International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Exploring the Causes and Consequences of Dropout Syndrome Among Students Using E-Learning Platforms

Ms. Pv Juvin Stephy[1], Dr. Edakkotte Shaji[2]

[1]PhD Scholar, Commerce, Government Arts & Science College Calicut Kerala
[2]Research Guide, Commerce, Government Arts & Science College Calicut Kerala

ABSTRACT
As the use of e-learning platforms rises, many students are experiencing difficulties that result in decreased engagement or complete withdrawal—a phenomenon known as dropout syndrome. This study examines the main causes of behaviour, focusing on elements like motivation levels, technological difficulties, economic and language barriers, personal factors, and digital fatigue based on data collected from 100 undergraduate students in the Palakkad district. Findings reveal that personal circumstances and accessibility challenges have the most significant impact on student satisfaction, while motivation and technical issues show minimal influence. Motivation and technical issues showed minimal influence likely because respondents had varied backgrounds and coping abilities, leading to different experiences and reduced overall impact. Although satisfaction plays a role, its link to app avoidance is limited, suggesting that dropout syndrome is driven by deeper, often unresolved, personal and contextual reasons. The study further supports the distinctiveness of each variable using HTMT analysis, improving the dependability of the findings. The research suggests that dropout or avoidance behaviour is less about app design or motivation, and more about external, real-life challenges faced by learners. Making e-learning app more accessible, inexpensive, and accommodating to a range of student demands should be the main goal of future initiatives to reduce dropout syndrome.

Keywords: dropout syndrome, app avoidance, E-learning app, online learning challenges.

INTRODUCTION
In recent years, the rise of e-learning platforms has completely changed the educational landscape, making learning more adaptable, scalable, and accessible. The COVID-19 pandemic rapidly accelerated this transformation, prompting universities worldwide to embrace technologies such as Google Classroom, Moodle, and Coursera to assure educational continuity (Dhawan, 2020). Online learning has consequently established itself as a permanent component of many academic systems, encouraging self-directed learning and digital literacy. Critical flaws have been revealed by this change, nevertheless, most notably the rising dropout rates in online courses. Unlike typical classroom contexts, e-learning lacks physical presence, frequently leading in feelings of isolation, decreased motivation, and limited participation (Lee & Choi, 2011). Inadequate instructor support, digital fatigue, time management problems, and technical difficulties all contribute to this issue, which is now known as dropout syndrome in online learning (Aljaraideh & Khader, 2020).

A complex combination of academic, technological, and personal factors contributes to the dropout syndrome, which causes students to stop using e-learning platforms. This phenomenon has major impacts for student academic achievement and psychological well-being, as well as the long-term credibility and effectiveness of online education systems (Xavier & Meneses, 2020). Understanding dropout syndrome is crucial for increasing the quality and effectiveness of online education. If the causes of dropout are not fully addressed, e-learning's promise to democratize and make education more inclusive will collapse. This is especially important for undergraduate students, who rely on these platforms for academic advancement and professional development. While some studies have concentrated on instructional approaches and technical difficulties, little study has been done on the psychological and engagement-related factors that contribute to dropout. Furthermore, few research examine the connections between these problems or the potential mediating role that student happiness and involvement may play in dropout rates.

Particularly after the COVID-19 epidemic, dropout syndrome among Indian students utilizing e-learning apps has grown to be a significant worry. A lack of interest and engagement brought on by repetitive material and little interaction is one of the main reasons (Muthuprasad et al., 2021). The rise of e-learning platforms has transformed Indian education and given students access to information and skills never before possible. Dropout rates, however, continue to be a major problem in spite of their promise, especially for students from a variety of socioeconomic backgrounds. This problem is caused by a number of factors, including lack of involvement, technological challenges, mental health issues, and financial obstacles. A diversified strategy that incorporates technology innovation, individualized learning, and robust support networks is needed to address these issues. E-learning may also be made more accessible and efficient by addressing the technical gap, providing various price options, and guaranteeing that the content is relevant to practical skills. In order to lower dropout rates and improve the overall learning experience, this study will examine the main causes of dropout syndrome in e-learning settings and offer workable remedies. The current study is to investigate the growing concern about dropout syndrome in e-learning apps by identifying its underlying causes and analyzing its impact on undergraduate students. The study specifically aims to comprehend the several elements that lead to students dropping out of online courses, including mental fatigue, technological difficulties, and a lack of motivation. It also looks at how this dropout behaviour affects students' academic achievement and determines their choices for further education. This study aims to offer insights that will aid in the creation of more inclusive and sustainable digital learning environments by addressing the research questions: What are the main causes behind e-learning dropout syndrome? Is there a significant relationship between student satisfaction and their likelihood to discontinue or avoid e-learning platforms?

LITRATURE REVIEW

Considerable study has been conducted on the effectiveness, challenges, and results of digital learning environments as a result of the growing dependence on e-learning platforms for education. Particularly, there has been a lot of interest in understanding precisely what causes dropout syndrome in online learning. E-learning helped businesses retain information, improve skills, and save money on training. Tracking student progress and personalizing content were also enhanced by the application of learning analytics. Giannakos et al. (2022). A thorough research review revealed that gamified components such as badges, leaderboards, and point systems significantly boosted learners' motivation, engagement, and involvement. By converting passive learning into an active process, these components improve understanding and retention Saleem et al. (2022). But even while gamification can increase motivation, Domínguez et al. (2013) cautioned that unless it is properly incorporated with educational objectives, it does not always result in improved academic achievement.

Research on mobile-supported e-learning and came to the conclusion that, when used in conjunction with traditional methods, mobile applications enhance learner autonomy, social collaboration, and engagement. However, they also stressed that excessive dependence on mobile devices without instructional support may have a detrimental effect on structured learning outcomes Wang and Sazalli (2024).The impact of affordability and accessibility on dropout rates has also been studied; results show that students from low-income families are especially at risk of dropping out because of their restricted access to technology and financial limitations (Gupta & Sharma, 2020; Biswakarma, 2020).

These technological issues cause students to become frustrated and disturb the learning process, which raises the dropout rate. Information overload is also a serious problem. Numerous apps overburden users with information without proper organization, which leads to mental and cognitive tiredness (Mishra et al., 2020). And argue that self-regulated learning skills, such as time management and goal-setting, are vital for online success; without these, learners often lose motivation and withdraw prematurely Lee and Choi (2011). Hence, important factors are carefully analyzed, including student involvement, technology constraints, motivational level, language or economic barriers and personal factors. In addition to summarizing previous studies, the review points up important gaps, inconsistencies, and unknown elements leading to additional investigation. In addition to improving the research's academic rigor, the review provides a clear and pertinent context by grounding the current investigation in known theoretical and empirical findings. The development of focused, research-based tactics to lower dropout rates and enhance the general efficacy and inclusiveness of e-learning platforms is supported by this foundation.

CONCEPTUAL FRAMEWORK AND HYPOTHESES

Based on the previous significant studies and theories, as discussed earlier, the researchers propose an theoretical model that consist of five attributes of dropout syndromes in e-learning apps that is technical issue, motivational level, digital fatigue, personal factor, language or economical barrier. H1 through H5 have been found to be important variables that either directly or indirectly impact dropout rates by first lowering student satisfaction and engagement. By mapping both direct and indirect pathways, the framework underscores the complex, interconnected nature of dropout behaviour and highlights the critical role of learner engagement in preventing it.

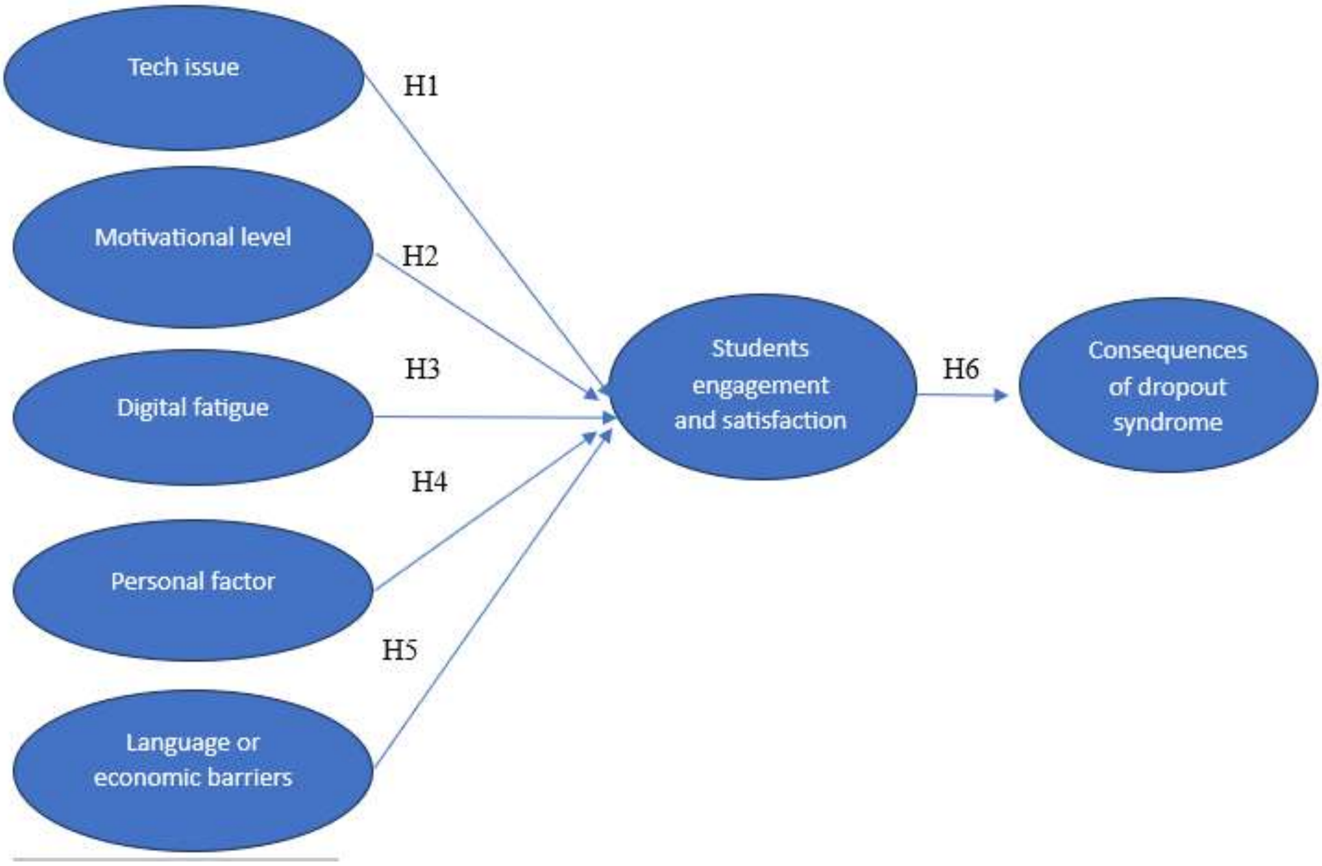

Fig.1 conceptual framework

Students experiences and results can be greatly impacted by a number of outcomes. Lack of motivation is one of the most common causes of disinterest and leaving. Students are significantly more likely to lose interest in and give up on their studies when they feel disengaged or lack a clear learning purpose. Similar to this, dissatisfaction and dropout might result from bad internet or gadget problems. Students find it challenging to fully engage in online learning activities due to technical issues like sluggish internet speeds or unsuitable equipment, which create access obstacles. An abundance of data material is another factor, which frequently leads to withdrawal and anxiety. Pupils may become stressed and burned out and stop participating in the learning process if they are given too much stuff to understand.

When learning experiences aren't personalized, students may feel excluded since they don't think the material is catered to their requirements, interests, or learning style. Feelings of frustration or inadequacy may arise from this. Another factor that might contribute to a loss of mental health is isolation, particularly in online learning situations where students do not have access to peer and teacher support and social contact. Depression, anxiety, and loneliness can all be exacerbated by an absence of community. Lastly, language and economic barriers pose significant challenges to access difficulties. Students who are not proficient in the language of instruction may struggle to comprehend course materials, while those facing economic hardships may lack the necessary resources (such as devices or internet access) to participate in online learning, further limiting their educational opportunities.

Hence , we propose the following hypotheses:

H1: Technological issues have a significant impact on students' engagement and satisfaction in e-learning platforms.

H2: Motivational level significantly affects the students' engagement and satisfaction in e-learning platforms.
H3: Digital fatigue negatively affects students' engagement and satisfaction in e-learning platforms.
H4: Personal factors (such as time management, family responsibilities, etc.) significantly influence students' engagement and satisfaction in e-learning platforms.
H5: language or economic barriers positively influence students' engagement and satisfaction.
H6: Students' engagement and satisfaction mediate the relationship between the above factors and the consequences of dropout syndrome, such as poor academic performance, psychological issues, and avoidance of future e-learning.

METHODS

The data are collected through a structured questionnaire obtaining responses from 100 undergraduate students from Palakkad district. The data collected for this study is conducted using a questionnaire with five-point Likert scales. An online version of the questionnaire was sent to the undergraduate students, accompanied by a cover letter. The data awas collected through purposive random sampling and was shared with students in an online class in arts and science. A conceptual framework is proposed for this study to provide a structured and logical foundation for understanding the factors contributing to dropout syndrome in e-learning. It helps to clearly define the relationships between key variables such as learner motivation, socio-economic background, technological access, mental well-being, and academic outcomes. And the study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4.0 software to analyze the relationships between latent constructs.

DEMOGRAPHIC PROFILE OF E-LEARNING APP USERS

The analytic sample comprised of 100 respondents. As can be seen in table 1. The demographic analysis reveals that the majority of respondents (95%) were between the ages of 18 and 25, emphasizing the dominance of young adult learners in e-learning participation. Only 2 percent were younger than 18 and 3 percent were between the ages of 26 and 35. Gender distribution was 66% female and 34% male, indicating that women were more likely to participate in the study. And among disciplines Commerce students made up 55% of the sample, followed by Arts (34%), and Science (11%), demonstrating that commerce learners are well represented in the utilization of e-learning platforms.
In terms of platform utilization, LinkedIn Learning was the most popular (59%), indicating a focus on professional development. Other platforms were Coursera (16%), Khan Academy (12%), Udemy (9%), and Duolingo (4%).

Table 1. Demographic profile of e-learning app users (n=100)

Category	Options	Frequency	Percentage
Age	Under 18	2	2
	18-25	95	95
	26-35	3	3
	36-45	0	0
Gender	male	34	34
	Female	66	66
Discipline	Arts	34	34

	Commerce	55	55
	Science	11	11
	others	0	0
Most used platforms	Khan academy	12	12
	LinkedIn learning	59	59
	Coursera	16	16
	Udemy	9	9
	Duolingo	4	4
	Others	0	0

DATA ANALYSIS AND RESULTS

MEASUREMENT MODEL ASSESSMENTS

The measurement models are assessed for internal consistency (Cronbach's alpha and composite reliability), convergent and discriminant validity. As shown in table 2, the Cronbach's alpha and composite reliability values were above 0.6 and 0.7 , reflecting internal consistency reliability. Convergent validity was analyzed using indicator reliability and average variance extracted (AVE) (Hair et al., 2019).

Most constructs, including Technical Issues, Motivational Level, and E-learning App Avoidance, have good internal consistency (Cronbach's alpha > 0.7), strong composite reliability (CR > 0.7), and reasonable convergent validity (AVE > 0.5). However, the Satisfaction construct has a low AVE (0.304), indicating poor convergent validity and maybe requiring change. The measuring model is generally trustworthy and valid, with the exception of the satisfaction items.

Table 2. Measurement model evaluation: Internal consistency and convergent validity.

construct	**indicator**	**Survey question**	**alpha**	**CR**	**AVE**
Technical issue	TI1	I have consistent access to a reliable internet connection.	0.947	0.936	0.767
	TI2	I experience technical difficulties that disrupt my online learning.			
	TI3	The e-learning platform I use is user-friendly and accessible.			
	TI4	Technological issues reduce my willingness to continue learning online.			
	TI5	Poor connectivity affects my participation in online classes.			
Motivational level	M1	I feel motivated to attend and complete online classes.	0.671	0.918	0.841
	M2	My interest in course content keeps me engaged in e-learning.			
	M3*	I set personal goals to stay focused during online learning.			
	M4*	I stay motivated even without in-person interaction.			

Digital fatigue	DF1	I feel mentally exhausted after long hours of online learning.	0.742	0.869	0 .599
	DF2	Prolonged screen time affects my concentration during classes.			
	DF3	I take breaks to avoid digital fatigue.			
	DF4	Digital fatigue decreases my motivation for e-learning.			
	DF5*	I experience physical symptoms (eye strain, headaches) due to screen use.			
Personal factors	PF1*	I manage my time effectively for online learning.	.626	0.733	.532
	PF2*	Family responsibilities interfere with my learning.			
	PF3	I have a quiet space for studying at home.			
	PF4	I delay or miss tasks due to other responsibilities.			
	PF5	Personal commitments reduce my engagement in e-learning apps.			
Language or economic barrier	ES1*	My instructors provide timely feedback and support.	0.640	0.741	0.544
	ES2*	I feel encouraged through peer interaction.			
	ES3	I can easily reach instructors/support staff when needed.			
	ES4*	I feel supported emotionally in the online learning environment.			
	LE5	It makes me difficult to adapt the language			
Satisfaction	S1*	I feel actively involved in online learning.	0.637	0.709	0.304
	S2	I am satisfied with the overall quality of my e-learning experience.			
	S3	I would recommend e-learning platforms to other students.			
	S4	Online learning is as effective as classroom learning.			
	S5*	Online learning is as effective as classroom learning.			
E -learning app avoidance	E1*	Due to my past negative experiences, I am unwilling to enroll in online courses in the future.	0.711	0.720	0.630
	E2*	Even if online courses are more flexible, I would still choose in-person classes because I learn better in that setting			

	E3	I intentionally avoid registering for online courses whenever possible.			
	E4	The lack of interaction and support in online learning has made me reluctant to continue with this mode of education.			
	E5	I believe that online learning does not meet my academic or personal needs, and I prefer to avoid it going forward.			

* Items removed due to low loadings.

DISCRIMINANT VALIDITY ASSESSMENT

According to Henseler et al. (2015), discriminant validity is best evaluated based on heterotrait-monotrait (HTMT) values , which have to be under 0.85. With a single exception, all values respected this rule. The table 3 shows The HTMT assessment for discriminant validity outperforms the Fornell and Larcker criterion, as well as the assessment of cross-loadings (Henseler et al., 2015).

The correlation matrix provides useful information about the relationships between the six variables. Some variables, like PF and TI, have very strong positive correlations (0.879), but other variables, like S and TI, only have weak correlations (0.197). The majority of the correlations have moderate to weak associations, with a few exceptions, such as ES and M (0.703), showing a high positive link. However, the unusually high correlation between E and DF (1.299) requires more examination because it exceeds the conventional correlation value.

Table 3. Discriminant validity assessment using Heterotrait-Monotrait ratio (HTMT) criterion

	E	**DF**	**ES**	**M**	**PF**	**S**	**TI**
E							
DF	1.299						
ES	0.049	0.399					
M	0.287	0.218	0.703				
PF	0.302	0.335	0.824	0.268			
S	0.229	0.216	0.581	0.188	0.358		
TI	0.370	0.234	0.742	0.879	0.313	0.197	
*E= e -learning app avoidance, DF= digital fatigue, ES = language or economic barrier, M = motivational level, PF= personal factors, S= satisfaction, TI= technical issue							

Note: Values represent heterotrait-monotrait ratios of correlations (HTMT values).

COLLINEARITY ASSESMENT

Before assessing structure model, we checked collinearity issues. Our inner model variances inflation factor (VIF) values ranged between 1.049 to 3.066 suggesting no collinearity issues. The table 4 presents the relationship between various independent variables and their influence on e-learning app avoidance, mediated by satisfaction. With satisfaction being regarded as both a dependent variable (impacted by the independent constructs) and a predictor of e-learning app avoidance, the values represent the relative effects or path coefficients obtained from the structural model. Technical problems have the largest impact (3.019) on user satisfaction among the independent variables, suggesting that frequent technical issues raise the risk of e-learning app avoidance by drastically lowering user satisfaction. Additionally, motivation level exhibits a strong influence (2.783), indicating that user engagement and satisfaction are significantly impacted by lower motivation levels. Digital fatigue (1.124), personal factors (1.076), and language or economic barriers (1.223) all have an impact on satisfaction, with the exception a smaller one. In the model, satisfaction plays a mediating role, as evidenced by its direct path coefficient of 1.000 towards e-learning app avoidance.

Table 4. Measurement model evaluation: Internal consistency and convergent validity.

Hypothesis	Path coefficient	P -value	F^2	Supported?
H1:Technical issues -> satisfaction	-0.016	0.843	0.002	No
H2:Motivational level ->satisfaction	0.030	0.921	0.000	No
H3: Digital fatigue -> satisfaction	0.030	0.201	0.075	No
H4:Personal factors -> satisfaction	0.208	0.045	0.051	Yes
H5:Language or economic barrier -> satisfaction	0.331	0.033	0.115	Yes
H6: E-learning app avoidance -> satisfaction	0.157	0.055	0.025	Yes (marginal)
Control variables				
Age -> e-learning app avoidance	0.042	0.862	0.002	No
Gender -> e-learning app avoidance	0.144	0.459	0.021	No
Purpose of usage -> e-learning app avoidance	0.211	0.310	0.046	No

Table 5. collinearity assessment using variances inflation factor (VIF)

Independent variables	**Dependent variables**	
	Satisfaction	**Satisfaction -> E -learning app avoidance**
Digital fatigue	1.124	1.000
Language or economic barrier	1.223	
Motivational level	2.783	
Personal factors	1.076	

Technical issue	3.019	

Note: Inner variance inflation factor (VIF) values.

STRUCTURAL MODEL RESULT

We evaluated the size and significance of path coefficients as well as the model's explanatory power in accordance with established guidelines (Hair Jr., Hult, Ringle, & Sarstedt, 2017). Additionally, collinearity assessment was reported using effect sizes (f2), predictive relevance (Q2), and inner VIF values. Age, gender, and purpose of usage were the three control variables included.

In fig 2. refined structural model, after removing low-loading indicators, highlights key predictors of satisfaction (S) in e-learning. Language or economic barriers (β = 0.331), digital fatigue (β = 0.256), and personal factors (β = 0.208) have the strongest positive impacts on satisfaction. In contrast, technical issues (β = –0.061) and motivation (β = 0.030) show minimal influence. Satisfaction moderately predicts e-learning app avoidance (E) (β = 0.157). The removal of low-loading indicators has improved the measurement quality, ensuring that each construct is represented by strongly loading items (generally above 0.7), enhancing the reliability and validity of the model. Overall, the refined model offers a clearer picture of which factors most strongly impact user satisfaction and subsequent avoidance behaviour in e-learning environments.

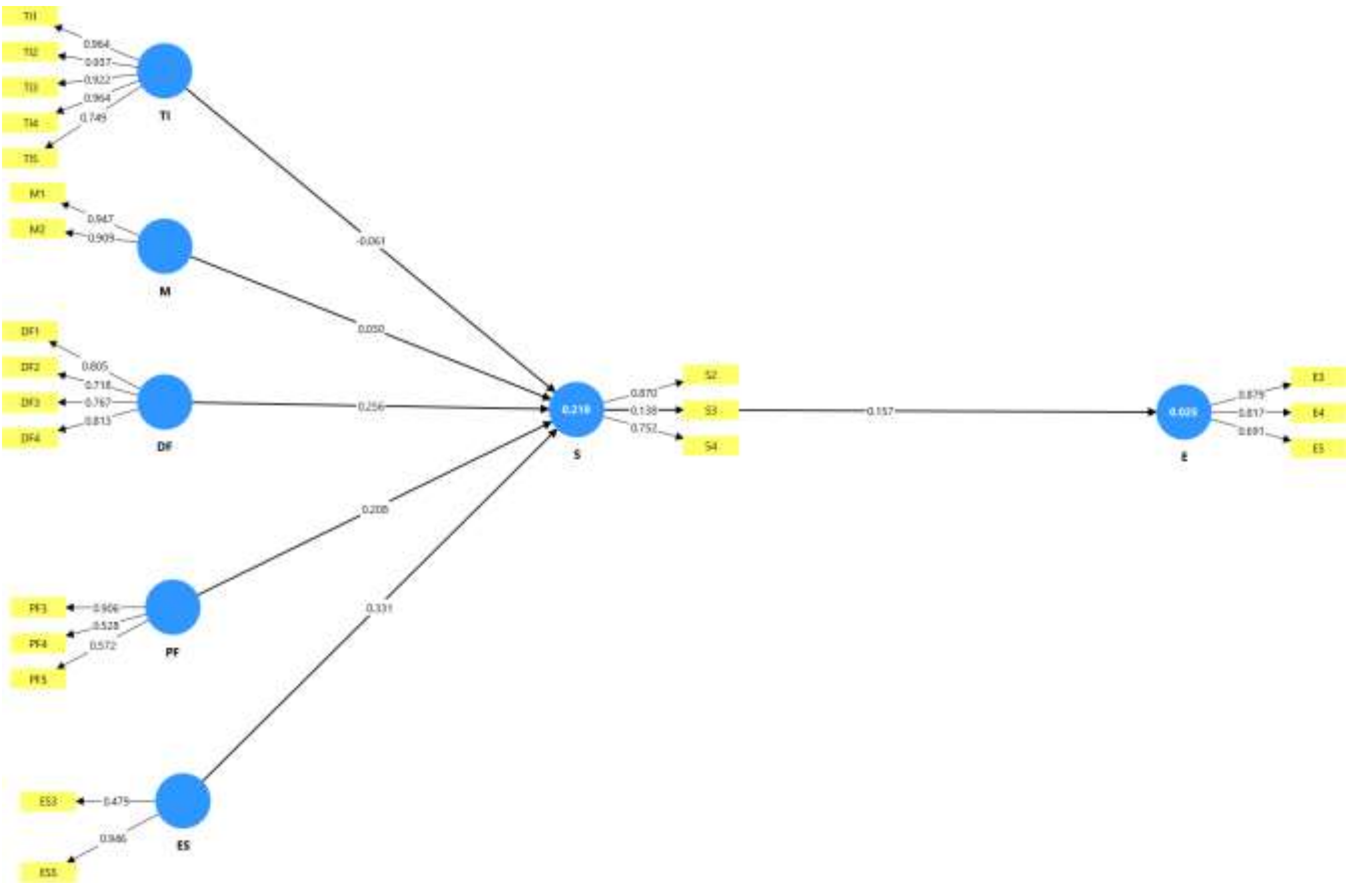

Fig.2 Structural model

Structural model analysis revealed that personal factors (β = 0.208, p = 0.045) and language or economic barriers (β = 0.331, p = 0.033) have a significant positive impact on satisfaction, thus supporting H4 and

H5. E-learning app avoidance also showed a marginally significant effect on satisfaction (β = 0.157, p = 0.055), supporting H6. However, technical issues (β = -0.016, p = 0.843), motivational level (β = 0.030, p = 0.921), and digital fatigue (β = 0.030, p = 0.201) did not significantly affect satisfaction. Similarly, the control variables — age (β = 0.042, p = 0.862), gender (β = 0.144, p = 0.459), and purpose of usage (β = 0.211, p = 0.310) — were not significant predictors of e-learning app avoidance.

DISCUSSION

As the usage of digital learning platforms grows more popular, concerns have emerged about students' decreased interest or outright disengagement from these technologies over time. Even if e-learning is accessible and flexible, many users opt to cut back on or stop using it because of a variety of environmental, psychological, and personal issues. The findings of the study provide insight into the fundamental causes of app avoidance behaviour, including technological difficulties, personal factors, lack of motivation, and digital tiredness. These findings are analysed in the context of previous studies to determine the ways in which these factors influence disengagement.

Although technical problems including erratic internet availability and usability issues were observed, were noted but did not significantly predict satisfaction or app engagement, suggesting that infrastructure alone is not the primary deterrent. Despite their conceptual significance, motivational level and digital fatigue had little statistical impact, suggesting that although students may feel tired and have varying drive, these factors may not be the actual cause of dropout. Personal factors and language or economic barriers, on the other hand, had a major impact, demonstrating how participation can be meaningfully disrupted by domestic duties, challenges in understanding content, and difficulty in accessing support. These obstacles were strongly associated with avoiding e-learning apps; many students expressed a preference for traditional learning because of the lack of engagement, bad experiences in the past, and unfulfilled academic or personal demands.

Constructs like e-learning app avoidance, digital fatigue, motivational level, technical issues, personal factors, satisfaction, and language or economic barriers were sufficiently different from one another, as evidenced by the fact that the HTMT values for all construct pairs fell within the acceptable threshold (usually < 0.85 or 0.90). The HTMT analysis, for example, verified that there was no statistical overlap between measurements that could seem theoretically linked, such as technical challenges and motivational level or personal factors and language barriers. By assuring that observed correlations are founded on distinct and well-defined constructs, this enhances the validity of additional structural path analysis and the measurement model's reliability. Digital fatigue, motivation levels, and technical challenges did not have any significant impact, suggesting that these problems might not significantly affect how students utilize the apps. This implies that students may continue to use the apps despite minor issues or fatigue. However, individual factors such as prior technological expertise and learning patterns did have a noticeable impact, demonstrating that each learner's background matters. Language and money-related issues also had a strong impact, which means e-learning apps should be made more affordable and easier to understand for everyone. App avoidance showed a weak but noticeable link, which means some students may avoid using these apps for reasons that need to be studied more, such as difficulty in use or low interest. Students' avoidance of the app was not significantly impacted by age, gender, or the reason for using it, indicating that these elements are not as significant in this situation.

The results can be used to enhance e-learning applications by emphasizing individual needs and lowering linguistic or financial obstacles to increase user satisfaction. This knowledge can be used by governments and educational institutions to develop support networks that improve learning opportunities and accessibility. App developers can incorporate features to lessen screen fatigue and maintain student engagement because digital tiredness still has certain effects. The little impact of technical problems and motivation indicates that these are less of an issue at this time, freeing up future efforts to concentrate on more important aspects. Since digital fatigue still has some effect, strategies to reduce screen time or include engaging, varied content can be implemented to maintain student interest this suggests there are other unmeasured factors that might be influencing avoidance more strongly.

CONCLUSION

The educational landscape has changed significantly as a result of the increasing usage of e-learning platforms, which offer flexibility, accessibility, and convenience. But in addition to these advantages, problems like dropout and app avoidance have also emerged. This study clarifies the complex network of variables that affect students' satisfaction and willingness to continue with e-learning apps. The results contradict the common belief that problems like technical challenges and motivational factors are significant barriers. Although they existed, technical issues like slow internet access or unusable apps did not have a major impact on user satisfaction or cause app avoidance. Similarly, although digital fatigue and motivational issues were conceptually relevant, they did not strongly predict user disengagement, indicating that students may tolerate minor inconveniences or motivational dips without fully abandoning the platforms.

Economic or language limitations, as well as personal variables, were the most significant factors contributing to app usage and satisfaction. These included problems including personal factors, a lack of experience with digital tools, budgetary limitations, and difficulties in understanding the app's content because of language barriers. These factors were strongly associated with e-learning app avoidance and had a significant effect on user happiness. This implies that individual circumstances and access-related difficulties, rather than broad perceptions of technology or small technical issues, greatly influence student participation. Additionally, by using HTMT analysis to validate the uniqueness of the components used—such as economic/language barriers, personal factors, and satisfaction—the study improved the model's dependability. Further research is necessary because the minimal variance explained in app avoidance behaviour suggests that disengagement may be caused by other, as yet unidentified causes.

These findings enhance the effectiveness and adoption of e-learning platforms, developers and educational policymakers must prioritize addressing personal, linguistic, and financial barriers. Customizing learning experiences, offering multilingual support, and providing financial aid or infrastructure support can improve engagement. It would be more beneficial to focus on customizing platforms to accommodate the various demands of students, even though technological and motivational issues should not be disregarded. This strategy can reduce app avoidance, raise student satisfaction, and guarantee that different learner groups can fully benefit from e- learning apps.

LIMITATION AND FURTHER RESEARCH

This study has certain limitations, but it also helps us understand why some students discontinue using e-learning applications. The information may not always be entirely accurate because it is based on what students say about their personal experiences. Since the survey was conducted at a certain moment in time, it cannot reveal how students' attitudes and behaviours may evolve over time. Furthermore, the findings may not be applicable to all children because they are based on a particular student population. Some

crucial elements, such as stress, students comfort level using technology, or how easily get distracted, were not thoroughly examined. Additionally, the study omitted students' own narratives or in-depth viewpoints, which may have indicated why they refrain from utilizing the apps.
To observe how students' use of e-learning apps evolves over time, research should track them. Speaking with students directly via interviews or group discussions might also be beneficial in order to gain a deeper understanding of their wants and issues. Researchers can examine how student engagement is impacted by elements including engaging learning resources, tailored material, and user-friendly designs. Studying students from diverse origins is also crucial to understand how factors like language, culture, or financial status impact their educational experiences. Lastly, it is important to investigate the potential influence of school policies, classmates, and teachers. This can assist educational institutions and app developers in producing better, more user-friendly educational resources.

REFERENCE

1. Aljaraideh, Y., & Khader, F. (2020). E-learning dropout: A qualitative study on the challenges faced by university students in Jordan. *Education and Information Technologies*, 25(6), 5731–5745.
2. Biswakarma, J. (2020). Impact of COVID-19 on digital education in India. *International Journal of Creative Research Thoughts (IJCRT)*, 8(6), 2327-2332.
3. Dhawan, S. (2020). Online learning: A panacea in the time of COVID-19 crisis. *Journal of Educational Technology Systems*, 49(1), 5–22. https://doi.org/10.1177/0047239520934018
4. Domínguez, A., Saenz-de-Navarrete, J., de-Marcos, L., Fernández-Sanz, L., Pagés, C., & Martínez-Herráiz, J. J. (2013). Gamifying learning experiences: Practical implications and outcomes. *Computers & Education, 63*, 380–392. https://doi.org/10.1016/j.compedu.2012.12.020
5. Giannakos, M. N., Krogstie, J., & Chrisochoides, N. (2022). Reviewing the role of e-learning systems in professional development and training. *Information Systems Frontiers, 24*(1), 31–50. https://doi.org/10.1007/s10796-020-10097-2
6. Gupta, A., & Sharma, A. (2020). Learning from Home: An analysis of Indian students' experiences during the COVID-19 pandemic. *Asian Journal of Distance Education*, 15(1), 144-153.
7. Hair Jr., J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). SAGE Publications.
8. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2019). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (2nd ed.). SAGE Publications.
9. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115-135. https://doi.org/10.1007/s11747-014-0403-8
10. Lee, Y., & Choi, J. (2011). A review of online course dropout research: Implications for practice and future research. *Educational Technology Research and Development*, 59(5), 593–618. https://doi.org/10.1007/s11423-010-9177-y
11. Mishra, L., Gupta, T., & Shree, A. (2020). Online teaching-learning in higher education during lockdown period of COVID-19 pandemic. *International Journal of Educational Research Open*, 1, 100012. https://doi.org/10.1016/j.ijedro.2020.100012
12. Muthuprasad, T., Aiswarya, S., Aditya, K. S., & Jha, G. K. (2021). Students' perception and preference for online education in India during COVID-19 pandemic. *Social Sciences & Humanities Open*, 3(1), 100101. https://doi.org/10.1016/j.ssaho.2020.100101

13. Saleem, H., Noori, N. M., & Awang, N. H. (2022). Gamification applications in e-learning: A literature review. *International Journal of Advanced Computer Science and Applications (IJACSA), 13*(1), 567–574. https://doi.org/10.14569/IJACSA.2022.0130173
14. Wang, Y., & Sazalli, A. N. (2024). The effectiveness of mobile applications in blended learning environments: A systematic review. *International Journal of Communication Networks and Information Security*, *16*(1), 34–42.
15. Xavier, M., & Meneses, J. (2020). Dropout in online higher education: A scoping review from 2014 to 2018. *Computers & Education*, 147, 103778.

BIBLOGRAPHY

1. https://www.sciencedirect.com/science/article/pii/S0040162524003627#bb0270