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Understanding how medical students learn in the era of artificial intelligence: a mixed methods study

Salah Eldin Kassab^{1*} , Ramya Rathan² , David CM Taylor² , Shadi Hamouri^{3,4} and Hossam Hamdy¹

Abstract

Background As medical education evolves, current teaching practices often remain misaligned with how today's digitally native students prefer to learn. While the use of digital tools is widespread, there is limited clarity on students' learning behaviors, particularly their preferences for self-paced, assessment-driven, and technology-supported strategies. This study explores these patterns using a mixed-methods approach to inform more responsive medical curricula.

Methods A mixed-methods, cross-sectional study was conducted among undergraduate medical students ($n=432$) from three universities in the UAE and Jordan. A 23-item questionnaire, developed through literature review and expert validation, included both quantitative and qualitative components. Exploratory and confirmatory factor analyses (EFA and CFA) were used to establish construct validity. Free-text responses were analyzed using thematic analysis to complement and contextualize the quantitative findings.

Results CFA supported a five-factor, 17-item structure with good model fit ($\chi^2 = 180.02$, $df = 102$, $\chi^2/df = 1.77$, CFI = 0.97, RMSEA = 0.04, SRMR = 0.053). The identified dimensions were: self-paced learning, exam-oriented learning, partnership in learning, collaborative learning, and AI-enhanced learning. Thematic analysis of 218 qualitative responses revealed eight key themes: flexible learning options, enhanced formative assessment, active teaching, study skills development, collaborative learning, use of technology, clinically focused learning, and resource accessibility. These qualitative themes reinforced and expanded upon the quantitative constructs.

Conclusions Medical students in the AI era adopt a complex, multidimensional approach to learning that is personalized, flexible, and technology driven. The convergence of quantitative and qualitative data underscores the urgent need to align curricula with students' preferences by promoting self-regulated, interactive, and AI-enhanced learning environments. These findings have critical implications for faculty development, curriculum reform, teaching, student assessment, and the future of learner-centered medical education.

Keywords Medical students, Learning strategies, Artificial intelligence, Digital learning, Mixed methods, Curriculum reform

*Correspondence:

Salah Eldin Kassab
salah.eldin@dmu.ae; Drkassabe@med.suez.edu.eg

¹College of Medicine, Dubai Medical University, Dubai, United Arab Emirates

²College of Medicine, Gulf Medical University, Ajman, United Arab Emirates

³Department of Surgery, Faculty of Medicine, Al-Balqa Applied University, Salt, Jordan

⁴Department of General Surgery and Urology, Faculty of Medicine, Jordan University of Science and Technology, Irbid, Jordan



Introduction

Medical education has undergone significant transformation over the past two decades, driven in large part by rapid technological advances, shifting pedagogical paradigms, and evolving learner expectations. Traditional teacher-centered models, characterized by passive knowledge transmission in lecture halls, are increasingly challenged by the needs and preferences of modern learners who have grown up in an era of prevalent digital technology [1, 2]. While digital enhanced learning broadly encompasses digital tools used in education, artificial intelligence (AI) introduces qualitatively new capabilities such as adaptive tutoring, generative text and image support, predictive analytics, and immersive simulations. These AI-specific affordances extend beyond earlier approaches by offering personalized, context-aware, and interactive learning opportunities that reshape how medical students engage with knowledge [3]. The AI era has not only changed what is possible in terms of instructional delivery but has also reshaped how students engage with content, collaborate with peers, and manage their own learning processes. In this context, understanding how medical students learn in the AI-enhanced learning environments is both timely and necessary for guiding curriculum reform, instructional design, and faculty development.

Numerous studies have demonstrated that today's learners approach learning in ways that are distinctly different from previous generations. In his famous book "On the Horizon", Prensky indicated quarter-century ago that *"Our students have changed radically. Today's students are no longer the people our educational system was designed to teach"* [4]. These students are comfortable using digital tools, accessing vast online resources, engaging in asynchronous learning, and utilizing mobile applications to supplement their understanding [4]. With the emergence of AI and easy accessibility of information, more methods of learning are used by medical students. While Prensky's notion of "digital natives" has been influential, subsequent scholarship has challenged the assumption that all students are equally adept with digital technologies. Research indicates considerable variability in learners' digital skills, confidence, and critical engagement, suggesting that the label "digital native" oversimplifies a complex reality [5]. This highlights the need to move beyond generational stereotypes and instead examine how diverse students use and experience technology in learning contexts. While there has been significant interest in integrating technology-enhanced learning (TEL) into medical curricula, there is a growing concern that educational practices have not kept pace with students' evolving needs [2, 6].

Medical education frameworks have traditionally emphasized structured, face-to-face instruction with a

linear progression from basic sciences to clinical practice. Although this structure provides a clear scaffold for knowledge acquisition and professional development, it may not reflect how students today interact with information or build conceptual understanding. Evidence suggests that students now prefer self-paced learning, increased autonomy, and personalized pathways through the curriculum; elements often underrepresented in traditional course designs [7, 8].

While several studies have explored general learning styles and digital literacy [9, 10], few have systematically identified the dimensions of learning behaviors that are unique to medical students in AI-enhanced environments. Furthermore, despite these observed changes in learning behavior, there remains a lack of robust, psychometrically sound tools to assess how medical students learn in the AI era.

This study is underpinned by contemporary learning theories that offer a comprehensive understanding of how medical students engage with learning in the AI era. Illeris's three-dimensional theory of learning offers a valuable conceptual lens [11]. His model posits that meaningful learning occurs through the dynamic integration of three dimensions: content (knowledge and skills acquired), incentive (motivation and emotional engagement), and interaction (social and environmental influences) [11]. This framework acknowledges the importance of not only cognitive acquisition but also the emotional and social dimensions of learning; factors that are increasingly influenced by AI-driven tools and environments.

In addition, Connectivism provides another critical lens for understanding how digital tools, online platforms, and artificial intelligence are reshaping learning behaviors and knowledge acquisition [12]. It emphasizes the importance of learning through networks and accessing diverse information sources, making it particularly applicable in digitally-rich educational contexts [12].

Despite the increasing availability of digital tools and instructional technologies, many medical programs continue to rely heavily on conventional lectures and summative assessments, which may not effectively engage students or support long-term knowledge retention. As such, there is a misalignment between how students are taught and how they prefer or need to learn to succeed in increasingly complex and information-rich clinical environments. Given these challenges, there is a critical need to develop validated instruments that can measure how medical students learn in the AI era and to use these instruments to inform the design of contemporary teaching, learning, and assessment strategies. The aim of this study is to address this gap by developing and validating a psychometric scale that captures the core dimensions of learning among medical students in AI-enhanced

environments and better understanding of student preferences and expectations.

Methods

Study context

This cross-sectional, multi-institutional study was conducted among undergraduate medical students enrolled at three universities: Gulf Medical University (Private) and Dubai Medical University (Private) in the United Arab Emirates, and Al-Balqa Applied University in Jordan (Public). Together, these variations provided a broader perspective on medical students' learning behaviors across different educational environments.

Development of the study instrument

The present study aimed to develop a new questionnaire to assess how medical students learn in the AI era. To develop the study instrument, a comprehensive review of extant literature was conducted to identify prevailing themes related to how medical students learn in the digital age. Themes of particular focus included self-paced learning, technology use, assessment-driven study habits, and collaborative approaches. Both Illeris's three-dimensional theory and Connectivism were employed because they provide complementary perspectives on student learning: Illeris emphasizes the interplay of content, incentive, and interaction, while Connectivism highlights learning through digital networks and distributed knowledge sources [11, 12]. Together, these frameworks guided construct definition and item generation, ensuring that the scale captured both the dimensions of learning and the unique influences of AI-enhanced environments. An initial pool of items was generated to reflect key behaviors and preferences observed among AI oriented learners. The initial questionnaire was drafted in English and reviewed by a panel of four medical education experts with over 10 years of experience in curriculum design, assessment, and educational research. Based on their feedback, minor revisions were made to improve clarity, remove redundant items, and adjust the response scale wording. Subsequently, a pilot study was conducted with 20 undergraduate students to test item comprehension and variability of responses. Minor refinements were made based on pilot feedback, resulting in a final English version consisting of 23 items.

Evidence of construct validity: factor analysis

To explore the underlying structure of the instrument, exploratory factor analysis (EFA) was first performed using data collected from 210 students. Principal component analysis (PCA) with Varimax rotation was applied to examine factor loadings and communalities, with the goal of identifying coherent dimensions

within student learning behaviors. This analysis served to uncover the latent constructs informing students' learning approaches.

Following the EFA, confirmatory factor analysis (CFA) was carried out to test the validity of the factor structure and assess the model fit. CFA was conducted on a larger independent sample of 432 students enrolled in the medical program. Model fit was evaluated using several established indices: Chi-square (χ^2), chi-square to degrees of freedom ratio (χ^2/df), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), Standardized Root Mean Square Residual (SRMR), and Akaike Information Criterion (AIC), in accordance with previous guidelines [13, 14]. These indicators collectively informed the judgment of the degree of fitness between theoretical and measurement models.

Construct reliability (CR)

To assess internal consistency of the latent constructs, composite reliability (CR) was calculated. This metric considers both the standardized factor loadings (λ) and the corresponding error variances (ϵ) for each item [15]. CR values provided insight into the reliability and stability of each identified factor within the final model.

The formula for calculating construct reliability is:

$$CR = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + (\sum \epsilon_i)}$$

whereby, λ (lambda) is the standardized factor loading for item I , and ϵ is the respective error variance for item i . The error variance (ϵ) is estimated based on the value of the standardized loading (λ) [15].

The quantitative data were processed and analyzed using SPSS (version 28.0). For studies requiring confirmatory factor analysis, AMOS (version 21) was employed. Statistical significance was set at a p-value of less than 0.05.

Qualitative data analysis

To complement the quantitative findings and gain deeper insights into students' learning practices, a qualitative component was embedded in the questionnaire. Students were invited to provide free comments describing additional learning methods they employ beyond those captured by the closed-ended items. This open-ended prompt aimed to reveal emerging or personalized strategies reflective of student learning in the digital era. A total of 218 valid responses were collected and analyzed using thematic analysis, following the six-step framework [16]. The analysis was facilitated by NVivo version 12, a qualitative data analysis software that supported

systematic coding, organization, and retrieval of textual data.

The process began with data familiarization, during which two members of the research team independently read all responses multiple times within NVivo, noting initial impressions and generating memos. In the second phase, open coding was conducted line by line to create initial codes (nodes) capturing distinct learning practices or ideas reported by students.

Reflexivity

These codes were then collaboratively reviewed to ensure coding consistency and minimize subjective researcher bias. In the third phase, related codes were grouped into preliminary themes using NVivo’s node classification tools, enabling clear visualization and categorization of patterns. The themes were iteratively refined through constant comparison with the original data.

The resulting themes were reviewed for internal coherence and external distinctiveness, and each was clearly defined to reflect its core meaning. To ensure the trustworthiness of the analysis, a third researcher independently reviewed the emerging themes for alignment with the study’s objectives. Any discrepancies were resolved through team discussion until consensus was achieved.

Verbatim quotes were selected to illustrate key themes in the results section, preserving the authenticity of student voices and enhancing the interpretive depth and credibility of the findings.

Results

Demographic characteristics

The study used convenient sampling from a target population of undergraduate students of medicine. As shown in Table 1, the highest response rate (71.9%) was obtained from Gulf Medical University with much lower rates in the other two universities. The study sample comprised 64.6% females (*n* = 279) and 35.4% males (*n* = 153). Most

of the students were enrolled at Gulf Medical University (71.9%, *n* = 310), followed by Al-Balqa Applied University in Jordan (20.4%, *n* = 88), and Dubai Medical University (7.6%, *n* = 33). In terms of ethnicity, 55.6% of participants identified as Middle Eastern (*n* = 240), 36.1% as Asian (*n* = 136), 4.9% as African, 0.9% as Western, and 2.5% as belonging to other ethnic backgrounds. The age distribution indicated that the largest proportion of students were between 17 and 20 years old (58.6%, *n* = 335), followed by those aged 21 to 24 years (19%, *n* = 82). A small minority of students (3.5%, *n* = 15) were older than 24 years.

Construct validity evidence of the questionnaire

Exploratory factor analysis

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.84, indicating that the dataset was suitable for factor analysis, and Bartlett’s test of sphericity was significant ($\chi^2 = 3125.25$, *df* = 253, *p* < .001), supporting the factorability of the correlation matrix. An unrotated exploratory factor analysis of all items (Harman’s single-factor test) revealed that the first factor accounted for only [23%] of the total variance, which is well below the 50% threshold, indicating that common method bias was unlikely to substantially affect the results. Based on the criterion of eigenvalues greater than one, the rotated matrix revealed six factors, accounting for 59.32% of the total variance. Communalities ranged from 0.35 to 0.80, suggesting that the items shared a substantial proportion of variance with the extracted factors.

The first factor, labeled *Self-paced learning*, included items related to the use of recorded lectures, online learning, time optimization strategies (e.g., watching at 2x speed), and reduced in-person attendance when not mandatory. This reflects a shift toward individualized, on-demand learning formats. The second factor, *Partnerships in learning*, captured students’ desire to collaborate with faculty in course design and resource curation, along with valuing interprofessional engagement. The third factor, *AI-enhanced learning*, encompassed the use of artificial intelligence for writing support and simulation-based learning (AR/VR/XR). The fourth factor, *Collaborative learning*, reflected engagement in peer collaboration, co-development of resources, and participation in digital discussion groups. The fifth factor, *Exam-oriented learning*, comprised reliance on exam-specific materials, including past papers, AI tools for preparation, and repeated review of recorded content. The sixth factor, *Learning context preferences*, included preferences for self-paced learning, comfortable learning environments, social media use, and sourcing high-quality content from international educators.

The item “I use social media platforms for learning and sharing educational content with my colleagues like

Table 1 Study sample characteristics

Category	Subgroup	<i>n</i>	%
Gender	Female	279	64.6%
	Male	153	35.4%
University	Gulf Medical University	310	71.9%
	Al-Balqa Applied University	88	20.4%
	Dubai Medical University	33	7.6%
Ethnicity	Middle Eastern	240	55.6%
	Asian	156	36.1%
	African	21	4.9%
	Western	4	0.9%
	Other	11	2.5%
Age Group	17–20 years	335	77.5%
	21–24 years	82	19.0%
	> 24 years	15	3.5%

– YouTube, Google, etc.” was dropped after EFA because it did not load on any factor with more than 0.4. On the other hand, three items cross-loaded on two factors “I prefer spending more time in the workplace, hospitals, and clinics than attending lectures”, “I prefer self-paced learning and discussions, not just listening to a lecture”, “I revisit the content in recorded lectures as needed to reinforce learning”. Two other items were excluded because they did not fulfill the criteria for making a single factor: “I seek out the highest quality lectures and resources from top international educators worldwide” and “I prefer learning in comfortable or familiar settings, such as libraries, homes, or cafes”.

Confirmatory factor analysis

Confirmatory factor analysis (CFA) was conducted to evaluate the fitness of the six-factor model identified through exploratory factor analysis. However, the sixth factor identified in the EFA was removed during confirmatory factor analysis because the initial 22-item, six-factor model proved to be over-parameterized, with too many free parameters to be reliably estimated. The three items that defined this factor exhibited weak or cross-loadings, lacked theoretical coherence, and did not contribute to a stable or parsimonious structure. Accordingly, guided by the EFA results, the three items representing the sixth factor were deleted and the 19-items model was tested for fitness. However, as shown in Table 2, the model fitness criteria were still below the acceptable level. Guided, by the modification indices, two more items were deleted, and the 17-items model was tested for fitness. This model demonstrated a good overall fit to the data. The chi-square statistic was significant ($\chi^2(102) = 180.02$, $p < .001$); however, given the sensitivity of chi-square to sample size, other fit indices were considered. The chi-square to degrees of freedom ratio (CMIN/DF) was 1.77, which falls within the acceptable range of 1 to 3, indicating an adequate model fit. The Root Mean Square Error of Approximation (RMSEA) was 0.043 with a 90% confidence interval of 0.033 to 0.053, and a high p-close value of 0.863, suggesting a close fit of the model to the data. Further, incremental fit indices supported the model's adequacy. The Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) were both 0.970 and 0.950 respectively, exceeding the commonly accepted threshold of 0.90 for good fit. The Normed Fit Index (NFI=0.921) and Incremental Fit Index (IFI=0.963) also indicated

strong model performance. The parsimony-adjusted indices, including PCFI (0.722) and PNFI (0.691), reflected a well-balanced model in terms of fitness and simplicity. The Expected Cross-Validation Index (ECVI=0.743) was lower than that of the saturated (0.789) and independence models (5.572), suggesting better generalizability. The Hoelter index indicated that the sample size was adequate for model stability at both the 0.05 ($n = 296$) and 0.01 ($n = 323$) significance levels. Collectively, these results confirm that the 17-item, five-factor structure provides a robust and theoretically meaningful representation of students' learning practices in the digital age (Figure 1). The final version of the 17-item questionnaire is available in Appendix 1.

Construct reliability of the study questionnaire

The 17-item questionnaire demonstrated excellent construct reliability (0.96). In addition, the construct reliability coefficients of the five themes were as follows: self-paced learning (0.91), exam-oriented learning (0.89), partnership in learning (0.79), collaborative learning (0.84), and AI-enhanced learning (0.81).

Qualitative data findings

The qualitative data findings are shown in Table 3. When asked to suggest other methods of learning not addressed in this questionnaire: 386 students replied, with 243 offering no new suggestions. There were 50 suggestions for techniques that could be used more widely to bolster the teaching sessions, with increasing the amount of interactive learning being the most popular idea. This was supported by other students indicating that they wished for more small group work, and an increase in the number of near-peer and peer-to-peer teaching sessions. After the suggestions to improve the teaching sessions, the next most frequent request was for faculty to review the policy of mandatory teaching sessions, and the suggestion that all teaching sessions should be recorded and made available for review after the session.

In increase in the use of technology was advocated, including the use of local Apps, and online applications, and a request for an on-line student discussion forum. Assessment figured strongly, there were 21 explicit requests for more formative assessment, and 4 candidates supported the idea of specifically teaching to the examinations.

Table 2 Model fit for two measurement models of the medical students learning in the era of artificial intelligence questionnaire ($n = 432$)

Study scales	χ^2	df	χ^2/df	CFI	RMSEA (90% C.I.)	SRMR	AIC
Five latent factors – 19 items	383.12	135	2.84	0.90	0.07 (0.05 – 0.08)	0.08	531.12
Five latent factors – 17 items	180.02	102	1.77	0.97	0.04 (0.03 – 0.05)	0.05	316.02

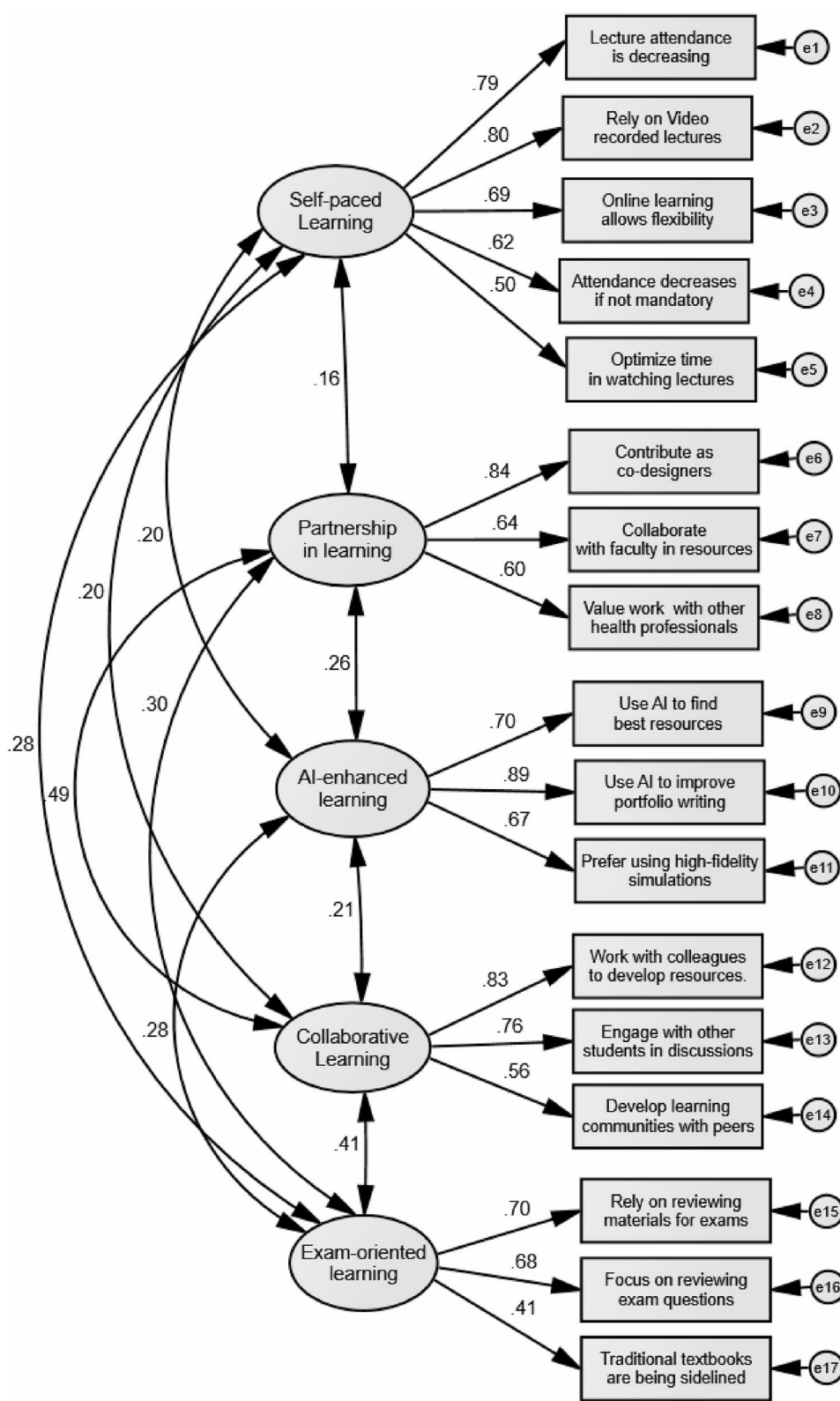


Fig. 1 Confirmatory factor analysis of medical students learning in the era of artificial intelligence (n = 432)

Table 3 Themes and suggestions from the qualitative comments of medical students on how they learn in the era of artificial intelligence

Theme	Suggestions	Number of respondents	Total
Flexible learning options	Video recordings of lectures to be made available	22	40
	Choice of on-line or on-site	12	
	Non-mandatory attendance	6	
Enhance formative assessment	Formative assessment	22	26
	focus on assessment	4	
	open book exams	1	
Active teaching	Interactive learning	17	53
	Games and quizzes	9	
	Teach study skills	9	
	Case based demonstrations	4	
	Simplification/shorter lectures	4	
	Flipped classroom	4	
	Flash cards	3	
	Research skills	3	
Study skills	Mind maps	2	14
	Notetaking	3	
	Blurting and repeating	2	
	Revision and review	7	
Collaborative learning	Small groups	20	30
	Near peer	3	
	Peer to peer	7	
Use of technology	Using Apps	21	34
	Use of AI	9	
	Student learning platform	4	
Ideas	More work-based/clinically focused learning	15	17
	Certificate for portfolio	1	
	Guest lecturers	1	

Seventeen students asked for formal training in study skills, and a similar number asked for a more work-based and clinically focused teaching (this in addition to the related suggestion in “teaching techniques”).

Discussion

The aim of health professions education institutions is the transformation of learners who care about the community. In doing so, how students learn using AI becomes critical; this has major implications curriculum, teaching, assessment, quality assurance, and even the physical facilities. This study provides empirical evidence to better understand how medical students learn in the context of rapid evolution of the AI spectrum influencing the whole ecosystem of medical education. In addition, it offers a validated psychometric tool that can be used by educators and researchers to assess and monitor learning behaviors over time. Furthermore, it addresses a critical gap in the literature by aligning contemporary student learning preferences with curricular and pedagogical

reforms. Confirmatory factor analysis revealed a robust five-factor model comprising self-paced learning, exam-oriented learning, partnership in learning, collaborative learning, and AI-enhanced learning. These dimensions reflect the diverse strategies students employ and point to the evolving demands of a generation shaped by technological integration. Thematic analysis of qualitative responses further validated and enriched these dimensions, offering deeper understanding and practical direction for educational reform.

Interpretation of study findings

The five factors can be understood through Illeris's three-dimensional theory and Connectivism. *Self-paced* and *exam-oriented learning* highlight the content and incentive dimensions, reflecting both knowledge acquisition and performance-driven motivation. *Collaborative learning* and *partnerships in learning* align with the interaction dimension, emphasizing the social and environmental aspects of engagement. *AI-enhanced learning* spans across dimensions, reshaping both content and interaction through technology. From a Connectivist perspective, all five factors illustrate how students increasingly rely on digital networks and AI tools to access, share, and construct knowledge in interconnected learning environments. On the other hand, self-paced learning findings align with the Self-Determination Theory [7], which identifies autonomy as a key component of intrinsic motivation. They also reflect adult learning theory, which emphasizes the importance of self-directed learning among mature learners [17].

Self-paced learning emerged as a dominant theme in both quantitative and qualitative data. Students consistently expressed a strong preference for autonomy in managing their study schedules, with widespread endorsement of recorded lectures, online modules, and accelerated playback features. Several students specifically requested more flexibility in attendance and learning modes, including the choice between online and in-person sessions. These preferences point to the value of asynchronous, student-centered approaches such as flipped classrooms, which allow learners to access material at their own pace and revisit it as needed [18]. The move toward individualized learning environments should be supported by policies that make learning resources consistently available and accessible across platforms.

Exam-oriented learning was another salient factor, reflecting students' preoccupation with performance and assessment outcomes. Many participants noted their reliance on past exam questions, summarized notes, and AI tools to enhance their preparation. The qualitative responses echoed this trend, with explicit calls for increased formative assessment, open-book exam

formats, and exam-aligned teaching. These behaviors are symptomatic of an assessment-driven culture prevalent in medical education, where high-stakes exams heavily influence study strategies [8] and also the access to learning resources during exams [19]. While assessments are essential for certifying competence, overemphasis on examination success may compromise deeper learning and critical thinking [20]. To counterbalance this tendency, medical educators should design assessments that measure not only factual recall but also application, synthesis, and reflective thinking [21]. Digital tools that support adaptive testing and personalized feedback could further align student assessment behaviors with long-term learning goals.

Partnership in learning, emerging as a distinct factor, captures students' aspiration to engage as active contributors in their educational experience. The concept of "students as partners" marks a paradigm shift from the traditional view of students as passive recipients of knowledge to recognizing them as active contributors to the learning process. Such partnerships can take various forms and occur at multiple levels, including curriculum co-design and the delivery of education through approaches like peer mentoring and peer-assisted learning [22]. Quantitative data showed that learners value collaboration with faculty in shaping content and selecting resources. Qualitative feedback reinforced this theme, with students suggesting guest lectures, more clinically focused sessions, and the integration of diverse perspectives in teaching. These findings align with the growing literature on student-faculty partnerships, which highlight the benefits of co-creation for student engagement, motivation, and institutional innovation [22, 23]. Co-creation fosters a sense of ownership and mutual respect, which can significantly enhance engagement and academic identity [24]. This is also consistent with constructivist theory, where knowledge is co-constructed through dynamic interactions between learners and educators [25]. Institutions should formalize opportunities for student voice in curriculum planning, such as through advisory boards or co-design workshops, to foster shared responsibility and mutual respect.

Collaborative learning also featured prominently in both data strands. The factor analysis identified student collaboration, peer discussions, and co-development of materials as key indicators, while the qualitative data added further depth. Students emphasized the importance of small group sessions, peer-to-peer teaching, and near-peer mentorship. These findings are supported by social constructivist theory, which views learning as a socially mediated process, enhanced by dialogue and cooperative problem-solving [25]. Research shows that collaborative learning enhances academic performance, critical thinking, and communication skills [26].

The students' preference for smaller group sessions and discussion-based formats reinforces prior findings that such environments enhance comfort, participation, and deeper learning [27]. Moreover, working in teams helps students build professional identities and develop interpersonal competencies essential to healthcare practice. Embedding structured collaborative learning methods such as team-based learning (TBL), case-based learning (CBL), and interprofessional education (IPE) into the curriculum can strengthen engagement and learning outcomes [28, 29].

AI-enhanced learning represents a newer but rapidly expanding dimension of student learning behavior. In this study, students reported using AI-powered tools for exam preparation, summarizing content, generating written assignments, and simulating clinical scenarios. The qualitative data further supported this theme, with students advocating structured access to apps, digital platforms, and AI-based tools like chatbots and simulation environments. While these tools offer opportunities for personalized, adaptive learning, their effective use requires guidance. Faculty must be equipped to support students in integrating AI ethically and critically into their study practices, including fostering awareness of potential misinformation, over-reliance, or lack of contextual understanding. Digital literacy training should therefore become an integral part of faculty development and student orientation programs.

The qualitative analysis also revealed themes not fully captured by the closed-ended questionnaire. One such theme was the explicit need for training in study strategies. Students asked for guidance in notetaking, mind mapping, review techniques, and efficient information retrieval, skills essential for self-regulated learning. This indicates a gap in institutional support structures and suggests the need for dedicated modules or workshops focused on academic skills development. Another emergent theme was the desire for more work-based or clinically focused teaching, echoing the call for experiential learning opportunities where knowledge is applied in realistic contexts [30]. Importantly, emergent themes such as study skills development and clinically focused learning, which extended beyond the original questionnaire, highlight opportunities to refine future iterations of the instrument to more comprehensively capture students' evolving learning practices of medical students.

The integration of findings showed that qualitative themes largely confirmed the five-factor structure. *Self-paced learning* was reinforced by requests for recorded sessions, while *collaborative learning* was echoed in students' calls for more small-group and interactive activities. *Partnerships in learning* were extended by suggestions for peer-to-peer and near-peer teaching, and *AI-enhanced learning* was supported by interest

in digital platforms and online forums. Finally, exam-oriented learning was consistent with students' calls for more formative assessments and a stronger emphasis on assessment-focused teaching. Together, these convergences strengthen the validity and practical relevance of the identified factors.

Implications for medical education

Collectively, these findings have important implications for curriculum design and faculty development. First, institutions must strike a balance between synchronous and asynchronous delivery to accommodate flexible, self-directed learning. Second, curricula should incorporate a broader range of assessment methods that promote reflection, feedback, and application. Third, faculty must be trained to design and deliver active, AI-enhanced learning experiences. Fourth, institutions should provide structured mechanisms for student involvement in educational planning. Finally, targeted support for developing study skills and responsible use of technology should be integrated into academic advising and orientation programs.

Strengths and limitations

The inclusion of students from three universities across different countries and curricular models enhances the transferability of our findings by capturing diverse educational contexts. This multi-site sampling reduces the risk of institutional bias and strengthens the applicability of results beyond a single setting. Nevertheless, this study has several limitations that should be acknowledged. First, although data were collected from three institutions, the sample was imbalanced, with the majority of participants drawn from a single university and limited to the UAE and Jordan. This regional concentration may introduce cultural and institutional influences that restrict the generalizability of the findings. Second, the exploratory factor analysis sample was drawn as a subsample from the total dataset of students used for confirmatory factor analysis.

This overlap could introduce bias, as the EFA and CFA were not conducted on completely independent samples. Third, the cross-sectional design precludes drawing causal relationships between learning behaviors of medical students and influencing factors. Fourth, while the mixed-methods approach provided complementary insights, the reliance on self-reported data raises the possibility of recall bias and social desirability effects. Future studies addressing these limitations will help to strengthen the robustness and transferability of the instrument.

Future research

Future studies should explore the validation of this instrument across broader and more diverse health professions education contexts and populations. Longitudinal research is also recommended to assess changes in learning behaviors over time and to evaluate the impact of AI-enhanced learning strategies on academic performance and professional competencies. Additionally, intervention studies could examine how targeted faculty development and digital literacy training influence both student engagement and learning outcomes in AI-supported environments.

Conclusion

This study provides a validated and empirically supported instrument that captures how medical students learn in digitally enriched and AI-enhanced environments. The findings reveal five key dimensions of learning behavior—paced, exam-oriented, collaborative, partnership-based, and AI-enhanced learning, each reflecting evolving student preferences toward flexibility, autonomy, and technology-supported engagement in learning.

The integration of quantitative and qualitative findings confirms the internal validity and practical utility of the tool while offering insights for curriculum reform and faculty development. By highlighting students' emphasis on self-directed, collaborative, and AI-integrated learning, this study demonstrates the need for medical education programs to foster adaptable, learner-centered, and evidence-informed approaches to teaching and assessment.

Supplementary Information

The online version contains supplementary material available at <https://doi.org/10.1186/s12909-025-08145-z>.

Supplementary Material 1.

Acknowledgements

None.

Clinical trial number

Not applicable.

Authors' contributions

HH initiated the idea of the research and developed the research protocols. RR was responsible for collecting and entering all study-related data. SEK conducted the statistical analysis and developed the first draft of the manuscript. SH provided the raw data of Al-Balqa University and reviewed the initial draft. DT conducted qualitative data analysis and methodology. All authors contributed to the revision, editing, and finalizing the manuscript.

Funding

No funding.

Data availability

The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate

The research protocol was approved by the Research Ethics Committee (REC) at Gulf Medical University (IRB-COM-FAC-100-Feb-2025) and conducted in accordance with the 1964 Declaration of Helsinki and its later amendments. Prior to data collection, all students filled an online informed consent and a detailed information sheet explaining the purpose of the research, potential benefits and ensuring that participation is voluntary and the right to refuse participation or to withdraw without any reasons and without any negative consequences. Confidentiality was ensured by keeping the questionnaire anonymous and avoiding mentioning any identifying features of the participants. Finally, one of the author's contact pieces of information was available for the participants to provide any needed clarification.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

Received: 27 June 2025 / Accepted: 10 October 2025

Published online: 30 October 2025

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