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AI-Based Personalized Learning and Student Performance: Evidence from Indian Higher Education

Muruganandham S K
Computer Science and Design Engineering, Raja Rajeswari College of Engineering, Bengaluru, Karnataka, India
0009-0000-7412-4178, drmurugax@gmail.com

Abstract

While the number of AI-powered educational platforms being developed and widely adopted in higher education institutions in India is rapidly increasing, there is not a lot of empirical evidence to determine whether such systems are effective for enhancing student outcomes. The study involved giving a structured quantitative questionnaire of the selected colleges of India to undergraduate and postgraduate students. Out of the 506 responses obtained, there were 497 responses that were retained after informed consent screening. The instrument measured four constructs related to AI-based personalized learning, students' learning engagement, and their satisfaction and performance using a 24-item, five-point Likert-scale. Descriptive statistics, Pearson correlation, multiple regression, and bootstrapped mediation analysis were conducted. Personalized learning based on AI, along with engagement and satisfaction, accounted for 75.1 % of the variance in academic performance ($R2 = 0.751$, $p < 0.001$), with both mediators shown to be significant. The results provide empirical insights on how to guide institutions, policymakers, and EdTech companies to reinforce learning outcomes through AI for personalisation in Indian higher education.

Keywords: Artificial Intelligence, Personalized Learning, Academic Performance, Learning Engagement, Student Satisfaction, Indian Higher Education

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1. Introduction

While much investment has been made in higher education over the last decades, the one size fits all classroom approach to teaching continues to be the reality. This is starting to change with the use of AI in learning platforms: AI systems are now capable of identifying how well a student is doing at each moment and adapting the content to that level, and of suggesting learning routes to take based on what the student has already shown their ability. What the study will tell us is whether or not this ability will actually lead to a boost in student achievement. It is all the more pressing in the Indian context. As per the University of the States and University Grants Commission (UGC), there are 1006 universities and 42,022 colleges in India enrolling more than 43 million students in various courses, resulting in one of the largest and most diverse higher education systems in the world, which is still facing challenges of shortage of qualified faculty, infrastructure gaps, and varying levels of student preparation [21]. Using platforms like BYJU'S, Unacademy, upGrad or Vedantu, hundreds of millions of students are able to learn, and the number of Indians accessing these services has increased significantly during the pandemic of COVID-19 [10]; however, little outcome research has matched the rapid growth in uptake. Previous studies of the adoption in India are about the intention to adopt or perceptions of achievement [22, 25] and few (if any) investigated learning engagement and satisfaction as mediators between personalization–performance.

This study contributes to filling this gap. This survey was designed to use a 24 item, 5-point Likert scale that was given to the undergraduate and postgraduate students of selected Indian Institutions (N = 506, n = 497). Seven hypotheses based on Technology Acceptance Model [7], Self-Determination Theory [8] and IS Success Model [9] were tested using multiple regression and bootstrapped mediation analysis. The four goals for the work were: (1) capture the usage patterns with the AI platform; (2) explore the potential direct impact of AI personalization on performance; (3) identify the connection between the AI platform and performance through the mediating factors of engagement and satisfaction; and (4) draw implications for the institution, curriculum designers, and EdTech providers. The paper continues by conducting literature review, presenting the theoretical framework, presenting the methodology, presenting the results, conducting discussion and then a conclusion.

2. Literature Review

Bloom's two-sigma discovery [1] - that AI tutoring at scale is capable of improving learning by 2 sigmas compared to conventional learning - set the ceiling that AI based personalized learning aspires to. The results of the meta-analysis strongly support the efficacy of intelligent tutoring systems, with average achievement gains of 0.4–0.8 compared to traditional teaching and learning [19,27,29] but this can vary depending on the quality of the implementation and the characteristics of the student population [5]. In contrast to the first generation of tutoring systems, state-of-the-art AI approaches automatically adapt to individual learners and adapt the sequencing of content, the timing of feedback, and the difficulty level of the assessments on the fly, and are based on continually updated representations of each student [24, 26]. Learning engagement is one of the most powerful ones to predict learning outcomes [14] and is the mechanism through which AI personalization is theorised to yield better performance learning across behavioural, cognitive and emotional levels [12]. Adaptive platforms can keep learning opportunities challenging within each learner's zone of proximal development (ZPD) [30] and maintain effortful processing opportunities for learning gains. Huang2020 (in a sample of a university) confirmed much higher engagement with the use of adaptive systems; Filgona2020 found that engagement was a full mediator on this technology-achievement link and Panigrahi2018 found similar in Indian e-learning contexts. Student satisfaction is an alternative course of action. Satisfaction has been found to be a motivational mechanism to achieve better performance outcomes as found in the Technology Acceptance Model [7] or IS Success Model [9] in Taiwan [28], in Brazil [3] and in the United States [18].

Table 1. *The prior work*

Author(s)	Year	Country	Method	Key Finding
Bloom [1]	1984	USA	Experiment	Tutoring exceeds conventional instruction by ≈2SD
VanLehn [29]	2011	USA	Meta-anal.	AI tutoring approaches human effectiveness; d≈0.76
Ma et al. [19]	2014	Global	Meta-anal.	Significant ITS gains across subjects and grade levels
Sun et al. [28]	2008	Taiwan	Survey	Satisfaction predicts e-learning outcomes
Cidral et al. [3]	2018	Brazil	SEM	Satisfaction mediates quality to performance link
Panigrahi et al. [25]	2018	India	Survey	TAM predicts e-learning adoption in Indian HEIs

Dhawan [10]	2020	India	Qualitative	EdTech potential post-COVID; outcome gap noted
Huang et al. [16]	2020	China	Survey	Adaptive systems raise student engagement
Filgona et al. [11]	2020	Nigeria	Quasi-exp.	Engagement mediates technology–achievement link
modi2025 & insights [22]	2021	India	Survey	Positive AI tool perceptions in Indian engineering colleges

Whilst India's National Education Policy 2020 has set AI personalization as a key direction to pursue in the field of education [20] and a small domestic EdTech industry is expected to be over a USD 10 billion market by 2025 [17], there is poor interest in rigorous outcome research in higher education in India. There have been existing studies that have looked into adoption intentions [2] or perceptions but with no measured performance [10,22]. This is covering the missing area in the existing literature as none of these studies simultaneously look at engagement/satisfaction as mediators in the personalization–performance relationship in an Indian undergraduate and postgraduate sample. The prior work is summarized in key aspects in Table 1. The concept model is supported by 3 complementary frameworks. The Technology Acceptance Model (TAM)[7] is a theory that states that perceived usefulness and perceived ease of use are the main factors to encourage satisfaction and continuous engagement on the platform. The "why?" behind AI personalization that deepens learning is explained in Self-Determination Theory [8]: Sustaining challenge with each learner's zone of proximal development fosters the three basic needs for intrinsic motivation and deeper cognitive processing, namely autonomy, competence and relatedness. According to IS Success Model [9] there is a relationship between system quality and satisfaction which can be linked to net benefits which in this study is academic performance through satisfaction. The three frameworks together suggest that personalisation with AI has a 180-degree effect on performance, in direct and indirect (mediated) ways, both with regard to engagement and satisfaction. Figure 1 shows the conceptual model that was integrated into the developed conceptual model, and Table 2 shows that 7 hypotheses were stated in accordance with the integrated conceptual framework.

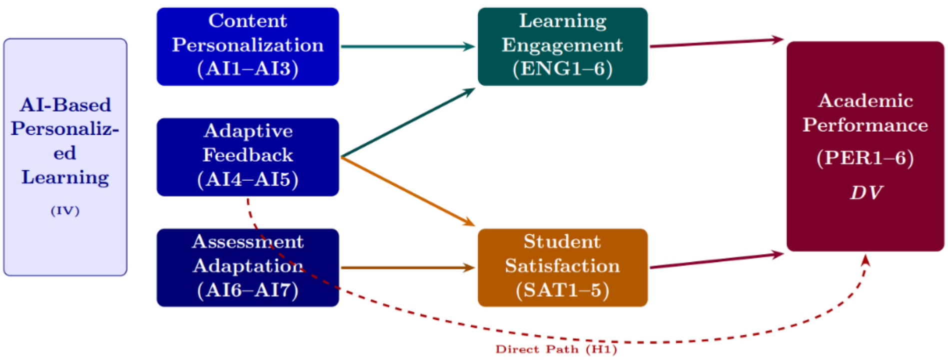

Figure 1. Integrated conceptual framework. Solid arrows = hypothesized paths; dashed = direct path (H1). TAM [7]; SDT [8]; IS Success Model [9]

3. Research Methodology

3.1 Research Design and Sampling

The study is a quantitative, cross section survey [6]. For undergraduate and post-graduate students in India Higher Education Institutes (HEI) with direct experience of using AI learning platform were targeted. A combination of purposive samples with the snowball sample (using academic networks, departmental messaging groups, and institutional e-mail lists was used to improve the chances of respondents having the needed experience). The survey was conducted online using google forms. From a total of 506 returned questionnaires, 13 were omitted who refused to provide informed consent, and there were 497 valid questionnaires which is slightly more than the minimum amount of 384 questionnaires obtained by Cochran's formula [4] with regard to informed consent (confidence level: 95%, margin of error: 5%) which is the power needed for regression and bootstrapped mediation analysis [13]. The procedure for screening is shown in the figure 2

Table 2. *Research Hypotheses Summary*

Hyp.	Statement	Path Type	Dir.
H1	AI personalization directly influences academic performance	Direct	+
H2	AI personalization positively affects learning engagement	Direct	+
H3	Learning engagement positively affects academic performance	Direct	+
H4	AI personalization positively affects student satisfaction	Direct	+
H5	Student satisfaction positively affects academic performance	Direct	+
H6	Engagement mediates AI personalization and performance	Mediation	+
H7	Satisfaction mediates AI personalization and performance	Mediation	+

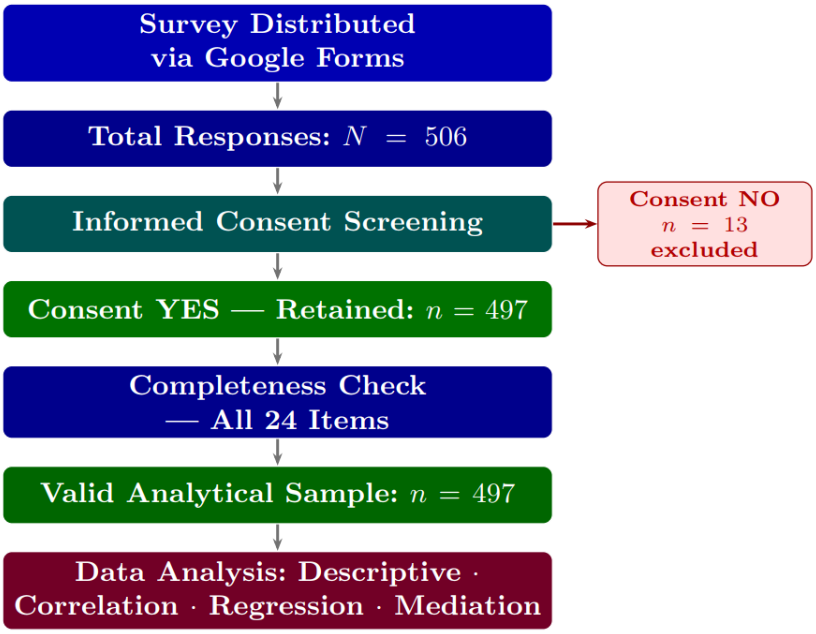

Figure 2. Data collection and screening procedures.

3.2 Measurement Instrument

The instrument consisted of 24 items which were given a 5-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Don't Know, 4 = Agree, 5 In each of the 4 constructs the (SAH) strongly agree indicated that the item received high agreement responses. Personalized learning items with the use of AI. The technology affection (AI1 to AI7) items were based on the items from Davis [7] and Pane et al. [24], the learning engagement items (ENG1 for ENG6) were based on the items from Fredricks et al. [12] and the student satisfaction items (SAT1 to SAT5) were based on the items from DeLone and McLean [9] and the academic performance items (PER1 to PER6) were based on the items from Cidral et al. [3] and Kuo et al. [18]. All items were reviewed by three ET faculty members to ensure their clarity and relevance and were pilot tested with 30 students who found them to be acceptable and showed good levels of reliability (α > 0.80) with some minor changes to items. A final Cronbach's alpha ranged from 0.898 to 0.929 and indicated a good coefficient for each of the four scales (> 0.70) [23]. All of the 24 items are listed in table 3.

Table 3: *Measurement Instrument — All 24 Scale Items*

Code	Item
AI-Based Personalized Learning (IV, 7 items) — Davis [7]; Pane et al. [24]	
AI1	The AI platform adapts learning content to my individual needs
AI2	The system recommends materials based on my learning performance
AI3	The learning pace is adjusted according to my understanding level
AI4	The AI system provides customized feedback on my performance
AI5	The content provided by the AI system matches my learning preferences
AI6	The system identifies my weak areas and suggests improvement strategies
AI7	The AI platform personalizes assessments based on my progress
Learning Engagement (Mediator, 6 items) — Fredricks et al. [12]	
ENG1	I feel actively involved when using AI-based learning systems
ENG2	AI-based learning increases my interest in the subject
ENG3	I spend more time learning when using AI-personalized tools
ENG4	The AI system motivates me to participate actively in learning tasks
ENG5	I concentrate better when learning through AI-personalized systems
ENG6	AI-based platforms make learning more interactive
Student Satisfaction (Mediator, 5 items) — DeLone & McLean [9]	
SAT1	I am satisfied with the AI-based personalized learning experience
SAT2	The AI system meets my learning expectations
SAT3	I find AI-based learning more effective than traditional methods
SAT4	I would recommend AI-based personalized learning to others
SAT5	I am pleased with the overall performance of AI learning platforms
Academic Performance (DV, 6 items) — Cidral et al. [3]; Kuo et al. [18]	
PER1	My academic performance has improved due to AI-based personalized learning
PER2	I understand concepts better when using AI-personalized platforms
PER3	My grades have improved after using AI learning systems
PER4	AI-based learning has increased my learning efficiency
PER5	I complete assignments more effectively using AI tools
PER6	AI-based personalized learning has enhanced my overall academic achievement

3.3 Data Analysis

Analysis proceeded in five stages: (1) descriptive statistics for all items and demographics; (2) Cronbach's alpha per scale; (3) Pearson correlations among construct scores with multicollinearity check ($r < 0.90$ criterion); (4) simultaneous multiple regression of academic performance on all three predictors; and (5) bootstrapped mediation analysis ($B = 5{,}000$ resamples, 95 % bias-corrected CI) testing H6 and H7 [15]. All analyses were conducted in Python using pandas, NumPy, and SciPy.

4 Results

4.1 Sample Profile

The sample ($n = 497$) was 52.1 % female, 55.5 % aged 18–20, and 75.5 % undergraduate. Engineering and Technology students dominated (87.3 %), with 97.6 % from private institutions. Over 83 % engaged with AI learning tools at least sometimes, with ChatGPT and similar chatbots in the most widely used category. Table 4 presents the full breakdown.

4.2 Descriptive Statistics and Reliability

Construct means ranged from 3.764 (student satisfaction) to 3.893 (AI personalization) on the five-point scale, indicating broadly positive perceptions. Cronbach's alpha ranged from 0.898 to 0.929, all exceeding the 0.70 threshold [23] and classified as excellent. Table 5 reports full statistics.

Table 4. *Demographic Profile (n = 497)*

Variable	Category	n	%
Gender	Female	259	52.1
	Male	232	46.7
	Prefer not to say	6	1.2
Age Group	18–20 years	276	55.5
	21–23 years	216	43.5
	24–26 years	5	1.0
Level of Study	Undergraduate	375	75.5
	Postgraduate	122	24.5
Institution Type	Private	485	97.6
	Government	12	2.4
AI Usage Frequency	Sometimes	158	31.8
	Very Frequently	130	26.2
	Often	127	25.6
	Occasionally	46	9.3
	Rarely	36	7.2

Table 5. *Descriptive Statistics and Reliability (n = 497)*

Construct	Items	M	SD	Min	Max	α
AI Personalization (IV)	7	3.893	0.785	1.00	5.00	0.898
Learning Engagement	6	3.809	0.864	1.00	5.00	0.921
Student Satisfaction	5	3.764	0.859	1.00	5.00	0.901
Academic Performance (DV)	6	3.798	0.889	1.00	5.00	0.929

Note. Scale: 1 = Strongly Disagree, 5 = Strongly Agree

4.3 Correlation Analysis

All pairwise correlations were positive and significant ($p < 0.01$), ranging from $r = 0.681$ (AI personalization – performance) to $r = 0.837$ (satisfaction – performance), all below the 0.90 multicollinearity threshold. The comparatively lower direct correlation for AI personalization signals the importance of the mediating pathways. Table 6 reports the matrix.

Table 6. *Pearson Correlation Matrix (n = 497)*

Construct	1	2	3	4
1. AI Personalization	1.000			
2. Learning Engagement	0.735**	1.000		
3. Student Satisfaction	0.701**	0.816**	1.000	
4. Academic Performance	0.681**	0.811**	0.837**	1.000

** $p < 0.01$, two-tailed

4.4 Multiple Regression Analysis

The model was significant ($F(3, 493) = 496.93$, $p < 0.001$) and explained 75.1 % of variance in academic performance (R2 = 0.751, Adj. R2 = 0.750). Student satisfaction was the strongest predictor (β = 0.503, p < 0.001), followed by learning engagement (β = 0.347, p < 0.001). The direct effect of AI personalization remained significant after controlling for both mediators (β = 0.073, p = 0.034), confirming H1. Full results are in Table 7.

Table 7. *Multiple Regression Results — DV: Academic Performance (n = 497)*

Predictor	B	SE	β	t	p
Constant	0.159	0.104	—	1.525	0.128
AI Personalization	0.083	0.039	0.073	2.130	0.034*
Learning Engagement	0.357	0.044	0.347	8.207	<0.001**
Student Satisfaction	0.520	0.042	0.503	12.516	<0.001**

$*p < 0.05$; $**p < 0.001$

4.5 Mediation and Path Analysis

Both indirect effects were significant. The effect of AI personalization on academic performance via learning engagement was IE = 0.561 (95 % BC CI [0.471, 0.653]), and via student satisfaction was IE = 0.561 (95 % BC CI [0.476, 0.648]). Both intervals exclude zero, confirming H6 and H7 [15]. All seven hypotheses were supported. Table 8 and Figure 3 summarise the full path structure.

Table 8. *Bootstrapped Mediation Analysis (B = 5,000, n = 497)*

Mediator (Hyp.)	Indirect	Effect	95 % BC CI
Learning Engagement (H6)	0.561	Significant	[0.471, 0.653]
Student Satisfaction (H7)	0.561	Significant	[0.476, 0.648]

Note. BC CI excludes zero ⇒ mediation confirmed [15].

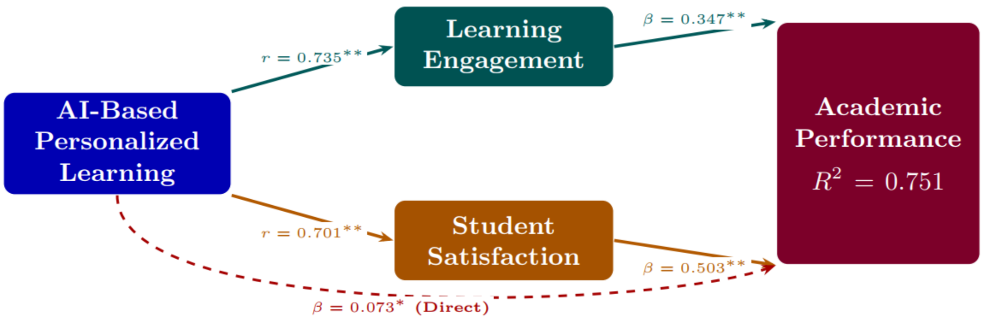

Figure 3. Structural path diagram with standardised coefficients. $*p < 0.05$; $**p < 0.001$. Dashed = direct path after controlling for mediators.

5. Discussion

This three-predictor model accounted for a high (for such a parsimonious model) 75.1 % of the variance in academic performance and all seven hypotheses were supported. This large direct effect of AI Personalization (β = 0.073, p = 0.034) after taking into account both mediators, aligns with the findings of VanLehn [29] and Ma et al. [19] that AI Personalization results in a direct effect on structural performance which is not mediated through motivational effects. The finding of this effect in an Indian sample where quality of platforms, access to devices and digital literacy are quite different, portrays the strength of the phenomenon at the underlying level. But it is the mediated pathways' sizes that are the prevailing finding. The indirect effects (IE = 0.561) are much higher, making it clear that AI personalization helps to boost performance by increasing engagement levels and satisfaction as well as by directly delivering content. The engagement pathway is consistent with Fredricks et al [12] who relate this to Fredricks et al [13] 'productive challenge within each person's ZPD [30] maintaining the behavioural, cognitive, and emotional engagement relates to greater learning gains. This is similar to the discovery in China [16] and in Nigeria [11] where the engagement mediation structure was discovered in the educational space of the HEIs in South Asia. Consistent with the IS Success Model [9] – reproduced in Taiwan [28] and Brazil [3] – the results confirmed, as predicted by TAM [7] that perceived usefulness translates into consistent and effortful use which in turn can lead to an increase in learning gains over time. The higher β for satisfaction of 0.503 than that in similar past studies might be due to the unique importance of affective evaluations given the relative novelty of using AI tools, particularly for students. There is a high correlation between engagement and satisfaction ($r = 0.816$), but they do regress independently and significantly on performance, so they do seem to be reflecting genuinely different variances in performance. Interventions in either path alone (just engagement or just satisfaction) will be limited in the increments to performance resulting. The pathway of integrating TAM–SDT–IS Success framework [7-9] could explain 75.1 % of outcome variance, which indicated that none of these theories is sufficient for explaining the outcome and the combination of these theories is suitable in AI-based learning study. Caution should be used in generalisation when using the composition of samples. However, students under control of engineering/technology (87.3 %) at private educational institutes (97.6 %) are likely to be more digitally fluent and better resourced, as compared to the overall student population in the country [21]. The findings are pertinent to this sizeable and expanding user group – one of the highest levels of EdTech use in the country – however, if NEP 2020's hope of broad rolling out of AI personalization throughout India's entire HE system is to be realised, evidence from contexts such as arts and humanities, government funded and rural institution contexts must also be considered.

6. Conclusion

Survey data from 497 Indian undergraduate and postgraduate students indicate that when we offer personalized learning based on AI, it not only directly enhances academic performance ($\beta = 0.073$, $p = 0.034$), but also indirectly via the mediators learning engagement (IE = 0.560, 95 % CI [0.470, 0.652]) and student satisfaction (IE = 0.560, 95 % CI [0.475, 0.647]). The three-predictor model explained 75.1 % of outcome variance (R2 = 0.751, $F(3, 493) = 496.93$, $p < 0.001$), with all seven hypotheses supported. The main performance improvement comes as a result of this increased engagement and satisfaction and not simply the provision of content on its own - which reinforces the mediation structures identified in other studies in China [16] and Nigeria [11] and demonstrates their generalizability to the South Asian context. This structure is represented in the integrated TAM – SDT-IS success framework [7-9] which has two separate, although related and non-redundant, explanatory pathways coming from TAM and SDT.This has implications that are far and out there and not just sidewalks. AI learning programmes need to shift from the fringes to the core, with a focus on the pedagogical curriculum of faculty orientation, student orientation and usability of the platform. Ban on the use of artificial intelligence or not, service designers and developers in the EdTech space should focus on satisfaction as a key performance metric – because residences of pupils on this metric on SAT3 ($M = 3.680$) suggests that there is still some degree of uncertainty that AI doesn't have an advantage over traditional approaches, which can be resolved through good design and communication. Policy makers pursuing NEP 2020's vision of AI personalisation should also focus on providing infrastructure and connectivity, which are prerequisites to engagement and satisfaction as mechanisms to achieving the benefits. These conclusions build on four limitations: the cross-sectional design does not allow for causal inferences; all constructs are self-reported; the sample is heavily skewed towards Engineering students from private schools and their ability to generalize to other fields and across all schools is limited; and, AI personalization is considered one construct, even though practice varies across platforms. Future research will include longitudinal or experimental research, increasing beyond populations in Arts/Humanities and Government supported institutions, and disaggregating results based on platform type, while including rural institution populations. Then sixty years after the insightful two sigma gap identified by Bloom [1] the question is, whether AI personalization will be able to do so in India or not will primarily depend on how much these three stakeholders viz., institutions, developers, and policymakers will take cognizance of the human factors that this study highlights.

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Authors' Declaration Conflicts of Interest: The author declares no conflict of interest.

Authors' Contribution Statement:

Muruganandham SK: Conceptualization, Methodology, Data collection, Formal analysis, Investigation, Writing - original draft, Writing - review & editing

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