Identifying Necessary Conditions for AI Adoption: Medical Students' Perspectives Across the COVID-19 Timeline

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Abstract

The integration of artificial intelligence health technologies (AIHTs) into medical practice depends on the readiness of future physicians. This study examines medical students' behavioral intentions to adopt AIHTs across three timeframes – pre-, peri-, and post-COVID-19 – using Necessary Condition Analysis (NCA). Unlike traditional methods, NCA identifies essential, non-compensable factors influencing adoption. Findings reveal that belief in AIHTs' role in medicine is a persistent necessary condition, while the perceived importance of AIHTs in the curriculum emerges as critical post-COVID-19. Despite increased familiarity and experimentation with AIHTs, these alone are insufficient to drive adoption. These insights underscore the need for medical curricula to emphasize AI literacy, hands-on training, and interdisciplinary collaboration. By identifying key conditions for AI adoption, this study informs educators and policymakers on preparing medical students for a technology-driven healthcare landscape.

Keywords

Artificial intelligence, Digital health, IT adoption, AI Literacy, Necessary condition analysis, COVID-19

Introduction

The mindset of the younger generation is undergoing a profound transformation, ranging from altered communications patterns (Tirocchi, 2024) to a growing prioritization of mental well-being, trends driven by digital transformation, rapid technology advancements, shifting societal values, and greater access to information (Benvenuti et al., 2023). This generation, often referred to as digital natives, exhibits a natural inclination toward adopting and adapting to technological solutions in their daily lives and professional environments (Keary, 2024). They tend to value efficiency, innovation, and connectivity, which are hallmarks of modern technological ecosystems (Alruthaya et al., 2021; Techstep, 2024) Moreover, their expectations are shaped by global challenges such as economic shifts, climate change, and pandemics, which have collectively reinforced the importance of resilience, adaptability, and evidence-based approaches in decision-making (Wagner et al., 2025).

Medical students, as part of this generation, are no exception. Their perceptions and intentions regarding digital health (dHealth) technologies are shaped by a combination of their evolving experiences, exposure, and changing professional landscapes. As the healthcare sector undergoes a digital transformation, fueled by advances in artificial intelligence (AI), telehealth, and mobile health technologies, the need for medical professionals to integrate these tools into their practice has become increasingly apparent (Fatehi et al., 2020). However, the adoption of AI technologies in medical practice is contingent on the readiness and willingness of future physicians, which are strongly influenced by their educational experiences and individual mindsets (Wagner et al., 2023).

The development of medical students' perspectives on dHealth technologies, in general, and AI technologies in particular, is a dynamic process, shaped by various factors such as curriculum content, and hands-on exposure to digital tools (Cheng et al., 2018; Waseh & Dicker, 2019). For instance, structured experimentation with electronic medical records (EMR) and AI-based diagnostic tools can significantly enhance students' confidence in using these technologies (Cheng et al., 2020). Additionally, external disruptions, such as the COVID-19 pandemic, have accelerated the adoption of dHealth technologies such as AI, providing a unique lens to examine how real-world events influence students' views and intentions (Srinivasan et al., 2022; van Hattem et al., 2021).

AI technologies have emerged as critical tools in modern healthcare and are a driving force behind its digital transformation (Silcox et al., 2024). By leveraging machine learning algorithms and predictive analytics, AI can assist in early disease detection, personalized treatment planning, and automation of administrative tasks, ultimately reducing healthcare costs and improving patient outcomes. AI-driven tools are particularly impactful in optimizing healthcare resource allocation, especially for vulnerable populations such as the elderly and socially isolated (Shiwani et al., 2023; Torres et al., 2024). Furthermore, AI innovations have significantly transformed care delivery by enhancing the efficiency, accuracy, and accessibility of medical services. AI-powered applications enable real-time patient monitoring, advanced image analysis, and intelligent decision-support systems, capabilities that proved invaluable during global health crises like the COVID-19 pandemic (Dananjayan & Raj, 2020; Vaishya et al., 2020). As a result, physicians are expected to develop AI literacy, including the ability to interpret AI-generated recommendations, ensure the ethical use of AI in clinical practice, and integrate AI tools seamlessly into patient care workflows.

However, despite the growing emphasis on AI integration in healthcare (Subbiah, 2023), there remains a gap in understanding the preconditions necessary for medical students to develop a strong intention to adopt these technologies. Existing research has largely focused on factors that facilitate adoption (Kaseka & Mbakaya, 2022; Wagner et al., 2023), yet it remains unclear which conditions are essential and non-compensable in shaping medical students' behavioral intentions. Furthermore, little is known about how these necessary conditions have evolved in response to external disruptions such as the COVID-19 pandemic, which has significantly accelerated the adoption of dHealth technologies.

This study investigates the evolution of medical students' mindsets toward AI health technologies (AIHTs) by examining their behavioral intentions across three distinct timeframes: pre-, peri-, and post-COVID-19. Using Necessary Condition Analysis (NCA), this research identifies the essential factors that must be present for medical students to develop the intention to integrate AIHTs into their future medical practice. Unlike traditional variance-based approaches, NCA uncovers essential conditions that cannot be compensated by the presence of other factors, providing a nuanced understanding of the determinants of behavioral intention (Dul, 2016).

The study addresses the following research questions: What are the necessary conditions for medical students to develop a strong intention to integrate AIHTs into their future medical practice? How do the importance of AIHTs in the curriculum and the perceived role of AIHTs in future medical tasks evolve as necessary conditions across pre-, peri-, and post-COVID-19 periods?

By exploring these questions, the study contributes to the growing literature on digital transformation in medical education and practice. By identifying non-compensable factors necessary for future physicians to embrace AI, the research provides targeted insights into how digital transformation can be effectively embedded within medical training frameworks, equipping students to navigate a technology-driven healthcare environment.

The remainder of this paper is structured as follows. The next section presents the theoretical framework and methodology, including the application of NCA. This is followed by an analysis of findings and a discussion of their implications for medical education and practice. Finally, the paper concludes with recommendations for integrating AIHTs into medical curricula to address the evolving needs of future healthcare professionals.

Background

To better understand the adoption of AIHTs among medical students, this study draws on the Consolidated Framework for Implementation Research (CFIR) and the Capabilities, Opportunities, Motivation, and

Behavior (COM-B) model. The CFIR identifies individual characteristics as pivotal determinants in implementing evidence-based innovations, emphasizing the role of personal skills, motivations, and external conditions (Damschroder et al., 2022). Complementing this, the COM-B model highlights how behavior is influenced by the interaction of capabilities (e.g., knowledge and experiential competences), opportunities (e.g., exposure to AI technologies), and motivation (e.g., belief in AI's potential in healthcare) (Michie et al., 2011).

Prior research has shown that experiential competences, such as hands-on engagement with dHealth tools, play a critical role in fostering positive attitudes and behavioral intentions toward AI adoption (Kaseka & Mbakaya, 2022). Experiential competences are particularly important for medical students, who must navigate increasingly complex digital systems while maintaining a patient-centered approach. These skills enable future physicians to apply AI tools effectively, such as predictive analytics and decision-support systems, in clinical settings (Liang et al., 2021; Subbiah, 2023). Despite this, evidence suggests that most medical students possess limited hands-on experience with AIHTs, highlighting a significant gap in current medical curricula (Ringeval et al., 2024; Wagner et al., 2023).

In addition to experiential competences, students' perceptions of the role of AIHTs in future medical practice significantly shape their willingness to adopt these technologies. A positive perception of AI as a transformative tool can enhance students' motivation to integrate AI into their workflows. For instance, students who view AI as augmenting clinical tasks, rather than replacing human decision-making, are more likely to embrace its use (Park et al., 2021). However, negative perceptions, often fueled by misconceptions or a lack of formal training, can hinder adoption efforts (Subbiah, 2023).

Importantly, these factors can be influenced by external disruptions, such as the COVID-19 pandemic. The pandemic served as a catalyst for the adoption of dHealth technologies, accelerating familiarity with telehealth, mobile health apps, and AI-based tools. It also underscored the importance of integrating AIHTs into medical education to prepare students for a digitally driven healthcare environment (Dave et al., 2023; van Hattem et al., 2021).

Methodology

This study examined the evolution of medical students' intentions to adopt AIHTs over three distinct timeframes: pre-COVID-19 (t_0), peri-COVID-19 (t_1), and post-COVID-19 (t_2). A longitudinal survey-based design was used to track shifts in students' perceptions, beliefs, and behavioral intentions in response to the pandemic and its aftermath.

Study Context and Population

The research was conducted at a large Canadian medical school offering a five-year undergraduate medical curriculum. Although no formal AI training was integrated into the core curriculum, students were provided with opportunities to attend workshops and seminars on EMR systems, mobile technologies, AI applications, and ethical considerations related to dHealth technologies. The study targeted all 1,462 medical students enrolled at the institution, spanning all academic levels from preparatory year to final-year clerkship.

Data Collection

Data were collected through online surveys administered at three points in time: February 2020 (t_0, pre-COVID-19, N=184), January 2021 (t_1, peri-COVID-19, N=138), and May 2023 (t_2, post-COVID-19, N=177). The surveys were distributed using the Qualtrics platform and promoted via institutional mailing lists and student association newsletters. Participation was voluntary, with no incentives provided.

The survey captured five key dimensions: demographic characteristics (e.g., age, gender, academic level); familiarity with and experimentation using AIHTs; perceptions of the importance of AIHTs education in the medical curriculum; beliefs about the role of AIHTs in future medical practice; and behavioral intentions to integrate AIHTs into future professional activities. Items were scored using five-point Likert scales (ranging from "strongly disagree" to "strongly agree") and binary yes/no response formats.

Questionnaire Development and Validation

No existing questionnaire suitable for assessing the variables included in this study was found. Consequently, a new instrument was developed and refined through multiple iterations, ensuring alignment with validated survey instruments used in related contexts (e.g., Teo, 2010). The final version of the questionnaire consisted of 70 five-point Likert scale items and 8 yes/no items to measure Intention to use AIHTs in future medical practice. Contrary to the other four variables, Intention is an «index» variable (8 yes/no items), not a «scale» variable, which explains why the max mean of Intention can be up to 8. To ensure validity, the instrument was assessed by a panel of 10 medical students who were excluded from the main study sample.

Data Analyses

The survey data were first analyzed using descriptive statistics and analyses of variance to explore patterns and significant differences across the three timeframes. To address the research questions, Necessary Condition Analysis (NCA) was applied to each of the three samples (t_0, t_1, and t_2). The NCA was conducted using Dul's (2023) NCA package in R (version 3.3.1) to identify essential conditions for desired behavioral outcomes, offering insights into key factors shaping medical students' intentions to adopt AIHTs.

Results

Demographic and descriptive statistics

In the initial survey conducted at time-point t_0 (pre-COVID-19), 184 students participated, representing a 13% response rate. At time-point t_1 (peri-COVID-19), for the subsequent survey, 138 students responded, accounting for a 10% participation rate. Finally, at t_2 (post-COVID-19), for the third survey, the sample consist of 177 students, with a 12% response rate. The majority of participants were female, constituting 65% at t_0 and increasing to 75% at t_1 and 70% at t_2. The respondents' average age was approximately 23 years in all three samples, aligning with the median age of medical students at the university where the study was conducted.

Differences between medical students' views and intentions at t_0, t_1 and t_2

As shown in Table 1, most medical students reported limited opportunities to familiarize themselves - and experiment - with AIHTs during their medical education, be it at time-point t_0, t_1 or t_2. Secondly, the overwhelming majority of participants in all three samples agreed that AI education should be a mandatory component of medical training. Thirdly, although students across groups were of similar average age, analysis revealed that students in the t0 group (n=184) had a significantly higher average academic level than those in the t2 group (n=177). Finally, analysis of variance (ANOVA) results comparing the students' views and intentions with regard to AI at t_0, t_1 and t_2 revealed significant differences between the three student groups, notably between the post COVID-19 group and the other two groups. Indeed, students in the post-Covid group were found to have a significantly greater level of familiarity and experimentation with AIHTs, a stronger belief in the role of AIHTs in future medical tasks, and most importantly a stronger intention to use AIHTs in their future medical practice.

Research sample **Research variables**	**pre-COVID-19** (t_0, n = 184) mean SD min max	**peri-COVID-19** (t_1, n = 138) mean SD min max	**post-COVID-19** (t_2, n = 177) mean SD min max	**ANOVA F**
Individual Background				
Age	22.9 3.4 18 38	22.6 2.6 18 35	22.9 3.3 18 30	0.5
Academic level	2.9_a 1.4 1 5	2.6 1.2 1 5	2.4_b 1.2 1 5	6.9***
Academic level (frequency) 1 :	40 (22%)	28 (20%)	38 (22%)	
2 :	36 (20%)	32 (23%)	75 (42%)	
3 :	43 (23%)	56 (41%)	32 (18%)	
4 :	33 (18%)	8 (6%)	18 (10%)	
5 :	32 (17%)	14 (10%)	14 (8%)	

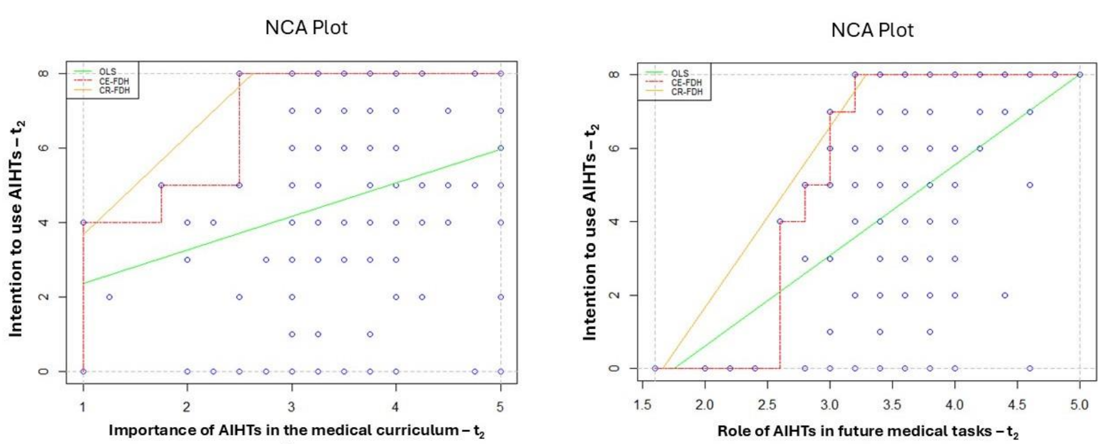
Conditions				
Familiarity with AIHTs	1.9 0.9 1.0 5.0	1.8$_b$ 0.8 1.0 4.3	2.1$_a$ 0.7 1.0 4.8	6.3**
Experimentation with AIHTs	1.3$_b$ 0.5 1.0 4.0	1.2$_b$ 0.4 1.0 3.7	1.5$_a$ 0.6 1.0 3.8	15.1***
Importance of AIHTs in the medical curriculum	3.5 0.8 1.0 5.0	3.5 0.7 1.0 5.0	3.7 0.8 1.0 5.0	2.4
Role of AIHTs in future medical tasks	3.6 0.6 2.0 5.0	3.5$_b$ 0.5 2.4 5.0	3.7$_a$ 0.5 1.6 5.0	5.2**
Outcome				
Intention to use AIHTs in future med. practice	3.9$_b$ 3.1 0 8	3.6$_b$ 3.2 0 8	4.8$_a$ 2.9 0 8	5.9**
*: $p < 0.05$ **: $p < 0.01$ ***: $p < 0.001$ *Nota*. Within rows, different subscripts ($_{a,\,b}$) indicate significant ($p < 0.05$) pairwise differences between means on Tamhane's T2 (post hoc) test.				

Table 1. Breakdown of the research variables by sample

Necessary condition analyses

The NCA method differs from - and thus complements - traditional causal methods (e.g., regression, structural equation modeling) and configurational methods (e.g. qualitative comparative analysis) in that it is based on a causal logic of "necessity" rather than "sufficiency" (Dul, 2024). Using this alternative view of causality, one seeks to identify the degree to which certain "conditions" (say, having a strong belief in the role of AIHTs in the future of medicine) are "necessary" (but not "sufficient") to achieve a certain "outcome" (say, having a strong intention to use AIHTs in one's future medical practice) (Frommeyer et al., 2022). Note here that a sample size of 50 to 100 is needed for NCA analyses to detect necessary conditions with an effect size greater than 0.30 ('moderate' to 'large' effect) and a power greater than the 0.80 threshold (Dul, 2024).

The NCA method starts by drawing a scatterplot between each condition (X) and the outcome (Y). In our case, this produced 12 such scatterplots (4 conditions x 3 time-points), two of which are presented as examples in Figure 1. Next, two "ceiling lines" are drawn in each scatterplot, i.e. the Ceiling Envelopment-Free Disposal Hull (CE-FDH) and the Ceiling Regression-Free Disposal Hull (CR-FDH), thus separating the "ceiling zone" (i.e. the empty space in the upper-left corner where a high degree of X is necessary for a high degree of Y) from the "scope" (i.e. the full space of actual and potential observations), and doing so with as much accuracy as possible. In this study, the CR-FDH was used as ceiling line because the conditions and outcome are continuous rather than discrete (Dul, 2016).



Legend. OLS = Ordinary Least Squares CE-FDH = Ceiling Envelopment-Free Disposal Hull CR-FDH – Ceiling Regression-Free Disposal Hull

Figure 1. Example of the scatterplots drawn by the NCA

Given the chosen ceiling technique (CR-FDR) and as presented in Table 2, the NCA procedure then calculates, for each condition, the "effect size" and significance level of this effect ("p-value") to determine if the condition is truly "necessary" to attain the desired outcome (Solaimani & Swaak, 2023). Ranging from 0 to 1, the effect size is calculated as the quotient of the ceiling zone over the scope, with an effect size less than 0.1 being "small", between 0.1 and 0.3 being "medium", between 0.3 and 0.5 being "large", and greater than 0.5 being "very large" (Dul, 2016). Moreover, for a condition to be considered necessary, its effect size must not only be greater than 0.1 but its p-value must also be less than 0.05, as the ceiling zone as observed may be due to random chance (Dul et al., 2020). Returning to Table 2 with this last necessity criterion in mind, one finds that two out of the four conditions are indeed necessary for medical students to have a strong intention to use AIHTs in their future medical practice.

Conditions		**Outcome**: Intention to use AIHTs in future medical practice				
		ceiling accuracy	ceiling zone	scope	effect size	p-value
Familiarity with AIHTs	t_0	100%	0.000	32	0.000	1.000
	t_1	100%	0.000	27	0.000	1.000
	t_2	100%	0.000	30	0.000	1.000
Experimentation with AIHTs	t_0	100%	0.000	24	0.000	1.000
	t_1	100%	0.000	21	0.000	1.000
	t_2	100%	0.000	22	0.000	1.000
Importance of AIHTs in the med. curriculum	t_0	100%	2.890	32	0.090	0.141
	t_1	100%	4.744	32	0.148	0.299
	t_2	100%	3.521	32	0.110	0.020
Role of AIHTs in future medical tasks	t_0	100%	3.935	24	0.164	0.030
	t_1	100%	3.009	21	0.145	0.000
	t_2	100%	7.020	27	0.258	0.000
Nota. CR-FDH used as ceiling technique						
Legend. CR-FDH = ceiling regression-free disposal hull						

Table 2. Results of the necessary condition analyses

The first finding is that a strong belief in AIHTs' role in the future of medicine is the most important necessary condition (NC) for students to eventually use these technologies in their medical practice. Indeed, this condition was found to be necessary at all three time-points, that is, before, during and after the COVID-19 pandemic. This would behove medical educators to instill this belief by developing their students' knowledge of - and experience with - AIHTs. Another finding is that a high degree of importance accorded by medical students to AIHTs within their curriculum has emerged as a second NC in the post COVID-19 era. Indeed, medical educators must now answer this demand by redesigning the curriculum to make greater room for dHealth technologies in general, and AI-based technologies in particular, including not only generative AI but also machine learning and big data analytics as they actually and potentially apply to the practice of medicine.

The preceding results may be further nuanced, as the NCA method qualifies the necessity of a condition not only "in kind" (a high level of X is necessary to attain a high level of Y) but also "in degree" (a certain level of X is necessary to attain a certain level of Y). Returning to Figure 1, this is done through the Y = aX +b regression equation where a is the ceiling line (CR-FDH) and b is the intercept. As presented in Table 3, a "bottleneck" table is thus produced, in which a specific level of the outcome is associated to a specific level of the four conditions. For instance, at t_2, to attain a 60% level in the Intention to use AIHTs, the minimum level required of the Role of AIHTs is 30.6%, whereas the minimum level required of the Importance of AIHTs is 10.6%. Overall, one finds a notable increase in these percentages for the Role of AIHTs condition when comparing the post COVID-19 sample with the other two groups, whereas such an increase is found for the Importance of AIHTs condition when comparing the peri COVID-19 sample with the pre Covid-19 one. This is in line with the preceding results regarding these two NCs, and when contrasted with the "not necessary" (NN) conditions (i.e. Familiarity with AIHTs and Experimentation with AIHTs).

Outcome	**Conditions**											
Intention to use AIHTs	Familiarity with AIHTs			Experimentation with AIHTs			Importance of AIHTs			Role of AIHTs		
	t_0	t_1	t_2	t_0	t_1	t_2	t_0	t_1	t_2	t_0	t_1	t_2
0	NN	NN	NN	NN	NN	NN	0.7	NN	NN	NN	NN	1.9
10	NN	NN	NN	NN	NN	NN	2.3	NN	NN	3.1	NN	6.7
20	NN	NN	NN	NN	NN	NN	4.0	1.6	NN	6.4	NN	11.5
30	NN	NN	NN	NN	NN	NN	5.7	5.8	NN	9.7	NN	16.2
40	NN	NN	NN	NN	NN	NN	7.4	10.0	NN	13.1	4.0	21.0
50	NN	NN	NN	NN	NN	NN	9.0	14.3	3.1	16.4	10.7	25.8
60	NN	NN	NN	NN	NN	NN	10.7	18.5	10.6	19.7	17.3	30.6
70	NN	NN	NN	NN	NN	NN	12.4	22.7	18.1	23.0	23.9	35.4
80	NN	NN	NN	NN	NN	NN	14.0	27.0	25.6	26.4	30.5	40.1
90	NN	NN	NN	NN	NN	NN	15.7	31.2	33.1	29.7	37.2	44.9
100	NN	NN	NN	NN	NN	NN	17.4	35.4	40.6	33.0	43.8	49.7
Nota. CR-FDH used as ceiling technique												
Legend. NN = not necessary CR-FDH = ceiling regression-free disposal hull												

Table 3. Results of NCA bottleneck level (%)

Discussion

This study provides new insights into the factors influencing medical students' intention to integrate AIHTs into their future medical practice, with a focus on the evolution of these intentions across pre-, peri-, and post-COVID-19 periods. By employing NCA, this research identified key conditions that are indispensable for fostering strong behavioral intentions among medical students.

Our findings reveal that a strong belief in the role of AIHTs in the future of medicine consistently emerged as the most critical necessary condition across all three time points. However, belief alone does not equate to a positive attitude or readiness for integration. Students may recognize AI's potential yet feel unprepared to use it effectively. This highlights the need for structured AI literacy and competency-building within medical education. Educators should leverage this belief by incorporating AI-focused coursework covering clinical decision support, predictive analytics, and ethical considerations. Additionally, immersive training using augmented reality-based simulations could provide dynamic and adaptive environments where students can interact with AI tools, analyze their performance, and better understand their limitations. Such technologies allow medical trainees to experiment with AI in scenarios where it may fail, helping them develop a more nuanced appreciation of AI's strengths and weaknesses while increasing their confidence in real-world applications.

Another key finding is the increased importance placed on the integration of AIHTs into medical curricula in the post-COVID-19 period, reflecting students' growing awareness of AI's relevance to their future practice. While familiarity with AIHTs alone is insufficient, structured interdisciplinary collaboration and real-world exposure can bridge the gap between theoretical knowledge and application. Medical schools should encourage collaborations with AI and data science experts, integrate AI-assisted decision-making into clinical rotations, and emphasize human-AI collaboration to ensure that future physicians can critically assess AI outputs rather than rely on them passively. Furthermore, as AI reshapes medical specialties, career-oriented discussions and adaptability training should be prioritized to prepare students for the evolving healthcare landscape.

The results also underscore the evolving nature of medical students' intentions. Post-COVID-19, students demonstrated significantly higher levels of familiarity, experimentation, and intention to use AIHTs compared to their pre- and peri-pandemic counterparts. This evolution may be attributed to the accelerated adoption of dHealth technologies during the pandemic, which showcased the critical role of AI in remote patient monitoring, telemedicine, and predictive analytics (Litchfield et al., 2021; Sun et al., 2023). However, the necessity results suggest that familiarity with and hands-on experimentation using AIHTs alone are insufficient; they must be complemented by curriculum-wide initiatives that instill the perceived importance of AIHTs in clinical practice.

Compared to prior research, this study offers a unique perspective by focusing on the necessary conditions for medical students' behavioral intentions to adopt AIHTs, rather than variance-based predictors. While prior research such as Wagner et al. (2023) and Kaseka & Mbakaya (2022) emphasized experiential competences and exposure to dHealth tools as facilitators of adoption, the present study highlights belief in the role of AIHTs and their integration into medical curricula as indispensable conditions. Similarly, the study extends insights from Park et al. (2021), which explored discipline-specific perceptions of AI, by adopting a broader approach to general medical education across distinct timeframes.

This manuscript also builds on findings from Ringeval et al. (2024), which assessed shifts in medical students' perceptions of dHealth technologies pre- and post-COVID-19. While both papers underscore the pandemic's role as a catalyst for increasing familiarity with and interest in dHealth tools, this article uniquely employs NCA to identify thresholds that must be met for behavioral intention formation. Unlike Ringeval et al. (2024), which used a structural model approach (PLS-SEM) to explain variance, the present study seeks to uncover which conditions are absolutely essential for the intention to adopt AIHTs, offering a complementary yet distinct perspective. By applying the CFIR and COM-B frameworks, this article further contextualizes its findings within the broader theoretical landscape, demonstrating how motivation and belief systems interact with capabilities and opportunities to influence behavior.

In doing so, the findings highlight critical areas for curriculum reform and provide actionable opportunities for medical educators. Incorporating AIHTs into the medical curriculum is paramount, with an emphasis on both technical skills (e.g., using machine learning algorithms) and ethical considerations (e.g., ensuring patient data privacy). Additionally, structured exposure to AI tools through simulations, workshops, and internships could enhance familiarity and build confidence among students. Medical educators should also address students' concerns and misconceptions about AI's impact on healthcare professions, ensuring they view AI as a complement to, rather than a replacement for, human decision-making.

While interest in AIHTs is growing, meaningful integration into the formal curriculum remains a challenge. Relying on voluntary workshops is insufficient; structured exposure through required courses and clinical rotations is essential. This requires institutional support, including curriculum reform and policies that address medico-legal concerns, such as liability protections for AI use. Highlighting real-world successes can also help legitimize AIHTs and foster broader institutional acceptance. Without such support, student curiosity may fade, limiting the impact of digital transformation in medical education.

Additionally, our analyses revealed no significant differences between gender groups regarding the intention to use AIHTs, nor any significant gender-related effects across the three time points. While previous studies have noted gender-based differences in technology receptiveness in clinical settings (e.g., Qu et al., 2024), such patterns were not observed within our student sample.

While this study provides important contributions, it is not without limitations. The relatively low response rates (10-13%) across the three time points may introduce selection bias, as students with a pre-existing interest in AIHTs might have been more likely to participate. Additionally, the study was conducted at a single teaching institution, which may limit the generalizability of findings to other educational contexts or countries. Future longitudinal research could explore cross-institutional comparisons that examine the long-term impact of AI training on clinical practice.

Conclusion

This article provides a nuanced understanding of the necessary conditions for medical students to develop strong intentions to adopt AIHTs. By employing NCA, we identified beliefs in the transformative role of AIHTs and the importance of AI integration into the curriculum as critical thresholds for fostering intention. These findings highlight the need for medical education to prioritize both attitudinal and structural factors, ensuring medical students are equipped with the skills and mindset necessary to leverage AI in their future practice.

While experiential competences such as familiarity and experimentation with AIHTs are beneficial, they alone are insufficient to drive behavioral intention. Rather than passive exposure, medical students must engage in deep, hands-on experiences with AIHTs, allowing them to integrate these technologies into clinical reasoning and decision-making. Targeted curriculum reform should not only emphasize the relevance of AIHTs but also incorporate structured, immersive training ensuring that students develop the confidence and competence needed for effective adoption. These insights offer actionable recommendations for medical educators, particularly in light of the growing integration of generative AI technologies into healthcare.

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