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Investigating Academic Achievement Satisfaction of Students in India: An Application of ANN Model

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Abstract

This study deliberates how online learning impacts Academic Achievement Satisfaction (AAS) among higher education professional course students in India. Online learning offers students more flexibility and convenience, but it also presents challenges, such as a lack of face-to-face interaction with instructors and peers, technical difficulties, and difficulty in maintaining motivation and engagement. Artificial Neural Networks (ANN) are trained on this data to create a predictive model that identifies the most important predictors of AAS in online learning environments. The results showed that the 'distracting elements' are the most critical factor while measuring the AAS, followed by the 'Institutional Support' factor. 'Social Synergy', 'Own Room', 'Internet Potency', and 'Technical Self Efficacy' have also been found to impact the AAS. Ultimately, the findings of this study could contribute to the ongoing efforts to improve the quality of online learning for higher education professional course students.

Keywords

Academic Achievement; Satisfaction; ANN; Online learning; Self-determination theory.

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1. Introduction

The traditional education system has been disrupted by technological innovations, leading to the rapid growth of online learning platforms across all educational segments. Over the past decade, online education has been enhanced by advancements in information and communications technology and the use of cloud-based platforms. As of 2022, the online education market in India was valued at US $6.4 Billion and is expected to reach US $14.1 Billion by 2027 (IMARC, 2022). However, the adoption of online learning is impeded by Indians' preference for face-to-face learning and the inability of online channels to replicate certain aspects of offline learning, such as peer interaction and soft skill development. Additionally, there is a lack of formal recognition and inadequate digital infrastructure in the country. As humankind faces increasing numbers of unforeseeable and unprecedented situations, the resulting impact can be long-lasting despite swift resolution. The recent COVID-19 outbreak is a prime example of this, as it created an immeasurable health crisis while also leading to notable positive societal changes, such as the rapid adoption of digital learning. This shift from traditional classroom learning to online education was a silver lining in a difficult time, demonstrating the potential benefits of blended learning - a combination of face-to-face instruction and online techniques - as advocated by experts like Bonk and Graham (2012)and Allen and Seaman (2010), who suggest that up to 79% of course content could be delivered online.

The potential of online learning to revolutionize education in India is significant, and there is increasing investment in digital infrastructure and online learning platforms by both private and public entities in the country. The enrollment in online education programs has increased significantly. As reported by Gohain (2022), there is a 170% increase in students enrolled in online education programs. Higher educational institutions are also increasingly offering online programs, with a 38% increase. By taking advantage of modern digital technologies, educators can create engaging digital content and reach out to students using the growing availability of the internet. This provides students with access to high-quality education at an affordable cost, helping them become knowledgeable and skilled. But for the students to learn online becomes a challenge when there is a lack of motivation, engagement, disruption-free internet services, and a disturbance-free learning environment. This study is formulated to explore these challenges at the students' level and their impact on Academic Achievement Satisfaction (AAS).

2. Literature review

The COVID-19 pandemic has resulted in widespread disruption to the education system, affecting nearly 1.6 billion students worldwide (Alkubaisi et al., 2021). In response, many educational institutions turned to online learning platforms to continue academic activities during the pandemic (Muthuprasad et al., 2021). As a result, online learning has become the new norm in the education sector, with many global institutes shifting their teaching pedagogy to online modes such as synchronous or non-synchronous teaching methods (Almahasees et al., 2021). MOOCs (Massive Open Online Courses) have gained popularity in developed and under-developed countries alike due to their accessibility and ability to act as a unified platform for learning (Kiran &Popuri, 2013). However, the use of programmed software in Learning Management Systems (LMS) lacks the real-time interaction component of a physical classroom environment (Cavus et al., 2006). To address this, educational institutions should adopt a collective and exhaustive approach involving students, teachers, and administrative staff to ensure the same level of service quality in online systems as in traditional ones (Ramírez-Hurtado et al., 2021). The factors which influence the service quality of online education differ from traditional education, which creates a need to explore these influencers. A learner-centered approach with specific learning styles and timely feedback can enhance the effectiveness of online learning (Eom et al., 2006). Successful online learning also requires flawless communication between learners and teachers and flexibility for students to work at their own pace (Elshami et al., 2021). Learners' own motivation plays a crucial role in their satisfaction with online learning, and self-regulated learners tend to be more satisfied with online learning techniques when their locus of control is centered on their learning outcomes (Hettiarachchi et al., 2021). Students' academic performances are also impacted by their household environments and available facilities (Jain &Mohta, 2019). Providing separate study rooms for students can enhance their ability to concentrate and make continuous progress in their studies. Overall, the use of technology to develop web-based teaching and learning systems has brought significant changes to the education system, requiring a comprehensive and collaborative approach to maintain service quality and ensure positive outcomes for students.

Online learning has become increasingly popular among students, but many still believe that traditional classrooms cannot be replaced. One issue hindering the effectiveness of online education is the lack of proper training for teachers in delivering and developing online material. In addition, the scarcity of technical support is a major concern (Kulal& Nayak, 2020). A shift to online classrooms has disrupted the study behavior of both educators and students Chandra (2020), like the increase in screen time during online learning led to anxiety issues and mental health concerns among students (Harjule et al., 2021). The pressure to perform well in the new system, along with the struggle of handling the educational workload, is also a major concern for students (Fitzgerald & Konrad, 2021). Low income is also a contributing factor to increased anxiety levels among students. The inability to purchase the gadgets to participate in digital platforms is a leading cause of stress (Irawan et al., 2020). Also, the social interaction between the instructor and learner is critical for student progress. Online classes lack this interaction, but it can be improved through the implementation of asynchronous online discussions in small groups (Akcaoglu& Lee, 2016). This sustained social interaction is the key to effective online learning (Cockerham et al., 2021), and institutions must prioritize this aspect of the online learning experience. Although online learning has its benefits, technical literacy, and technological competency were key challenges during the hasty shift to online learning caused by the pandemic (Barrot et al., 2021). Institutions face the challenge of creating an infrastructure that is aligned with external factors and well-suited for internal users (Nawaz & Khan, 2012). Many institutions in India struggled with limited resources, which made it difficult to invest in the necessary hardware, software, and digital infrastructure required for online learning.

2.1 Lens of Self-Determination Theory

Just like hunger, sleep, and other physiological needs, psychological needs are crucial for any individual's well-being. These needs act as a key motivator for any individual for pursuing any behavior. Many earlier theories focus on human behavior but fail to factor in the reasons responsible for such behavior (Patrick & Williams, 2012). Self-determination theory (SDT) offers a comprehensive perspective of human motivation and how several intrinsic and extrinsic conditions outline our behavior. How an individual responds in a particular situation depends on these conditions and human cognitive development (Legault, 2017). Human beings are either energetic or unassertive. The behavior of an individual is mostly the result of the social conditions in which they evolve.

According to research by Ryan and Deci (2000), when the psychological needs – relatedness to society, competence to do tasks, and autonomy are satisfied, the mental health and the self-motivation of an individual are enhanced, and when these needs are hindered, result in diminished motivation. SDT in education reveals that fostering intrinsic motivation enhances academic achievement (Chiu, 2023). Students who experience a sense of control, competence, and connection tend to exhibit higher levels of engagement and perform better academically.

Though the transition of education from the traditional classroom to digital mode was very much a necessity of the time, a very considerable issue of distraction from the new learning mode arose. Social media addiction is one of the most prominent reasons causing this distraction. The crucial factors which were leading to this social media distraction were FoMO and self-regulatory capabilities. Digital media, despite being an easy source of remaining in contact and being available for everyone in daily life became a major distraction for anyone pursuing online learning (Koessmeier & Büttner, 2021). Social distancing methods adopted during the outbreak resulted in the changing pattern in the usage of smartphones among adolescents. This significant overuse leads to paramount addiction among young students. With the widespread of personal digital devices, the deleterious effect of the use of smartphones on academic performance has been very much conspicuous (Dontre, 2021). These studies reflect the relevance of self-determination for successful online learning. It has been observed that enrolment in online courses is high, but the actual earning of certificates or actual knowledge gain is not substantial. With this backdrop, the present study is an attempt to identify the predictors of AAS to focus on the most important explored factor of AAS.

3. Research Methodology

This study employed a survey questionnaire to examine the dimensions affecting Online Learning. The questionnaire was developed after an in-depth analysis of extant studies (such as Eom et al., 2006; Jain & Mohta, 2019; Nawaz & Khan, 2012; Warden et al., 2020; Mutalib et al., 2022). The authors examined the significance, content and comprehensiveness of the scale items in context to measure the AAS of the students. A 26-item questionnaire was designed and distributed through google forms, an online survey technique. The primary data for the study were collected from individuals who indulge in online studying or certification programs. The items which were used to gather the demographic data were gender, age, location, educational background, monthly family income, nature of family type from nuclear to joint family, the total number of family members residing in the house, total number of siblings residing in the house, separate/independent personal space. Other than the items above, information regarding internet connectivity, gadget usage and additional relevant information for the study was collected. The questionnaires were administered to individuals who indulge in online studying or certification programs, and 610 responses were collected from one of the largest Universities in North India. The collected responses were coded per the 5-point likert scale for the questionnaire items. 1 through 5 were coded from 'strongly disagree' to 'strongly agree'. Out of 610 responses, 563 (approximately 92%) valuable responses were later used for the study. A response rate of at least 20% is satisfactory for a valid assessment in empirical surveys (Yu & Cooper, 1983). The collected data were validated and analyzed using IBM's Statistical Packages for Social Sciences.

4. Test Results and Discussions

4.1 Exploratory Factor Analysis

In the current study, Exploratory Factor Analysis (EFA) was conducted using the SPSS analysis tool. The EFA method used in the study serves two primary purposes. The first purpose is to find the factors formed by the internal correlations of the direct variables of the study. These factors are not directly observed but are configured by the directly measured indicators of the analysis (Johnson & Wichern, 2007). The second purpose is to find the maximum contribution to the study's objective by the current obtained information while trying to keep the factors at the minimum level. The reliability of the factors should be maintained at the highest level possible (Johnson & Wichern, 2007; Hair et al., 2016). Bartlett's sphericity test in the EFA is highly accepted among researchers for determining the adequacy of the data. A statistically significant value of less than 0.05 should be there in the output of the Bartletts test to continue with the further analysis. The acceptable value for indicating sample adequacy is any value greater than 0.5. A KMO value of 0.812 is measured in the study, indicating sufficient data for conducting the EFA. The EFA's total variance table output showed that the total of observed 16 variables has now been reduced to 5 unobserved complex components. These five components can explain approximately 61.51% of the total variance in the study. The five components extracted from the EFA results are given below (Table I) with their label descriptions. F1: Internet Potency (IP)-This factor consists of 3-items that underline the power of the internet. F2: Institutional Support (IS)-This factor consists of 4 items primarily representing the 'institutional support aspects'. F3: Social Synergy (SS) -This factor consists of 4-items which highlight the social aspects of online learning set-up. F4: Distracting elements (DE)- This factor consists of 3-items that highlight distraction's role during online learning set-up. F5: Technical Self-Efficacy (TSE)-This factor consists of 2-items that explain the significance of sound technical skills for the success of online learning set-up.

Table 1: *Factors Explored*

		Component				
Factor	Related Items	1	2	3	4	5
Internet Potency (IP	Internet_Disconnects	.834				
	Internet_Assignments	.875				
	Internet Access	.840				
Institutional Support (IS)	LMS_Availability		.690			
	LMS_Use		.799			
	Engaged Learning		.575			
	Grievances		.736			
Social Synergy (SS)	Classmates Interaction			.659		
	Social Contact			.646		
	Panic_Online			.707		
	Expectations Unaware			.657		
Distracting elements (DE)	Indulge_Activities				.609	
	Household_Chores				.757	
	Conducive Environment				.652	
Technical Self-Efficacy (TSE)	Browse_Internet					.807
	Technical Ability					.637

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

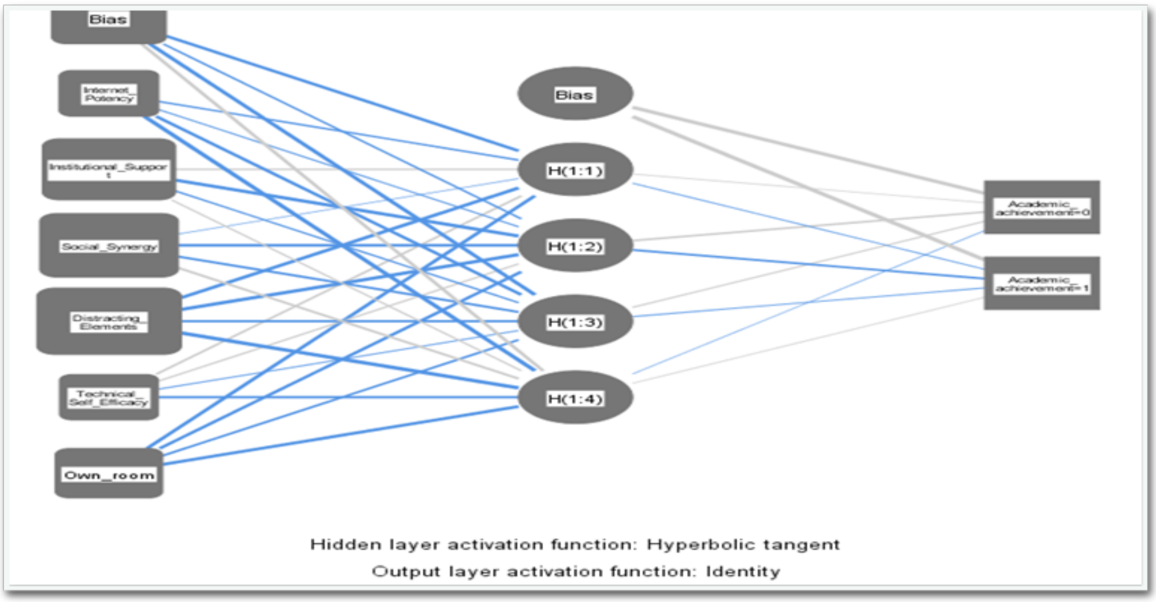
Rotation converged in 6 iterations.

4.2 Artificial Neural Network (ANN) Analysis

Constructive predictive analytics necessitates more than merely identifying past data trends. Predictive analysis requires associating the relationships between the existing data and representing the probability of a desired outcome based on the estimated significance of those relationships. Here comes the Artificial Neural networks, which are often considered excellent techniques for modeling the association between the predicting and outcome variables when no mathematical formula is known to relate both variables (Mahanta, 2018). Researchers originally developed the neural network technique to mimic the neurophysiological workings of a human brain (SAS Insights, 2023). The neural networks have three primary layers: the Input layer, the hidden layer, and the output layer. The most crucial part is the input layer, as it takes the input neurons for analyzing and predicting the probability of the outcome variable. The hidden layer attaches weights to these neurons, determining the magnitude of the outcome variables. The ANN technique learns by adjusting the weights attached to those neurons, thereby minimizing the error by making predictions for outcome variables.

The robustness against small sample sizes, outliers, and noise makes ANN an excellent choice for further predictive analysis. Furthermore, ANN can be applied over non-normal data distributions and over data where there is a non-linear relationship between the exogenous and endogenous variables. The ANN analysis in the present study is conducted using the neural network module in SPSS. The unique capability of the ANN algorithm in capturing the relationship between non-linear and linear data makes it very useful for further analysis (Teo et al., 2015). There are two main steps in the ANN: training and testing, which predict the outcomes of the input variables. To minimize the error in the training phase, the output layer error is propagated backward to the input layer, and the process continues until the model reaches minimal error. Thus, using a feed-forward-backward-propagation algorithm, the ANN technique makes the model smarter during each process repetition (Taneja & Arora, 2019).

Figure 1: *Artificial Neural Network Diagram (Hidden Layer Activation Function: Hyperbolic Tangent; Output Layer Activation Function: Identity)*



In the study, the five significant factors from the EFA results were taken as input neurons for the ANN. In the ANN, the multilayer perception technique used hyperbolic tangent, see Fig. 1, as the hidden layer activation function and identity as the output layer activation function. After several rounds of training in the learning process, the error in the model can be minimized, and the model's accuracy can be further increased (Idrissi et al., 2019). 70% of the samples were allocated for training purposes, and the remaining 30% were earmarked to test the optimized model. A ten-fold cross-validating procedure was adopted to avoid over-fitting the generated model, and the RMSE values were obtained (Ooi& Tan, 2016). Table II portrays the obtained RMSE values after running the model ten times. The mean RMSE values of training and testing samples were 0.4427 and 0.4419, respectively. The result of both phases of the ANN analysis suggests an excellent fit for our model predicting AAS among students (Alam et al., 2021).

Table 2: *Root Mean Square Values*

Training			Testing			
N	SSE	RMSE	N	SSE	RMSE	Total Samples
394	79.814	0.4501	169	31.522	0.4319	563

411	82.693	0.4486	152	27.949	0.4288	563
397	78.968	0.4460	166	33.086	0.4464	563
409	80.425	0.4434	154	30.581	0.4456	563
384	75.915	0.4446	179	32.454	0.4258	563
392	73.581	0.4333	171	35.849	0.4579	563
412	79.405	0.4390	151	30.381	0.4486	563
389	75.379	0.4402	174	35.059	0.4489	563
384	74.850	0.4415	179	34.466	0.4388	563
397	77.077	0.4406	166	33.111	0.4466	563
Mean	77.811	0.4427	Mean	32.446	0.4419	
Standard Deviation	2.74348	0.004677	Standard Deviation	2.28385	0.009722	

Note: SSE = Sum square of errors, RMSE = Root Mean Square of Errors, N= Sample Size

The sensitivity analysis (Table III) in ANN analyzed the predictive power strength of each input neuron. Sensitivity analysis results of the model determine how much sensitives are the model's parameters regarding the whole model. Sensitivity in the model refers to the overall changes in the structure of the model following the change in the value of the input parameters. A high sensitivity value can drastically change the system performance, whereas a low value poses a lesser significant threat to the overall system. The normalized importance was further calculated by dividing the importance of each neuron by the neuron of the maximum significance and was later presented as a percentage (Nourani & Fard, 2012a). One of the demographic variables was also added to the primary factors obtained in the earlier EFA. This demographic variable of owning a separate room added a distinct feature to the study by supporting the earlier found aspects. The results showed that the 'distracting elements' are the most critical factor while measuring the AAS, followed by the 'Institutional Support' factor, with a normalized importance of 87.9%. These two factors were followed by 'Social Synergy' with a significance of 79.8%, 'Own Room' with 29%, 'Internet Potency' with 24%, and Technical Self Efficacy with the least important of 17.2%. Table III depicts the sensitivity analysis between the ANN output and input neurons based on the first-order partial derivation method (Nourani & Fard, 2012b).

Table 3: *Sensitivity Analysis*

Neural Network(NN)	IP	IS	SS	DE	TSE	OR
NN(i)	0.075	0.275	0.207	0.351	0.028	0.064
NN(ii)	0.067	0.218	0.209	0.316	0.076	0.114
NN(iii)	0.097	0.200	0.233	0.341	0.043	0.086
NN(iv)	0.071	0.225	0.252	0.279	0.067	0.106
NN(v)	0.088	0.310	0.208	0.289	0.039	0.066
NN(vi)	0.052	0.327	0.265	0.262	0.026	0.068
NN(vii)	0.035	0.209	0.233	0.366	0.062	0.094
NN(viii)	0.122	0.339	0.226	0.194	0.032	0.087
NN(ix)	0.083	0.243	0.292	0.242	0.056	0.084
NN(x)	0.019	0.256	0.238	0.320	0.080	0.088
Average Importance	0.071	0.260	0.236	0.296	0.051	0.086
Normalized Importance ` (%)	24.0	87.9	79.8	100.0	17.2	29.0

Note: IP = Internet Potency, IS = Institutional Support ,SS = Social Synergy , DE = Distracting Element, TSE = Technical Self Efficacy, OR = Own Room

5. Discussion

Artificial Neural Networks (ANN) can be a powerful tool for predictive analytics. The key to using ANNs to predict the AAS of students is to identify the factors that are likely to influence their satisfaction while learning online. The exploratory factor analysis of the data collected has provided these relevant factors. The patterns and relationships between the factors and satisfaction have been identified using ANN. This information generated may be used to predict what leads to academic achievement satisfaction.

Internet Potency: The availability and disruption of internet access can have a significant impact on online learning, especially in areas where internet infrastructure is weak or unstable. Several studies have identified the digital divide as a major barrier to online learning. The students in low-income countries were less likely to have access to high-speed internet and the necessary technology to participate in online learning (Ndibalema, 2022). This can lead to disparities in access to education and can exacerbate existing inequalities. Internet disruptions can also have a significant impact on online learning. A systematic review studyMutalib et al. (2022) also identified internet issues as one of the prevalent problems in effective online learning. Disruptions can also lead to frustration and disengagement, which can negatively impact student motivation and learning outcomes. To mitigate the impact of internet disruptions, several strategies have been proposed. One approach is to design online courses that are less reliant on high-speed internet, such as providing downloadable materials and using low-bandwidth tools for communication and collaboration. Another approach is to provide alternative means of internet access, such as mobile data plans or community internet centers. However, these strategies may not be feasible in all contexts, especially in areas where internet infrastructure is weak or unstable. In such cases, governments and other stakeholders need to invest in digital infrastructure to ensure that all students have access to high-speed internet and the necessary technology for online learning. A study by the United Nations Educational, Scientific, and Cultural Organization (UNESCO) found that the COVID-19 pandemic has highlighted the need for increased investment in digital infrastructure, particularly in low-income countries('Education in a post-COVID World,' 2022). Mitigating the impact of these disruptions requires careful planning and investment in digital infrastructure to ensure that all students have access to high-quality education.

Institutional Support: Students seek support from the institution in the form of trained and efficient faculty, staff, and online learning platforms (Omar et al., 2021). Many faculty members in Indian universities may not be comfortable with online teaching and lack the necessary skills and training to effectively deliver online courses. Similarly, students may not be familiar with online learning platforms and may struggle to adapt to online learning environments. Despite these challenges, many educational institutions in India are investing in online learning infrastructure. Many universities in India are partnering with online learning platforms and investing in digital infrastructure to offer online courses. Investing in digital infrastructure can improve internet connectivity and provide access to technology. Providing training and support for faculty and students will ensure that they are comfortable with online teaching and learning, and online courses are to be deigned that are interactive and engaging.

Distracting Element: Self-determination is essential for success in online learning. This study also showed that the distracting elements are the most critical factor while measuring the AAS. Learners must take responsibility for their learning, set goals, manage time effectively, remain motivated, and seek help when needed (Omar et al., 2021). According to SDT, when individuals are able to satisfy these psychological needs, they are more likely to be intrinsically motivated and engaged in their activities. The aversion of distraction while studying online can be justified by SDT, as it relates to individuals' need for autonomy and competence. Autonomy refers to the need for individuals to feel in control of their own lives and make their own decisions. Competence refers to the need for individuals to feel capable and effective in their activities. When students are studying online, they may face numerous distractions, such as social media, email, or other online activities. These distractions can interfere with their autonomy and competence by taking away their control over their learning environment and reducing their ability to focus and effectively engage with their studies. By minimizing distractions while studying online, students are able to satisfy their need for autonomy by taking control of their learning environment and ensuring that they have a distraction-free space to focus on their studies. They are also able to satisfy their need for competence by creating an environment that allows them to be more effective and efficient in their studying, thus enhancing their feelings of capability and effectiveness. Overall, SDT justifies the aversion of distraction while studying online as a means of satisfying individuals' innate psychological needs for autonomy and competence. By minimizing distractions, students can create an environment that allows them to be more intrinsically motivated and engaged in their learning activities, leading to improved academic performance and outcomes.

Social Synergy: Social interaction has a positive and significant impact on the effectiveness of online learning. Online learning can be isolating, and without social interaction, students may struggle to feel engaged and motivated. Collaborative activities such as group discussions, peer reviews, and group projects create a sense of community and increase students' investment in their own learning. Social interaction also encourages students to take an active role in the learning process (Baber, 2021), which can lead to better retention and understanding of course material. Furthermore, social interaction allows students to receive support and feedback from their peers and instructors, which can help them to improve their learning outcomes. Peer feedback can be especially valuable, as it allows students to receive multiple perspectives on their work (Wright & Horta, 2018) and to learn from their peers' experiences. Social interaction also builds social and emotional connections. This can be especially important for students who are learning remotely or who are in asynchronous courses. By incorporating social interaction into their online courses, educators can improve the learning outcomes of their students.

Overall, social interaction is a critical component of effective online learning, as it enhances engagement, facilitates active learning, provides support and feedback, and builds social and emotional connections.

Technical Self-efficacy: Students differ in technology readiness to learn online. This also impacts their self-efficacy, class engagement, and achievement satisfaction (Warden et al., 2020). A study by Wei & Chou (2020) also assessed the perception of students for online learning and they found that students' computer self-efficacy influences their satisfaction in academics. In this study, this factor does not impact much on AAS as the students may have gained requisite knowledge and have been conditioned to use online resources.

Own Room: Limited space or non-availability of own room is a common challenge that many students face, especially those who are learning from home. It is true that limited space can make it difficult for students to find a quiet and distraction-free environment to learn in, and the presence of family members or other household members can add to the noise and distractions. Yeung and Yau (2022) also identified in their qualitative study the importance of disturbance free space to learn online. Not having a disturbance-free space is not ideal and can have negative consequences on a student's ability to learn effectively (Mathrani et al., 2021). The availability of own room or a disturbance-free space is one of the relevant predictors of AAS in our study. While some students may be able to adapt and focus despite the noise, many others may struggle and find it difficult to concentrate or participate fully in their online classes. This can lead to low AAS.

6. Future Implications

Several research studies, like the one conducted by Castro and Tumibay (2021), have indicated that online learning can be as effective as traditional classroom-based learning. However, it's important to note that the effectiveness of online learning may depend on various factors, such as the design of the online course, the level of student engagement, and the availability of support and resources for online learners. India's Swayam Massive Open Online Courses (MOOC) is outperforming with more than 2 crore students enrolled, but the success in terms of the students who have earned the certificates is less. There are many possible reasons why a student may enroll in an online program but struggle to complete it successfully. It is important for students to carefully consider their motivations and needs before enrolling in an online program and to seek out the necessary support to ensure their success.

India's Digital University initiative aims to create a network of digital universities across India to provide high-quality online education to students. Under the Digital University initiative, the UGC has set up a Digital Infrastructure for Knowledge Sharing (DIKSHA) platform, which provides a range of digital resources for learners and teachers, including e-books, e-journals, videos, and interactive courses. The platform is designed to be user-friendly and accessible to students from anywhere in the world. The Digital University initiative is still in its early stages, but it has the potential to transform higher education in India by making quality education accessible to more students, regardless of their location or socioeconomic background. The initiative also aligns with the government's Digital India campaign, which aims to promote digital literacy and digital infrastructure development across the country. Online education has the potential to play a significant role in India's efforts to achieve a Gross Enrolment Ratio (GER) of 50% in higher education by 2035. Online education can provide flexible, accessible, and affordable learning opportunities to students who may not have access to traditional classroom-based education. It can also help to address the issue of limited physical infrastructure and faculty resources in many parts of the country.

However, there are also challenges associated with online education that must be addressed to ensure its effectiveness and to avoid exacerbating existing disparities in access to higher education. For example, not all students have access to reliable internet connections or the necessary technology to participate in online classes. Additionally, online education may not be suitable for all types of learners, and some students may struggle with the lack of separate spaces to study and face-to-face interaction with instructors and peers. To ensure the success of online education in India, it will be important to develop strategies to address these challenges and to provide support and resources to students who are learning online. This may include providing access to technology and reliable internet connections, offering training and support for students and faculty to facilitate effective online learning, and ensuring that online courses are designed in a way that is engaging, interactive, and inclusive. Overall, online education has the potential to be a powerful tool for expanding access to higher education in India, but it must be implemented thoughtfully and with a focus on ensuring equity and quality in education.

7. Conclusion

The purpose of this paper was to investigate the impact of online learning on the AAS of the students of higher educational courses. The results showed that the 'distracting elements' are the most critical factor while measuring the AAS, followed by the 'Institutional Support' factor. These two factors were followed by 'Social Synergy', 'Own Room', 'Internet Potency', and 'Technical Self Efficacy'. An understanding and acknowledgment of the impact of such factors on the AAS of the students is important for designing successful interventions and strategies for promoting online education. Most notably, this paper confirms the integral role of the determination of the learner in the success of any online course.

Additionally, institutional support, access to space and network facilities, and confidence in the technical capabilities of the learner facilitate the AAS of the students. These factors offer opportunities to researchers, policymakers, and practitioners to reflect on the antecedents leading to academic achievement satisfaction among students in an online setup. Therefore, self-determination, institutional support, access to the internet and space etc., must be taken care of while administering an online course for enabling AAS.

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