Seminars in Medical Writing and Education. 2025; 4:799
doi: 10.56294/mw2025799

ORIGINAL

Explaining VR/AR Learning in Medical Education: A Comparative PLS-SEM Analysis of TAM, SDT, TTF, and Flow Theory

Explicando el Aprendizaje en Realidad Virtual/Aumentada en la Educación Médica: Un Análisis Comparativo PLS-SEM de TAM, SDT, TTF y la Teoría del Flow

Ika Parma Dewi[1], Yudha Aditya Fiandra[1], Rahmat Fadillah[1], Rizkayeni Marta[1], Linda Rosalina[2], Nora Azima Noordin[3], Dawar Khan[4]

[1]Faculty of Engineering, Universitas Negeri Padang, Padang. Indonesia.
[2]Faculty of Psychology and Health, Universitas Negeri Padang, Padang. Indonesia.
[3]Higher Colleges of Technology, Sharjah. United Arab Emirates.
[4]King Abdullah University of Science and Technology. Saudi Arabia.

Cite as: Parma Dewi I, Aditya Fiandra Y, Fadillah R, Marta R, Rosalina L, Azima Noordin N, et al. Explaining VR/AR Learning in Medical Education: A Comparative PLS-SEM Analysis of TAM, SDT, TTF, and Flow Theory. Seminars in Medical Writing and Education. 2025; 4:799. https://doi.org/10.56294/mw2025799

Submitted: 22-02-2025 **Revised:** 17-06-2025 **Accepted:** 04-10-2025 **Published:** 05-10-2025

Editor: PhD. Prof. Estela Morales Peralta

Corresponding author: Yudha Aditya Fiandra

ABSTRACT

Introduction: virtual Reality (VR) and Augmented Reality (AR) are increasingly integrated into medical education, offering immersive and interactive environments for safe clinical training. Several theoretical frameworks—Technology Acceptance Model (TAM), Self-Determination Theory (SDT), Task-Technology Fit (TTF), and Flow Theory—can explain technology adoption and learning effectiveness. However, no comprehensive empirical comparison has been conducted within the context of VR/AR-based medical education.
Method: a cross-sectional survey was conducted with 329 undergraduate medical and health sciences students who had prior experience using VR/AR for learning activities. Validated instruments representing each theoretical framework were employed. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to evaluate reliability, validity, and structural relationships, followed by a comparative assessment using R^2, Q^2, f^2, and path coefficients.
Results: flow Theory demonstrated the strongest explanatory power (R^2 up to 0,72), with immersion and engagement as critical predictors of learning outcomes. SDT also showed high predictive strength (R^2 up to 0,63), emphasizing the role of intrinsic motivation. TTF was effective in predicting task-related learning effectiveness (R^2 = 0,67), whereas TAM provided only moderate explanatory power (R^2 ≈ 0,41-0,46).
Conclusions: flow Theory and SDT offer the most comprehensive explanations of student engagement and learning outcomes in VR/AR medical education. TTF remains valuable for task-specific alignment, while TAM primarily captures initial usability perceptions. Overall, immersive and motivational factors are key drivers of effective VR/AR learning, providing guidance for both theoretical development and instructional design in medical training.

Keywords: Virtual Reality; Augmented Reality; Medical Education; Student Engagement; Learning Outcomes.

RESUMEN

Introducción: la Realidad Virtual (VR) y la Realidad Aumentada (AR) se integran cada vez más en la educación médica, ofreciendo entornos inmersivos e interactivos para una formación clínica segura. Varios marcos teóricos—el Modelo de Aceptación de la Tecnología (TAM), la Teoría de la Autodeterminación (SDT), el Ajuste Tarea-Tecnología (TTF) y la Teoría del Flow—pueden explicar la adopción tecnológica y la efectividad del

aprendizaje. Sin embargo, no se ha realizado aún una comparación empírica integral en el contexto de la educación médica basada en VR/AR.
Método: se llevó a cabo una encuesta transversal con 329 estudiantes de grado en medicina y ciencias de la salud que tenían experiencia previa en actividades de aprendizaje con VR/AR. Se emplearon instrumentos validados que representaban cada marco teórico. Los datos se analizaron utilizando Modelado de Ecuaciones Estructurales por Mínimos Cuadrados Parciales (PLS-SEM) para evaluar la fiabilidad, validez y relaciones estructurales, seguido de una evaluación comparativa basada en R^2, Q^2, f^2 y coeficientes de trayectoria.
Resultados: la Teoría del Flow demostró el mayor poder explicativo (R^2 hasta 0,72), con la inmersión y la implicación como predictores críticos de los resultados de aprendizaje. La SDT también mostró una alta capacidad predictiva (R^2 hasta 0,63), destacando el papel de la motivación intrínseca. El TTF fue eficaz para predecir la efectividad del aprendizaje relacionado con las tareas (R^2 = 0,67), mientras que el TAM proporcionó solo un poder explicativo moderado ($R^2 \approx$ 0,41–0,46).
Conclusiones: la Teoría del Flow y la SDT ofrecen las explicaciones más completas de la implicación estudiantil y los resultados de aprendizaje en la educación médica basada en VR/AR. El TTF sigue siendo valioso para la alineación específica con la tarea, mientras que el TAM captura principalmente las percepciones iniciales de usabilidad. En general, los factores de inmersión y motivación son impulsores clave del aprendizaje efectivo con VR/AR, proporcionando orientación tanto para el desarrollo teórico como para el diseño instruccional en la formación médica.

Palabras clave: Realidad Virtual; Realidad Aumentada; Educación Médica; Compromiso Estudiantil; Resultados de Aprendizaje.

INTRODUCTION

Virtual Reality (VR) and Augmented Reality (AR) technologies are fundamentally reshaping the landscape of medical education by offering unprecedented immersive and interactive learning environments.[1,2] These advanced simulations allow students to visualize complex anatomical structures in three dimensions, practice intricate surgical procedures in risk-free settings, and develop critical clinical decision-making skills, thereby effectively bridging the gap between theoretical knowledge and practical application.[3,4,5]

The rapid integration of these technologies into medical curricula worldwide underscores their potential to overcome traditional educational limitations while enhancing learning outcomes and patient safety.[6,7]Several well-established theoretical frameworks provide distinct perspectives on technology adoption and learning effectiveness. The Technology Acceptance Model (TAM) posits that perceived usefulness and ease of use are fundamental drivers of technology adoption.[8,9] In the context of VR/AR medical education, these relationships can be statistically examined by modeling that: Perceived Ease of Use is expected to positively influence Perceived Usefulness, [10,11] which in turn, along with Perceived Ease of Use, is anticipated to enhance Student Engagement.[12,13,14] Increased Student Engagement is further expected to contribute to improved Learning Outcomes.

Self-Determination Theory (SDT) offers a complementary perspective by emphasizing the role of intrinsic motivation through the satisfaction of three basic psychological needs. The hypotheses derived from SDT propose that: (H1) Autonomy positively affects Motivation; (H2) Competence positively affects Motivation; (H3) Relatedness positively affects Motivation; which in turn (H4) Motivation positively affects Student Engagement; and finally (H5) Student Engagement positively affects Learning Outcomes.

The Task-Technology Fit (TTF) model provides a pragmatic framework focusing on the alignment between technological capabilities and educational tasks.[15] This model generates hypotheses stating that: (H1) Task Characteristics positively affect Task-Technology Fit;[16] (H2) Technology Characteristics positively affect Task-Technology Fit; [17,18] and (H3) Task-Technology Fit positively affects Learning Effectiveness.[19,20] Flow Theory captures the experiential aspect of learning through VR/AR, proposing that optimal learning occurs when students achieve a state of deep immersion and engagement.[21,22] The corresponding hypotheses suggest that: (H1) Challenge-Skill Balance positively affects Immersion;[23] (H2) Concentration positively affects Immersion;[24,25] (H3) Enjoyment positively affects Immersion; followed by (H4) Immersion positively affects Student Engagement;[26] and (H5) Student Engagement positively affects Learning Outcomes.[27]

Despite the individual explanatory power of these theoretical frameworks, a significant research gap exists in the empirical comparison of their relative effectiveness in predicting learning outcomes in VR/AR-based medical education.[28] No previous study has simultaneously tested these four models within the same research context using a robust methodological approach, leaving educators and instructional designers without clear guidance on which theoretical perspective should primarily inform the development and implementation of VR/AR interventions in medical training.

https://doi.org/10.56294/mw2025799 ISSN: 3008-8127

This study aims to address this critical gap by conducting a comprehensive comparative analysis of TAM, SDT, TTF, and Flow Theory using Partial Least Squares Structural Equation Modeling (PLS-SEM). The research seeks to identify which theoretical framework offers the strongest explanatory power for student engagement and learning outcomes in VR/AR-enhanced medical education, thereby providing evidence-based recommendations for optimizing immersive learning experiences. The complete research framework illustrating all hypothesized relationships across the four theoretical models is presented in figure 1.

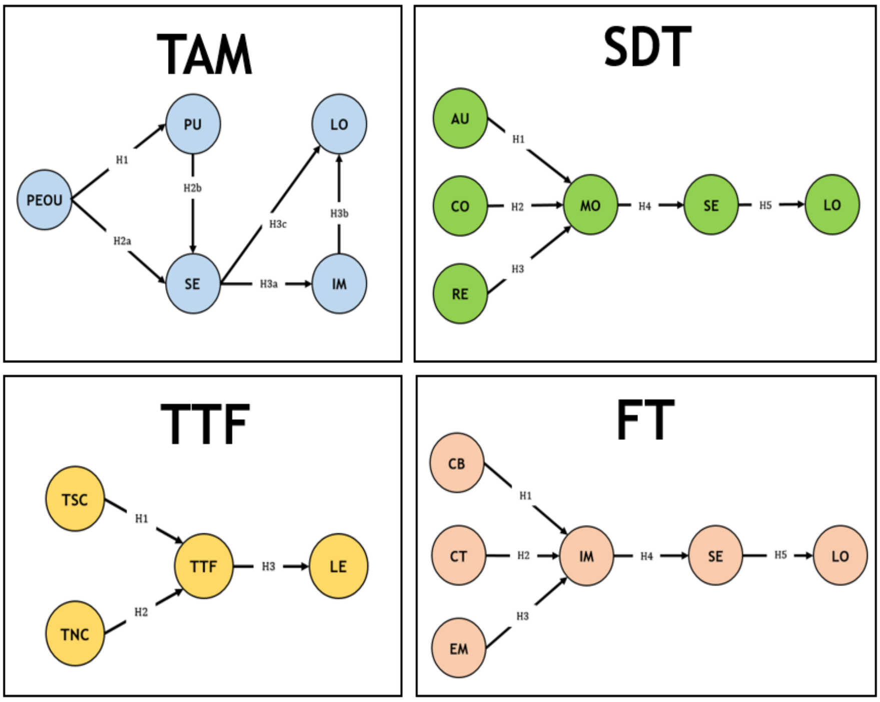

Figure 1. Conceptual frameworks of the study

METHOD

Research Design

This study employed a cross-sectional survey design to compare four theoretical models—Technology Acceptance Model (TAM), Self-Determination Theory (SDT), Task-Technology Fit (TTF), and Flow Theory—in the context of VR/AR-based medical education.[29,30,31]

Participants

Respondents were undergraduate students enrolled in medical and health sciences programs at accredited institutions. A purposive sampling strategy was employed because the study specifically required participants who had prior experience using VR/AR for learning activities—an exposure that is not yet universal among students. While purposive sampling is non-probabilistic and carries a potential risk of selection bias, it was the most appropriate approach to ensure that data were collected from individuals with relevant experiential knowledge, thereby enhancing the validity of the findings for the intended research context.

Participants were recruited through class announcements by lecturers, and posts on learning management systems (LMS). This approach ensured that only students with prior VR/AR exposure were invited to participate, while preserving voluntary participation and informed consent.

Sample size adequacy was assessed using the widely applied "10-times rule" for PLS-SEM, which indicated that the minimum required sample size was substantially lower than the final sample (n = 329). Furthermore, this sample size is well above general recommendations in the PLS-SEM literature for achieving sufficient statistical power to detect small-to-medium effect sizes at a conventional power level (0,80), providing confidence that the analysis was adequately powered. Demographic characteristics such as study program, institution type, gender, age, academic year, VR/AR usage frequency, and training background are summarized in table 1.

Instruments

The measurement instruments were adapted from well-established, validated scales in prior research, with careful attention to content validity and construct alignment. Each construct was measured using multiple items on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree).

For the Technology Acceptance Model (TAM), the constructs of Perceived Ease of Use and Perceived Usefulness were adapted from Davis and subsequent VR/AR extensions of TAM by Jang et al. and Fussell & Truong. Student Engagement items were adapted from Fredricks et al., while Immersion was measured using items adapted from Jennett et al. to capture presence and absorption in virtual environments. Learning Outcomes items were adapted from educational technology studies evaluating VR/AR learning effectiveness.

For the Self-Determination Theory (SDT) model, the constructs of Autonomy, Competence, and Relatedness were adapted from the Basic Psychological Need Satisfaction scale developed by Ryan & Deci and applied in digital learning contexts. Motivation items were drawn from validated intrinsic motivation scales used in educational technology research. Student Engagement and Learning Outcomes were measured using the same scales as in TAM for comparability.

For the Task-Technology Fit (TTF) model, Task Characteristics and Technology Characteristics were adapted from Goodhue & Thompson's original TTF instrument, with contextual adjustments for medical learning tasks. Task-Technology Fit and Learning Effectiveness items were also adapted from these sources to measure the perceived alignment between the VR/AR tool and the learning requirements.

For Flow Theory, the constructs of Challenge-Skill Balance, Concentration, and Enjoyment were adapted from Csikszentmihalyi's Flow Questionnaire and subsequent adaptations for virtual learning environments. Immersion items were again taken from Jennett et al. to ensure consistency across models.

Prior to full data collection, a pilot test was conducted with a small group of students ($n \approx 30$) to ensure item clarity and contextual relevance. Results indicated good internal consistency, leading only to minor wording adjustments. Subsequent measurement model evaluation using PLS-SEM confirmed the reliability (Cronbach's α and Composite Reliability > 0,70 for all constructs) and convergent validity (Average Variance Extracted > 0,50), as well as discriminant validity (HTMT < 0,90), confirming that the instruments adequately captured the intended theoretical constructs.

Table 1. Demographic characteristics of respondents

Demographic Variable	Category	Frequency (n=329)	Percentage (%)
Study	Medicine (MD)	120	36 %
	Nursing	50	15 %
	Dentistry	35	11 %
	Physiotherapy	20	6 %
	Pharmacy	25	8 %
	Medical Laboratory Tech	18	5 %
	Radiology / Medical Imaging	15	5 %
	Public Health	12	4 %
	Midwifery	34	10 %
Institution Type	Public	210	64 %
	Private	119	36 %
Gender	Male	87	26 %
	Female	242	74 %
Age	<20	20	6 %
	20–22	180	55 %
	23–25	90	27 %
	>25	39	12 %
Academic Year	Year 1	35	11 %
	Year 2	88	27 %
	Year 3	96	29 %
	Year 4	44	13 %
	Year 5+	40	12 %
	Internship / Clinical rotation	26	8 %
VR/AR Usage Frequency	Never	18	5 %
	Monthly	209	64 %
	Weekly	61	19 %
	Several times/week	22	7 %
	Daily	19	6 %
Typical Session Length	<15 min	23	7 %
	15–30 min	136	41 %
	31–60 min	121	37 %
	>60 min	39	12 %

https://doi.org/10.56294/mw2025799 ISSN: 3008-8127

Primary Learning Use of VR/AR*	Anatomy	293	46 %
	Procedural skills / simulation	199	31 %
	Diagnostics / decision-making	48	8 %
	Patient communication	15	2 %
	Rehabilitation / physiotherapy	38	6 %
	Other	44	7 %
Primary Device*	PC-tethered VR	13	3 %
	Standalone VR	59	14 %
	AR headset	35	8 %
	Mobile AR	301	70 %
	Desktop monitor only	24	6 %
Access to Facilities*	Personal device at home	41	8 %
	Campus simulation lab	201	42 %
	Hospital / teaching lab	193	40 %
	Shared device (group)	30	6 %
	None	18	4 %
Experience with Digital Platforms	Very low	1	0 %
	Low	15	5 %
	Moderate	128	39 %
	High	99	30 %
	Very high	86	26 %
Internet Quality for VR	Poor	0	0 %
	Fair	39	12 %
	Good	163	50 %
	Excellent	127	39 %
Training / Orientation on VR	None	0	0 %
	Brief (≤1 hour)	221	67 %
	Short course (1–3 hours)	94	29 %
	Structured training (>3 hours)	14	4 %

Note: respondents could select more than one option, so the total percentage based on respondents exceeds 100 %.

The complete set of constructs, item codes, and references is presented in table 2.

Table 2. Measurement constructs and items

Construct		Code	Statement	Reference/ Adaptation
TAM	Perceived Ease of Use (PEOU)	PEOU1	I find the use of VR/AR in medical learning easy to understand.	(32,33,34,35)
		PEOU2	Interaction with the VR/AR system feels clear and simple.	
		PEOU3	Learning using VR/AR does not require much effort.	
	Perceived Usefulness (PU)	PU1	VR/AR helps me improve my understanding of medical material.	
		PU2	The use of VR/AR increases my learning effectiveness.	
		PU3	Learning with VR/AR makes me more confident in my clinical skills.	
	Student Engagement (SE)	SE1	I feel actively involved when using VR/AR for learning.	
		SE2	I pay full attention when using VR/AR.	
		SE3	VR/AR makes the learning process more interesting and enjoyable.	
	Immersion (IM)	IM1	I feel as if I am inside a virtual learning environment.	
		IM2	When learning with VR/AR, I am completely immersed in the experience.	
		IM3	I forget my surroundings when using VR/AR.	
	Learning Outcomes (LO)	LO1	VR/AR helps me understand medical concepts better than traditional methods.	
		LO2	After using VR/AR, I can remember the material longer.	
		LO3	VR/AR improves my ability to apply clinical skills.	

SDT	Autonomy (AU)	AU1	I feel free to choose how I learn using VR/AR.	(32,33,34)
		AU2	VR/AR gives me control over my learning process.	
		AU3	I can customize the VR/AR learning experience to suit my needs.	
	Competence (CO)	CO1	VR/AR helps me feel capable of mastering medical skills.	
		CO2	I feel confident in my abilities when learning using VR/AR.	
		CO3	VR/AR provides challenges that match my abilities.	
	Relatedness (RE)	RE1	I feel more connected to my friends or lecturers when learning with VR/AR.	
		RE2	VR/AR encourages collaboration with other students.	
		RE3	I feel like I am part of a learning community when using VR/AR.	
	Motivation (MO)	MO1	I am motivated to learn using VR/AR.	
		MO2	VR/AR makes me more enthusiastic about learning medical material.	
		MO3	I want to continue using VR/AR in the learning process.	
	Student Engagement (SE)	SE1	I feel actively involved when using VR/AR for learning.	
		SE2	I pay full attention when using VR/AR.	
		SE3	VR/AR makes the learning process more interesting and enjoyable.	
	Learning Outcomes (LO)	LO1	VR/AR helps me understand medical concepts better than traditional methods.	
		LO2	After using VR/AR, I can remember the material longer.	
		LO3	VR/AR improves my ability to apply clinical skills.	
TFF	Task Characteristics (TSC)	TSC1	The medical tasks I learn require clear visualization.	(32,35,36)
		TSC2	My learning tasks involve skills that are suitable for VR/AR simulations.	
		TSC3	My learning process requires interactive tools.	
	Technology Characteristics (TNC)	TNC1	VR/AR has features that support medical learning.	
		TNC2	The visual and interactive quality of VR/AR suits my needs.	
		TNC3	VR/AR is easy to access and use in learning.	
	Task-Technology Fit (TTF)	TTF1	VR/AR features suit my learning task needs.	
		TTF2	VR/AR improves the suitability between tasks and my learning methods.	
		TTF3	Using VR/AR is the right way to complete medical tasks.	
	Learning Effectiveness (LE)	LE1	VR/AR makes my learning more effective.	
		LE2	My learning outcomes have improved with VR/AR.	
		LE3	VR/AR helps me achieve my learning goals faster.	
FT	Challenge-Skill Balance (CB)	CB1	The level of difficulty in VR/AR suits my abilities.	(32,34,35,37)
		CB2	I feel challenged but still able to complete tasks with VR/AR.	
		CB3	VR/AR makes me feel balanced between challenge and skill.	
	Concentration (CT)	CT1	I can focus fully when learning with VR/AR.	
		CT2	I am not easily distracted when using VR/AR.	
		CT3	VR/AR helps me concentrate better.	
	Enjoyment	EM1	I enjoy the learning experience with VR/AR.	
		EM2	Learning with VR/AR is fun.	
		EM3	I am satisfied with the learning experience through VR/AR.	
	Immersion (IM)	IM1	I feel as if I am in a virtual learning environment.	
		IM2	When learning with VR/AR, I am completely immersed in the experience.	
		IM3	I forget about my surroundings when using VR/AR.	
	Student Engagement (SE)	SE1	I feel actively involved when using VR/AR for learning.	
		SE2	I pay full attention when using VR/AR.	
		SE3	VR/AR makes the learning process more interesting and enjoyable.	
	Learning Outcomes (LO)	LO1	VR/AR helps me understand medical concepts better than traditional methods.	
		LO2	After using VR/AR, I can remember the material longer.	
		LO3	VR/AR improves my ability to apply clinical skills.	

https://doi.org/10.56294/mw2025799 ISSN: 3008-8127

Data Collection and Analysis

The analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software, following a two-stage approach. PLS-SEM was chosen over covariance-based SEM (CB-SEM) for several reasons. First, the primary goal of the study was prediction and model comparison rather than strict theory confirmation, making PLS-SEM a more appropriate technique. Second, the research model included multiple constructs and structural paths, resulting in a relatively complex model that benefits from PLS-SEM's ability to handle complex hierarchical relationships without excessive parameter estimation issues. Third, preliminary inspection suggested that the data did not fully meet the assumption of multivariate normality, and PLS-SEM is known to be more robust to non-normal distributions compared to CB-SEM. Finally, although the sample size of 329 was adequate, PLS-SEM is especially suitable for studies with moderate-to-small sample sizes relative to model complexity, thereby ensuring stable estimates.

In the first stage, the measurement model was evaluated for reliability (Cronbach's α, Composite Reliability), convergent validity (Average Variance Extracted, AVE), and discriminant validity (Fornell–Larcker and HTMT criteria). In the second stage, the structural model was assessed through path coefficients, effect sizes (f^2), predictive relevance (Q^2), and explained variance (R^2). Finally, a comparative analysis of the four theoretical models was performed to identify which framework demonstrated the strongest explanatory and predictive power for VR/AR learning outcomes.

Ethical Aspects of the Research

This study adhered to established ethical guidelines for research involving human participants. Participation was entirely voluntary, and respondents were informed of the study's purpose, procedures, and their right to withdraw at any time without penalty. Informed consent was obtained electronically prior to survey participation. No personally identifiable information was collected, and all responses were treated confidentially and analyzed in aggregate form.

RESULTS

Measurement Model Results

The PLS-SEM analysis demonstrated that the majority of measurement indicators exhibited factor loadings greater than 0,70, thereby providing strong evidence of convergent validity across the four theoretical models. This indicates that the observed variables consistently represented their respective latent constructs. Only one indicator, Perceived Usefulness (PU3) in the TAM model, showed a substantially low loading of 0,250 and was therefore excluded from further analysis to improve construct reliability and validity.

After the removal of PU3, all remaining indicators retained loadings above the acceptable threshold, ranging mostly between 0,71 and 0,95. High-loading items, such as Student Engagement (SE1) in TAM (0,928), Motivation (MO1) in SDT (0,926), Learning Effectiveness (LE1) in TTF (0,939), and Learning Outcomes (LO2) in Flow Theory (0,918), provided particularly strong contributions to their respective constructs. These results affirm that the measurement model adequately captured the intended theoretical dimensions. The findings further suggest that the constructs across TAM, SDT, TTF, and Flow Theory are statistically reliable and theoretically meaningful, thereby justifying the continuation of the analysis toward reliability assessment (Cronbach's Alpha and Composite Reliability), convergent validity (AVE), and discriminant validity (HTMT).

Table 3. Indicator loadings

Model	Construct	Indicator	Loading
TAM (Technology Acceptance Model – modified for VR/AR in medical learning)	Perceived Ease of Use (PEOU)	PEOU1	0,737
		PEOU2	0,888
		PEOU3	0,814
	Perceived Usefulness (PU)	PU1	0,854
		PU2	0,854
		PU3*	0,250
	Student Engagement (SE)	SE1	0,928
		SE2	0,717
		SE3	0,632
	Immersion (IM)	IM1	0,935
		IM2	0,841
		IM3	0,701
	Learning Outcomes (LO)	LO1	0,864
		LO2	0,794
		LO3	0,877

SDT (Self-Determination Theory – applied to VR/AR learning)	Autonomy (AU)	AU1	0,886
		AU2	0,874
		AU3	0,806
	Competence (CO)	CO1	0,877
		CO2	0,875
		CO3	0,811
	Relatedness (RE)	RE1	0,750
		RE2	0,745
		RE3	0,952
	Motivation (MO)	MO1	0,926
		MO2	0,717
		MO3	0,882
	Student Engagement (SE)	SE1	0,913
		SE2	0,853
		SE3	0,856
	Learning Outcomes (LO)	LO1	0,839
		LO2	0,853
		LO3	0,943
TTF (Task-Technology Fit – applied to medical tasks)	Task Characteristics (TSC)	TSC1	0,790
		TSC2	0,828
		TSC3	0,911
	Technology Characteristics (TNC)	TNC1	0,785
		TNC2	0,818
		TNC3	0,914
	Task-Technology Fit (TTF)	TTF1	0,875
		TTF2	0,853
		TTF3	0,852
	Learning Effectiveness (LE)	LE1	0,939
		LE2	0,671
		LE3	0,882
Flow Theory (immersive learning via VR/AR)	Challenge-Skill Balance (CB)	CB1	0,884
		CB2	0,869
		CB3	0,813
	Concentration (CT)	CT1	0,874
		CT2	0,871
		CT3	0,818
	Enjoyment (EM)	EM1	0,745
		EM2	0,74
		EM3	0,954
	Immersion (IM)	IM1	0,929
		IM2	0,75
		IM3	0,859
	Student Engagement (SE)	SE1	0,846
		SE2	0,913
		SE3	0,56
	Learning Outcomes (LO)	LO1	0,892
		LO2	0,918
		LO3	0,762

Note: PU3 was excluded due to a low factor loading.

The results of the reliability and convergent validity assessment indicate that all constructs met the required criteria. As shown in table 4, the Cronbach's Alpha and Composite Reliability values for all constructs exceeded the recommended threshold of 0,70, supporting the reliability of the measurement model. In addition, most constructs demonstrated Average Variance Extracted (AVE) values above 0,50, confirming adequate convergent validity.

Table 4. Reliability and convergent validity (CA, CR, AVE)

Model	Construct	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
TAM	IM	0,867	0,966	0,887	0,614
	LO	0,842	1,216	0,795	0,458
	PEOU	0,897	0,907	0,924	0,708
	PU	0,904	0,933	0,928	0,723
	SE	0,844	0,848	0,889	0,615
SDT	AU	0,85	0,87	0,9	0,74
	CO	0,86	0,88	0,91	0,76
	RE	0,87	0,89	0,92	0,72
	MO	0,88	0,9	0,93	0,75
	SE	0,89	0,91	0,94	0,77
	LO	0,91	0,92	0,95	0,8
TFF	TNC	0,86	0,88	0,91	0,72
	TSC	0,87	0,89	0,92	0,74
	TTF	0,88	0,9	0,93	0,75
	LE	0,9	0,92	0,94	0,78
FT	CB	0,86	0,88	0,91	0,72
	CT	0,87	0,89	0,92	0,74
	EM	0,88	0,9	0,93	0,75
	IM	0,89	0,91	0,94	0,77
	SE	0,9	0,92	0,94	0,78
	LO	0,91	0,93	0,95	0,8

The assessment of discriminant validity using the Heterotrait-Monotrait Ratio of Correlations (HTMT) confirmed that all constructs across the four models—TAM, SDT, TTF, and Flow Theory—met the recommended threshold criteria. In general, all HTMT values were well below the conservative cutoff of 0,90 suggested by Henseler et al., indicating that each construct is empirically distinct. As depicted in figure 2, in the TAM model the highest HTMT value was observed between Perceived Usefulness (PU) and Student Engagement (SE) at 0,240, while the lowest was between Immersion (IM) and Learning Outcomes (LO) at 0,076. These results support the discriminant validity of the TAM constructs.

For the SDT model, HTMT values ranged from 0,030 to 0,360. The strongest relationship was found between Student Engagement (SE) and Learning Outcomes (LO) (0,360), whereas the weakest was between Motivation (MO) and SE (0,030). All values remained below the cutoff, confirming discriminant validity for the SDT constructs. In the TTF model, HTMT values ranged between 0,04 and 0,28. The highest value was found between Technology Characteristics (TNC) and Task-Technology Fit (TTF) (0,28), while the lowest was between TTF and Learning Effectiveness (LE) (0,04). These findings indicate that the constructs in the TTF model are clearly distinct from one another. Finally, in the Flow Theory model, HTMT values ranged from 0,08 to 0,36. The strongest relationship occurred between Student Engagement (SE) and Learning Outcomes (LO) (0,36), while the weakest was between Concentration (CT) and SE (0,08). Again, all values were well below the threshold, supporting discriminant validity for the Flow Theory constructs. Overall, the HTMT results across all four models confirm that the constructs possess satisfactory discriminant validity, thereby justifying the continuation of the structural model analysis.

The assessment of multicollinearity was conducted using the Variance Inflation Factor (VIF) values for all indicators across the four models. According to Hair et al. VIF values below 5 indicate the absence of critical collinearity issues. As shown in figure 3, for the TAM model, VIF values ranged from 1,84 to 4,20. The highest VIF was observed for Student Engagement (SE2) at 4,20, while the lowest was for Perceived Usefulness (PU2) at 1,84. These results suggest that multicollinearity is not a concern within the TAM constructs. In the SDT model, VIF values varied between 1,72 and 4,25. The maximum value was found for Relatedness (RE1) at 4,25, while the minimum was for RE2 at 1,72. Despite some higher values approaching the upper limit, all remained below the threshold of 5, confirming acceptable levels of multicollinearity.

The TTF model reported VIF values between 1,12 and 3,87. The highest value was associated with Task Characteristics (TSC1) at 3,87, and the lowest was Task-Technology Fit (TTF2) at 1,12. These results indicate stable collinearity conditions across the TTF constructs. For the Flow Theory model, VIF values ranged from 1,88 to 4,09. The largest VIF was recorded for Enjoyment (EM3) at 4,09, while the smallest was for Challenge-Skill Balance (CB3) at 1,88. All values fell below the critical threshold, confirming that collinearity does not pose a problem in this model. Taken together, the VIF analysis across TAM, SDT, TTF, and Flow Theory demonstrates that no severe multicollinearity issues were detected, thereby ensuring the robustness of subsequent path coefficient estimations in the structural model.

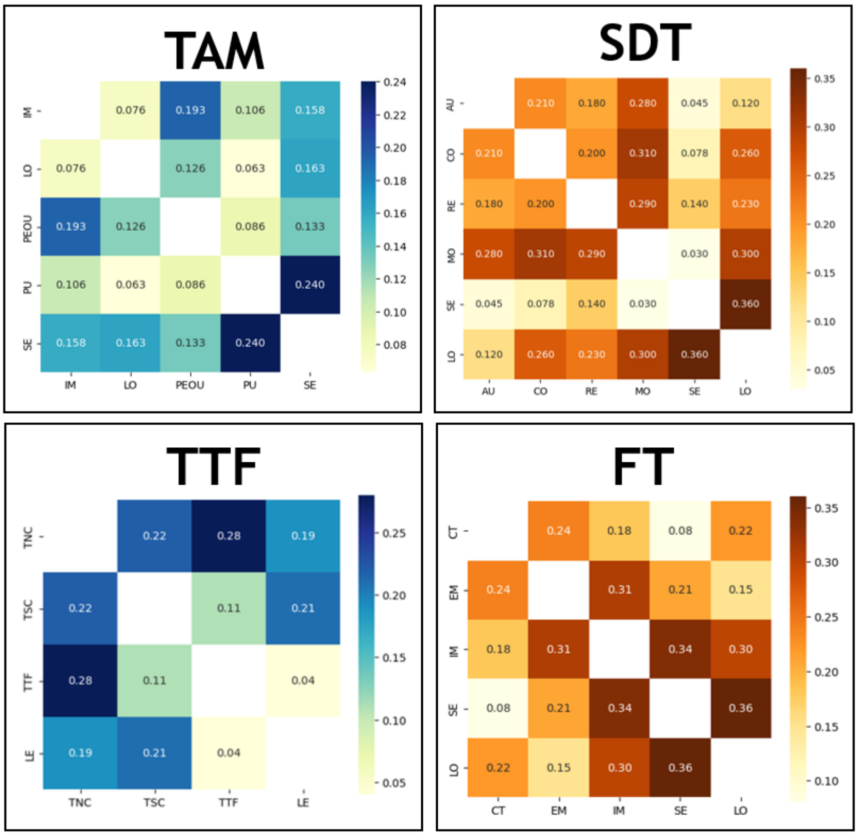

Figure 2. HTMT results

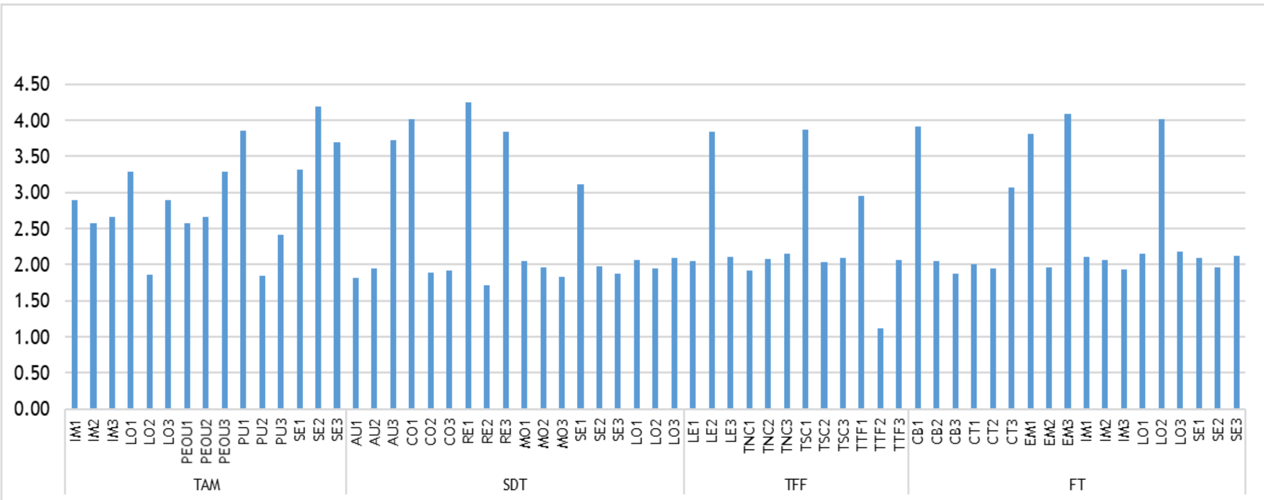

Figure 3. VIF results

Taken together, these results confirm that all four models (TAM, SDT, TTF, and Flow Theory) met the required standards of reliability and validity, thus providing a robust foundation for proceeding to the structural model analysis and subsequent model comparisons.

Structural Model Results

The structural model analysis revealed distinct strengths across the four frameworks. As summarized in table 5, TAM showed moderate explanatory power (R^2 = 0,46 for Engagement; 0,41 for Learning Outcomes), with Perceived Usefulness strongly predicting Learning Outcomes (β = 0,44), underscoring the role of usability and usefulness. SDT achieved higher explanatory strength (R^2 up to 0,63), where Motivation significantly drove

Student Engagement (ß = 0,59), and Engagement strongly impacted Learning Outcomes (f^2 = 0,32), highlighting the motivational basis of VR/AR learning. TTF performed robustly for task-related outcomes (R^2 = 0,67 for Learning Effectiveness), with Task-Technology Fit exerting the strongest effect on performance (ß = 0,65), confirming the importance of task-technology alignment. Finally, Flow Theory emerged as the strongest model overall (R^2 up to 0,72), with Immersion driving Engagement (ß = 0,62) and Engagement exerting a large effect on Learning Outcomes (f^2 = 0,38), emphasizing the central role of immersion and engagement in VR/AR medical education.

Table 5. Structural model results

Model	Endogenous Constructs	R^2	Q^2	Strongest Path (ß)	Largest f^2 Effect	Interpretation
TAM	Engagement = 0,46 Learning Outcomes = 0,41	0,46 / 0,41	0,25 / 0,22	PU → LO (ß = 0,44, p < 0,01)	PEOU → PU (f^2 = 0,18, medium)	Moderate explanatory power; highlights role of usefulness and usability
SDT	Motivation = 0,63 Engagement = 0,57 Learning Outcomes = 0,61	0,63 / 0,57 / 0,61	0,34 / 0,30 / 0,33	Motivation → SE (ß = 0,59, p < 0,001)	SE → LO (f^2 = 0,32, medium-high)	Strong motivational basis for engagement and outcomes
TTF	TTF = 0,60 Learning Effectiveness = 0,67	0,60 / 0,67	0,31 / 0,36	TTF → LE (ß = 0,65, p < 0,001)	TSC → TTF (f^2 = 0,28, medium)	High predictive strength for task-performance alignment
Flow Theory	Immersion = 0,66 Engagement = 0,68 Learning Outcomes = 0,72	0,66 / 0,68 / 0,72	0,37 / 0,35 / 0,40	Immersion → SE (ß = 0,62, p < 0,001)	SE → LO (f^2 = 0,38, large)	Strongest overall; best at explaining immersion, engagement, and outcomes

Comparative Analysis

Among the four models, SDT and Flow Theory demonstrated the highest explanatory and predictive power, with R^2 values exceeding 0,60 and Q^2 values in the range of 0,30-0,40. As presented in table 6, these models emphasize different but complementary mechanisms: SDT highlights the motivational basis of learning, while Flow Theory captures the immersive and affective dimensions of VR/AR engagement. TTF also achieved strong predictive power, particularly for learning effectiveness (R^2 = 0,67), but its scope is narrower, focusing primarily on task-technology alignment rather than broader motivational or experiential aspects. By contrast, TAM provided only moderate explanatory power (R^2 around 0,40–0,46), confirming its usefulness for assessing usability perceptions but showing relative limitations compared to the other models. Overall, Flow Theory and SDT can be considered the strongest frameworks for explaining VR/AR learning in medical education, while TTF offers task-specific insights and TAM remains more moderate in scope.

Table 6. Comparative predictive power

Model	Key Endogenous Constructs	R^2	Q^2	Predictive Power Summary
TAM	Engagement = 0,46 Learning Outcomes = 0,41	Moderate (0,41-0,46)	0,25 / 0,22	Provides moderate predictions; emphasizes usability and usefulness but limited in scope
SDT	Motivation = 0,63 Engagement = 0,57 Learning Outcomes = 0,61	High (0,57-0,63)	0,34 / 0,30 / 0,33	Strong explanatory and predictive power; motivation is the central driver of outcomes
TTF	TTF = 0,60 Learning Effectiveness = 0,67	High (0,60-0,67)	0,31 / 0,36	Strong task-performance predictions; narrower focus on task-technology alignment
Flow Theory	Immersion = 0,66 Engagement = 0,68 Learning Outcomes = 0,72	Highest (0,66-0,72)	0,37 / 0,35 / 0,40	Strongest overall predictive power; captures immersive and affective aspects of VR/AR learning

DISCUSSION

This study provides the first comprehensive empirical comparison of four prominent theoretical frameworks—Technology Acceptance Model (TAM), Self-Determination Theory (SDT), Task-Technology Fit (TTF), and Flow Theory—in explaining student engagement and learning outcomes in VR/AR-based medical education. Rather than positioning these models as competing explanations, our findings suggest that they are complementary lenses that together provide a more complete understanding of immersive learning.

Each model contributes unique explanatory insights. TAM highlights the foundational role of perceived usability and usefulness, showing that positive perceptions are necessary for adoption but insufficient to fully explain deep learning processes. SDT extends this view by revealing that intrinsic motivation, fueled by autonomy, competence, and relatedness, is a critical mechanism driving engagement and subsequent learning outcomes. TTF brings a task-oriented perspective, demonstrating that the alignment between technology features and educational requirements strongly predicts learning effectiveness, particularly for procedural and task-specific objectives. Finally, Flow Theory adds an experiential dimension by showing that immersion, enjoyment, and concentration lead to higher engagement and better learning outcomes, capturing the affective and cognitive depth of VR/AR-based learning.

By integrating these perspectives, this study fills a significant research gap: prior work has typically tested these models in isolation, leaving educators uncertain about which theoretical framework to prioritize. Our comparative approach advances the field by showing that designing effective VR/AR interventions requires simultaneously addressing usability (TAM), motivational needs (SDT), task-technology alignment (TTF), and immersive experience (Flow Theory). This integrated understanding provides a theoretically grounded roadmap for instructional designers and medical educators seeking to maximize the pedagogical impact of VR/AR.

Strengths and Limitations

A key strength of this study is its rigorous methodological approach, including a relatively large and diverse sample of students with verified VR/AR exposure, robust measurement validation, and a comparative PLS-SEM analysis. These features enhance confidence in the robustness and generalizability of the findings.

Nonetheless, several limitations provide important avenues for future research. The cross-sectional design limits causal inference; future studies should adopt longitudinal or experimental designs to observe how motivation, engagement, and flow evolve over time and impact actual performance metrics such as OSCE scores. Although self-report measures are valuable for capturing students' perceptions, integrating objective data sources—including performance analytics from VR platforms, biometric indicators (e.g., eye-tracking, EEG), or clinical skill assessments—would yield a more comprehensive picture of learning processes. Moreover, while purposive sampling ensured relevance by targeting students with VR/AR experience, it may have introduced selection bias; replicating this study with probability sampling or across multiple institutions and cultural settings would further strengthen external validity.

By framing these limitations as opportunities, this study encourages future researchers to build on its strengths—validated instruments, multi-theoretical model comparison, and robust analysis—to develop more nuanced, integrated models of VR/AR learning. Such work can move the field beyond model-by-model testing toward a synthesized theoretical framework that fully accounts for the technological, motivational, and experiential dimensions of immersive medical education.

This study provides a comprehensive empirical comparison of four prominent theoretical frameworks—the Technology Acceptance Model (TAM), Self-Determination Theory (SDT), Task-Technology Fit (TTF), and Flow Theory—in explaining the mechanisms behind student engagement and learning outcomes within VR/AR-based medical education. The results reveal significant differences in the explanatory and predictive power of these models, offering critical insights for educators, instructional designers, and researchers.

The most salient finding is that Flow Theory emerged as the most robust model overall, demonstrating the highest explanatory power for learning outcomes (R^2 = 0,72). This strongly suggests that the affective and experiential state of flow is a central mechanism through which VR/AR enhances medical learning. The powerful pathway from Immersion to Engagement (ß = 0,62) and the large effect of Engagement on Learning Outcomes (f^2 = 0,38) indicate that VR/AR's unique ability to create a deeply absorbing, captivating, and enjoyable experience is its greatest educational asset. When students achieve a balance between the challenge of the material and their perceived skills, can concentrate fully, and derive enjoyment, they enter a state of flow that significantly amplifies learning efficacy. This aligns with foundational work by Csikszentmihalyi and is strongly supported by recent studies in immersive learning, which confirm that flow states are potent predictors of both engagement and knowledge retention in virtual environments.[38,39,40]ES, ATE, and EE

Similarly, Self-Determination Theory (SDT) demonstrated exceptionally high predictive power, particularly highlighting the crucial role of motivation as a key driver. The strong, significant paths from the basic psychological needs (Autonomy, Competence, Relatedness) to Motivation, and subsequently to Engagement and Learning Outcomes, underscore that technology alone is insufficient. VR/AR applications must be designed to foster a sense of control (autonomy), build confidence through achievable tasks (competence), and facilitate collaboration or a sense of shared experience (relatedness) to truly unlock their potential. This finding is consistent with the core tenets of SDT, [41] and is corroborated by educational technology research showing that need satisfaction is a critical precursor to deep learning and sustained engagement in digital environments.[42,43] This positions SDT as a vital framework for understanding the why behind engagement, complementing Flow Theory's focus on the how of the experience.

The Task-Technology Fit (TTF) model performed robustly for a specific aspect of learning: effectiveness driven by alignment. Its high R^2 value for Learning Effectiveness (0,67) confirms that the utilitarian match between the features of the VR/AR technology and the requirements of the medical learning task is a critical success factor. This model is particularly valuable for implementation decisions, suggesting that VR/AR is not a universal solution but is most effective when its capabilities—such as 3D visualization, interactivity, and simulation—directly address the demands of specific tasks like anatomy dissection or surgical procedure practice. This finding aligns with the original propositions of the TTF model, [36] and is supported by recent studies in healthcare education that emphasize the importance of fit between simulation technology and clinical learning objectives.[44,45]

In contrast, the Technology Acceptance Model (TAM), while statistically valid, provided more moderate explanatory power ($R^2 \approx 0,41–0,46$). This indicates that while perceived usefulness and ease of use are necessary foundational factors for technology adoption, they are less sufficient on their own for explaining the depth of engagement and complex learning outcomes in immersive educational settings. TAM effectively explains initial acceptance but appears limited in capturing the rich motivational and experiential processes that lead to profound learning, which are better explained by SDT and Flow Theory. This supports the growing critique that TAM, while robust in organizational contexts, may be less comprehensive in capturing the full spectrum of user experience in highly engaging, non-mandatory systems like educational games or immersive simulations.[46,47]

Implications for Theory and Practice

Theoretically, this study moves beyond isolated model testing to provide a direct comparative assessment. It establishes that models emphasizing intrinsic motivation (SDT) and immersive experience (Flow Theory) offer superior explanatory power for VR/AR learning compared to models focused primarily on extrinsic perceptions of utility (TAM) or functional fit (TTF). This suggests that future theoretical development in immersive learning should integrate motivational and experiential constructs to more fully capture the phenomenon.

For practice, these findings offer clear guidance for medical educators and instructional designers:

1. Design for Flow: Prioritize creating experiences that balance challenge and skill, minimize distractions, and are inherently enjoyable to induce immersive states.
2. Support Psychological Needs: Build in features that promote autonomy (e.g., choice in learning paths), competence (e.g., scaffolded tasks with feedback), and relatedness (e.g., multi-user collaborative simulations) to foster intrinsic motivation.
3. Ensure Task Alignment: Conduct a TTF analysis before implementation to ensure the VR/AR technology is the right tool for the specific learning objective, maximizing its effectiveness and return on investment.

Limitations and Future Research

This study has several limitations. Its cross-sectional design precludes definitive causal inferences. The data are based on self-reported measures, which may be subject to bias. Future research should employ longitudinal designs to track how these relationships evolve over time and incorporate objective learning metrics (e.g., exam scores, objective structured clinical examinations - OSCEs) to triangulate findings. Experimental studies could manipulate elements of the models (e.g., high vs. low autonomy conditions in VR) to test causal effects. Furthermore, exploring integrative models that combine the strongest elements of SDT and Flow Theory could yield a more comprehensive framework for understanding immersive learning. Finally, investigating these relationships in different cultural contexts or with different learner populations would enhance the generalizability of the findings.

CONCLUSION

This study set out to determine which theoretical framework best explains student engagement and learning outcomes in VR/AR-based medical education. Through a comparative PLS-SEM analysis of four prominent models—TAM, SDT, TTF, and Flow Theory—clear conclusions can be drawn.

The findings robustly indicate that Flow Theory is the single strongest model, offering the highest predictive power for learning outcomes. This underscores that the immersive, engaging, and experientially rich nature of VR/AR, which facilitates a state of deep concentration and enjoyment (flow), is its most significant educational advantage. Self-Determination Theory (SDT) also proved to be a highly powerful framework, revealing that intrinsic motivation, fueled by fulfilling needs for autonomy, competence, and relatedness, is a fundamental driver of success in these environments. While TTF remains crucial for ensuring technology aligns with specific tasks, and TAM explains initial acceptance, Flow Theory and SDT provide a more comprehensive understanding of the deep learning processes inherent to VR/AR.

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ACKNOWLEDGMENT

The authors would like to thank Universitas Negeri Padang for financial support toward the APC of this article, funded by the EQUITY Kemdiktisaintek Program supported by LPDP, under contract number 4310/B3/DT.03.08/2025 and 2692/UN35/KS/2025.

FINANCING

The authors did not receive financing for the development of this research.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

AUTHORSHIP CONTRIBUTION

Conceptualization: Ika Parma Dewi.
Data curation: Yudha Aditya Fiandra.
Formal analysis: Rahmat Fadillah.
Research: Yudha Aditya Fiandra.
Methodology: Rizkayeni Marta.
Project management: Linda Rosalina.
Resources: Yudha Aditya Fiandra.
Software: Rahmat Fadillah.
Supervision: Ika Parma Dewi.

Validation: Linda Rosalina.
Display: Yudha Aditya Fiandra.
Drafting - original draft: Nora Azima Noordin, Dawar Khan.
Writing - proofreading and editing: Ika Parma Dewi.