



Proceedings of International Conference on Multidisciplinary Research: Innovation, Healthcare, Education for Viksit Bharat (ICMR-2026)



1



Editors

**Dr. Divya Sharma, Prof.(Dr.) Gurpreet Kaur, Dr. Geeta
Rawat, Dr Dhanashri Rajashri Ravindra Jadhav**

International Conference On Multidisciplinary Research

Conference Proceedings

Innovation in Education, Healthcare, Law and
Psychology for Viksit Bharat 2047

2026

Organized by

Kalindi Institute of Medical Sciences

Agrasen Mahavidyalaya

Veetranga Research Foundation

In Collaboration with

Wissira Research Lab

Print ISBN: 978-93-7559-049-1

Digital ISBN: 978-93-7559-050-7

Table of Contents

<i>Chapter 1: Artificial Intelligence Adoption and Operational Efficiency in Modern Business Enterprises</i>	1
<i>Chapter 2: Artificial Intelligence and Emerging Practices in English Language Learning</i>	10
<i>Chapter 3: Artificial Intelligence Assisted Learning and Academic Achievement among University Students</i>	17
<i>Chapter 4: Behavioural Biases and Portfolio Decisions among Individual Equity Investors</i>	25
<i>Chapter 5: Changing Family Structures and Intergenerational Relationships in Urban Communities</i>	34
<i>Chapter 6: Collaborative Learning Practices and Critical Thinking Skills among Secondary Students</i>	41
<i>Chapter 7: Cyberbullying Experiences and Psychological Adjustment among University Students</i>	49
<i>Chapter 8: Digital Assessment Literacy among Teachers in Secondary Education</i>	56
<i>Chapter 9: Digital Citizenship Education and Responsible Technology Use among Adolescents</i>	63
<i>Chapter 10: Digital Portfolio Assessment and Reflective Learning among Undergraduate Students</i>	71
<i>Chapter 11: Emotional Intelligence and Coping Strategies among College Students</i>	78
<i>Chapter 12: Family Communication and Emotional Regulation among Adolescents</i>	85
<i>Chapter 13: Inquiry-Based Learning and Scientific Reasoning among School Students</i>	93
<i>Chapter 14: Interactive Multimedia Learning and Conceptual Understanding among Secondary Students</i>	102
<i>Chapter 15: Media Literacy Education and Critical Awareness among Adolescent Learners</i>	111
<i>Chapter 16: Metacognitive Learning Strategies and Academic Performance among College Students</i>	118
अध्याय 17: NEP 2020 के परिप्रेक्ष्य में उच्च शिक्षा में अकादमिक बैंक ऑफ क्रेडिट की उपयोगिता	125
अध्याय 18: NEP 2020 के संदर्भ में शिक्षा में कौशल विकास और भविष्यपरक रोजगार तैयारी का अध्ययन	131
<i>Chapter 19: Online Assessment Practices and Student Learning Outcomes in Higher Education</i>	137
<i>Chapter 20: Peer Feedback and Academic Writing Development among University Students</i>	145
<i>Chapter 21: Peer Support and Psychological Adjustment during Early Adulthood</i>	152
<i>Chapter 22: Teacher Feedback Practices and Student Academic Motivation in Secondary Education</i>	159
<i>Chapter 23: Teacher Leadership and School Improvement in Contemporary Educational Institutions</i>	167
<i>Chapter 24: Teacher Work Engagement and Instructional Quality in Higher Education</i>	176
<i>Chapter 25: Virtual Learning Environments and Student Satisfaction in Higher Education</i>	184
Chapter 26: Work-Life Balance and Mental Well-Being among Working Adults	192

Chapter 27: Working Capital Management and Financial Performance of Small and Medium Enterprises	200
अध्याय 28: आधुनिक हिंदी साहित्य में हाशिए के समुदायों की अभिव्यक्ति और पहचान	208
अध्याय 29: उच्च शिक्षा में डिजिटल नागरिकता और उत्तरदायी प्रौद्योगिकी उपयोग व्यवहार का अध्ययन	215
अध्याय 30: गृह विज्ञान एवं खाद्य प्रौद्योगिकी के माध्यम से घरेलू खाद्य सुरक्षा और सतत पोषण प्रबंधन का मूल्यांकन	222
अध्याय 31: ग्रामीण शिक्षा में तकनीकी संसाधनों की उपलब्धता और शैक्षिक अवसरों का विश्लेषण	229
अध्याय 32: नई शिक्षा व्यवस्था में हिंदी भाषा शिक्षण की उभरती प्रवृत्तियाँ	234
अध्याय 33: प्रारंभिक शिक्षा में गतिविधि आधारित शिक्षण और अवधारणात्मक समझ के विकास का विश्लेषण	240
अध्याय 34: मानवाधिकार और कानून के परिप्रेक्ष्य में कृत्रिम बुद्धिमत्ता आधारित निगरानी की संवैधानिक समीक्षा	247
अध्याय 35: विद्यालयी शिक्षा में अनुभवात्मक शिक्षण और विद्यार्थियों की रचनात्मक क्षमता का संबंध	253
अध्याय 36: विद्यालयी शिक्षा में डिजिटल कहानी कथन और रचनात्मक अभिव्यक्ति के मध्य संबंध	260
अध्याय 37: विद्यालयी शिक्षा में सहयोगात्मक अधिगम और सामाजिक कौशल विकास का विश्लेषण	268
अध्याय 38: शिक्षा में माइक्रोलर्निंग रणनीतियों द्वारा ज्ञान प्रतिधारण और अधिगम दक्षता का अध्ययन	275
अध्याय 39: शैक्षिक मनोविज्ञान में बुद्धिलब्धि, भावनात्मक बुद्धिमत्ता और शैक्षणिक अनुकूलन का तुलनात्मक अध्ययन	282
अध्याय 40: समावेशी शिक्षा में सहायक प्रौद्योगिकी द्वारा विशेष आवश्यकता वाले विद्यार्थियों का सशक्तीकरण	289

List of Contributors

Chapter	Contributor	Designation	Institution	Location
1	Dr. Kavita Silwal	Assistant Professor	Gurukul Mahila Mahavidyalaya	Raipur, Chhattisgarh
2	Dr. Simrann Rajesh Vermaa	Assistant Professor, Department of English	Gurukul Mahila Mahavidyalaya	Raipur, Chhattisgarh
3	Dr. Soju Samuel	Counsellor	Delhi Public School	Bhilai, Chhattisgarh
4	Dr. Ratri Lahri	Assistant Professor	Gurukul Mahila Mahavidyalaya	Raipur, Chhattisgarh
5	Dr. Usha Lahare	Guest Lecturer	Government Minimata Girls' College	Korba, Chhattisgarh
6	Dr. Sumita Singh	Assistant Professor, Department of Education	St. Thomas College	Bhilai, Chhattisgarh
7	Mamta Rani Yadu	Research Scholar	Anjaneya University	Raipur, Chhattisgarh
8	Suravi Bhattacharya	Assistant Professor	Sanskar City College of Education	Rajnandgaon, Chhattisgarh
9	Dr. Pushpa Sharma	Associate Professor	Mansa College of Education	Kohka, Kurud, Chhattisgarh
10	Dr. Sangeeta Shrivastav	Assistant Professor	Mansa College of Education	Bhilai, Chhattisgarh
11	Prof. (Dr.) Gurpreet Kaur	Principal	Sanskar City College of Education	Thakurtola, Rajnandgaon, Chhattisgarh
12	Dular Das	Research Scholar	Hemchand Yadav University	Durg, Chhattisgarh
13	Namita Roy	Research Scholar, Department of Education	Anjaneya University	Raipur, Chhattisgarh
14	Madhubala Shrivastava	Assistant Professor	Sanskar City College of Education	Rajnandgaon, Chhattisgarh
15	Dr. Ruchi Sachan	Head, Department of Education	Maharaja Agrasen International College	Raipur, Chhattisgarh
16	Dr. Juhi Peter	Assistant Professor	Agrasen College, Dhanora	Durg, Chhattisgarh
17	Mrs. Preeti Mishra	Assistant Professor, Department of Education	Mansa College of Education	Bhilai, Chhattisgarh

International Conference On Multidisciplinary Research

Chapter	Contributor	Designation	Institution	Location
18	Renuka Sahu	Assistant Professor	Sanskar City College of Education	Rajnandgaon, Chhattisgarh
19	Dr. Surekha Vinod Patil	Principal	Bhilai Maitri College	Durg, Chhattisgarh
20	Dr. Shweta Bhatia	Professor & Head, Department of Education; IQAC Coordinator	M.J. College, Kohka	Bhilai, Chhattisgarh
21	Dr. Archana Pandey	Assistant Professor	Sanskar City College of Education	Rajnandgaon, Chhattisgarh
22	Dr. Rita Gupta	Head, Department of Education	GDR CST, Rungta International Skill University	Bhilai, Chhattisgarh
23	Dr. Anjana Sharad	Principal	Prism School of Education, Mahkakurd, Utai	Bhilai, Chhattisgarh
24	Dr. Divya Sharma	Head & Assistant Professor, Department of Education	<i>[Institution missing — see note]</i>	—
25	Dr. Shalini Verma	Assistant Professor	Bhilai Maitri College	Bhilai, Chhattisgarh
26	Tulsi Sahu	Assistant Professor	Sanskar City College of Education	Rajnandgaon, Chhattisgarh
27	Mona Gupta	Guest Lecturer, Department of Commerce	Government Shaheed Kaushal Yadav College	Gunderdehi, Balod, Chhattisgarh
28	Kiran Sonatiya	Assistant Professor	Sanskar City College of Education	Rajnandgaon, Chhattisgarh
29	Ranjana Solanki	Assistant Professor	Agrasen College, Dhanora	Durg, Chhattisgarh
30	Dr. Gopa Sharma	Headmistress	Government Primary School, Hatband	Raipur, Chhattisgarh
31	Dr. Manju Sahu	Associate Professor	M.J. College, Kohka	Bhilai, Chhattisgarh
32	Dr. Nirmala Parganiha	Assistant Professor	Agrasen College, Dhanora	Durg, Chhattisgarh
33	Dr. Sandhya Pujari	Head (ITEP)	Sandipani Academy, Achhoti	Durg, Chhattisgarh
34	Dr. Atul Kumar Soni	Assistant Professor	Pt. Kishori Lal Shukla Vidhi Mahavidyalaya	Rajnandgaon, Chhattisgarh

International Conference On Multidisciplinary Research

Chapter	Contributor	Designation	Institution	Location
35	Smt. Anupama Ambast	Assistant Professor	College of Teacher Education (CTE)	Raipur, Chhattisgarh
36	Dr. Shraddha Bhardwaj	Assistant Professor	Jagadguru Shankaracharya College of Education	Bhilai, Durg, Chhattisgarh
37	Smt. Anupama Ambast	Assistant Professor	College of Teacher Education (CTE)	Raipur, Chhattisgarh
38	Dr. Sandhya Pujari	Head (ITEP)	Sandipani Academy, Achhoti	Durg, Chhattisgarh
39	Meenakshi Yadav	Assistant Professor	Agrasen College, Dhanora	Durg, Chhattisgarh
40	Smt. Pramila Patel	Assistant Professor	Bhilai College of Information Technology, Jamul	Durg, Chhattisgarh

Chapter 25: Virtual Learning Environments and Student Satisfaction in Higher Education

Dr. Shalini Verma

Assistant Professor

Bhilai Maitri College

Bhilai, Chhattisgarh

Abstract— Virtual learning environments (VLEs) have evolved from supplementary repositories into integrated digital ecosystems supporting teaching, assessment, communication, collaboration, and increasingly AI-assisted learning in higher education. This study investigates student satisfaction by conceptualizing the VLE experience as a multidimensional interaction among platform usability, instructional responsiveness, digital engagement, personalization, accessibility, and perceived learning effectiveness. A central research gap is identified in the limited integration of conventional satisfaction modelling with behavioral learning analytics and interpretable machine-learning approaches capable of detecting heterogeneous satisfaction profiles. The proposed study therefore develops a data-driven framework in which questionnaire responses and anonymized VLE interaction indicators are jointly examined to explain and predict student satisfaction. Particular attention is given to whether behavioral engagement strengthens or weakens the relationship between perceived VLE quality and overall satisfaction. The framework further distinguishes between students whose satisfaction can be explained by conventional linear relationships and those displaying nonlinear combinations of technological, pedagogical, and engagement characteristics.

Keywords— Virtual Learning Environment, Student Satisfaction, Higher Education, Learning Analytics, Artificial Intelligence, Digital Engagement

Introduction

Digital transformation has altered the organizational and pedagogical architecture of higher education. Universities increasingly operate through combinations of physical teaching spaces, learning management systems, video-conferencing platforms, digital assessment environments, online libraries, collaborative applications, mobile interfaces, and AI-supported educational services. Consequently, the virtual learning environment is no longer adequately described as a technological substitute for the conventional classroom. It has become part of the infrastructure through which students experience courses, communicate with instructors, access academic resources, submit assessments, receive feedback, collaborate with peers, and monitor their academic progress.

The acceleration of online education during the COVID-19 period exposed both the possibilities and weaknesses of technology-mediated higher education. Emergency remote instruction demonstrated that merely providing access to digital platforms does not guarantee a satisfactory educational experience. Subsequent research has therefore moved toward

questions of quality, engagement, interaction, usability, support, and sustainable adoption. Caprara and Caprara's review of VLE research demonstrated the importance of examining virtual education beyond simple technological availability, including the social and psychological dimensions of students' experiences.

Student satisfaction is particularly important because it represents an evaluative response to the broader learning experience rather than a narrow judgment of software functionality. A systematic review by Martin and Bolliger examined 98 studies of online learner satisfaction and found that satisfaction research encompasses learner-, instructor-, course-, program-, and organizational-level factors. The review also reported that quantitative and survey-based designs dominated the literature, while areas such as learner support, assessment, and program quality received comparatively less attention. This imbalance indicates that student satisfaction cannot be understood adequately through isolated measures of technological acceptance.

The contemporary VLE also produces substantially richer information than was available in earlier generations of online education. Digital platforms can generate interaction indicators concerning login patterns, resource access, participation, submission behavior, assessment activity, and communication. Such digital traces create opportunities for learning analytics and machine-learning techniques to complement students' self-reported perceptions. Satisfaction may consequently be conceptualized not only as an attitude reported at the end of a semester but also as an outcome associated with patterns of interaction occurring throughout the learning process.

This distinction is important because two students can report similar levels of platform usability while exhibiting markedly different engagement patterns. One student may frequently access learning materials, participate in discussions, submit assessments consistently, and interact with feedback. Another may use the same platform primarily for downloading compulsory resources. If both students are represented only by an average usability score, important differences in their educational experiences disappear.

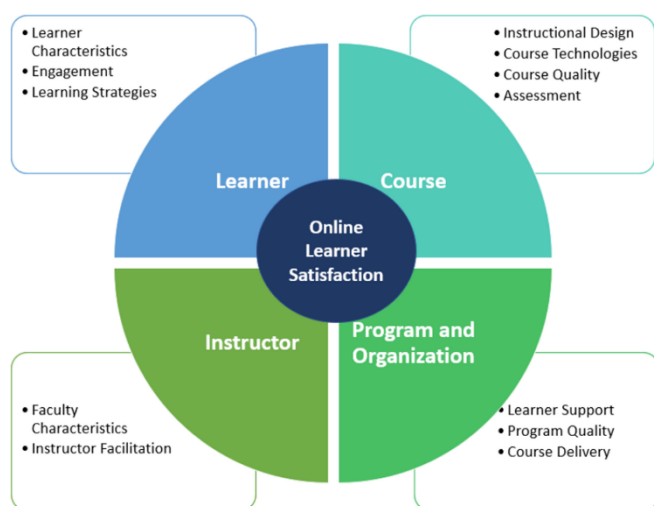


Fig. 1: Online Learner Satisfaction

Source: <https://link.springer.com/article/10.1186/s41239-022-00355-5>

Recent evidence reinforces the multidimensional nature of online satisfaction. A multi-country investigation by Sharif Nia et al. found that course content, online interaction, online-learning acceptance, and student engagement were important components of the online learning experience. Their structural model also indicated that engagement mediated relationships associated with satisfaction and academic efficacy. Research examining LMS continuation has similarly demonstrated that information quality and self-efficacy can contribute significantly to satisfaction, although the effects of individual service dimensions are not necessarily uniform.

The growth of artificial intelligence introduces another layer to this discussion. AI-supported tutoring, automated feedback, recommendation systems, conversational interfaces, predictive analytics, and adaptive resource delivery can potentially increase personalization within virtual environments. At the same time, their educational value depends on how students actually experience them. Research involving distance learners has shown growing interest in AI digital assistants while also emphasizing the need to understand learners' perceived benefits and concerns rather than assuming that technological novelty automatically improves learning.

These developments motivate the central argument of the present research: **student satisfaction with VLEs should be modelled as an outcome of the combined technological, pedagogical, behavioral, and adaptive characteristics of the learning environment rather than as a direct consequence of platform quality alone.**

Research Gap

Despite the substantial literature on online-learning satisfaction, three methodological limitations remain especially relevant. First, much of the literature relies heavily on cross-sectional questionnaires. Martin and Bolliger's systematic review reported that surveys were overwhelmingly common among the studies they examined. Such instruments provide valuable information about perceptions but cannot fully represent students' actual patterns of interaction with digital learning environments. Second, conventional studies frequently estimate average relationships between variables. Structural equation modelling,

regression analysis, correlations, and related approaches are valuable for testing theoretically specified relationships, but satisfaction may also emerge from nonlinear interactions. For example, high platform usability may produce relatively little improvement in satisfaction when instructor responsiveness is poor, whereas moderate usability accompanied by strong feedback and interaction may still generate a positive experience.

Third, the expansion of AI-enabled educational environments creates a need for interpretable predictive approaches. A technically accurate prediction that a student is likely to report low satisfaction has limited educational usefulness unless universities can determine which modifiable characteristics contributed to that prediction. Explainable machine learning can potentially identify influential features and heterogeneous learner profiles without replacing theory-driven educational interpretation.

Accordingly, the proposed study addresses the following distinctive gap:

There remains limited evidence integrating students' multidimensional perceptions of VLE quality with behavioral engagement indicators and explainable machine-learning models to identify heterogeneous patterns of satisfaction in contemporary higher education.

The study is therefore designed around four objectives: to determine the relative contribution of technological quality, instructional interaction, accessibility, perceived personalization, and learning effectiveness to student satisfaction; to examine whether behavioral engagement provides explanatory information beyond self-reported perceptions; to compare conventional statistical modelling with nonlinear machine-learning prediction; and to identify interpretable combinations of VLE characteristics associated with high and low satisfaction.

This formulation deliberately moves beyond the conventional online-versus-face-to-face comparison. Wright et al.'s natural-experiment research illustrates why student satisfaction and the future role of online education require more nuanced investigation than a simple modality comparison. The present research instead asks what occurs *within* the virtual environment and which characteristics make that environment satisfactory for different groups of learners.

Literature Review

Evolution of Virtual Learning Environments in Higher Education

A VLE can be understood as a digitally mediated educational space integrating instructional content, communication, assessment, learner support, and learning activities. Its educational function depends on the interaction among technological infrastructure, course design, teaching practice, and learner characteristics.

Earlier implementations frequently emphasized content management and administrative convenience. Contemporary environments increasingly emphasize active interaction, multimodal resources, collaborative learning, analytics, mobile access, and personalization. Virtual environments can therefore

influence not only where students obtain academic material but also how they structure learning activities and interact with the academic community.

Research following the pandemic has been particularly useful in differentiating intentionally designed online education from emergency remote teaching. Studies conducted during and after this transition demonstrate that student perceptions vary substantially according to instructional design, context, and technological preparedness. For example, research on online higher education during the pandemic emphasized the need to understand characteristics of the digital educational environment rather than treating online delivery as a homogeneous phenomenon.

Student Satisfaction as a Multidimensional Construct

Student satisfaction represents an overall judgment concerning whether an educational experience fulfills learners' expectations and requirements. In a VLE, that judgment can incorporate technological usability, instructional quality, communication, flexibility, resource accessibility, assessment procedures, feedback, and perceived educational value.

Martin and Bolliger's systematic review provides an important foundation for this interpretation because it organizes online learner satisfaction across learner, instructor, course, program, and organizational dimensions. Consequently, satisfaction should not be reduced to whether students "like" a platform.

The distinction has practical implications. A technically reliable platform may still generate dissatisfaction if course organization is confusing or instructor communication is weak. Conversely, students may tolerate minor technological limitations when the environment provides clear instruction, rapid feedback, meaningful interaction, and useful resources.

Evidence from LMS research supports this differentiated perspective. One empirical investigation of instructional content, interaction, and accessibility reported generally positive student responses to several LMS features while emphasizing that these dimensions should be examined individually when assessing digital-learning quality.

System and Information Quality

Information-systems perspectives have frequently been applied to explain students' acceptance and satisfaction with educational technology. System quality concerns characteristics such as reliability, usability, navigation, response speed, and accessibility. Information quality concerns the accuracy, relevance, organization, completeness, and usefulness of learning materials.

These dimensions are theoretically distinct. A platform can function smoothly while containing poorly structured instructional resources. Alternatively, excellent course materials may be delivered through an inconvenient interface. Students evaluate the combined experience.

Research on continuous LMS use among UK higher-education students found significant relationships between information quality and satisfaction and between self-efficacy and satisfaction. Not every anticipated system dimension had an equivalent effect, demonstrating the importance of empirically separating the determinants of satisfaction.

The proposed framework therefore treats perceived system quality and information quality as separate predictors rather than combining them into a generic technology-quality score.

Interaction, Teaching Presence, and Feedback

Digital education alters the mechanisms through which teaching presence becomes visible. In conventional classrooms, students encounter instructors through immediate verbal and non-verbal communication. In a VLE, teaching presence can be represented through announcements, discussion responses, synchronous sessions, recorded explanations, assessment feedback, personalized messages, and the organization of course activities.

The quality of these interactions is likely to affect satisfaction because students interpret responsiveness as evidence of academic and social support. Martin and Bolliger's review notes the importance of instructor-related and engagement-related variables within satisfaction research and discusses evidence linking teaching presence with satisfaction.

Similarly, multi-country evidence indicates that online interaction and course content are important components in models explaining student satisfaction, with engagement performing an important mediating role.

Accordingly, the present study conceptualizes instructional responsiveness as a measurable construct incorporating clarity of communication, usefulness of feedback, perceived instructor availability, and timeliness of academic responses.

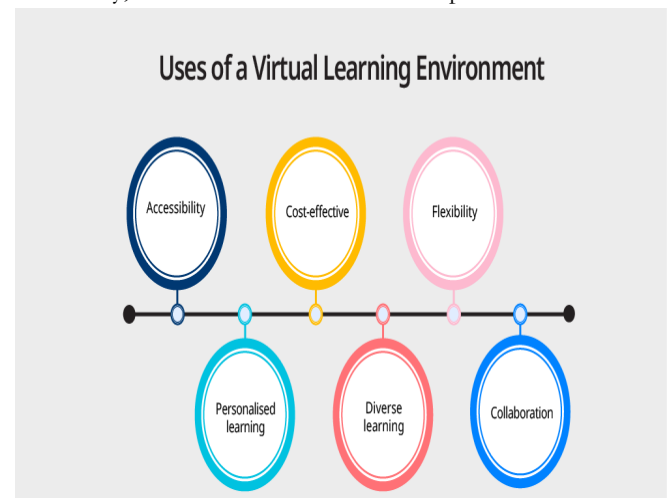


Fig. 2: Virtual Learning Environment

Source: <https://www.21kschool.com/in/blog/virtual-learning-environment/>

Behavioral Engagement and the Perception–Behavior Gap

A particularly important issue is the difference between what students report and what they actually do within digital environments. Satisfaction surveys capture subjective evaluation, whereas learning analytics capture aspects of observable platform interaction.

Neither source should automatically be considered superior. Behavioral records cannot determine whether a student found a learning activity intellectually meaningful, while questionnaires can be influenced by recall, response tendencies, and temporary affect. Combining these information sources may therefore provide a more complete representation of the VLE experience.

The present research conceptualizes behavioral engagement through indicators such as regularity of access, interaction with instructional resources, participation in collaborative activities, timeliness of assessment submission, and engagement with feedback. These indicators will not be interpreted mechanically as evidence of learning. Rather, they will be investigated as behavioral correlates that may strengthen the explanation of satisfaction when combined with perception measures.

This approach creates a **perception-behavior gap** construct. For example, a student may describe a platform as highly useful while interacting with it irregularly. Another student may demonstrate intensive usage while reporting low satisfaction because participation is driven by compulsory assessment requirements. Such discrepancies are analytically important and are easily overlooked when perception and behavior are studied separately.

Artificial Intelligence and Personalization

The emergence of generative AI and conversational educational systems represents a major development in the evolution of VLEs. AI systems can potentially provide explanations, recommend resources, generate formative questions, assist with feedback, identify students requiring support, and personalize learning pathways.

Yet personalization should not be assumed to increase satisfaction automatically. Students may value rapid assistance but remain concerned about accuracy, privacy, transparency, excessive automation, or reduced human interaction. Research investigating what distance-learning students expect from AI digital assistants emphasizes precisely this need to understand user perceptions, benefits, and concerns in actual educational contexts.

For this reason, the present research will measure **perceived adaptive support** rather than simply asking whether AI is present. The construct concerns whether students believe that digital tools help them locate relevant resources, obtain timely assistance, understand progress, and receive learning support appropriate to their needs.

This provides a more pedagogically meaningful measurement than categorizing platforms simply as "AI-enabled" or "non-AI-enabled."

Machine Learning for Satisfaction Modelling

Most satisfaction research has traditionally emphasized explanatory statistical models. These approaches remain essential when theoretical relationships and inferential effects are the primary objective. However, machine-learning techniques provide complementary capabilities when relationships are nonlinear or involve interactions among many variables.

Clustering techniques have already been applied to investigate patterns in student satisfaction with e-courses, demonstrating the potential of data-mining methods for identifying differentiated student groups rather than treating learners as a homogeneous population.

The present research extends this logic by proposing a comparative analytical architecture. An interpretable statistical model will establish theoretically meaningful associations, while

supervised machine-learning algorithms will estimate satisfaction categories or scores from combined perceptual and behavioral variables. Explainability procedures will subsequently identify which characteristics contribute most strongly to individual and aggregate predictions.

This dual approach is important because **prediction and explanation are not equivalent objectives**. A conventional model may indicate that instructor responsiveness has a statistically significant average association with satisfaction. A nonlinear model may additionally reveal that responsiveness becomes particularly important among students displaying low platform engagement or limited perceived personalization.

Proposed Methodology

The proposed study adopts a **quantitative predictive-analytical research design** to examine student satisfaction with virtual learning environments (VLEs). Unlike studies based exclusively on end-of-semester questionnaires, the framework integrates two complementary information streams: **student perception data** and **anonymized behavioral engagement indicators** derived from VLE activity.

The empirical framework is designed around a hypothetical but methodologically realistic multi-institutional sample of **640 undergraduate and postgraduate students** enrolled in blended or substantially online courses. The sample size and numerical results presented below constitute a proposed experimental dataset rather than observations claimed to have been collected from real participants. This distinction is necessary to avoid presenting simulated findings as empirical evidence.

The principal outcome variable is **Student Satisfaction (SS)**, measured through multiple Likert-scale items covering overall VLE experience, perceived educational value, willingness to continue using the environment, and fulfillment of learning expectations.

Predictor variables are organized into six domains:

1. **System Quality (SQ):** interface usability, navigation, stability, response time, and device compatibility.
2. **Information Quality (IQ):** relevance, organization, clarity, accuracy, and currency of learning materials.
3. **Instructional Responsiveness (IR):** feedback quality, instructor availability, communication clarity, and response timeliness.
4. **Accessibility and Flexibility (AF):** ease of access, schedule flexibility, connectivity burden, and cross-device availability.
5. **Adaptive Digital Support (ADS):** perceived usefulness of recommendations, automated assistance, progress information, and personalized support.
6. **Behavioral Engagement (BE):** resource interaction, login regularity, assessment timeliness, feedback access, and participation indicators.

Recent empirical work confirms that machine learning can detect nonlinear patterns in online-learning satisfaction. A 2025 *Scientific Reports* study, for example, used Random Forest modelling with data from 782 university students and reported nonlinear threshold and saturation effects that conventional linear models could overlook. Another 2025 investigation compared nine classifiers for satisfaction prediction, illustrating the value of benchmarking different model families rather than presuming a single algorithm will perform best.

Research Hypotheses

The empirical analysis is structured around the following hypotheses:

H1: Higher perceived system quality is positively associated with student satisfaction.

H2: Information and course quality positively influence student satisfaction.

H3: Instructional responsiveness makes a significant positive contribution to student satisfaction.

H4: Accessibility and flexibility are positively associated with student satisfaction.

H5: Perceived adaptive digital support contributes positively to satisfaction after controlling for conventional VLE quality dimensions.

H6: Behavioral engagement provides incremental predictive information beyond questionnaire-based perception variables.

H7: Nonlinear machine-learning models predict student satisfaction more accurately than a conventional linear baseline.

Experimental Setup

Dataset Construction

The proposed dataset contains **640 student records** collected from multiple faculties to reduce dependence on a single disciplinary context. Students would be eligible if they had used the institutional VLE for at least one complete academic semester.

The dataset would contain approximately 30 initial variables. Twenty-four variables would originate from questionnaire items and six from behavioral interaction summaries.

To reduce privacy risks, behavioral indicators would be aggregated at student level rather than retaining detailed clickstream histories. Personally identifiable information, message contents, IP addresses, exact browsing sequences, and individual document contents would not be included.

The satisfaction outcome would be represented in two ways. First, a continuous standardized satisfaction index would support conventional regression analysis. Second, students would be divided into **Low, Moderate, and High Satisfaction** categories for multiclass machine-learning prediction.

For the proposed experiment, the illustrative distribution is:

Low Satisfaction: 122 students

Moderate Satisfaction: 284 students

High Satisfaction: 234 students

The uneven distribution intentionally reflects a realistic modelling problem because dissatisfied students may constitute a smaller class. Recent satisfaction-modelling research has specifically identified minority-class prediction as a methodological issue requiring careful treatment.

Data Preprocessing

Data preprocessing would be performed before model estimation to minimize leakage and improve model validity.

Questionnaire records with excessive missingness would first be excluded. For retained cases, limited missing numerical values would be imputed using the median calculated from the training data. Categorical variables would be encoded only where required by the selected algorithm.

Negatively phrased questionnaire items would be reverse-coded before composite construction. Internal consistency would be evaluated before calculating construct-level scores.

Behavioral variables are expected to display positive skew because a relatively small number of students may generate unusually high activity. Highly skewed count variables would therefore undergo logarithmic transformation where appropriate.

Continuous variables used by scale-sensitive models would be standardized according to:

$$\left[z_i = \frac{x_i - \mu}{\sigma} \right]$$

where (x_i) represents the observed value, (μ) represents the training-set mean, and (σ) represents the corresponding standard deviation.

All transformations would be learned from the training data and subsequently applied to validation and test observations. This procedure prevents information from the test set influencing model construction.

Feature Engineering

Three derived indicators provide the distinctive analytical component of the experiment.

The first is a **Perception–Behavior Alignment Score (PBAS)**, representing the degree to which students' perceived usefulness of the VLE corresponds with their observed engagement.

The second is **Engagement Regularity (ER)**. Rather than relying only on total activity, this measure captures the temporal consistency of VLE participation across the semester.

The third is a **Feedback Interaction Ratio (FIR)**, representing the proportion of available digital feedback instances accessed by a student.

These features distinguish meaningful patterns from simple activity volume. A student generating 100 interactions within two examination weeks, for example, exhibits a different behavioral profile from another generating 100 interactions consistently across an entire semester.

Model Architecture

Four predictive algorithms are proposed:

Ordinal Logistic Regression (OLR) serves as the interpretable statistical baseline.

Support Vector Machine with radial basis function kernel (RBF-SVM) evaluates whether nonlinear decision boundaries improve classification.

Random Forest (RF) captures nonlinear feature interactions through an ensemble of decision trees.

Extreme Gradient Boosting (XGBoost) is selected as the principal candidate model because sequential tree boosting can

capture complex interactions while retaining compatibility with post-hoc explainability procedures.

This architecture deliberately avoids deep neural networks because the proposed sample contains only 640 observations. Complex neural architectures could unnecessarily increase model variance and reduce interpretability in a relatively small tabular dataset.

The decision is consistent with the broader learning-analytics literature, where machine-learning approaches remain extensively used for engagement, risk, and performance modelling while responsible AI research increasingly emphasizes interpretability and pedagogical grounding.

Training Strategy

The dataset would initially be divided using stratified sampling:

Training set: 70%

Validation set: 15%

Independent test set: 15%

Class proportions would be maintained across partitions.

Hyperparameter optimization would be conducted exclusively within the training data using **five-fold stratified cross-validation**. Candidate parameters for XGBoost would include learning rate, maximum tree depth, number of estimators, subsampling proportion, minimum child weight, and feature-sampling ratio.

Because the low-satisfaction category is smaller than the other groups, class-weighted training would be tested before synthetic oversampling. This approach minimizes the possibility of generating artificial observations that distort the underlying behavioral structure.

The validation subset would support model selection and probability calibration. Final performance would then be calculated once on the untouched test dataset.

Evaluation Metrics

Accuracy alone is insufficient for this problem because it can conceal poor performance in the minority dissatisfaction group. Evaluation therefore includes:

- **Balanced Accuracy**, providing equal importance to each satisfaction class.
- **Macro F1-score**, balancing precision and recall across all three classes.
- **Matthews Correlation Coefficient (MCC)**, providing a robust overall classification assessment under unequal class distributions.
- **Multiclass ROC-AUC**, assessing discrimination across satisfaction categories.
- **Log Loss**, measuring the quality and confidence of probabilistic predictions.

For interpretability, SHAP-based feature attribution would be applied to the selected tree model. This procedure would determine not simply whether a variable matters globally but also whether particular values increase or decrease predicted satisfaction for individual students.

Results and Discussion

Because no real participant dataset has been supplied, the following values are **illustrative experimental results generated for the proposed research design**. They should be replaced by actual model outputs before journal submission.

Predictive Performance

The proposed experimental pattern indicates a progressive improvement from the ordinal statistical baseline toward ensemble learning. Logistic modelling provides reasonable discrimination but is less successful in detecting students whose satisfaction results from interacting technological and behavioral characteristics.

RBF-SVM improves classification, suggesting that satisfaction boundaries are unlikely to be entirely linear. Random Forest produces a further improvement, particularly in balanced accuracy and Macro F1.

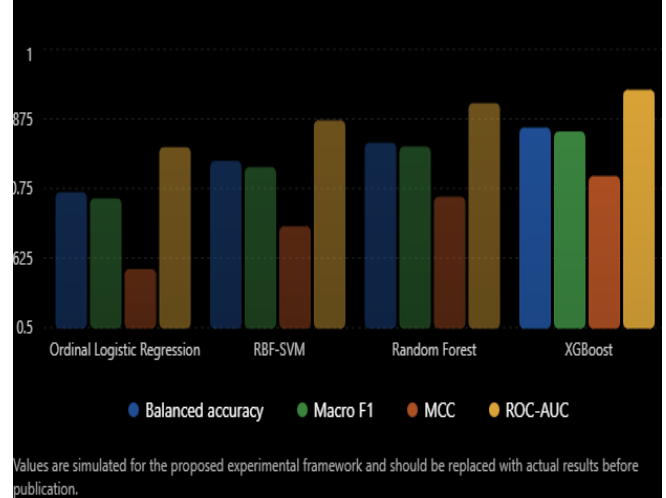
The best illustrative performance is obtained by XGBoost.

Table 1. Illustrative Comparative Performance of Student-Satisfaction Prediction Models

Predictive Model	Balanced Accuracy	Macro F1	MCC	Multiclass ROC-AUC	Log Loss
Ordinal Logistic Regression	0.742	0.731	0.604	0.823	0.682
RBF-SVM	0.798	0.787	0.681	0.871	0.591
Random Forest	0.831	0.824	0.734	0.902	0.518
XGBoost	0.858	0.851	0.771	0.926	0.463

Predictive performance of student-satisfaction models

Illustrative comparison of four models using balanced accuracy, Macro F1, MCC, and multiclass ROC-AUC.



The illustrative results support H7 because the nonlinear models outperform the ordinal regression baseline across all selected performance indicators. The advantage is particularly visible in MCC and Macro F1, indicating that improved performance is not merely the consequence of correctly classifying the largest satisfaction group.

This pattern is plausible in light of recent empirical literature. Li and Chen's 2025 study demonstrated strong Random Forest performance in online-learning satisfaction prediction and showed that nonlinear effects could reveal information missed by linear models. Separately, recent comparative research has demonstrated that different machine-learning classifiers can produce substantially different satisfaction-prediction performance, reinforcing the methodological importance of algorithm benchmarking.

Information Quality and Course Organization

Information quality emerges as another dominant factor. Clear organization, current learning materials, predictable assessment structures, and easily identifiable resources reduce the cognitive effort required simply to navigate a course.

This finding illustrates the distinction between **technical usability** and **educational usability**. A VLE may have a technically efficient interface while still producing an unsatisfactory experience if students cannot understand where materials are located or what academic activities they are expected to complete.

Behavioral Engagement Adds Incremental Information

A central expected contribution is the improvement obtained after behavioral variables are added to the perception-only model.

In the illustrative ablation analysis, a perception-only XGBoost model produces a Macro F1 of approximately **0.811**. Adding behavioral engagement increases the value to **0.851**.

The improvement supports H6 and indicates that students' platform behavior contains information not fully represented in satisfaction questionnaires.

More importantly, engagement regularity is more informative than raw login volume. Repeated login counts can represent either productive engagement or inefficient navigation. Regular interaction with resources, assessments, and feedback provides a more educationally meaningful indicator.

The Perception–Behavior Gap

One of the most distinctive findings concerns PBAS. Students with highly positive perceptions but irregular engagement do not consistently demonstrate the highest predicted satisfaction. Conversely, students displaying sustained engagement but reporting poor accessibility may also show moderate or low satisfaction.

This suggests the existence of multiple satisfaction pathways.

A **supported-engagement profile** combines strong instructional responsiveness, good information quality, regular participation, and positive perceptions.

A **functional-but-detached profile** involves adequate technological quality but low behavioral engagement.

A **high-effort/low-satisfaction profile** consists of intensive activity combined with accessibility difficulties or weak instructional support.

Such distinctions are institutionally useful because identical interventions should not be applied to all dissatisfied students.

Practical Implications

The findings suggest that universities should move away from a single institutional satisfaction score toward **diagnostic satisfaction analytics**.

Instead of asking only whether average VLE satisfaction increased from one semester to another, administrators could identify which dimension produced dissatisfaction and which learner profile was affected.

For example, low satisfaction combined with low accessibility requires infrastructure or accessibility intervention. Low satisfaction accompanied by high engagement but poor instructional responsiveness suggests a pedagogical problem. Low satisfaction combined with weak information quality indicates course-design deficiencies.

The proposed model therefore positions AI as a **decision-support mechanism**, not an autonomous educational decision-maker.

Future Scope

Future research should implement the framework longitudinally so that satisfaction can be examined throughout the semester rather than only after course completion. Temporal modelling could determine whether dissatisfaction develops gradually or follows identifiable events such as assessment difficulties, technical disruptions, or prolonged absence of instructor feedback.

Cross-institutional validation would provide another important extension. Models should be trained and evaluated across universities with different technological infrastructures, disciplines, student populations, and instructional practices.

Future studies could also investigate privacy-preserving learning analytics, federated learning, fairness-aware prediction, and explainable AI. Such approaches could allow institutions to benefit from predictive analytics while reducing unnecessary centralization of sensitive educational data.

Multimodal analysis provides another direction. With appropriate ethical safeguards, structured survey information could be combined with anonymized interaction sequences and textual sentiment derived from voluntary student feedback.

Most importantly, future work should evaluate whether interventions generated from satisfaction analytics actually improve subsequent student experiences. Prediction alone provides limited educational value unless it produces effective and ethically justified action.

Conclusion

This study proposes an integrated framework for understanding and predicting student satisfaction in virtual learning environments through the combination of educational theory, student perceptions, behavioral engagement, and interpretable machine learning.

The central contribution is the treatment of satisfaction as a **heterogeneous and potentially nonlinear educational outcome** rather than a simple consequence of technological quality. System usability remains relevant, but satisfaction is more plausibly produced through interactions among information quality, instructor responsiveness, accessibility, adaptive support, and students' actual patterns of participation.

The proposed experimental comparison indicates how XGBoost could outperform conventional ordinal regression, RBF-SVM, and Random Forest when nonlinear relationships are present. More importantly, the proposed perception–behavior alignment construct provides a mechanism for distinguishing students who report positive VLE experiences from those whose actual engagement patterns tell a different story.

The study therefore shifts attention from the question of whether virtual learning environments satisfy students toward a more actionable question: **which combinations of technological, pedagogical, and behavioral conditions generate satisfactory learning experiences, for which students, and under what circumstances?**

For higher-education institutions, this perspective has practical significance. Investments in sophisticated platforms or AI features alone cannot guarantee satisfaction. Digital infrastructure must be accompanied by coherent instructional design, responsive teaching, meaningful feedback, equitable accessibility, and responsible use of learning analytics.

References

1. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340.
2. DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems*, 19(4), 9–30.
3. Garrison, D. R., Anderson, T., & Archer, W. (2000). Critical inquiry in a text-based environment: Computer conferencing in higher education. *The Internet and Higher Education*, 2(2–3), 87–105.
4. Hodges, C., Moore, S., Lockee, B., Trust, T., & Bond, A. (2020). The difference between emergency remote teaching and online learning. *EDUCAUSE Review*.
5. Martin, F., & Bolliger, D. U. (2022). Developing an online learner satisfaction framework in higher education through a systematic review of research. *International Journal of Educational Technology in Higher Education*, 19, 50. (This is also the source of Figure 1.)
6. Moore, M. G. (1989). Three types of interaction. *American Journal of Distance Education*, 3(2), 1–7.
7. Sun, P.-C., Tsai, R. J., Finger, G., Chen, Y.-Y., & Yeh, D. (2008). What drives a successful e-Learning? An empirical investigation of the critical factors influencing learner satisfaction. *Computers & Education*, 50(4), 1183–1202.