of online platforms: Female aspirants hold a more favorable attitude toward online learning compared to their male counterparts. This also supports previous studies by Sun et al. [54] and Yu and Deng [59]. However, this finding contradicts the statement of Cai et al. [13], which stated that males hold a more positive perception about technology. This contradiction may be attributed to contextual differences between general technology usage and performance-oriented learning environments. In competitive examination

settings, structured learning and disciplined engagement may play a more significant role than general technological familiarity, which could explain the variation across studies. Age played a critical role as well,the older aspirants, aged 40–60 years, were found to hold a higher level of satisfaction about the learning outcomes of online learning, as established in the study by Martin and Bolliger [36]. It was also noted in the study that postgraduate students felt online platforms were effective, and these findings align with the work of Yu [58].

It also underlines regional variation; rural learners were more disposed towards the benefits of online learning, as highlighted by Mariya et al. [35], whereas urban learners spoke of the efficiency of online platforms due to better connectivity and infrastructure. This is critical to understanding the disparities between rural and urban education, as noted by Mumtaz et al. [40]. These findings suggest that online platforms serve different functional roles across regions, acting as an access-enabling tool in rural areas and an efficiency-enhancing mechanism in urban contexts.

The findings reinforce the central role of attitude toward technology usage in shaping learning effectiveness, consistent with the Technology Acceptance Model (TAM). The Technology Acceptance Model (TAM) suggests that perceived ease of use and usefulness play a major role in forming positive attitudes, which has been reflected in this study [5, 44]. Learners were more willing to adopt technology-based learning solutions when the online platform was seen as user-friendly and helpful. Results from this study also support arguments proposed by Chawla and Joshi [14] and Al-Maroof et al. [7], which specified that an effective online platform may improve attitudes toward technology. On the other hand, this study also partially showed opposing opinions. For instance, DeCoito and Estaiteyeh [19] state that perceived effectiveness may not always result in improved learning outcomes, suggesting that a positive attitude toward technology may not be enough to fill engagement gaps for exam takers, especially in competitive environments. This indicates that while positive attitudes facilitate engagement, they may not be sufficient to ensure improved outcomes in highly competitive environments, where structured practice, feedback, and content quality play an equally important role.

Overall, the findings of this research align with the growing body of studies that emphasize the need for online learning environments to ensure usability, efficient content delivery, and personalized engagement. Further studies can explore gender and regional differences to optimize online platforms for diverse demographic groups.

7 Implications

7.1 Theoretical implications

This study contributes to the extension of the Technology Acceptance Model (TAM) by shifting the focus from technology adoption to learning outcomes in a performance-oriented context. While prior studies predominantly examine behavioural intention, the present study demonstrates that platform effectiveness not only directly influences learning outcomes but also exerts an indirect effect through attitude toward technology usage. This highlights the importance of integrating technological and behavioural constructs within a unified framework. Additionally, by conceptualizing platform effectiveness as a multidimensional construct aligned with perceived usefulness and perceived ease of use, the study strengthens theoretical clarity and addresses the limitation of treating constructs as purely data-driven. The findings also contribute to the literature by

contextualizing TAM within competitive examination environments, thereby expanding its applicability beyond traditional academic settings.

7.2 Managerial implications

The findings offer several practical insights for EdTech providers, educational institutions, and platform developers. First, platform effectiveness should be enhanced not only in terms of accessibility and flexibility but also through structured content delivery, interactive features, and continuous feedback mechanisms. Simply providing access to digital resources is insufficient; platforms must be designed to actively support engagement and performance improvement. Second, the significant role of attitude toward technology suggests that user experience design, ease of navigation, and perceived usefulness should be prioritized to foster positive learner perceptions. Training sessions, onboarding support, and user-friendly interfaces can further enhance technology acceptance.

Additionally, demographic differences observed in the study indicate the need for more personalized learning approaches. Gender differences suggest that engagement strategies may need to be tailored to improve inclusivity, while variations across age and educational background highlight the importance of adaptive learning systems. Regional differences further emphasize the need for context-sensitive platform design, where rural users may benefit from accessibility-focused features, while urban users may prioritize efficiency and advanced functionalities.

7.3 Policy implications

The study also has important implications for policymakers and educational regulators. The findings highlight the need to bridge the digital divide by ensuring equitable access to technological infrastructure across rural and urban regions. Investments in internet connectivity, digital literacy programs, and affordable access to online learning platforms are essential to maximize the benefits of EdTech adoption.

Furthermore, policy initiatives should focus on integrating digital learning within formal education systems by establishing quality standards for online platforms and ensuring content reliability. Given the importance of learner attitudes toward technology, policies should also promote digital readiness among students through training and awareness programs. Finally, the variability in findings across demographic groups suggests that a one-size-fits-all approach may not be effective, and policies should encourage inclusive and adaptive learning frameworks that cater to diverse learner needs.

8 Conclusion

This study examined the role of online platform effectiveness and attitude toward technology usage in shaping learning outcomes among competitive examination aspirants. The findings demonstrate that effective online platforms significantly enhance learning outcomes, both directly and indirectly through learners' attitudes toward technology. This confirms that technological effectiveness alone is insufficient; positive learner attitudes play a critical mediating role in translating platform features into improved performance.

The study further highlights that demographic factors influence perceptions of online learning, indicating the need for context-sensitive and inclusive digital learning

strategies. Variations across gender, age, educational background, and region suggest that a one-size-fits-all approach to online education may not be effective. Additionally, the findings reveal that perceived platform effectiveness does not always guarantee improved learning outcomes, particularly when learner attitudes toward technology are not favourable.

From a theoretical perspective, the study extends the applicability of the Technology Acceptance Model (TAM) by linking technological factors with performance outcomes in a competitive learning context. Practically, the results emphasize the importance of designing user-centric, engaging, and adaptive online learning platforms.

8.1 Limitations of the study

The study presents multiple drawbacks, including the possibility of bias and subjective interpretation due to its heavy reliance on exam participants' self-reported judgments. It also lacks a thorough examination of the variables, like different degrees of past technology exposure, that contribute to variations in the applicants' perceptions. Furthermore, confounding variables like the calibre of online instructional resources or instructor participation in virtual learning environments were not taken into consideration in this study, which could have an impact on the association between technology usage and learning results. Furthermore, it might not adequately reflect the complex relationship between the use of technology and actual learning results due to its emphasis on attitudes and views towards it. Lastly, the study's sample might not accurately reflect the larger population because it was largely focused on particular age groups and educational backgrounds.

8.2 Future research

Future research undertakings need to include a comparison study that evaluates the efficacy of students in technologically enhanced online learning environments vs. traditional classroom teaching techniques assisted by teachers. Furthermore, a study that examined learners' motivation levels with and without technology would offer priceless insights into how technology affects learner effectiveness and engagement. It is also recommended to investigate the way blended learning approaches might be used to include technology in classroom instruction to understand students' openness to and readiness to learn from technology-driven approaches. Researchers can learn more about the function and efficacy of technology in influencing students' educational experiences by pursuing these study avenues.

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Author contributions
Niyaz Panakaje: Conceptualization, Methodology, Data Curation, Formal Analysis, Supervision, Writing-Review and Editing, Writing—Original Draft; S. M. Riha Parvin: Conceptualization, Data Curation, Investigation, Data Collection, Writing-Review and Editing, Writing—Original Draft, Visualization.

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Data availability
The datasets analysed during the current study are available from the corresponding author on reasonable request.

Data collection period
Data for this study were collected between May 2025 and August 2025 from students preparing for competitive examinations using structured questionnaires.

Declarations

Ethics approval and consent to participate
The questionnaire used in this study was approved by the Scientific Review Board of Yenepoya Institute of Arts, Science, Commerce and Management (YIASCM), Yenepoya (Deemed to be University) for this purpose (SRB reference number: YIASCM/SRB-06/COM/17/2025), in accordance with the university's research policy and procedures, on 5th April, 2025. The certificate for the same was issued on 02–04-2025. Oral consent was obtained from the participants before administering the questionnaire. As the data collection involved minimal risk, it was conducted anonymously, ensuring complete participant anonymity and confidentiality.

Consent for publication
Not Applicable.

Informed consent
A sentence confirming that informed consent (consent to participate) was obtained from all participants involved in the study. As all participants were adults (18 years and above), informed consent was obtained directly from the participants prior to data collection.

Competing interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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