Educational Technology Adoption in India : Theory of Consumption Values Perspective

Vaibhav Aaradhi [1]
Debarun Chakraborty [2]

Abstract

Purpose : The Indian education sector has undergone significant reforms, accelerated by the nationwide lockdown after the pandemic, and this increased demand for EdTech platforms. Internet-based learning systems gained quick acceptance among students. India has experienced significant growth in digital teaching-learning systems and EdTech platforms in the past few years; this study explored the technology adoption behavior of Indian application users, focusing on the theory of consumption values and determining the factors that drive this behavior.

Design/Methodology/Approach : This study used an explorative mixed-method research approach to conduct focus group discussions with 100 users for questionnaire development and conducting a cross-sectional survey, which was conducted in both online and offline modes to EdTech application users; 513 complete responses so received were analyzed using structural equation modeling.

Findings : The functional, social, conditional, and epistemic values significantly impacted technology-adopted behavior in the Indian scenario for EdTech applications.

Research Implications : The results of this study provided policymakers and EdTech platform developers with valuable insights into the elements influencing technology adoption.

Originality/Value : Considering the Indian government's thrust toward online education and blended learning approach post-COVID-19, the EdTech sector anticipated exponential growth. Thus, the factors driving technology adoption required research.

Keywords : EdTech, online learning, theory of consumption values

JEL Classification Codes : L2, L8

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The Indian education sector has undergone significant transformations in recent decades, marked by numerous reforms. The nationwide lockdown imposed in response to the COVID-19 pandemic further accelerated the adoption of digital learning as the entire student population transitioned to remote learning from home (Ministry of Human Resource Development, Government of India, 2020). A recent educational technology (EdTech) market analysis indicates a rapid shift from traditional brick-and-mortar classrooms to online learning platforms across India (Dash & Chakraborty, 2021b). The Indian EdTech segment expects to grow

[1] *Research Scholar (Corresponding Author),* Symbiosis International (Deemed University), Pune - 412 115, Maharashtra. (Email : vaibhav.aaradhi2006@gmail.com) ; ORCID iD : https://orcid.org/0000-0001-6041-8255
[2] *Associate Professor,* Symbiosis Institute of Business Management (SIBM) Nagpur, Constituent of Symbiosis International (Deemed University), Pune - 412 115, Maharashtra. (Email : debarun84@gmail.com)
ORCID iD : https://orcid.org/0000-0002-0754-1120

by approximately 50% in the next decade, highlighting the potential and interest of researchers across the globe (Aaradhi & Chakraborty, 2023). Internet-based learning systems have gained widespread acceptance among students, whether due to necessity or preference. Digital teaching and learning platforms saw significant growth in India in 2020 (Gill et al., 2023), indicating a bright future for this market. In light of these developments, it is imperative to investigate the variables impacting EdTech platforms' technological uptake.

Multiple theories like the technology acceptance model (TAM) or unified theory of acceptance and use of technology (UTAUT) have been put forward by researchers across the globe to analyze and study the technology adoption behavior of a specific population (Shokeen et al., 2023). The TAM specifies that perceived usefulness and ease of use are the main determinants of an individual's intention to use technology (Saadé & Bahli, 2005). The UTAT integrates various models (including TAM) and includes additional constructs like performance expectancy, effort expectancy, social influence, and facilitating conditions (Abbad, 2021). The theory of consumption values (TCV) discusses consumer choice behavior governed by five fundamental values: Functional, conditional, social, emotional, and epistemic (Sheth et al., 1991). This theory provides a broad perspective on the technology adoption behavior of consumers considering significant values, viz. functional, social, conditional, emotional and epistemic. Considering the broad domains of scientific applicability, the TCV was used for the analysis.

This study intends to answer the following research question: In the context of the TCV, what are the main forces behind the adoption of technology, and how, given the impetus provided by the Ministry of Human Resource Development, Government of India (2020), and the fallout from the pandemic, do internet accessibility and information overload moderate this effect in the EdTech sector in India?

The following research questions (*RQ*) have been formulated for this analysis:

✥ **RQ1 :** Which consumer values affect the EdTech platform's technological adoption?

✥ **RQ2 :** Does the technology adoption behavior of the EdTech platform depend on a single consumption value or a set of values combined?

✥ **RQ3 :** Is there a moderating influence of Internet accessibility information overload upon the technology adoption of the EdTech platform?

Background Literature

Theory of Consumption Value

The TCV, which was first presented by Sheth et al. (1991), provides a thorough framework for comprehending the behavior of consumers while making decisions. It is composed of five essential values: functional, conditional, social, emotional, and epistemic. Though it was first primarily used in the hospitality industry, there isn't much research that covers other industries. Significant correlations between social, epistemic, conditional, and cultural values were found when the TCV was applied to food delivery (Kaur et al., 2018). Technology integration with empirical values within the context of TCV has been explored in the analysis of mobile banking adoption (Karjaluoto et al., 2021). Consumption values are crucial in determining how products and services are consumed, influencing user satisfaction (Choe & Kim, 2018). We have investigated the negatively moderated relationship between purchase intention and food delivery applications' visibility and preference value. Based on four distinct values, food consumption values closely align with the TCV. A structural equation modeling (SEM) approach was employed to explore green purchase intention, revealing a significant mediating effect of green trust (Amin & Tarun, 2021). Gender-based discrimination significantly influences consumption value-driven purchasing behavior, extending its impact on web-based purchasing intentions (Andrews et al., 2007). A multiple cognitive

paths design considered consumption values and relational service benefits for smartphone brand switching behavior (Wong et al., 2019). This demonstrates that social, emotional, epistemic, and confidence values contribute to increased customer commitment towards smartphone brands. A detailed analysis of food delivery applications, considering visibility and attitude, demonstrated the positive influence of consumption values on purchase intention. Stringer et al. (2020) explored fast fashion clothing purchase decisions and identified that openness to change positively correlates with purchase intention.

EdTech Applications

Establishing an educational environment centered on technology underscores the pivotal role of educators in facilitating student learning within online settings (Mou & Kao, 2021). This theme has garnered significant attention in academic discourse, driven by the recognition of e-learning as an advanced and effective tool for digitizing and enhancing teaching practices (Havryliuk et al., 2020). People with digital literacy abilities are frequently linked to positive views towards e-learning (Hamutoğlu et al., 2019). Factors influencing the decision to pursue online courses vary among individuals, with considerations such as quality and economic factors playing crucial roles in predicting course selections (Ognjanovic et al., 2016). Analyzing online learning data through analytics offers insights into challenges and promises, highlighting the datafication of educational processes (Selwyn & Gašević, 2020). The aftermath of the COVID-19 pandemic has witnessed a surge in emergency remote teaching and virtual learning (Arun Kumar, 2023), necessitating significant change management in educational institutions (Anthony Jnr & Noel, 2021). Models incorporating motivation, self-directed learning, communication efficacy, and learner control offer guidance for transitioning from traditional to online teaching methods (Thongsri et al., 2021). The successful integration of online learning platforms into organizational contexts depends heavily on workplace environments and corporate cultures (Newton et al., 2002). Efforts to enhance e-learning literacy and bridge the gap between online and offline learning modes have become increasingly pronounced (Iwasaki et al., 2019). Quality considerations significantly influence user interest levels, underscoring their high interdependence (Singh et al., 2021).

Learner readiness positively influences the acceptance of online learning (Kumar et al., 2023), while the application of recommender systems in e-learning represents an area for research (Lu et al., 2015). The design of online learning portals is informed by students' comprehension, skills, and attitudes, emphasizing the importance of effectively applying the information to enhance learning strategies (Carless & Boud, 2018). The global pandemic has prompted the widespread adoption of EdTech and technology-based platforms, albeit with challenges such as uncertainty in technology adoption among specific demographics (Alnusairat et al., 2021; Jordan et al., 2021). The online open course market is experiencing growth, accompanied by increased student motivation (Anand Shankar Raja & Kallarakal, 2021). However, despite significant changes brought forth by the pandemic, the Indian online distance education market has not exhibited much progress or direction in research in recent years (Arora & Srinivasan, 2020). Online course success is significantly influenced by collaborative learning, highlighting the significance of this element in course design (Saqr et al., 2018). The direction of online course design is informed by student perceptions and self-reports (Pardo et al., 2017).

### Extending the Theory of Consumption Values to EdTech Applications

In order to adapt and extend the TCV for EdTech applications, this study reviews relevant literature, conducts a pilot survey, and categorizes EdTech-specific values within the TCV framework: functional, emotional, social, epistemic, and conditional. The identified consumption values are listed in Table 1. The derived consumption values used for analysis are enlisted as follows:

Table 1. *Derived Consumption Values*

Consumption Value	Derived EdTech Specific Consumption Value	Description
Functional Value	Handling Ease	The ease of usage and handling of the application.
	Course Content	The content and the variety of courses available on the application.
	Certification	The certification obtained after course completion and its parity with the international courses.
Social Value	Prestige and Recognition	The self-satisfaction and improved image attained after completion of the courses from the applications.
Conditional Value	Course Fees	The amount (i.e., monetary value) charged for the course material as part of the fees.
	Affordability	The discount availability on the course of choice.
Emotional Value	Attentiveness	The feeling of connection toward the course content is available.
Epistemic Value	Novelty	The content is updated over a specific period to remain in sync with the time.
	Student Engagement	The users actively pursued the applications.

Model and Hypotheses Development

The proposed model studies the association between the TCV and how it predicts the technology adoption process of EdTech users (Figure 1).

Figure 1. *Proposed Research Model*
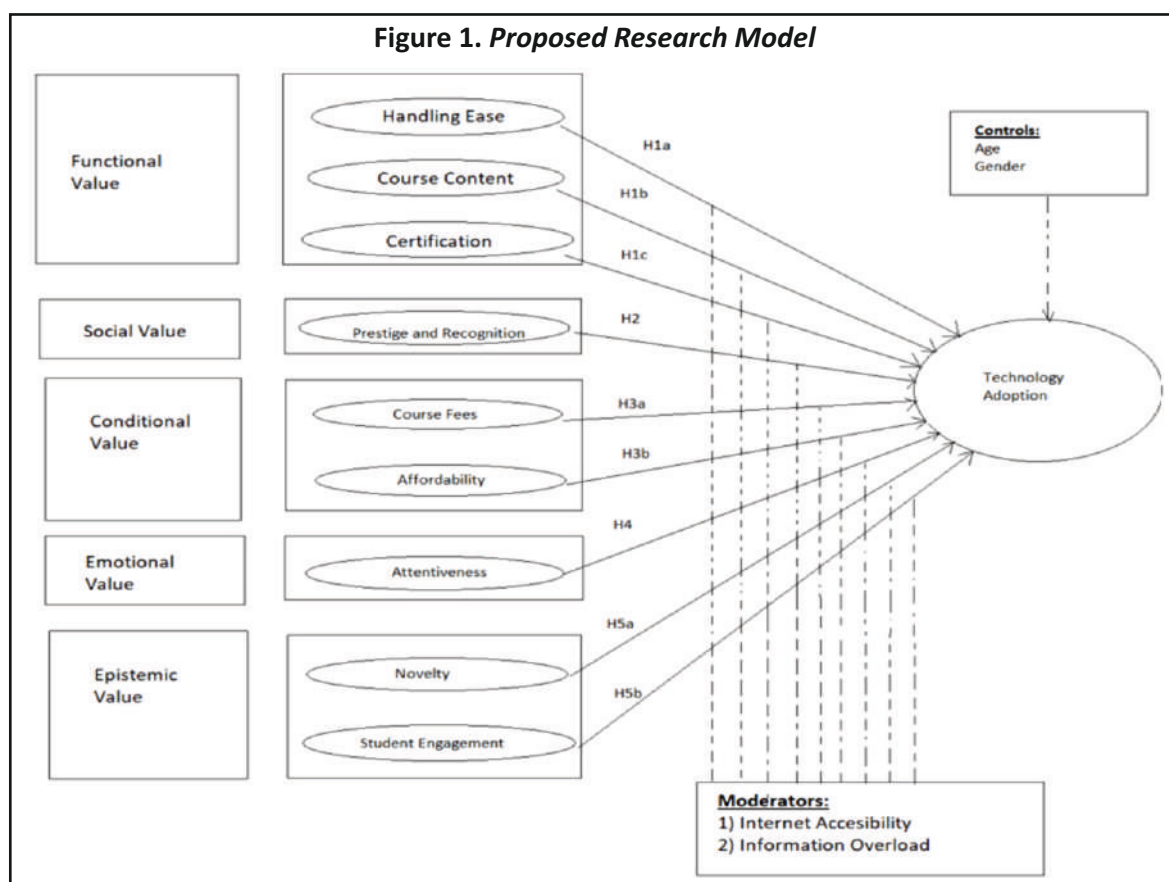
The independent variables are functional (handling ease, course content, and certification), social (prestige and recognition), conditional (course fees and affordability), and epistemic (novelty and student engagement). The controls for this analysis are age and gender; whereas, the moderators are Internet accessibility and information overload.

Functional Value

Functional value refers to the utility that the users anticipate from product features (Sheth et al., 1991). Extensively studied in the literature on consumer behavior, it frequently corresponds to convenience or ease of use (Cheung et al., 2021). When buyers comprehend the purpose and utility of a product, they are more inclined to purchase it (Cengiz & Kirkbir, 2007). Functional value significantly influences decisions, particularly for technology-enabled products and services, as emphasized by the technology acceptance model and the TCV (Zailani et al., 2019). It is expected to affect technology acceptance and consumer behavior (Kaur et al., 2021). Handling ease denotes the ease users navigate course sections and perform learning activities. Hence, we propose the following hypotheses :

✤ **H1a :** The ease of handling the EdTech platform positively correlates with the technology adoption process.

The second measure of functional value is the course content, which indicates the exactness of data required by the users. This forms the essential functional aspect that any course or its structure is expected to deliver whenever a course is offered. Thus, the following hypothesis is proposed :

✤ **H1b :** The course contents have a positive correlation with technology acceptance.

The third measure derived from the functional aspects is the final certification, which is expected to be at par with the offline courses that various universities provide. Hence, we have proposed the following hypothesis :

✤ **H1c :** The course certification has a positive correlation with technology acceptance.

Social Value

The social value of a product or service refers to the anticipated benefit of associating with a specific social class (Sheth et al., 1991), influencing consumers' image within their social circles (Zailani et al., 2019). Societal pressures can impact purchase intention or choice (Hung & Tzang, 2021), with norms or peer group influences shaping decision-making (Wang et al., 2021). Social influence significantly affects consumer choices in various product contexts (Srivastava et al., 2020). In this study, social value signifies the prestige and self-image enhancement experienced by consumers using EdTech applications, reflecting their social status gain. Thus, we propose the following hypothesis:

✤ **H2 :** The prestige and recognition gained after completion of the courses have a negative correlation with technology acceptance.

Conditional Value

Conditional value is the specific conditions that facilitate the purchase of a product or service from the buyer's viewpoint; it pertains to a product's or service's dependence on a particular context, such as a situation, time, or location (Sheth et al., 1991). Situations prompt the users to use a particular product or service (Dash &

Chakraborty, 2021a; Dash & Chakraborty, 2021b). It refers to a product's or service's reliance on a specific context, such as a circumstance, time, or location (Chakraborty & Paul, 2023). Based on the analysis, the research proposes the following hypothesis:

✤ **H3 :** The course fees and their affordability positively correlate with technology acceptance.

Emotional Value

The social value of a product or service relates to the perceived benefit of associating with a particular social class (Sheth et al., 1991), influencing one's image within their social circles (Zailani et al., 2019). Societal pressures can affect purchasing decisions (Chakraborty, Siddiqui, Siddiqui & Alatawi, 2022), with norms or peer group influences shaping choices (Wang et al., 2021). Social influence significantly impacts consumer decisions across various product contexts (Thomé et al., 2021). In this study, social value denotes the prestige and self-image enhancement experienced by consumers using EdTech applications, reflecting their social status gain. Hence, the following hypothesis is proposed :

✤ **H4 :** Attentiveness during the completion of the courses has a negative correlation with technology acceptance.

Epistemic Value

Epistemic value refers to the capacity of a product or service to spark curiosity, provide a sense of novelty, and satisfy information-seeking instincts (Sheth et al., 1991). Epistemic value pertains to cognitive achievements, encompassing aspects like true beliefs, justified beliefs, knowledge, and understanding (Tandon et al., 2021). This study uses two specific constructs, novelty and student engagement, which drive users toward using novel courses on the EdTech applications. Considering the same, the following hypotheses are proposed.

✤ **H5a :** The novelty of overall course structures positively correlates with technology acceptance.

✤ **H5b :** Student engagement positively correlates with technology acceptance.

Moderating the Role of Internet Accessibility and Information Overload

We have explored the influence of moderating variables to elucidate individual differences in consumer behavior; specifically, demographic variables, such as age and gender, have been scrutinized as potential moderating factors in various contexts (Rizvi & Nabi, 2021). Concerning the context of our study, Internet availability across the Indian demography and the high amount of data available (i.e., information overload) are suitable moderators for this study. Thus, we propose the following hypotheses:

✤ **H6a :** The relationship between functional values and technology adoption will be moderated and impacted by Internet accessibility.

✤ **H6b :** Internet accessibility will moderate the relationship between social values and technology adoption.

✤ **H6c :** The relationship between conditional values and technology adoption will be moderated by Internet accessibility.

✤ **H6d :** Internet accessibility will moderate the relationship between emotional values and technology adoption.

✤ **H6e :** Internet accessibility will moderate the relationship between epistemic values and technology adoption.

↳ **H7a** : The relationship between functional values and technology adoption will be moderated and impacted by information overload.

↳ **H7b :** The information overload will moderate the relationship between social values and technology adoption.

↳ **H7c :** The information overload will moderate the relationship between conditional values and technology adoption.

↳ **H7d :** The information overload will moderate the relationship between emotional values and technology adoption.

↳ **H7e :** The information overload will moderate the relationship between epistemic values and technology adoption.

Methodology

This research adopts a quantitative approach due to its systematic investigation and well-defined data collection methods, utilizing statistical techniques for precise outcomes. Quantitative research is crucial for hypothesis testing and exploring variable relationships in social science, education, and psychology. The chosen research design dictates data collection, analysis methods, and hypothesis evaluation, ensuring the relevance and suitability of gathered data. For this study, a descriptive research design was adopted, with an emphasis on gathering data through surveys, interviews, and observations in order to understand the characteristics of the group or phenomenon under investigation. Next, information is gathered to verify these theories. Supporting evidence substantiates the theories, which in turn validates the fundamental hypotheses.

Purposive sampling is a non-random selection technique that is specifically chosen for the study in order to achieve particular research goals. Based on preset standards that are in line with the objectives of the study, we choose participants or groups. The target population for this analysis is all Indian EdTech users who have actively used or are using the EdTech applications. In this research study, the concept of a sampling frame and unit is irrelevant as the population of interest and their geographic locations are clearly defined. The current research study used quantitative analysis to obtain precise descriptive and inferential data, employing appropriate statistical techniques. Data gathered from the structured questionnaire underwent examination via graphical and tabular representations alongside information from appendices. IBM SPSS 26 and IBM AMOS 26 were utilized for confirmation and exploratory factor analyses.

Data Collection, Survey Instrument, and Respondents' Profile

The survey and questionnaire were carried out to meet the sample size requirements. This study uses an explorative mixed-method approach wherein a questionnaire is developed based on the specific hypothesis to be tested. The expected data sampling shall be for Indian EdTech platform users. The survey used a 5-point Likert scale to carry out the measurements. Additional qualitative research techniques, such as personal interviews and surveys, were employed due to the extensive data analysis required for the study. The research utilized a two-staged data collection method, starting with a pre-tested method involving 100 respondents, followed by full-fledged testing. A pilot study with 100 respondents is planned, with an anticipated positive outcome from 75 respondents.

In the initial analysis phase, 78 responses were collected from the Indian population, ensuring balanced representation across age and gender. This pilot study occurred in May 2023 and was distributed via email to 250 recipients. Complete responses were received from all 78 participants without missing data. The survey used a

Table 2. *Demographic Profile*

Demographic Measure	Category	Frequency	Percentage
Age	Less than 25 years	82	15.98
	26–35 years	127	24.76
	36–45 years	135	26.32
	46–55 years	99	19.30
	Above 55 years	70	13.65
Gender	Male	219	42.69
	Female	294	57.31
Region	North India	130	25.34
	East India	110	21.44
	West India	148	28.85
	South India	125	24.37

5-point Likert scale (1 indicating *strong disagreement*, 5 *strong agreement*) (Gupta & Sukumaran, 2013). Insights from the pilot study helped rectify errors and refine the survey instrument. Subsequently, the survey was expanded to a broader audience, using a specified formula to determine the sample size by following the statistical formula for calculating the sample size when the size of the population is infinite (Chakraborty, Siddiqui, Siddiqui, & Alatawi, 2022).'

$$S = (Zcl \times P \times q)/E^2$$

Here, *S* is the sample size, *Zcl* is the square of the confidence level in standard error units (The *Z*-value for 95% confidence interval = 1.96), the *p*-value has been identified at 75%, and $1-p = q$ is 25%; Thus, from the above formula, the obtained value of sample size for infinite population shall be 289.

The final questionnaire was circulated to 836 respondents between November 2023 and January 2024, out of which 572 provided a response, and 513 responses were complete and usable after conducting the required checks on the final collected data. The demography profile of the respondents is shared in Table 2.

Data Analysis and Results

The data analysis in this study follows a two-step procedure. Initially, the reliability and validity of the measuring scales were assessed through exploratory factor analysis (EFA) and subsequently confirmed by confirmatory factor analysis (CFA). In the second step, the structural route of the proposed conceptual model is evaluated using

Table 3. *Constructs, Items, and Sources*

Consumption Value	Construct	Item No	Item	Source
Functional Value	**Handling Ease *(HE)***	*HE1*	I can easily find the information and courses I wish to enroll in from the EdTech Application.	(Chakraborty, Siddiqui, Siddiqui, Rana, & Dash, 2022 ; Dash &
		HE2	Handling and using EdTech applications requires more effort than offline learning mode.	Chakraborty, 2021a ; Dhir et al., 2021 ; Sheth et al., 1991)
		HE3	I feel the interface of the EdTech application is easy to use and interactively designed.	
	Course Content *(CC)*	*CC1*	The results of this study provided policymakers and EdTech platform developers	

			with valuable insights into the elements influencing technology adoption.	
		CC2	The course faculty from EdTech Learning courses drive me to enroll in further courses.	
		CC3	I feel that VR and artificial intelligence usage needs to be further enhanced in EdTech platforms for various courses.	
		CC4	I find many critical insights missing in the courses delivered from the EdTech applications.	
		CC5	The tie-ups and cross-collaboration of EdTech applications with various national/ international universities provide comprehensive course content and updated course structures.	
	Certification (CE)	CE1	I enroll in the courses even if they do not provide me certifications for courses attended.	
		CE2	The evaluation obtained from EdTech Learning and the certifications provided hold less importance than those obtained from conventional learning centers.	
		CE3	The certification obtained from EdTech Application courses is at par with offline courses from various universities.	
Social Value	Prestige and Recognition (PR)	PR1	I gained prestige and recognition in society after completing EdTech Learning courses.	(Chakraborty, Siddiqui, Siddiqui, Rana, & Dash, 2022 ; Dash & Chakraborty, 2021a ; Dhir et al., 2021 ; Sheth et al., 1991)
		PR2	I feel that using EdTech applications will improve my social image.	
		PR3	If I do not get recognized after using EdTech applications, I will stop using them.	
Conditional Value	Course Fees (CF)	CF1	I feel that course fees for various courses on the EdTech Applications are priced based on the content.	
		CF2	If the course fees are low, the courses are of poor quality.	(Chakraborty, Siddiqui, Siddiqui, Rana & Dash, 2022 ; Dash & Chakraborty, 2021a ; Dhir et al., 2021 ; Sheth et al., 1991)
		CF3	The payments made upon EdTech applications are secure and easy to process.	
	Affordability (AF)	AF1	The fees and processing for the EdTech Applications are accessible through the UUS online payment applications.	
		AF2	I feel that the courses on EdTech Platforms are high-priced and unaffordable.	
		AF3	The payment gateways for EdTech applications are secure, and all transactions are safe.	
Emotional Value	Attentiveness (AT)	AT1	I feel connected to the course contents, which drives me to complete the	(Chakraborty, Siddiqui, Siddiqui, Rana & Dash, 2022 ; Dash &

			EdTech Learning course attentively.	Chakraborty, 2021a ; Dhir
		AT2	The various course elements are enjoyable and drive me to use the applications further.	et al., 2021 ; Sheth et al., 1991)
		AT3	I regularly feel distracted while doing a course on EdTech Applications.	
		AT4	I feel that concepts are better explained offline, as using EdTech Applications leads to losing attentiveness during use.	
Epistemic Value	Novelty (NO)	NO1	The novelty of the overall course structure drives me to enroll for further courses.	(Chakraborty, Siddiqui, Siddiqui, Rana & Dash, 2022 ; Dash &
		NO2	I am interested to know about the new features that are to come up with the EdTech Applications and course contents.	Chakraborty, 2021a ; Dhir et al., 2021 ; Sheth et al., 1991)
		NO3	If some course content is new, it engages me to work on and complete the learning.	
	Student Engagement (SE)	SE1	I feel that the usage of AI and virtual reality in any course engages me to use the applications further.	
		SE2	The EdTech Applications will contribute to my overall career and personal growth.	
		SE3	I feel that a mix of online EdTech and offline EdTech is the way forward and will promote application-based learning.	
Effect of Moderators	Internet Accessibility (IA)	IA1	My Internet speed and connectivity allow me to use the EdTech applications effectively.	(Chakraborty, Siddiqui, Siddiqui, Rana & Dash, 2022 ; Dash & Chakraborty, 2021a ; Dhir
		IA2	I regularly face an issue with connectivity while using EdTech applications, which makes me unable to use the applications.	et al., 2021 ; Sheth et al., 1991)
		IA3	I feel that moving away from my location to a remote location will affect the internet connectivity and directly affect the learning experience.	
	Information Overload (IO)	IO1	The information available on the EdTech learning platforms is very difficult to understand.	
		IO2	If the information is split into multiple courses, it will provide a better understanding and increased usage of the applications.	
		IO3	In some cases, the information provided on the EdTech courses becomes too high to be understood and interpreted.	
Technology Adoption of EdTech Application	Technology Adoption of EdTech Applications (TA)	TA1	I am ready to adopt a complete online platform-based rather than classroom-based learning.	(Chakraborty, Siddiqui, Siddiqui, Rana & Dash, 2022 ; Dash & Chakraborty, 2021a ; Dhir
		TA2	EdTech applications still require much time to get blended into mainstream education and cannot	et al., 2021 ; Sheth et al., 1991)

		be the way forward.
TA3	EdTech applications blended with classroom education are the way forward in the education sector.	

SEM in both SPSS 26 and AMOS 26. Additionally, the impact of mediating and moderating variables was explored using the process macro 3.5.3. The dataset's normality was checked first, revealing no missing or unengaged responses. Skewness and kurtosis values were within acceptable limits (+3 to –3), ensuring data quality. Descriptive statistics for the constructs employed in the study are presented in Table 2. A multicollinearity test confirmed that all results remained below the three-point cut-off, indicating no issues.

In order to evaluate common technique bias in SPSS, Harman's single component test was used as an initial assessment. The results demonstrate that there were no problems with standard method bias in the data, with a single factor accounting for only 23.186% of the total variance, below the 50% criterion. The structures, elements, and sources taken into account in this analysis are listed in Table 3.

Fit indices, validity, and reliability are assessed using CFA after common method bias was determined. The factor loadings for each item, as shown in Table 4 and derived using CFA and SEM, are more than 0.7, indicating that they are considered suitable for further research. It is also important to note that the factor loading of each item was higher than suggested. Furthermore, as prior research has highlighted, of 0.7.

Table 4. *Constructs and Factor Loadings*

Factors	Items	CFA	SEM	Cronbach's Alpha
HE	*HE1*	0.787	0.9	0.794
	HE2	0.71	0.822	
	HE3	0.698	0.84	
CC	*CC1*	0.834	0.875	0.939
	CC2	0.767	0.907	
	CC3	0.791	0.844	
	CC4	0.809	0.912	
	CC5	0.852	0.903	
CE	*CE1*	0.875	0.957	0.917
	CE2	0.869	0.91	
	CE3	0.846	0.896	
PR	*PR1*	0.765	0.861	0.825
	PR2	0.706	0.863	
	PR3	0.773	0.895	
CF	*CF1*	0.81	0.891	0.893
	CF2	0.833	0.885	
	CF3	0.849	0.846	
AF	*AF1*	0.841	0.834	0.89
	AF2	0.824	0.831	
	AF3	0.827	0.868	
AT	*AT1*	0.807	0.876	0.947

	AT2	0.873	0.935	
	AT3	0.861	0.906	
	AT4	0.918	0.875	
NO	NO1	0.842	0.807	0.913
	NO2	0.874	0.719	
	NO3	0.865	0.824	
SE	SE1	0.817	0.834	0.859
	SE2	0.836	0.895	
	SE3	0.722	0.739	
IA	IA1	0.78	0.836	0.797
	IA2	0.653	0.697	
	IA3	0.719	0.736	
IO	IO1	0.785	0.825	0.807
	IO2	0.749	0.807	
	IO3	0.695	0.662	
TA	TA1	0.902	0.862	0.931
	TA2	0.874	0.724	
	TA3	0.87	0.685	

The confirmation of model fit through CFA indicated that all CFA values exceeded 0.7. Subsequently, the data was validated, and Table 5 presents the validity and reliability analysis. Initially, composite reliability was employed to gauge internal consistency among the different constructs in the study. The composite reliability values for all study constructs surpassed 0.7 (Table 5), aligning with the desired criteria. The study's outcomes further affirmed that the data met the requirements for convergent and discriminant validity and reliability. The average variance extracted (AVE) values for all constructs are 0.50, and the maximum shared variance (MSV) value is lower than the AVE values. This indicates that composite reliability (CR), AVE, and MSV are all within the specified range.

Table 5. *Validity and Reliability Analysis*

	CR	AVE	CC	AT	CE	NO	AF	CF	TA	PR	SE	IA	IO	HE
CC	0.939	0.756	**0.869**											
AT	0.948	0.819	0.206	**0.905**										
CE	0.919	0.791	0.232	0.041	**0.889**									
NO	0.914	0.78	0.187	0.604	0.184	**0.883**								
AF	0.891	0.731	0.216	0.057	0.103	0.085	**0.855**							
CF	0.894	0.737	0.197	0.246	0.153	0.294	0.218	**0.859**						
TA	0.932	0.821	0.265	0.48	0.278	0.48	0.243	0.095	**0.906**					
PR	0.827	0.616	0.213	0.456	0.296	0.361	0.103	0.131	0.487	**0.785**				
SE	0.864	0.681	0.184	0.437	0.226	0.417	0.153	0.091	0.484	0.42	**0.825**			
IA	0.802	0.576	0.228	0.018	0.172	0.026	0.166	0.076	0.367	0.089	0.048	**0.759**		
IO	0.81	0.59	0.241	0.138	0.196	0.152	0.119	0.12	0.349	0.15	0.145	0.472	**0.768**	
HE	0.803	0.579	0.309	0.082	0.414	0.113	0.181	0.042	0.221	0.222	0.123	0.134	0.149	**0.761**

The diagonal presentation of square roots of AVEs demonstrates values greater than the inter-construct correlation values, reinforcing the presence of discriminant validity.

We examined the goodness-of-fit criteria values to evaluate the model fit, revealing the following results: χ^2/degrees of freedom = 1.559, TLI (Tucker–Lewis index) = 0.970, CFI (comparative fit index) = 0.974, and RMSEA (root mean square error of approximation) = 0.033. The goodness-of-fit criteria values are statistical measures used to assess how well a proposed model fits the observed data. In the provided results:

↳ χ^2/degrees of freedom = 1.559:

This ratio is a normalized chi-square statistic. A lower value indicates a better fit. A value close to 1 suggests a good fit, and in this case, 1.559 indicates a reasonable fit.

↳ TLI = 0.970:

TLI assesses the improvement in fit compared to a baseline model. A value close to 1 (0.970 in this case) suggests a good fit, indicating that the proposed model improves the fit considerably compared to a baseline model.

↳ CFI = 0.974:

Similar to TLI, CFI also evaluates the improvement in fit. A value close to 1 (0.974 here) indicates a good fit, suggesting that the proposed model fits the data well.

↳ RMSEA = 0.033:

RMSEA measures the discrepancy between the observed data and the model. A value of 0.033 is considered low, suggesting a good fit. Generally, values below 0.05 indicate a close fit, and values up to 0.08 represent a reasonable fit. In summary, the provided goodness-of-fit criteria values (χ^2/degrees of freedom, TLI, CFI, and RMSEA) collectively suggest that the model fits the observed data well, with a reasonably low level of discrepancy. These results provide confidence in the reliability and validity of the proposed model.

The results show a strong correlation between a few factors and technological acceptability, as shown in Table 6. In particular:

↳ Functional value (H1b: ß = 0.323, $p < 0.001$), (H1c: ß = 0.331, $p < 0.001$).

↳ Social value (H2: ß = 0.214, $p < 0.001$).

Table 6. *Results of Hypotheses Testing*

Hypotheses	Path			Estimate	P	Support
H1a	*TA*	<---	*HE*	0.054	>0.05	No
H1b	*TA*	<---	*SE*	0.323	<0.001	Yes
H1c	*TA*	<---	*PR*	0.331	<0.001	Yes
H2	*TA*	<---	*AF*	0.214	<0.001	Yes
H3	*TA*	<---	*NO*	0.29	<0.001	Yes
H4	*TA*	<---	*CE*	0.1	<0.05	No
H5a	*TA*	<---	*AT*	0.222	<0.001	Yes
H5b	*TA*	<---	*CC*	0.062	>0.05	No

↳ Conditional value (H3: ß = 0.29, $p < 0.01$).

↳ Epistemic value (H5a: ß = 0.222, $p < 0.01$).

However, functional value (H1a: ß = 0.054, $p > 0.05$), emotional value (H4: ß = 0.1, $p < 0.05$), and epistemic value (H5b: ß = –0.062, $p > 0.05$) do not exhibit a substantial relationship with technology acceptance.

These findings add to a thorough knowledge of how several value dimensions interact and influence people's adoption of technology. They draw attention to important correlations while pointing out instances in which particular values might not have a bearing on technological acceptance.

Moderation Analysis

We examined the moderating effects of Internet accessibility and information overload on the relationship between consumption values and technology adoption behavior. India has seen significant growth in its information technology user base in recent years, with the government implementing programs to improve technology and Internet availability nationwide. While Internet availability in rural areas is gradual, nationwide challenges remain (Burgstahler, 2002). Information overload, the second factor, typically pertains to the abundance of data available on the Internet, making it difficult for individuals or organizations to process and manage effectively (Yen, 2024). Both factors are expected to critically moderate technology. The results of the moderation analysis are elaborated in Tables 7 and 8 and Figure 2.
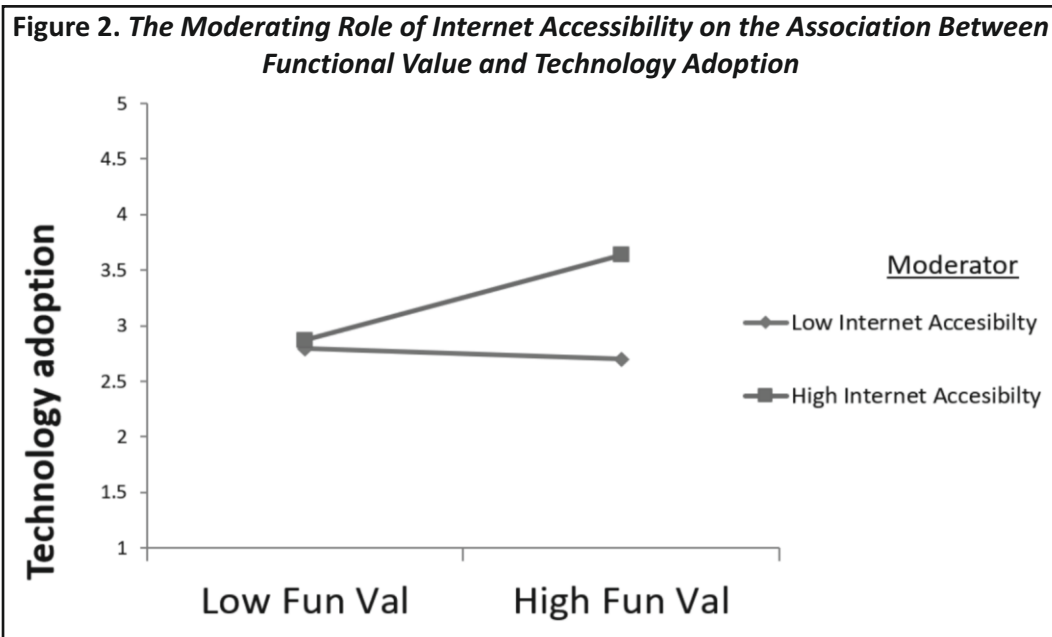
The results indicate that in some cases, internet accessibility moderates the relationship between functional values, social values, emotional values, and epistemic values. In contrast, information overload moderates the relationship in the case of conditional values. Figure 2 indicates the moderating role of Internet accessibility on the association between functional value and technology adoption.

Table 7. *Results of Moderation Analysis with Internet Accessibility as a Moderator*

Hypotheses		Path		Estimate	SE	CR	P	Moderation?
H6a	TA	<---	FV	0.168	0.065	2.583	0.01	Yes
H6b	TA	<---	SV	–0.097	0.047	–2.044	0.041	Yes
H6c	TA	<---	CV	–0.102	0.072	–1.418	0.156	No
H6d	TA	<---	EV	0.192	0.063	3.07	0.002	Yes
H6e	TA	<---	EPV	0.173	0.085	2.023	0.043	Yes

Table 8. *Results of Moderation Analysis with Information Overload as a Moderator*

Hypotheses		Path		β	SE	CR	P	Moderation?
H7a	TA	<---	FV	–0.082	0.061	–1.346	0.178	No
H7b	TA	<---	SV	0.042	0.044	0.951	0.341	No
H7c	TA	<---	CV	0.156	0.073	2.151	0.031	Yes
H7d	TA	<---	EV	–0.028	0.056	–0.505	0.613	No
H7e	TA	<---	EPV	–0.012	0.068	–0.178	0.858	No

Figure 2. *The Moderating Role of Internet Accessibility on the Association Between Functional Value and Technology Adoption*

Discussion

The research supports H1, H2, H3, and H5a. It shows that the technology adoption of EdTech platforms is significantly positively correlated with values related to handling ease, course content, certification, prestige and recognition, course costs, affordability, and novelty. This implies that how consumers view these elements has an impact on how well-informed they are about EdTech platforms and how supportive they are of them. The results confirm a clear impact of functional, social, and conditional value on the purchase and acceptance of technology. The results imply that the course content must focus on the platform's usability and overall experiences and provide certifications at par with offline universities.

The H2 is highly driven by the social acceptability and the prestige attained after course completion; thus, a focus on social media and promotion is required. The results also affirm that, from the perspective of Indian consumers, EdTech platforms play a crucial role in enhancing social perception and creating positive impressions. By utilizing the latest technology for learning new subjects, these platforms contribute to an increased consumption value, particularly in terms of prestige value. This derived value, in turn, positively influences their intentions to use EdTech platforms. The study suggests that such behavior may not be universally applicable and may vary across cultural settings. H3 indicates a critical aspect of course pricing and affordability. It positively drives the adoption behavior of the users of technology. For example, consumers in Western countries might perceive social value differently, seeing EdTech platforms as a quick and easy way to learn or access information. The cultural context shapes the association between consumption values and intentions to use EdTech platforms. Consequently, the study highlights the need for further research to explore and understand how these relationships may differ in diverse cultural settings, emphasizing the importance of considering cultural nuances in analyzing consumers' intentions to use EdTech platforms.

In the case of H5a, incorporating a novel course structure and redesign, considering the shorter attention spans, significantly impacts this value. Notably, during the COVID-19 pandemic, novelty for mobile apps surged as consumers faced limited alternatives. The closure of schools and colleges resulted in a notable uptick in the sales of mobile learning apps, underscoring the impact of increased visibility on consumer choices during the pandemic (Dash et al., 2022).

Theoretical and Practical Implications

The study offers a significant theoretical contribution by analyzing consumer behavior toward EdTech applications using consumption values. It introduces information overload and internet accessibility as moderators influencing technology adoption-related values. This innovative approach establishes connections between these factors, which have been explored in various contexts. Limited studies have examined the TCV in the context of EdTech applications. Additionally, we considered cultural and demographic factors and explored the moderating impact of internet accessibility and information overload, aligning with recent literature recommendations. This comprehensive approach enhances understanding of consumer behavior towards EdTech applications, contributing to the broader knowledge in the field.

This study holds practical implications for various stakeholders in the EdTech domain, including researchers, teachers, policymakers, and application developers. For app developers, the study suggests focusing on diverse consumption values such as monetary, quality, social status, information, and preference, as they positively influence purchase intention, albeit with varying relationships among them. This insight can guide developers in enhancing specific areas of their applications to positively impact perceived value, thereby increasing user satisfaction and purchase intention. For researchers and teachers, the study offers insights into overlooked areas in prior research, laying the groundwork for future studies to understand better factors influencing consumer behavior in EdTech applications. Finally, for policymakers, the study highlights upcoming areas of development within the EdTech sector, informing policy formulation to promote the creation and adoption of technology aligned with user expectations. Overall, the study provides practical guidance for optimizing strategies and offerings in the EdTech industry based on a nuanced understanding of consumer values and preferences.

Conclusion

EdTech applications are now a crucial component of the contemporary educational landscape. In this study, we identified factors that can forecast consumer behavior in adopting and utilizing learning apps. It is identified that tonal value, social value, and conditional value positively drive the technology adoption process for EdTech applications — as the moderating of the Internet is a crucial driver for technology adoption in India. The identified variables in this study are highly relevant in modern-day practice and thus will support the research community further.

Limitations of the Study and Scope for Future Research

Although this study has limitations, it adds significant empirical value to the consumer behavior literature on EdTech applications. The fact that all of the study's participants are from India may restrict how far the results may be applied outside of that country. Future researchers are urged to investigate this by doing replication experiments in various countries, enabling cross-cultural comparisons.

Authors' Contribution

The research objectives were developed by Vaibhav Aaradhi and Dr. Debarun Chakraborty, who also designed and carried out thorough literature reviews to develop the research hypotheses. A survey questionnaire that Vaibhav Aaradhi and Dr. Debarun Chakraborty created was modified from existing instruments. Participants' replies were then gathered and subjected to conventional statistical software analysis, and the results were interpreted objectively. In cooperation with Dr. Debarun Chakraborty, Vaibhav Aaradhi wrote this paper.

Conflict of Interest

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About the Authors

Vaibhav Aaradhi is a Research Scholar in Management at Symbiosis International (Deemed University). He has 15+ years of experience in business development and growth in the high-voltage switchgear industry. His area of work is on technology adoption and acceptance, and he has already published a paper in a Scopus and ABDC-indexed journal.

Dr. Debarun Chakraborty is an Associate Professor at Symbiosis Institute of Business Management, Nagpur, a constituent of Symbiosis International (Deemed University), Pune, India. He has published works on technology adoption, consumer behavior, and sustainability in high-impact factor journals. His research appears in top journals, namely, *Psychology & Marketing, Journal of Business Research*, *Technovation, IEEE Transmission Electron Microscopy*, *Journal of Retailing and Consumer Services, Journal of Hospitality Marketing & Management*, *International Journal of Consumer Studies*, *Journal of Computer Information Systems*, *Conflict Resolution Quarterly, British Food Journal,* among others.