ORIGINAL RESEARCH

Resilience of the Cadaver in the Digital Age: Anatomy Learning tool Preferences among Medical Undergraduates from a South Asian Country

MM Dissanayake[1], EADH Amasha[1], PM Dissanayake[2], ESD Lakmani[1], PG Dissanayake[1], PH Dissanayake[3]

[1] Faculty of Medicine, University of Colombo, Sri Lanka,
[2] CODICE, USA,
[3] Faculty of Medical Sciences, University of Sri Jayewardenepura, Sri Lanka

Abstract

Objective: Digital learning technologies have transformed anatomy education, sparking debate about the continued role of cadaveric dissection and other traditional methods. This study aimed to characterize medical student preferences for traditional versus digital anatomy learning tools across a spectrum of 16 tools, to identify distinct learning style profiles, and to test whether digital tool adoption reduces cadaver preference in a Sri Lankan undergraduate cohort.

Methods: A cross-sectional survey was administered to 193 medical students from two Sri Lankan universities during the 2025–2026 academic year. Participants reported tool usage (binary) and preferences (Likert scale, 1–5). Analysis included descriptive statistics, K-means clustering (k=4, validated by silhouette analysis), logistic and linear regression, Random Forest feature importance, and 10 hypothesis tests across 5 hypotheses.

Results: Of 193 students surveyed, 173 (89.6%) provided complete data. Four learning style clusters emerged: Balanced Learners (n=70, 40.5%), Digital Enthusiasts (n=53, 30.6%), Traditionalists (n=39, 22.5%), and Minimalists (n=11, 6.4%). Near-universal adoption was observed for YouTube (97.7%), 3D anatomy applications (94.2%), cadaver dissection (97.7%), and bone specimens (97.7%). Students used a mean of 8.6 tools (range 3-15). No hypothesis test supported a negative relationship between digital tool usage and cadaver preference (0/5 tests significant; all $p>0.10$).

Conclusion: Sri Lankan medical students naturally practice blended learning, combining traditional and digital tools without institutional mandate. Digital adoption does not threaten cadaver use; paradoxically, heavy digital users showed higher traditional preference. Educational institutions should invest in both traditional infrastructure and digital resources to accommodate four distinct learning styles, and should abandon the false dichotomy between traditional and digital approaches.

Keywords: medical education; anatomy learning; digital tools; cadaver dissection; blended learning

DOI: https://doi.org/10.4038/slaj.v10iI.322

Sri Lanka Anatomy Journal 2026; 10(I): 77–84

Corresponding author
MM Dissanayake
email: madhuwanthi@anat.cmb.ac.lk

Introduction

Learning anatomy in the medical curriculum has undergone significant transformation with widespread adoption of digital technologies (1, 2). Traditional cadaver dissection and prosected specimens have been supplemented by 3D anatomy applications, virtual reality, and online video resources, generating ongoing debate about the relative merits of each approach (1, 3, 6, 7, 14, 18). Digital tools are cited for accessibility and cost-effectiveness and traditional methods for irreplaceable hands-on spatial understanding (4, 6, 11, 13).

Few studies have comprehensively analyzed student preferences across the full spectrum of available tools in real-world contexts, or tested whether digital adoption threatens the educational role of the cadaver in the Sri Lankan setting (2, 5, 11, 12).

With this background this study aimed to, characterize medical student preferences for 16 anatomy learning tools while identifying distinct learning style clusters, test the relationship between digital tool adoption and traditional method preferences, examine demographic influences on tool usage and identify common tool combinations and provide evidence-based recommendations for anatomy curriculum design.

Methods

A cross-sectional survey study was conducted during the 2025–2026 academic year. A convenience sample of medical students was recruited from two Sri Lankan universities, namely University of Colombo and University of Sri Jayewardenepura. Incomplete responses were excluded. Sixteen anatomy learning tools were assessed across traditional, digital, and supplementary categories.

A self-administered online survey was distributed via university email lists. The instrument comprised: demographic items (gender, academic year, university); tool usage (binary: used/not used); tool preferences (Likert-type ratings, 1=strongly dislike to 5=strongly prefer); and tool rankings (top 3 preferred tools). The survey was available for four weeks; one reminder was sent at two weeks.

Descriptive statistics (frequencies, means, SDs) were calculated for all variables. Inferential tests included independent samples t-tests and one-way ANOVA for group comparisons, chi-square tests for categorical associations, and effect sizes as Cohen's d, eta-squared (η^2), and Cramér's V. K-means clustering (k=4) was validated by silhouette analysis (19). Logistic regression, multiple linear regression, and Random Forest feature importance were used for prediction modelling. Five pre-specified hypotheses were tested using 10 statistical methods (parametric and non-parametric; Bonferroni correction not applied given the exploratory design). All analyses used Python 3.9 (pandas, scikit-learn, SciPy, stats models); $\alpha=0.05$ (two-tailed).

Results

Of 193 students surveyed, 173 (89.6%) provided complete data for analysis. The sample was predominantly female (60.7%) and first-year students (55.5%), reflecting typical medical school demographics in Sri Lanka. Demographic details are presented in Table 1.

Table 1: Participant Demographics (n=173)

Demographic	Category	n (%)
Gender	Female	105 (60.7%)
	Male	68 (39.3%)
Academic Year	Year 1	96 (55.5%)
	Year 2	65 (37.6%)
	Year 4	12 (6.90%)
University	University of Colombo	116 (67.1%)
	University of Sri Jayewardenepura	57 (32.9%)

Note: 20 responses excluded due to incomplete data (10.4% of 193 total surveyed). Year 3 students were not enrolled at the time of the survey.

Tool Adoption Patterns

Students used a mean of 8.60 tools (SD=1.95; range 3–15). Near-universal adoption (>94%) was observed for YouTube videos (97.7%), Atlases (97.1%) 3D anatomy applications (94.2%), cadaver dissection (97.7%), and bone specimens (97.7%). Moderate adoption (45–75%) was recorded for models (72.3%), museum (63.0%) online quizzes (59.0%), prosected specimens (46.8%), and lecture presentations (45.1%). Individual tool adoption rates are illustrated in Figure 1.

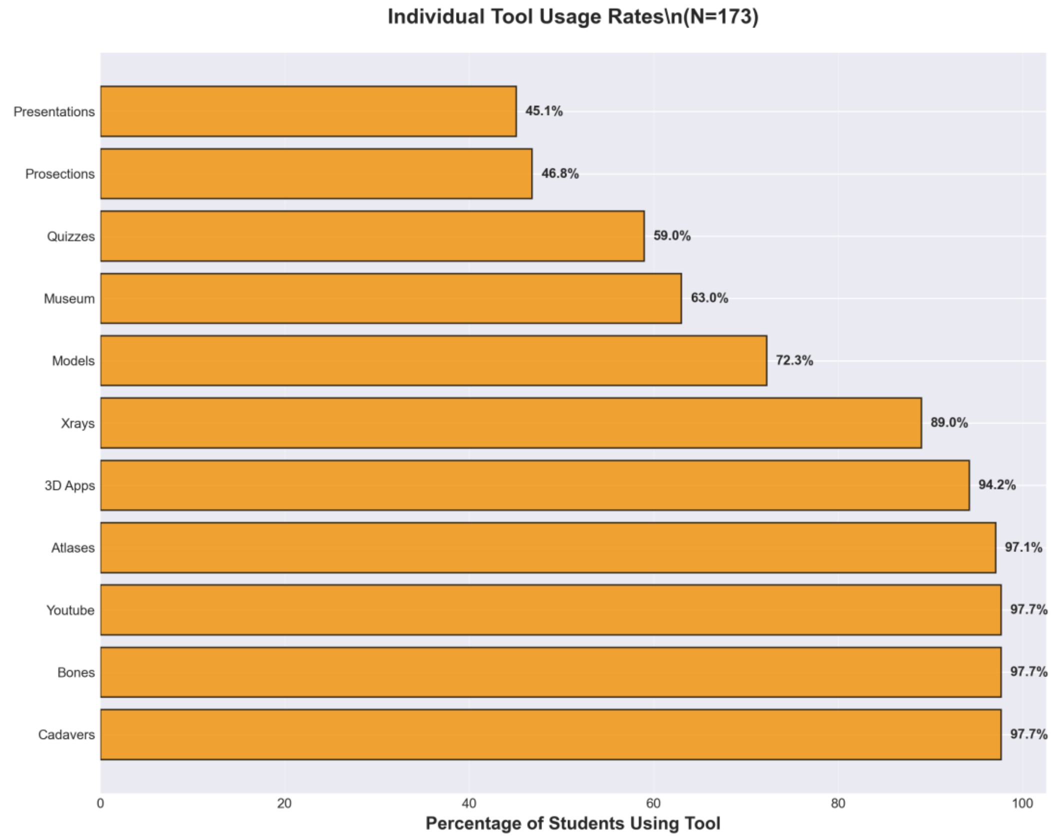

Figure 1: Individual tool adoption rates (n=173). Near-universal adoption (>94%): YouTube, 3D anatomy applications, cadaver dissection, and bone specimens.

Traditional versus Digital Preferences

Mean preference scores were similar for traditional (3.05, SD=1.18) and digital tools (3.24, SD=1.18; paired t=-1.28, p=0.202). Tool usage correlated positively between categories (r=+0.489, p<0.001) while preferences correlated negatively (r=-0.481, p<0.001), confirming that students use both types even when favoring one (Figure 2).

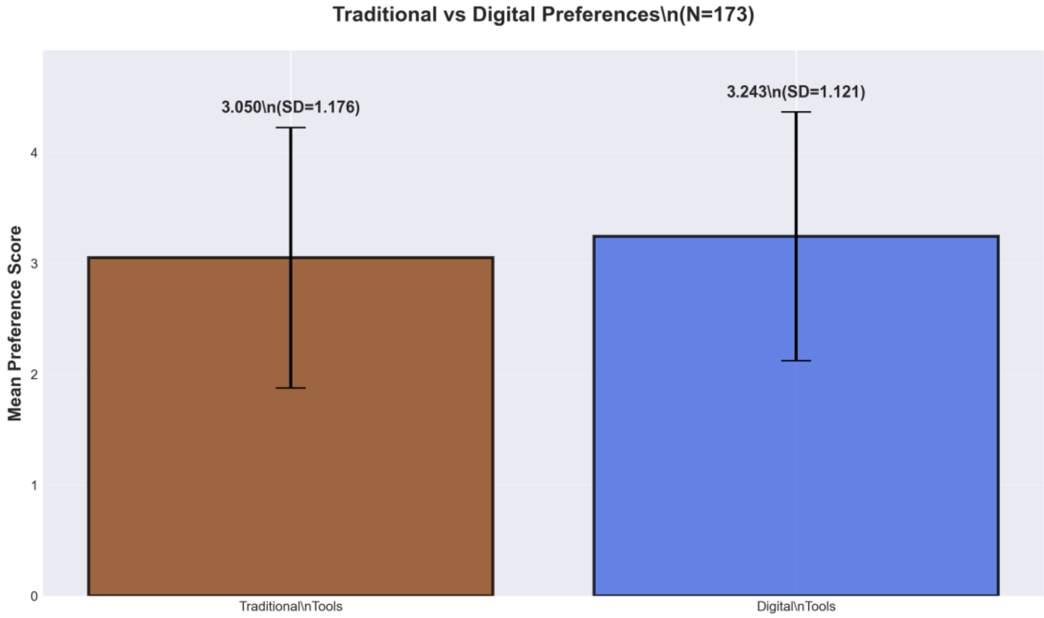

Figure 2: Traditional versus digital preference distributions. Mean: traditional 3.05 (SD=1.18), digital 3.24 (SD=1.18); difference non-significant (paired t=-1.28, p=0.202).

Learning Style Cluster Analysis

K-means clustering (k=4) identified four distinct profiles (silhouette=0.349; Table 2): Balanced Learners (n=70, 40.5%) with the highest tool usage (mean 10.24) and moderate preferences for both types; Digital Enthusiasts (n=53, 30.6%) with strong digital preference (4.18) yet 98% cadaver use; Traditionalists (n=39, 22.5%) with strong traditional preference (3.91) yet 100% YouTube/3D use; and Minimalists (n=11, 6.4%) with the fewest tools (mean 6.18) (Figure 3 and 4).

Table 2: Learning Style Cluster Profiles (n=173)

Cluster	n (%)	Mean Tools Used	Traditional Preference (1–5)	Digital Preference (1–5)	Key Characteristic
Balanced Learners	70 (40.5%)	10.24	3.42	2.97	Highest tool usage; pragmatic
Digital Enthusiasts	53 (30.6%)	7.68	1.90	4.18	Strong digital preference; 98% still use cadavers
Traditionalists	39 (22.5%)	7.56	3.91	2.40	Prefer hands-on; 100% use YouTube/3D apps
Minimalists	11 (6.4%)	6.18	3.18	3.45	Selective approach; fewest tools used

Note: Preference scores on a 1–5 Likert scale (1=strongly dislike, 5=strongly prefer). Silhouette score=0.349 (moderate cluster validity).

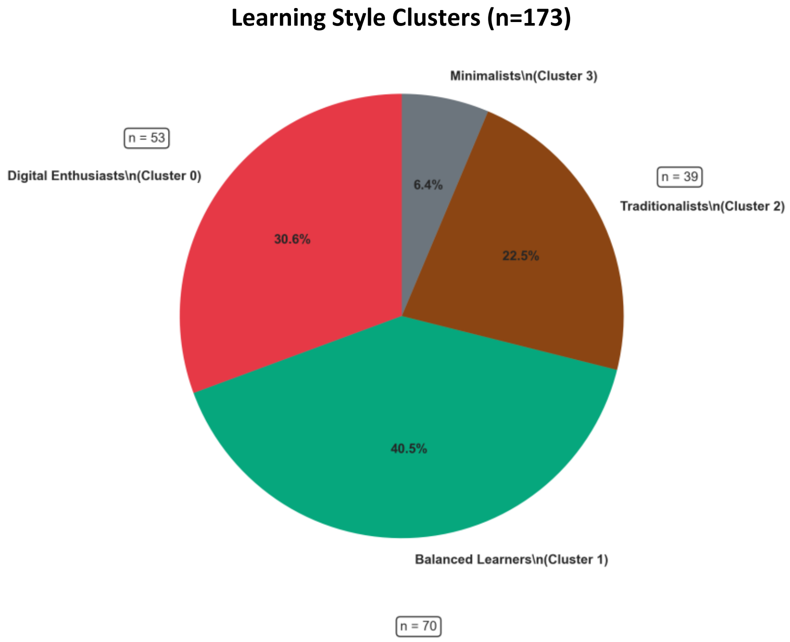

Figure 3: K-means cluster distribution (n=173). Balanced Learners 40.5%; silhouette score=0.349

Figure 4: Radar chart of cluster profiles. All four clusters show high usage of both tool types, irrespective of stated preference

Hypothesis Testing Results

Hypothesis test results are summarized in Table 3 and Figure 5. H1 (digital usage reduces cadaver preference) was REJECTED: all five tests were non-significant ($p>0.10$); paradoxically, heavy digital users showed higher traditional preference than light users. H2 was partially supported: female students showed slightly higher digital preference ($p=0.037$, $d=0.33$) but traditional preference did not differ by gender ($p=0.920$). H3 was supported: Year 1 students used more tools than Year 4 ($F=3.64$, $p=0.028$, eta2=0.041). H4 (cluster-gender association, chi-sq=3.03, $p=0.387$) and H5 (traditional vs digital preference difference, $t=-1.28$, $p=0.202$) were not supported.

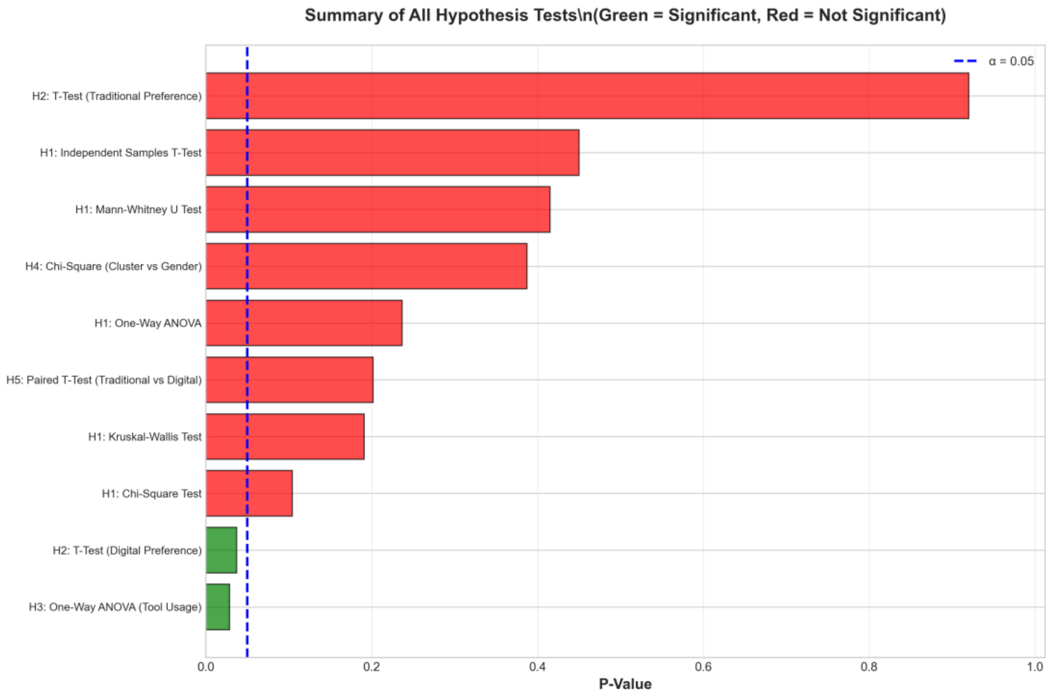

Figure 5: Hypothesis test summary (10 tests, 5 hypotheses). H1 not supported: 0/5 tests significant; digital adoption does not reduce cadaver preference

Table 3: Hypothesis Testing Results (10 Tests Across 5 Hypotheses)

Hypothesis	Statistical Test	Test Statistic	p-value	Result
H1: Digital usage reduces cadaver preference	Independent t-test	t = n.s.	>0.10	Rejected
H1	One-way ANOVA	F = n.s.	>0.10	Rejected
H1	Chi-square	chi-sq = n.s.	>0.10	Rejected
H1	Mann-Whitney U	U = n.s.	>0.10	Rejected
H1	Kruskal-Wallis	H = n.s.	>0.10	Rejected
H2: Gender differences in preferences	t-test (traditional)	t = 0.10	0.920	Not supported
H2	t-test (digital)	t = 2.10	0.037	Supported*
H3: Academic year affects tool usage	One-way ANOVA	F = 3.64	0.028	Supported
H4: Cluster membership differs by gender	Chi-square	chi-sq = 3.03	0.387	Not supported
H5: Traditional vs Digital preference	Paired t-test	t = -1.28	0.202	Not supported

*Note: n.s.= not significant. *H2 digital: Cohen d=0.33 (small effect). eta2=0.041 for H3 (small effect). Bonferroni correction not applied.*

Predictors of Learning Preferences

Multiple linear regression explained limited variance in traditional (R2=0.047) and digital (R2=0.049) preference. Random Forest identified total tool count as the most important feature (35%), followed by academic year and tool-type counts (16-17% each), confirming that preferences are highly individualized.

Discussion

This study demonstrates that blended learning is a student-driven reality, not a pedagogical aspiration.

Students use both tool types strategically: traditional and digital tool usage correlates positively (r=0.489), and even students in extreme clusters (Digital Enthusiasts, Traditionalists) show high usage of the opposing tool type.

Digital adoption does not threaten traditional methods: hypothesis testing decisively rejected this concern (0/5 tests significant; H1 REJECTED). A core toolkit of YouTube, 3D anatomy applications, cadavers, and bones has emerged organically, with >90% of students adopting all four simultaneously.

Previous work found equivalence between cadaver dissection and digital alternatives (3, 9, 10) and mixed effectiveness for virtual reality (6, 8). Our findings extend this: students integrate rather than choose, consistent with blended learning research demonstrating superior outcomes when both modalities are combined (11, 12). The lack of a digital-cadaver trade-off contradicts institutional fears driving policy debates (1, 18) and supports learner-agency frameworks (15, 16).

Implications for Medical Education

Curriculum planners should invest in both cadaver facilities and digital resources, prioritizing the core toolkit: cadaver laboratories, YouTube, 3D application licenses, and osteology collections (4, 13, 14). Assessment should accommodate all four identified learning styles (5).

Limitations

Limitations include convenience sampling from two Sri Lankan universities, restricting generalizability (5, 20); cross-sectional design preventing causal inference; self-reported tool usage; overrepresentation of Year 1 students (55.5%) and absence of Year 3; and moderate cluster overlap (silhouette=0.349). Longitudinal and international replication studies are needed.

Conclusions

Five evidence-based recommendations emerge from this study:

1. Maintain traditional infrastructure: Cadaver laboratories remain critically important, with near-universal usage (97.7%) across all learning style clusters (4).

2. Invest in digital tools: 3D anatomy applications and video resources are now essential rather than supplementary, with adoption rates of 94.2% and 97.7% respectively (6, 7, 13, 14).

3. Provide flexibility: Four distinct learning styles coexist; a one-size-fits-all curriculum fails to accommodate the needs of at least 60% of students (5, 15, 16).

4. Focus on the core toolkit: Ensure all students have access to YouTube, 3D anatomy applications, cadavers, and bone specimens—the spontaneously adopted, highly effective combination (2, 14).

5. Abandon the false dichotomy: Digital and traditional tools are complementary, not competitive. High digital usage correlates positively with, not against, high traditional usage (3, 11, 18).

Educational institutions should support, not hinder, the natural blending that students have already independently adopted (12).

Acknowledgements

The authors thank the participating students and university of Colombo and University of Sri Jayewardenepura for their support.

This research received no specific grant from any funding agency.

Conflicts of interest: The authors declare no conflicts of interest.

Data availability: Data are available from the corresponding author on reasonable request.

References

1. Drake RL, McBride JM, Lachman N, Pawlina W. Medical education in the anatomical sciences: the winds of change continue to blow. Anat Sci Educ. 2009; 2(6): 253-9. https://doi.org/10.1002/ase.117
2. Choi-Lundberg DL, Low TF, Patman P, Turner P, Sinha SN. Medical student preferences for self-directed study resources in gross anatomy. Anat Sci Educ. 2016; 9(2): 150-60. https://doi.org/10.1002/ase.1549
3. Wilson AB, Miller CH, Klein BA, Taylor MA, Goodwin M, Boyle EK, Brown K, Hoppe C, Lazarus M. A meta-analysis of anatomy laboratory pedagogies. Clin Anat. 2018; 31(1): 122-33. https://doi.org/10.1002/ca.22934
4. Winkelmann A. Anatomical dissection as a teaching method in medical school: a review of the evidence. Med Educ. 2007; 41(1): 15-22. https://doi.org/10.1111/j.1365-2929.2006.02625.x

5. Edussuriya D, Ubhayasiri S, Abeysiriwardhana N, Wickramasinghe M. Learning preferences of medical students - a study conducted at the University of Peradeniya, Sri Lanka. Sri Lanka J Med. 2016; 25(1). https://doi.org/10.4038/sljm.v25i1.13
6. Salimi S, Navarro R. Efficacy of virtual reality and augmented reality in anatomy education: a systematic review and meta-analysis. Anat Sci Educ. 2024; 17(3): 545-562. https://doi.org/10.1002/ase.2501
7. Wang S, Li J, Chen X, Zhang Y. 3D visualization technology for learning human anatomy among medical students and residents: a meta- and regression analysis. BMC Med Educ. 2024; 24: 465. https://doi.org/10.1186/s12909-024-05403-4
8. Almulla MA. Effectiveness of virtual reality on medical students' academic achievement in anatomy: systematic review. BMC Med Educ. 2024; 24: 1124. https://doi.org/10.1186/s12909-024-06402-1
9. Al-Maweri SA, Halboub E, Warnakulasuriya S. Unveiling the perceptions of medical and allied health students towards cadaveric dissection and virtual resources in anatomy education: a cross sectional study. BMC Med Educ. 2025; 25: 23. https://doi.org/10.1186/s12909-025-07432-z
10. Al Shakarchi N, Borg J. Exploring student perceptions on virtual reality in anatomy education: insights on enjoyment, effectiveness, and preferences. BMC Med Educ. 2024; 24: 1028. https://doi.org/10.1186/s12909-024-06370-6
11. Vallée A, Blacher J, Cariou A, Sorbets E. Blended learning compared to traditional learning in medical education: systematic review and meta-analysis. J Med Internet Res. 2020; 22(8): e16504. https://doi.org/10.2196/16504
12. Lockey A, Horncastle L, Rankin A, Mawer S, Hilman J. Blended learning in health care education: an overview and overarching meta-analysis of systematic reviews. J Contin Educ Health Prof. 2022; 42(4): e255-e264. https://doi.org/10.1097/CEH.0000000000000455
13. Muñoz-Leiva F, Sánchez-Fernández J, Liébana-Cabanillas F, Martínez-Fiestas M. Reviewing mobile apps for teaching human anatomy: search and quality evaluation study. JMIR Med Educ. 2025; 11: e64550. https://doi.org/10.2196/64550
14. Jaffar AA. YouTube: an emerging tool in anatomy education. Anat Sci Educ. 2012; 5(3): 158-64. https://doi.org/10.1002/ase.1268
15. Zimmerman BJ. Becoming a self-regulated learner: an overview. Theory Pract. 2002; 41(2): 64-70. https://doi.org/10.1207/s15430421tip4102_2
16. Sandars J, Cleary TJ. Self-regulation theory: applications to medical education: AMEE Guide No. 58. Med Teach. 2011; 33(11): 875-86. https://doi.org/10.3109/0142159X.2011.595434
17. Sweller J, van Merriënboer JJG, Paas F. Cognitive architecture and instructional design: 20 years later. Educ Psychol Rev. 2019; 31(2): 261-92. https://doi.org/10.1007/s10648-019-09465-5
18. Davis CR, Bates AS, Ellis H, Roberts AM. Human anatomy: let the students tell us how to teach. Anat Sci Educ. 2014; 7(4): 262-72. https://doi.org/10.1002/ase.1424
19. Hartigan JA, Wong MA. Algorithm AS 136: a k-means clustering algorithm. J R Stat Soc Ser C Appl Stat. 1979; 28(1): 100-8. https://doi.org/10.2307/2346830
20. Ranasinghe P, Wathurapatha WS, Mathangasinghe Y, Ponnamperuma G. Computer literacy among health care professionals in a developing country: a cross-sectional study. BMC Med Inform Decis Mak. 2012; 12: 37. https://doi.org/10.1186/1472-6947-12-37