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Effectiveness of virtual learning system in agricultural education in India

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Introduction: Virtual learning systems (VLS) have become increasingly significant in agricultural education, especially for enhancing accessibility and flexibility. However, their effectiveness in improving learners' engagement, satisfaction, retention, and overall outcomes remains uncertain, particularly within the Indian agricultural education context.
Methodology: A cross-sectional study was conducted among 400 students from Undergraduate (UG), Postgraduate (PG), and PhD programs across randomly selected agricultural universities. Effectiveness Index was constructed using entropy method. Multiple linear regression analysis was employed to identify key predictors.
Results: The findings indicate that 50.5% of students perceived a medium level of VLS effectiveness. Postgraduate and PhD students reported higher engagement and satisfaction than UG students. Self-regulation was the most significant predictor of learning effectiveness, followed by learners' attitudes and e-learning design. Gender differences were also observed, with female students performing better in virtual learning environments.
Discussion and conclusion: The study highlights the critical role of self-regulation, positive learners' attitudes, and well-structured e-learning design in enhancing the effectiveness of virtual learning. These insights can inform the development of strategies aimed at optimizing virtual platforms for agricultural education.

KEYWORDS

virtual learning, effectiveness, self-regulation, e-learning design, students

1 Introduction

Over the past few decades, the landscape of education has undergone a profound transformation, driven by advancements in digital technologies. The adoption of online platforms, multimedia tools, and the widespread availability of high-speed internet has transformed the delivery of education. Virtual learning system (VLS) has emerged as a powerful alternative to traditional face-to-face instruction, offering unprecedented flexibility and accessibility to learners across diverse geographical and temporal contexts (Chawinga and Zozie, 2016). By bridging physical distances, these platforms enable students to access educational content and interact with instructors at their convenience, thus making learning more inclusive, particularly for learners in remote and underserved regions (Bawa, 2016). Virtual learning refers to the use of electronic platforms to facilitate educational experiences, utilizing a mix of media such as text, video, audio, and interactive modules (Moore et al., 2011). This flexibility enables learners to pursue education at their own pace, overcoming the constraints of traditional classroom settings. Digital learning systems have gained significant attention in recent years, particularly due to the ongoing shift in educational methods driven by advancements in technology. Studies have shown that digital learning can provide substantial benefits, such as greater accessibility and flexibility, in various educational settings (Lu et al., 2021). Furthermore, the COVID-19 pandemic acted as a catalyst for the widespread adoption of technology-enhanced learning (TEL), highlighting the potential of remote learning environments to support higher education during disruptions (Enbeyle et al., 2022). This adaptability is particularly crucial in fields where access to on-campus learning facilities may be limited, and where practical knowledge is essential for skill development (Chawinga and Zozie, 2016). With the rise of online tools, such as Learning Management Systems (LMS), mobile applications, and virtual classrooms, the education sector is witnessing a shift toward digital learning that provides greater autonomy for students, especially in rural areas (Santally, 2016). Although virtual learning provides several benefits, such as personalized learning experiences and enhanced content engagement (Bond et al., 2021), its effectiveness is influenced by many factors. These factors include the learners' characteristics such as self-regulation, motivation, time management skills, and computer literacy, along with the design and functionality of the learning platform (Martin et al., 2020a). Research has shown that factors like system reliability, ease of use, interactivity, and content quality are critical in determining learners' satisfaction and engagement (Al-Fraihat et al., 2020). However, technical issues or poorly designed platforms can lead to frustration, disengagement, and increased dropout rates (Rahmani et al., 2024).

This study contributes to the broader discourse on technology-enhanced learning by offering insights into key factors such as learners' engagement, platform interactivity, and content design within virtual learning environments. These elements are foundational to the development of more advanced digital education tools, including simulation-based systems and virtual reality (VR) or augmented reality (AR) applications. Particularly in agricultural education, where experiential, hands-on training is essential, such insights are critical for informing the future integration of immersive technologies that can replicate field-based learning in virtual formats. Recent research highlights the growing relevance of these technologies; for instance, Bigonah et al. (2024) demonstrated how gamified AR and VR tools can enhance motivation and learning outcomes in agriculture by replicating real-world tasks like irrigation planning and pest management. Similarly, Li et al. (2025) provided instructional design guidelines for VR-based training, reinforcing the pedagogical importance of immersive environments. In agricultural education, where practical and field-based learning is a core part of the curriculum, these challenges are particularly pronounced. Many essential activities such as soil testing, irrigation planning, and pest management require physical presence, making it difficult to replicate these experiences effectively through virtual platforms. As a result, many students struggle with hands-on laboratory skill development and overall satisfaction with their online learning (Anderson, 2023; Long et al., 2024). Further research by Keramidas (2012) has highlighted that online students often face challenges with time management and meeting deadlines, which are less common in traditional face-to-face learning. Moreover, past studies have indicated a positive correlation between online learning and factors such as perceived academic challenge, learning gains, satisfaction, and improved study habits (Crawford et al., 2020; Muljana and Luo, 2019). However, Borup et al. (2020) reported that students in online environments may feel a lack of connection to instructors, leading to reduced confidence, motivation, and increased course dropouts. Providing timely feedback is a critical strategy in preventing students from feeling disconnected (Martin et al., 2018). In agricultural education, where practical and field-based learning is often integral to the curriculum, the shift to virtual learning presents a unique set of challenges. For example, Lehan (2023a) and Lehan (2023b) found that although students appreciated the flexibility of virtual instruction, many felt it lacked the experiential depth needed for agricultural competency development. Despite the growing interest in online education, research specifically exploring the effectiveness of virtual learning systems within agricultural education is limited (Joshi et al., 2020). While studies have addressed general outcomes such as learners' engagement, retention, and satisfaction in virtual learning, few have explored how these factors interact within specialized fields like agriculture (Rajabalee and Santally, 2021). Therefore, it is crucial to explore the factors influencing the success of virtual learning in this field.

Effectiveness in virtual learning is typically defined by its ability to support desirable outcomes, including learners' engagement, retention, satisfaction, and academic performance (Al-Fraihat et al., 2020). The effectiveness of these systems is influenced by several factors, including the design of the learning platform, the quality of technology, and individual learners' characteristics such as self-regulation, attitudes toward virtual learning, and demographic variables like age and gender (Panigrahi et al., 2018). While previous studies have examined the impact of these factors on virtual learning outcomes, gaps remain in understanding how specific learners' characteristics and course design elements interact to influence overall learning effectiveness (Bond et al., 2021). Leidner et al., (as cited in Selim, 2007) proposed that effective e-learning is influenced by three main factors: instructors' characteristics, technology, and students' characteristics. Moreover, studies indicate that learners' engagement is further affected by interactions with peers and instructors, which can enhance the learning experience by fostering collaborative learning and mutual support (Lynch and Dembo, 2004). However, research indicates that a lack of learners' interaction is a significant factor in the failure and dropout rates of online courses (Almarashdeh, 2016). Martin et al. (2020b) noted that learners' evaluation of a system's quality, reliability, and ease of use contributes significantly to learning efficiency, particularly in blended learning environments. Poor-quality technology, which fails to meet learners' needs, can diminish satisfaction (Almarashdeh, 2016; Al-Fraihat et al., 2020), highlighting the importance of ensuring that online platforms are technically reliable and user-friendly. Martin et al. (2019) noted that continued use of a Learning Management System is a key indicator of success in blended learning. However, dissatisfaction often arises from technological difficulties, lack of timely feedback, or unclear course instructions (Islam, 2014). This study aims to fill the gap in understanding how learners' characteristics (e.g., self-regulation, attitudes toward virtual learning, age, and gender) and design features (e.g., interactivity, system reliability, user interface, and content quality) interact to influence key factors such as learners' engagement, outcomes, retention, and satisfaction in virtual learning in agricultural education.

2 Conceptual framework

This study is grounded in two well-established theoretical perspectives: Self-Regulated Learning (SRL) Theory and the Community of Inquiry (CoI) Framework. The Self-Regulated Learning Theory, as proposed by Zimmerman (1989), underscores the learner's capacity to independently direct their cognitive, motivational, and behavioral processes to achieve learning goals. In the context of virtual education particularly within agricultural disciplines where direct supervision is minimal, self-regulation becomes indispensable (Panadero, 2017). Learners must effectively manage their time, sustain motivation, and adapt strategies to navigate online environments, all of which are pivotal for academic success.

Complementing this, the Community of Inquiry Framework (Garrison et al., 2000) provides a process-oriented model for online learning environments, highlighting three core elements: cognitive presence, social presence, and teaching presence. Teaching Presence refers to the design, facilitation, and direction of cognitive and social processes to achieve intended learning outcomes. In the context of this study, it is reflected through elements such as content organization, technical support, and user interface design. Cognitive Presence, on the other hand, denotes the degree to which learners can construct and confirm meaning through sustained reflection and dialog, which aligns with variables like learners' engagement, personalization, and interactivity. Finally, Social Presence captures the ability of learners to project themselves socially and emotionally in a community of inquiry, and in this study, it is indirectly measured through learners' satisfaction, peer interaction, and the support systems integrated into the virtual learning environment.

Together, SRL and CoI provide a comprehensive theoretical lens to examine the dynamics of virtual learning, particularly in the context of agricultural education where limitations in hands-on training pose unique challenges (Xu and Jaggars, 2013). These frameworks inform the conceptual model of this study (Figure 1), which visualizes the interaction between learners' characteristics (e.g., age, gender, prior e-learning experience, attitudes, and self-regulation) and design features of the virtual learning system (e.g., system reliability, interface quality, personalization, interactivity, and technical support) in influencing the overall effectiveness of virtual learning. Effectiveness is operationalized through four dimensions: learner engagement, satisfaction, retention, and learning outcomes.

3 Materials and methods

3.1 Sampling and data collection

3.1.1 Sampling frame

In India, agricultural education is primarily offered through State Agricultural Universities (SAUs), Deemed-to-be Universities, and, more recently, Central Agricultural Universities (CAUs). These institutions function under the aegis of the Indian Council of

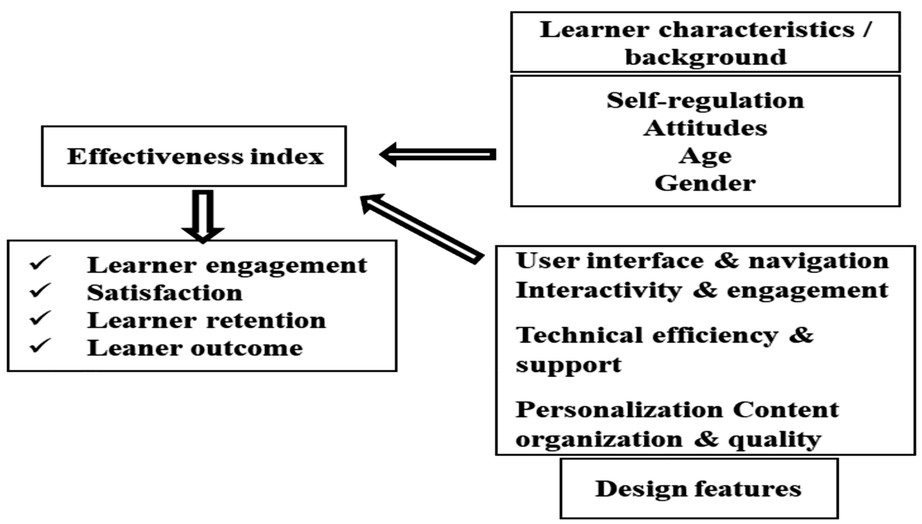

FIGURE 1
Conceptual framework of the study.

Agricultural Research (ICAR), the apex national body responsible for overseeing and standardizing agricultural education. Although several private universities have entered the field of agricultural education in recent years, they were excluded from the sampling frame due to considerable variations in their curricula and a lack of alignment with ICAR-accredited standards.

3.1.2 Data collection

The study was conducted across eight agricultural universities selected through simple random sampling from a total of sixty-four operating under the Indian Council of Agricultural Research (ICAR). To ensure institutional diversity within the ICAR framework, the sample included six State Agricultural Universities (SAUs) such as Professor Jayashankar Telangana State Agricultural University (PJTSAU), Telangana; Tamil Nadu Agricultural University (TNAU), Tamil Nadu; Punjab Agricultural University (PAU), Punjab; Maharana Pratap University of Agriculture & Technology (MPUAT), Udaipur; Punjabrao Deshmukh Krishi Vidyapeeth, Akola (PDKV), Maharashtra; Rajendra Prasad Central Agricultural University, Bihar (RPCAU) - Bihar and two Deemed Universities (DUs) such as Indian Agricultural Research Institute (IARI), New Delhi; and National Dairy Research Institute (NDRI), Karnal. These institutions were selected to represent a cross-section of regional diversity within the ICAR-affiliated agricultural education system in India.

A stratified random sampling technique was employed to ensure proportional representation of students across three academic levels: Undergraduate (UG), postgraduate (PG), and PhD. The population was divided into these strata, and samples were randomly selected from each subgroup, ensuring balanced representation of student experiences with virtual learning.

The sample size was determined using Yamane's formula for finite population sampling:

$$n = \frac{N}{1 + N(e)^2}$$

Where:

n = Required sample size; N = Total student population; e = margin of error (0.05).

Based on average enrolments across the selected universities approximately 150 UG, 90 PG, and 70 PhD students per institution, the total population (N) was estimated at 2,480 students. Using a 5% margin of error and a 95% confidence level, the minimum required sample size was calculated to be approximately 341 students.

However, to enhance reliability and ensure balanced representation across academic levels and institutions, the sample size was increased to 400. To further validate the adequacy of this sample size, a post-hoc statistical power analysis was conducted using G*Power 3.1.9.7 software. Assuming a medium effect size ($f^2 = 0.15$), a significance level (α) of 0.05, and five predictors in a multiple regression analysis, the statistical power achieved with a sample size of 400 was 0.9, which exceeds the conventional threshold of 0.80 (Faul et al., 2009). This confirms that the study had sufficient power to detect meaningful relationships between the variables under investigation.

Accordingly, 50 students were selected from each university, comprising 25 UG, 15 PG, and 10 PhD students, resulting in a total of 200 UG, 120 PG, and 80 PhD students.

The study included 193 male students (48.25%) and 207 female students (51.75%), with an average age of 23 years.

3.2 Data analysis

3.2.1 Effectiveness index

The study started with measuring effectiveness in virtual learning using a composite index, referred to as the Effectiveness Index (EI). This index was developed based on a review of relevant literature and expert opinion. Four key indices were identified to measure various aspects of effectiveness: Learner Engagement Index (LEI), Learning Outcomes Index (LOI), Learner Retention Index (LRI), and Learner Satisfaction Index (LSI) (Table 1). These indices contained different numbers of indicators: LEI had seven indicators, LOI included four, LRI had three, and LSI contained five. Given that the indicators varied in their meaning and scope, it was essential to assign appropriate weights to each of them. Literature suggests that there are both subjective and objective methods for assigning weights. While subjective methods rely on expert judgment, objective methods employ mathematical models to assign weights. In this study, the Shannon Entropy Method was chosen for its objective approach in determining weights. This method is widely used in multi-attribute decision-making problems when preference-based or decision-making experiments are not feasible (Lotfi and Fallahnejad, 2010).

The steps followed in obtaining the objective weights for the indicators were as follows:

Step 1: Normalization of data: As the raw data for each indicator may have different units or scales, normalization was performed to eliminate biases caused by these differences. Normalization ensures that all values are proportionally scaled between 0 and 1 for fair comparison:

$$r_{ij} = \frac{x_{ij}}{\sum_{j=1}^{m} x_{ij}}, i = 1, 2, \ldots, n$$

Where r_{ij} is the normalized value and x_{ij} = Raw value of the observation for the ith observation of the jth criterion.

Step 2: Calculation of entropy (h_i):

The entropy for each indicator was calculated as follows:

$$h_i = -h_o \sum_{j=1}^{m} r_{ij} \ln\left(r_{ij}\right), \left(i = 1, 2, \ldots, n\right)$$

Where h_o= $(\ln m)^{-1}$ is the entropy constant, where m is the number of indicators.

r_{ij} is the normalized value; if $r_{ij} = 0$, it is set to 0 to avoid undefined values.

Step 3: Calculation of the degree of diversification (d_i).

$$d_i = 1 - h_i, i = 1, 2, \ldots, n$$

Step 4: Determination of weights (W_i).

TABLE 1 Dimensions and their indicators.

Dimensions	Indicators	Measurement
Learner engagement	(X_1) Engagement with course materials	Measured by how actively students engage with the course materials such as readings, videos, and assignments.
	(X_2) Participation in online discussion	Measured by the frequency students participate in online discussions, such as course forums, chat groups, or discussion boards.
	(X_3) Level of interaction with instructors and peers	Assessed by the frequency of interactions between students, instructors, and peers during the course.
	(X_4) Do you feel connected in online learning	Measured by how connected students feel in the online learning environment, assessing their sense of community and belonging.
	(X_5) Do you feel motivated to engage online courses	Measured by the level of motivation students have to actively engage with online courses and learning activities.
Learner outcomes	(X_6) Effect of virtual learning on learning outcome	Measured by the extent to which students perceive virtual learning has improved their learning outcomes.
	(X_7) Learning objectives can be fulfilled in online learning	Measured by how effectively students feel they can achieve the learning objectives in an online environment.
	(X_8) Assessments of learning outcomes in virtual learning are clear	Measured by the clarity of assessments in evaluating learning outcomes in virtual courses.
	(X_9) Prepare adequately for assignments and assessments	Measured by the extent to which students feel they have prepared adequately for assignments and assessments in the virtual learning environment.
	(X_{10}) Learning outcomes are better in offline model	Measured by the students' comparison of learning outcomes between online and offline learning modes.
Learner retention	(X_{11}) Retention rate in virtual mode is high	Measured by how students perceive the retention rate in virtual learning modes.
	(X_{12}) How much percentage of course content do you expect to complete through virtual mode	Measured by the expected percentage of the course content that students believe they will complete through the virtual mode.
	(X_{13}) The course drop rate of students is high in virtual mode	Measured by how strongly students agree with the statement that the course drop rate is high in the virtual learning mode.
Learner satisfaction	(X_{16}) How satisfied are with the interactions in the virtual learning	Measured by the level of satisfaction students have with their interactions in the virtual learning environment (e.g., with instructors and peers).
	(X_{17}) Rate the extent of overall satisfaction with the virtual learning model	Measured by how satisfied students are with the overall virtual learning model.
	(X_{18}) Do you recommend the online learning to others	Measured by the likelihood of students recommending online learning to others.

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$$w_i = \frac{d_i}{\sum_{i=1}^{n} di}, \text{i} = 1,2,\ldots,n$$

These weights (w_i) represent the relative importance of each indicator in the overall index calculation.

Step 5: Calculation of final index values: After determining the weights, the final index values for each observation were calculated by aggregating the normalized values for all indicators. Before aggregation, the range-normalized values for each indicator were computed as follows:

$$Y_i = \frac{X_i - \min(X_i)}{\max(X_i) - \min(X_i)}, \text{i} = 1,2,\ldots,n$$

Where Y_i ensures that all indicator values are rescaled between 0 and 1 based on their range.

Finally, the Effectiveness Index (EI) for each observation was calculated by multiplying the range-normalized values with the corresponding objective weights:

$$f_i = Y_i \cdot W_i; \text{i} = 1,2,\ldots,n$$

3.2.2 Learners' characteristics and e-learning design

Attitude, self-regulation and e-learning design were measured using self-developed questionnaires, with all items rated on a five-point Likert scale, ranging from "Strongly Agree" to "Strongly Disagree. Attitude was assessed using 29 statements. Self-regulation among students was assessed using mean scores derived from 11 statements. The e-learning design questionnaire included 22 statements, which were categorized into five dimensions: (1) User Interface and Navigation, (2) Interactivity and Engagement, (3) Content Organization and Quality, (4) Technical Efficiency, and (5) Personalization and Support (see Supplementary material). The weighted mean score (WMS) was used to analyse the responses, providing insights into the perceived importance of each design feature.

To ensure the validity and reliability of the study instruments, content validation was conducted by a panel of experts in agricultural education and instructional technology. The instruments were reviewed for relevance, clarity, and coverage of the intended constructs. Based on their suggestions, some items were reworded or removed. The internal consistency reliability of the instruments was then tested using Cronbach's Alpha in SPSS. The attitude scale showed a reliability of 0.849, the self-regulation scale showed excellent internal consistency with a Cronbach's Alpha of 0.898, and the e-learning design scale demonstrated high reliability with a coefficient of 0.874, all exceeding the recommended threshold of 0.7 (Nunnally and Bernstein, 1994).

Independent samples t-test was used to explore the gender differences in virtual learning effectiveness. Finally, multiple regression analysis was conducted to identify significant predictors of virtual learning system effectiveness.

4 Results

4.1 Socio-demographic variables

The independent variables examined in the study included prior e-learning experience, place of residence, device used for accessing virtual learning, type of internet connectivity, and learning preference (Table 2). A large majority of respondents (93.5%) reported having prior experience with e-learning, while only 6.5% indicated no such experience. In terms of residential background, 58.25% of the students came from rural areas, and 41.75% were from urban settings. Regarding the primary device used for online learning, most students used either laptops or mobile phones (data not shown in the table snippet above), while 3.75% used tablets, and 9.75% reported using a combination of devices. For internet connectivity, mobile data was the most common mode (63.75%), followed by Wi-Fi (29.75%), and both mobile data and Wi-Fi (6.5%). When asked about their preferred learning mode, the majority of students (68.25%) favored a hybrid approach that combines online and in-person instruction. Fully in-person learning was preferred by 21.75% of the students, whereas only 10% preferred fully online learning.

4.2 Effectiveness index

Each of the constituent indicators of the indices Learner Engagement Index (LEI), Learner Outcome Index (LOI), Learner Retention Index (LRI), and Learner Satisfaction Index (LSI) carried different entropy weights, contributing to the overall Effectiveness Index (Table 3). The LEI contributed 27.85% to the total weight of the Effectiveness Index, with "Engagement with course materials" (X_1) carrying the highest weight (0.207), underscoring its critical role in keeping students actively involved in their learning. This was followed by "Level of interaction with instructors and peers" (X_3) with a weight of 0.205, highlighting the importance of communication and interaction. "Feeling connected in online learning" (X_4) had a weight of 0.200, reflecting the significance of a strong sense of connection in maintaining engagement. "Motivation to engage in online courses" (X_5) carried a weight of 0.197, emphasizing the importance of intrinsic

TABLE 2 Socio-demographic variables.

Variable	Categories	Frequency (%)
Prior e-learning experience	Yes	374 (93.5)
	No	26 (6.5)
Place of residence	Rural	233 (58.25)
	Urban	167 (41.75)
	Tablet	15 (3.75)
	All	33 (9.75)
Connectivity type	Wifi	119 (29.75)
	Mobile data	255 (63.75)
	Both	26 (6.5)
Learning preference	Fully online	40 (10)
	Fully in-person	87 (21.75)
	Hybrid	273 (68.25)

TABLE 3 Effectiveness index and weights of their respective indicators.

Index	Weight	Indicator	Weight
Learner Engagement Index	0.279	(X_1) Engagement with course materials	0.207
		(X_2) Participation in online discussion	0.191
		(X_3) Level of interaction with instructors and peers	0.205
		(X_4) Do you feel connected in online learning	0.200
		(X_5) Do you feel motivated to engage online courses	0.197
Learner Outcome Index	0.285	(X_6) Effect of virtual learning on learning outcome	0.202
		(X_7) Learning objectives can be fulfilled in online learning	0.194
		(X_8) Assessments of learning outcomes in virtual learning are clear	0.202
		(X_9) Prepare adequately for assignments and assessments	0.202
		(X_{10}) Learning outcomes are better in offline model	0.201
Learner Retention Index	0.162	(X_{11}) Retention rate in virtual mode is high	0.328
		(X_{12}) How much percentage of course content do you expect to complete through virtual mode	0.318
		(X_{13}) The course drop rate of students is high in virtual mode	0.354
Learner satisfaction Index	0.275	(X_{14}) How satisfied are you with virtual learning compared to traditional in-person	0.209
		(X_{15}) How satisfied are you with the flexibility for learning provided by the virtual learning	0.210
		(X_{16}) How satisfied are with the interactions in the virtual learning	0.165
		(X_{17}) Rate the extent of overall satisfaction with the virtual learning model	0.200
		(X_{18}) Do you recommend the online learning to others	0.208

motivation, while "Participation in online discussion" (X_2) had the lowest weight (0.191), yet remained critical for fostering understanding through peer interaction. The LOI had the highest contribution at 28.50%, with "Effect of virtual learning on learning outcome" (X_6), "Clarity of assessments in virtual learning" (X_8), and "Adequate preparation for assignments and assessments" (X_9) each holding the highest entropy weight (0.202), underscoring their paramount importance in the success of the virtual learning model. "Learning outcomes are better in the offline model" (X_{10}) followed with a weight of 0.201, while "Learning objectives can be fulfilled in the virtual model" (X_7) had the lowest weight (0.194), though still significant. The LRI contributed 16.17%, with "Course drop rate is high in virtual learning "(X_{13}) having the highest weight (0.354), emphasizing the need to reduce dropout rates, followed by "Retention rate in virtual learning is high "(X_{11}) with a weight of 0.328, and "Expected completion percentage through online learning "(X_{12}) with a weight of 0.318, highlighting the importance of feasible completion rates. Lastly, the LSI contributed 27.48 percent, making it a crucial component, with "Satisfaction with flexibility and learning choices in virtual learning "(X_{15}) carrying the highest weight (0.210), followed by "Satisfaction with virtual learning vs. traditional "(X_{14}) at 0.209, and "Overall satisfaction with virtual learning "(X_{17}) and "Recommendation of online learning to others "(X_{18}) both at 0.208, reflecting general satisfaction and acceptance. "Satisfaction with the interaction in virtual learning" (X_{16}) had the lowest weight (0.165) but remained vital for understanding overall student preference.

4.2.1 Overall effectiveness of the virtual learning system

The overall effectiveness of the virtual learning system was assessed using two methods: the Cumulative Cube Root Frequency (CCRF) method and the traditional mean ± standard deviation approach. The mean ± standard deviation method resulted in 73.25% of respondents being categorized as "medium," which limited the interpretive depth. In contrast, the CCRF method, commonly used in educational and social sciences, was employed to classify the data into ordinal categories, converting skewed continuous data (Walter et al., 2016). This method minimizes the impact of outliers and ensures a more balanced distribution, particularly for non-normally distributed data.

The CCRF classification produced the following distribution: 29.25 percent of respondents were categorized as low, 50.5 percent as medium, and 20.25 percent as high (Table 4). This approach offered a more evenly distributed picture, providing greater interpretive clarity.

When analysed by academic level, Undergraduate (UG) students showed a higher proportion in the low-effectiveness category (32.5%) compared to postgraduate (PG) and PhD. students (26%). In contrast, a majority of PG and PhD. students (59%) fell into the medium-effectiveness category, while only 42 Percent of UG students reported medium effectiveness. Similarly, the proportion of students reporting high effectiveness was greater among PG and PhD. students (24%) compared to UG students (17%) (Table 5).

4.3 Learners' characteristics

4.3.1 Gender

An independent t-test was conducted to compare the performance of male and female learner's in a virtual learning environment. Levene's Test for Equality of Variances indicated that the assumption of equal variances was met ($p = 0.081$). Results showed that male learners had a slightly lower mean performance ($M = 0.575$) compared to female learners ($M = 0.632$). The t-test revealed a statistically significant difference in performance ($t = -5.037$, $df = 398$, $p < 0.001$, two-tailed), indicating that female learners outperformed their male counterparts in virtual learning.

4.3.2 Self-regulation among students toward virtual learning

The findings in the Table 6 indicated notable strengths and areas for improvement in students' self-regulation. Strong performance was observed in goal-setting behaviors, with high scores for setting standards for assignments (3.9) and establishing short-term goals (3.7). Students also demonstrated a commitment to maintaining high-quality work, as reflected in scores for maintaining learning standards (3.7) and avoiding compromises in work quality (3.83). Effective distraction management was evident in students choosing suitable study locations (3.9) and times with minimal interruptions (3.74). Preparatory practices, such as taking thorough notes (3.75), preparing for discussions (3.56), and allocating extra study time (3.66), were consistently practiced, although scheduling daily or weekly study routines showed moderate consistency (3.68). Students were also engaged with supplementary resources, such as reading additional course content (3.88), which was a notable strength. However, strategies aimed at enhancing focus, such as reading aloud instructional materials to reduce distractions (3.54), were less commonly employed.

TABLE 4 Overall effectiveness of virtual learning system.

Category	Range	Frequency	Percentage
Low	<0.55	117	29.25
Medium	0.55–0.68	202	50.5
High	>0.68	81	20.25

$N = 400$.

TABLE 5 Level of effectiveness by academic level.

Academic level	Low (%)	Medium (%)	High (%)
UG	32.5	42	17
Pg and PhD	26	59	24

$n_1 = 200$ (UG); $n_2 = 200$ (PG and PhD).

TABLE 6 Mean score of self-regulation.

Statements related to self-regulation	Mean score
1. I set standards for my assignments in online courses.	3.9
2. I set short-term (daily or weekly) goals	3.7
3. I do not compromise the quality of my work in online learning	3.83
4. I choose the location where I study to avoid too much distraction during online class.	3.9
5. I choose a time with few distractions for studying for my online courses	3.74
6. I try to take more thorough notes for my online courses	3.75
7. I read aloud instructional materials posted online to fight against distractions.	3.54
8. I prepare myself before joining in the discussion.	3.56
9. I allocate extra studying time for my online courses because I know it is time-demanding.	3.66
10. I read extra materials for my online courses in addition to the assigned ones to master the course content.	3.88
11. I try to schedule the same time every day or every week to study for my online courses.	3.68

4.4 E-learning design features

The results from the Table 7 revealed varied perceptions of students regarding different aspects of e-learning design. The reliability of the items was found to be 0.874. The User Interface and Navigation dimension received the highest WMS of 4.57, emphasizing its importance in creating a seamless virtual learning experience, with students prioritizing ease of navigation, user-friendly menus, visually appealing layouts, mobile compatibility, and security of personal information. The Interactivity and Engagement dimension, with a WMS of 4.33, highlighted the value of collaborative opportunities, engaging course content (e.g., simulations, quizzes), supportive instructor interactions, and teamwork features. Content Organization and Quality, scoring a WMS of 4.23, underscored the importance of well-structured course materials, multimedia integration, alignment of assessments with objectives, and clear, organized content. Technical Efficiency received a moderate WMS of 3.72, pointing to the need for reliable internet, minimal technical disruptions, timely feedback, analytics tools for improvement, and technical support. Lastly, Personalization and Support had the lowest WMS of 3.45, indicating relatively lower importance placed on content recommendations and options for personalizing the learning experience.

4.5 Significant predictors of virtual learning effectiveness

The results of regression revealed a strong model fit (Table 8), with an R value of 0.822, indicating a high correlation between the predictors and virtual learning effectiveness. The model explained 67.6 Percent of the variance ($R^2 = 0.676$, Adjusted $R^2 = 0.670$), with a standard error of estimate at 0.067. To ensure the robustness of the model, multicollinearity diagnostics were performed. Variance Inflation Factor (VIF) values ranged from 1.032 to 1.631, and tolerance values ranged from 0.613 to 0.969 both well within acceptable thresholds indicating no serious multicollinearity issues among predictors (Salmerón et al., 2020). Additionally, residual statistics showed standardized residuals ranging from −2.178 to 6.296, with a mean of 0 and a standard deviation of 0.992. The Durbin-Watson value of 1.768 suggested no significant autocorrelation, supporting the assumption of independence of errors.

Among the predictors (Table 9), self-regulation emerged as the most significant factor ($\beta = 0.61$, $t = 16.323$, $p < 0.05$), followed by attitude ($\beta = 0.221$, $t = 6.144$, $p < 0.05$) and design features ($\beta = 0.067$, $t = 2.049$, $p < 0.05$). Conversely, age and gender did not significantly predict virtual learning effectiveness, with non-significant t-values of 0.969 and 1.862, respectively. These findings emphasize the importance of fostering self-regulation, positive attitudes, and effective design features in enhancing virtual learning outcomes.

TABLE 7 Weighted mean scores (WMS) of e-learning design features across dimensions.

Statements	WMS
User interface and navigation	
1. The virtual learning environment should be easy to navigate.	4.57
2. I should find the necessary menus and options without much effort.	
3. The layout of the virtual learning environment should be visually appealing.	
4. The virtual learning environment should be easy to use on mobile devices.	
5. The virtual learning environment should ensure the security of my personal information.	
Interactivity and engagement	
6. The VLE should provide opportunities for interaction with other students (e.g., discussion forums etc.)	4.33
7. Interactions with course content (e.g., through quizzes, simulations) should be engaging.	
8. My interactions with instructors (e.g., through discussions, feedback) should be supportive.	
9. Collaboration features (e.g., shared workspaces) should support group projects and teamwork.	
Technical efficiency	
10. Internet reliability and speed do not significantly impede my learning experience.	3.72
11. Technical issues, such as platform crashes or slow loading times, should be infrequent.	
12. Feedback on my assignments and performance should be timely and constructive.	
13. The analytics tools should be provided so as to identify areas where I need improvement.	
14. Technical support and help resources should be readily available when I encounter issues.	
Personalization and support	
15. The virtual learning environment should provide content recommendations tailored to my needs.	3.45
16. Settings should be provided so as to personalize my learning experience.	
17. The VLE should be accessible to all learners, including those with disabilities.	
18. Tracking progress and achievements within the virtual learning environment should be made easy.	
Content organization and quality.	
19. Course materials should be well-organized.	4.23
20. VLS should enable the use of multimedia (videos, images etc) to enhance my learning experience.	
21. The quality of digital materials (e.g., videos, interactive simulations) in the VLE should be high.	
22. Assessments (quizzes, assignments) should be clear and align with the course content.	

TABLE 8 Multiple linear regression model summary.

Modal summary			
R	R^2	Adjusted R^2	Std. error of estimate
0.822	0.676	0.667	0.066

TABLE 9 Predictors of effectiveness of virtual learning system.

Independent variables	Effectiveness			
	Beta coefficients	*t*	VIF	Tolerance
Design features	0.067	2.049*	1.246	0.803
Learners' characteristics				
Age	0.029	0.969	1.032	0.969
Gender	0.057	1.862	1.070	0.935
Self-regulation	0.614	16.323*	1.631	0.613
Attitude	0.221	6.144*	1.496	0.668

*Significant at 0.05 level of probability.

5 Discussion

5.1 Effectiveness of the virtual learning system

Among different sub-indices, the Learner Engagement Index (LEI) emerged as a crucial determinant of virtual learning effectiveness, reinforcing existing research that emphasizes its impact on academic performance in online settings (Park et al., 2019). Among the measured indicators, engagement with course materials (X_1) received the highest weight, reflecting the importance of well-structured and interactive content in sustaining learners' interest. Recent studies have emphasized that clear, well-organized, and interactive course content significantly enhances learners' motivation and engagement in virtual learning environments (Shehzad and Charles, 2023). The level of interaction with instructors and peers (X_3) also played a significant role, reflecting the importance of social presence in online learning, which fosters a sense of community and academic support (Wu, 2023). While motivation to engage (X_5) had a slightly lower weight, this can be attributed to its intrinsic nature, which varies among students and may be less universally impactful compared to structural elements like course content and communication (Ryan and Deci, 2020). Similarly, participation in online discussions (X_2), with the lowest weight, may be less prioritized in virtual environments due to the prevalence of asynchronous learning, where students can engage with materials independently, limiting the necessity for real-time interaction (Lowenthal and Moore, 2020).

The Learner Outcome Index (LOI) highlights the key factors influencing the effectiveness of virtual learning in achieving educational objectives. The highest contribution came from indicators like "Effect of virtual learning on learning outcome" (X_6), "Clarity of assessments in virtual learning" (X_8), and "Adequate preparation for assignments and assessments" (X_9), each with a high entropy weight, highlighting the importance of clear, well-structured assessments and preparation in ensuring positive learning outcomes. This aligns with the work of Garrison et al. (2010), emphasizing the importance of a structured and supportive online learning environment to enhance student achievement in virtual and hybrid settings. The second-highest weight was associated with the indicator "Learning outcomes are better in the offline model" (X_{10}), suggesting that traditional face-to-face learning still holds substantial value, particularly for complex learning objectives requiring immediate feedback and hands-on experiences. This is consistent with the findings of Martin et al. (2018), who emphasize that instructor presence, connectedness, and engagement are critical factors in promoting student success in online courses. Finally, "Learning objectives can be fulfilled in virtual learning" (X_7) received the lowest weight, pointing to the limitations of virtual learning in achieving all educational objectives, particularly due to the lack of direct interaction and real-time feedback, a challenge noted by Moore et al. (2011). These results underline the importance of balancing virtual and offline components within hybrid learning models to optimize educational outcomes.

The Learner Satisfaction Index (LSI), which measures students' overall contentment with the virtual learning system, highlights its significant role in determining the effectiveness of virtual education. The highest weight was assigned to "Satisfaction with flexibility and learning choices in virtual learning" (X_{15}), emphasizing the importance of flexibility in virtual learning environments. This aligns with research that highlights how students value the ability to manage their own learning schedules and select courses that fit their needs (Azizan et al., 2022). Following closely, "Satisfaction with virtual learning vs. traditional" (X_{14}) received a high weight, suggesting that students' comparison of virtual and traditional learning methods plays a crucial role in their satisfaction levels. Studies have shown that while many students appreciate the convenience of virtual learning, others still prefer traditional methods due to face-to-face interaction and structured environments (Adedoyin and Soykan, 2020). Additionally, both "Overall satisfaction with virtual learning" (X_{17}) and "Recommendation of online learning to others" (X_{18}) reflect general contentment with the virtual learning experience and students' likelihood of recommending it, key indicators of success in online education. Studies have shown that satisfaction is closely linked to the likelihood of recommending online learning, as satisfied students tend to advocate for the format (Sun et al., 2008). Finally, "Preference for virtual model over traditional models" (X_{16}) had the lowest weight but remained significant, suggesting that while virtual learning is favored by some, it is not the dominant preference. Research supports that while virtual models are gaining popularity, they may not universally meet the needs of all students, as preferences for learning modalities vary widely (Child et al., 2023).

5.1.1 Overall effectiveness of virtual learning system

The results indicate that the virtual learning system has been moderately effective overall, with a significant portion of students perceiving it as neither highly beneficial nor insufficient. The medium effectiveness reported by the majority of PG and PhD. students can be attributed to their academic maturity and ability to adapt to diverse learning environments (Hachey et al., 2023). This contrasts with UG students, who reported lower effectiveness, possibly due to their lack of prior exposure to virtual learning and less developed self-regulation skills (Kumar and Todd, 2022). The need for targeted interventions such as tailored training programs and enhanced support systems for UG students is evident, as they may struggle more with navigating online learning. These findings align with Arulkadacham (2024), which emphasizes that refining virtual learning designs to cater to diverse learners' needs can enhance outcomes and satisfaction across academic levels. Tailored interventions are critical to addressing the gaps observed in virtual learning experiences, particularly for UG students.

5.2 Learners' characteristics

The results of the independent t-test suggest that female learners significantly outperformed male learners in the virtual learning environment. In this study, the difference may reflect females' more positive attitudes, and greater familiarity with e-learning systems. This finding aligns with previous studies, such as Harter and Mendez-Carbajo (2024), which indicate that female learners tend to exhibit greater perseverance and engagement in online education.

The mean scores of self-regulation indicated a generally high level of self-regulation among students in virtual learning environments, with scores ranging from 3.54 to 3.9. The higher mean scores for behaviors such as setting standards for assignments and selecting a study location to minimize distractions suggest that students are consciously making efforts to create structured and focused learning environments. These behaviors align with prior research that emphasizes the role of strong organizational skills in successful online learning (Broadbent and Poon, 2015). Students emphasized maintaining high work quality, as reflected in high mean scores for not compromising the quality of work and reading additional materials, which indicates that students value deeper engagement and mastery of the content. This aligns with self-regulation theory, which suggests that motivation and goal-setting are linked to greater persistence and engagement in learning (Saks, 2024).

Students in online environments often rely on self-regulation strategies to succeed academically. Recent research highlights that digital note-taking, in particular, serves as an effective tool to enhance self-regulation and academic achievement in virtual learning contexts (Calamlam, 2023). However, moderate use of such strategies like consistent note-taking and dedicating extra time for study suggests a gap between students' awareness of these techniques and their regular implementation. This gap may reflect the ongoing challenges of maintaining self-discipline and structure in online settings, where external accountability is limited (Broadbent et al., 2023).

Additionally, the lower score for the behavior of reading aloud instructional materials suggests that students may prefer quieter methods of maintaining focus. This finding is consistent with research showing that self-regulation strategies are not universally effective and students select strategies based on personal preferences and the specific demands of the online learning environment (Hadwin et al., 2011).

5.3 E-learning design

Among the e-learning designs the highest priority for students is User Interface and Navigation, reflecting the importance of an intuitive, easy-to-use interface that facilitates smooth and seamless navigation. Students expect VLEs to have clear menus, visually appealing layouts, mobile compatibility, and robust security for their personal data. This supports existing research, which emphasizes that accessibility and a user-friendly interface are fundamental to reducing cognitive load and enhancing the overall user experience in online learning environments (Yulianandra et al., 2023). Therefore, VLEs should focus on designing interfaces that are both simple to navigate and visually engaging to ensure a positive experience for students. And Interactivity and Engagement emerged as another crucial aspect of e-learning design, underscoring the importance of fostering active student participation. Collaborative opportunities, interactive course materials such as simulations and quizzes, and effective instructor-student communication were identified as key factors. This aligns with the work of Martin and Bolliger (2018), who found that engagement through interactivity significantly enhances students' motivation and retention in online learning environments. It highlights that VLEs should incorporate interactive tools that encourage learners to actively engage with the content, peers, and instructors, making learning more dynamic and effective.

Students also placed significant value on Content Organization and Quality, recognizing the importance of well-structured, clearly organized course materials. This dimension highlights the need for alignment between assessments and learning objectives, alongside the use of multimedia resources. Research supports this finding, showing that students' perceptions of course quality are closely linked to their academic success (Lee et al., 2013). A well-organized course not only helps students understand the content better but also makes learning more manageable and accessible. VLEs should therefore prioritize clear, structured course design with rich multimedia content to enhance comprehension and engagement. While Technical Efficiency was still considered important, it was not as highly prioritized as the other design aspects. This dimension, which includes elements such as reliable internet connectivity, minimal technical disruptions, and timely feedback, is critical to ensuring that the virtual learning environment functions smoothly (Amoah and Le Roux, 2024). However, students may perceive these technical features as foundational requirements rather than distinguishing factors that directly enhance their engagement. As such, while reliable technical functionality is essential for creating a positive learning environment, its impact may not be as immediately noticeable as more interactive and user-centric design elements. This is consistent with the findings of Al-Fraihat et al. (2020), who suggested that students tend to take technical reliability for granted, only noticing issues when disruptions occur. Lastly, Personalization and Support received comparatively lower importance from students. Despite the growing trends in adaptive learning technologies and personalized learning experiences, students did not prioritize personalized learning paths or content recommendations in this study. This finding may reflect students' preferences for more structured learning environments with clear guidance from instructors, rather than relying on systems that automatically suggest personalized content. These results align with research by Evans (2013), which found that students tend to favor conventional, instructor-driven educational models, where personalization plays a secondary role to content delivery and instructor support.

5.4 Significant predictors of virtual learning effectiveness

The results from the regression analysis on significant predictors of virtual learning effectiveness provided valuable insights into the key factors that contribute to successful online learning. The overall model demonstrated a strong relationship between selected predictors and virtual learning effectiveness.

Among these, Self-regulation emerged as the most predominant factor, highlighting the crucial role that students' ability to manage their learning behaviors, emotions, and motivations plays in virtual learning success. This finding was consistent with previous research, which indicated that self-regulated learners tended to perform better in online settings due to their capacity to set goals, monitor their progress, and manage time effectively (Hunutlu, 2023). Given the lack of face-to-face interaction in virtual learning environments, students who exhibit high self-regulation are better equipped to navigate the autonomy and demands of online education. This finding suggests that fostering self-regulation through targeted interventions such as time management training, goal-setting exercises, and reflection strategies can significantly enhance virtual learning effectiveness. Attitude also emerged as a significant predictor, emphasizing the influence of students' perceptions and mindset toward virtual learning. A positive attitude toward online education is crucial for motivation, persistence, and overall engagement in virtual courses (Broadbent and Poon, 2015). Students who approach online learning with a positive attitude are more likely to overcome challenges and maintain consistent engagement throughout the course. Therefore, creating an environment that supports and nurtures positive attitudes toward virtual learning, such as through clear communication, timely feedback, and a sense of community, could lead to improved outcomes. Design features, while also a significant predictor, showed a comparatively smaller impact on virtual learning effectiveness. This suggests that while the design of virtual courses such as ease of navigation, clarity of instructions, and the inclusion of interactive elements plays an important role in facilitating learning, its influence is less pronounced than that of learners' characteristics like self-regulation and attitude (Mayer, 2021). However, this does not diminish the importance of course design, as it can provide the structure and support needed for students to engage with the material effectively. Interestingly, age and gender did not significantly predict virtual learning effectiveness, indicating that these demographic factors are less relevant in determining success in online learning environments. This finding is consistent with recent literature suggesting that factors such as self-regulation, attitude, and course design have a more substantial impact on virtual learning outcomes than demographic characteristics (Yu, 2021).

6 Conclusion

This study provides important insights into the effectiveness of virtual learning in agricultural education, particularly in relation to learners' engagement, satisfaction, and retention. The findings reveal that self-regulation is a key factor influencing successful learning outcomes, highlighting the role of personal motivation and independent learning skills. Additionally, the quality of e-learning design such as user-friendly interfaces, interactivity, and content relevance significantly contributes to maintaining student interest and enhancing their overall virtual learning experience. While virtual platforms offer clear benefits in terms of accessibility and flexibility, the study also indicates that their effectiveness is more pronounced in delivering theoretical knowledge. Practical, hands-on training a core component of agricultural education remains difficult to fully replicate in virtual formats. These insights underline the complexity of implementing virtual learning in agriculture and the need for thoughtful integration that supports both knowledge acquisition and experiential learning.

6.1 Theoretical implications

This study makes several theoretical contributions to the field of virtual learning:

- It introduces a comprehensive model highlighting the key factors influencing virtual learning effectiveness, such as learners' engagement, self-regulation, and course design, offering a useful framework for future research in various educational contexts.
- The study underscores the importance of self-regulation in online learning, extending existing theories on self-regulated learning to the virtual environment and emphasizing behaviors like goal-setting and time management.
- It advances models of learners' satisfaction by emphasizing the role of flexibility and content organization, demonstrating that satisfaction is shaped not only by content but also by how it is delivered and structured.
- The research supports the idea that hybrid learning models, combining virtual and face-to-face components, may provide the most effective approach to meet diverse learners' needs, adding to theories on blended learning.
- By exploring the interaction between learners' characteristics and virtual learning design, the study broadens research on virtual learning systems, suggesting that both learners'-related and design-related factors should be integrated for improved online education outcomes.

6.2 Practical implications

This research provides several actionable recommendations for educators, administrators, and policymakers to enhance virtual learning systems:

- This research emphasizes the importance of structuring course content in a clear, organized, and interactive way to enhance student motivation and retention. Educators should focus on making materials easy to navigate and engaging.
- Institutions should provide more opportunities for learners' interaction, such as discussions, quizzes, and peer feedback, to foster a sense of community, which is crucial for engagement in virtual environments.
- As self-regulation plays a significant role in online learning success, institutions should implement interventions to support students in goal-setting, time management, and progress tracking. Workshops on time management, goal-setting, and strategies for maintaining motivation in online settings could be beneficial.
- Offering flexible learning options and continuous support is vital to improving learners' satisfaction. Students should have access to personalized tutoring, technical assistance, and guidance on course navigation, particularly for those less familiar with online platforms.
- Blending online learning with traditional face-to-face components may be the most effective approach for meeting diverse student needs. Policymakers and institutions should consider incorporating hybrid learning models, combining the flexibility of online learning with in-person interaction and feedback.
- Virtual learning platforms should cater to diverse learning preferences by providing personalized learning paths that adapt content to individual student needs, abilities, and prior knowledge, thereby improving overall learning outcomes.

6.3 Limitations and strategies for future research

This study provides valuable insights into virtual learning in agricultural education, is has certain limitations that should be considered when interpreting the findings. Firstly, the use of cross-sectional data due to time and logistical constraints, limits the ability to assess the long-term outcomes of virtual learning, which future longitudinal studies could address. Additionally, the study was confined to a specific set of institutions, which may not fully capture the diversity of agricultural contexts across India. expanding future research to include a broader range of institutions, especially in rural and under-resourced areas, would help generalize findings more effectively. Thirdly, the study included only current users of virtual platforms, as they were more accessible for data collection, thereby overlooking the experiences of non-users; future research should include this group to better understand barriers to adoption, such as lack of access to technology, poor infrastructure, or resistance to digital learning.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

KS: Conceptualization, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. RP: Conceptualization, Data curation, Formal analysis, Methodology, Resources, Supervision, Validation, Writing – original draft. RS: Methodology, Resources, Software, Writing – review & editing, Supervision, Visualization. SuS: Methodology, Resources, Software, Writing – review & editing, Data curation, Formal analysis. KP: Methodology, Resources, Software, Visualization, Writing – review & editing. CV: Formal analysis, Methodology, Visualization, Writing – review & editing. SR: Conceptualization, Formal analysis, Methodology, Writing – review & editing. SA: Formal analysis, Methodology, Writing – review & editing. PY: Methodology, Writing – review & editing. ShS: Conceptualization, Formal analysis, Writing – review & editing. SM: Conceptualization, Formal analysis, Writing – review & editing. BG: Formal analysis, Methodology, Resources, Writing – review & editing. SeS: Resources, Writing – review & editing. NL: Resources, Visualization, Writing – review & editing. SP: Resources, Writing – review & editing.

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The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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