

Perception of AI in medical research among medical students and doctors in Nigeria: impact of a structured AI training program using a pre-post quasi-experimental design

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Abstract

Background:

The integration of artificial intelligence (AI) into medical research and education is rapidly advancing. Despite being aware, Nigerian medical students and doctors demonstrate low utilization of AI in medical research with a major barrier being limited access to structured training in its research applications. This study aims to assess and measure the impact of a well-structured intervention on the perception, knowledge and ethical concerns of AI in medical research among medical students and doctors in Nigeria.

Methods:

A pre-test posttest quasi-experimental design was utilized among medical students and doctors across Nigeria. The intervention was delivered as a 2-day online webinar workshop via Microsoft Teams and data were collected via questionnaires consisting of Likert-scale questions assessing demographic information, baseline perceptions across eight domains derived from the Health Belief Model supplemented with additional constructs: perceived knowledge and ethical concerns, and changes following the intervention. Data were analyzed with R version 4.5.2 and IBM SPSS Statistics Version 27. Statistical significance was set at $p\text{-value} < 0.05$.

Results:

135 participants were included in the study. 77.0% of participants had no formal AI training, though 31.9% had attended a prior AI workshop. At baseline, perceived knowledge of AI was the lowest while perceived benefits was the highest. Following the training intervention, statistically significant improvements were observed across seven of the eight domains. Knowledge increased from 3.16 ± 0.73 to 4.18 ± 0.50 ($Z = -9.787$, $p < 0.001$, $r = 0.84$), Perceived susceptibility from 3.83 ± 0.72 to 4.18 ± 0.72 ($Z = -5.022$, $p < 0.001$, $r = 0.43$), and Perceived severity from 3.75 ± 0.75 to 4.04 ± 0.72 ($Z = -4.540$, $p < 0.001$, $r = 0.39$). Perceived benefits showed a smaller but significant improvement 4.17 ± 0.64 to 4.33 ± 0.53 ($Z = -2.654$, $p = 0.008$, $r = 0.23$), while Perceived barriers decreased significantly ($Z = -5.147$, $p < 0.001$, $r = 0.44$). Cues to action and Self-efficacy also improved significantly ($p < 0.001$ for both; $r = 0.53$ for each). Ethical concerns showed no significant change ($Z = -0.559$, $p = 0.576$). Satisfaction with the intervention was high, with 93–97% of participants endorsing the training as relevant, well-organized, and worth recommending to colleagues.

Conclusion:

Perception of AI among Nigeria medical students and doctors is good, however research-oriented literacy and application is limited. Structured intervention can significantly improve the perception and knowledge of AI in medical research, however ethical concerns about AI in medical research need to be given more emphasis in future interventions.

Background

The field of medicine is continuously advancing with innovative technologies and discoveries. One of the emerging technologies is artificial intelligence (AI), which is defined as machine intelligence, as opposed to human or other life forms of intelligence.^{1,2} AI systems can anticipate problems and address them, thereby functioning in an intentional, intelligent, and adaptive way. AI is built to learn and identify patterns and relationships from large datasets; for example, it could translate a patient's medical record into a single number that represents a likely diagnosis.³ The field of AI is broad and

varied, encompassing areas like search algorithms, knowledge graphs, natural language processing (NLP), expert systems, evolutionary algorithms, machine learning (ML), and deep learning (DL).⁴

Healthcare systems globally encounter major obstacles in attaining the “quadruple aim” for healthcare: to enhance population health, improve the patient's care experience, improve caregiver satisfaction, and curb the rising costs of care.⁵ AI and machine learning technologies have emerged as tools to tackle these obstacles due to their precision capabilities. In the past, the idea of AI in healthcare was frequently linked only to robots executing surgical operations. Nonetheless, the area has advanced swiftly, resulting in a more extensive comprehension of its uses. The newly developed ecosystem has now been classified into categories that encompass physical AI and virtual AI.⁶ Physical AI includes smart medical gadgets, wearables, and surgical robots.⁷ Conversely, virtual AI refers to software applications and algorithms that analyze complex medical data to offer insights, forecasts, and assistance in clinical decision-making.⁸ The impact or possibilities of AI and various types of ML on health and healthcare delivery, such as virtual health assistants, precision imaging, robotic surgery, and AI-assisted drug discovery, have been documented worldwide.⁹ The broad benefits of AI in various fields of healthcare include making faster and more accurate diagnoses, reducing errors due to human fatigue, reducing medical costs, and lowering mortality rates overall.¹⁰

Today, AI is adopted in the areas of medical research and medical writing as well.¹¹ Medical research is globally regarded as a structured and logical way to discover new scientific knowledge and understand our environment. Typically, research adopts a systematic and thorough approach to gather and examine data, particularly in the medical field, frequently utilizing experimental and observational techniques.¹¹ Academic research has traditionally depended on manual techniques to organize and synthesize large volumes of data, a process that is time-consuming and prone to human error.¹² Recently, however, large language models (LLMs) have shown improved performance on complex tasks, offering a shift away from these manual approaches. A LLM is a machine-learning model capable of mimicking human intelligence by analyzing large datasets and generating responses based on the text it has learned from.¹² The large volume of data in medical research requires strict methodologies and a structured approach to writing. AI-powered algorithms have become essential for examining large and complex datasets that serve as a basis for modern medical research. AI tools have significantly influenced the writing process of medical research papers, allowing researchers to draft well-structured manuscripts with accuracy and speed using AI algorithms such as Generative Pre-trained Transformer (GPT-3).¹³ AI has also accelerated the publication of medical research, including the automation of manuscript submission and peer review. This reduces administrative work and speeds up the dissemination of significant research findings. In addition, AI-driven recommendation systems help match articles with appropriate journals and reviewers to increase the chances of publication. AI tools can also detect plagiarism by analyzing the similarity of the text to existing published works.¹³ Similarly, editors use AI to complete repetitive tasks, such as correcting grammatical errors.¹⁴

Despite significant advancements in medicine over the past few decades and growing interest in AI, the adoption of healthcare AI in Africa is primarily limited to pilot programs and experimental cases.¹⁵ The healthcare education system in most African countries encounters major difficulties, such as outdated curricula, insufficient educational facilities, and persistent resource limitations that have failed to equip healthcare professionals for the evolving technological environment.¹⁶ Medical education primarily still remains rooted in traditional curricula.¹⁷ It lacks the basic principles needed to understand AI. Research conducted in Nigeria, the UK, and Pakistan indicated that while the majority of medical students across these countries acknowledged the significance of AI in healthcare, only a small number had undergone formal AI training, highlighting a significant educational gap.^{18–20} Medical students and doctors are currently using generative AI tools, frequently informally, to study, create notes, and summarize information. However, they have not been taught to cross-check outputs with clinical guidelines or original literature or to evaluate the trustworthiness and uncertainty of responses produced by models.²¹

Given the need for structured AI training in medicine and research, it is essential to assess the knowledge, perception, and ethical concerns of AI in medical research among medical students and doctors. Though previous studies have mainly evaluated the knowledge, awareness, attitudes, and perceptions of AI among medical students and doctors, they offer limited insight into the behavioral factors that affect the use of AI in medical research. These factors can be examined using the Health Belief Model (HBM), which is among the most utilized frameworks for understanding the potential barriers or motivators for adopting favorable health behaviors.²² Studies done among Nigerian medical students and doctors showed a significant awareness of AI tools, with ChatGPT being the most acknowledged. Nevertheless, the knowledge of their use in research was poor.^{19,23} This discrepancy indicates that although students and doctors recognize AI tools, many do not possess the essential skills needed to use them effectively in medical research.²³ Although numerous studies have investigated the awareness, perception, and application of AI in healthcare and medical education worldwide, there is still a significant gap in research focusing on the use of AI tools in medical research by medical students and doctors.

This study aims to evaluate the effect of a structured AI training program on the perceptions of AI in medical research among medical students and doctors. A quasi-experimental design will be employed, comparing participants' perceptions before and after the training intervention, to determine whether structured exposure to AI tools measurably shifts perception and confidence. Considering Nigeria's growing research output and the global shift towards AI-assisted scientific exploration, this research is both relevant and essential. It sheds light on the benefits of AI in medical research among medical students and doctors, and provides information that can guide focused training, policy formulation, and investment in AI capacity-building for researchers in Nigeria.

Methods

Study setting and design

This study employed a one-group pretest–posttest quasi-experimental design to evaluate the impact of a structured AI training workshop on the perceptions of AI in medical research among medical students and doctors in Nigeria. The training workshop was delivered as an online webinar workshop over a weekend via Microsoft Teams, a choice necessitated by the national scope of the study and the logistical challenges of in-person data collection across multiple institutions. All communications were conducted through the Internal Medicine Interest Group of Nigeria (IMGN) social media platforms.

Intervention

Overview of IMGN

The Internal Medicine Interest Group of Nigeria (IMGN) is a non-profit independent organization dedicated to promoting interest and excellence in Internal Medicine among medical students and early career medical doctors in Nigeria.

Program description

It was a structured webinar workshop consisting of four sessions delivered over two days by experts in artificial intelligence, medical research, and medical education. Session 1 introduced participants to AI in healthcare and research, covering definitions, types of AI, current applications in medical research, and real-time demonstrations of AI tools. Session 2 addressed ethical considerations and limitations, including algorithmic bias, data privacy, transparency, accountability, and regulatory frameworks. Session 3 provided practical, hands-on demonstrations of AI-assisted literature review, data analysis tools, and guidance on critically appraising AI-generated outputs. Session 4 offered a practical overview of the Chisquares platform, covering research design, sample size calculation, data collection, analysis, and scientific writing. The

webinar sessions were recorded and made available to registered participants, though only those who attended live and completed the post-webinar assessment were included in the primary analysis.

Study population and Sampling

The study population comprised medical students and doctors across Nigeria. Eligible participants were medical students enrolled in any accredited Nigerian medical school or medical doctors (house officers, residents, medical officers, or consultants), provided informed consent, completed both pre- and post-test questionnaires, and had participated fully in the workshop. Individuals who did not attend all sessions or did not complete the post-webinar assessment were excluded from the final analysis, as were individuals in non-medical fields.

Using G*Power software with an assumed moderate effect size (Cohen's $d = 0.4$), alpha of 0.05, and power of 0.80, the minimum required sample size was calculated as 52 participants. To account for potential attrition common in online studies, the sample size was increased by 10%, aiming for a minimum of 60 participants who complete both assessments. A convenience sampling technique was employed, recruiting all eligible individuals who registered for and attended the webinar.

Data collection and Instruments

Data collection occurred in three phases. Three days before the webinar, registered participants received a link to the pretest questionnaire via WhatsApp and Email, administered using KoboToolBox. The pretest collected demographic information and assessed baseline perceptions across eight domains derived from the Health Belief Model and supplemented with additional constructs: perceived knowledge, susceptibility, severity, benefits, barriers, cues to action, self-efficacy, and ethical concerns. Attendance was monitored throughout the webinar via a questionnaire, and only participants who attended all four sessions were included. Immediately following the webinar, participants received a link to the posttest questionnaire, which included the same Likert-scale questions to measure changes in perceptions, along with additional items assessing satisfaction, perceived usefulness, and likelihood of applying the knowledge gained.

The questionnaire was adapted from previously validated instruments, modified to focus specifically on AI in medical research, and reviewed by experts in medical education, research methodology, and AI. It was pilot-tested among 15 medical students and doctors (who were not included in the main study) to assess clarity and comprehensibility, with minor revisions made based on feedback. The finalized instrument comprised 35 Likert-scale items across the eight domains, demographic and professional information, 5 workshop feedback items, and optional open-ended questions. All items used a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The instrument is available as an additional file [see **Additional file 1**].

Statistical analysis

Mean $\pm$ standard deviation (SD) was calculated for continuous variables. Frequencies and percentages were calculated for categorical variables. The normality of distribution for the change scores (posttest minus pretest) were assessed using the Shapiro-Wilk test. Given the non-normal distribution of most change scores (Shapiro-Wilk $p < .001$), non-parametric statistical tests were employed. Internal consistency of each domain scale was assessed using Cronbach's alpha, with $\alpha \geq 0.70$ considered acceptable. The Wilcoxon signed-rank test was used to compare pre- and post-intervention scores for each domain, with effect sizes reported as $r = Z/\sqrt{N}$. Subgroup comparison was done using Kruskal-Wallis and Mann-Whitney U tests. Post-hoc pairwise tests were conducted when the Kruskal-Wallis test was significant. Pearson correlation was used to investigate whether there were any correlations among the change scores of each domain. To identify independent predictors of change, eight separate multiple linear regression models were conducted to obtain confidence intervals and p-values. A p-value < 0.05 was considered statistically significant. All statistical analyses were done using R

Results

Figure 1 presents the participant flow diagram for the AI in Medical Research Training Program. Among the 160 participants that attended the workshop, 152 completed the post-webinar survey, and 17 were excluded due to incomplete attendance, yielding a final matched sample of 135 participants who were included in the main analysis.

Figure 1. Participant Flow Diagram for the AI in Medical Research Training Program

Participant Characteristics and Baseline AI Exposure

Table 1 summarizes the demographic and professional characteristics of the 135 participants. The mean age was 26.24 ± 7.64 years. The sample included 78 males (57.8%) and 57 females (42.2%). Regarding level of training, 22 (16.3%) were preclinical students, 55 (40.7%) clinical students, 15 (11.1%) house officers, 7 (5.2%) medical officers, 16 (11.9%) resident doctors, 4 (3.0%) consultants, and 16 (11.9%) classified as other which mostly included academicians. Geopolitically, 57 participants (42.2%) were affiliated in Northern Nigeria and 78 (57.8%) in Southern Nigeria. Formal AI training was reported by 31 participants (23.0%), while 104 (77.0%) had no such training; 43 (31.9%) had attended a previous AI workshop or course, and 92 (68.1%) had not. Tech-savviness was basic for 27 (20.0%), intermediate for 75 (55.6%), and advanced for 33 (24.4%).

Figure 2 displays prior exposure to AI tools. The most frequently used tool was ChatGPT (97.8% of respondents), followed by Gemini (79.3%), DeepSeek (42.2%), Claude (37.0%), Perplexity (28.1%), Consensus (12.6%), Elicit (5.2%), and Scite (2.2%). 12.6% reported using other tools such as Grok, Copilot, Meta, Note LM, e.t.c.

Figure 3 shows the primary self-reported purposes for using AI. The most common purpose was Learning / general education (91.1%), followed by Clinical training (63.7%), Research idea generation (60.0%), Academic writing (51.1%), Summarization (46.7%), Literature review (43.7%), Data analysis (32.6%), Coding (20.0%), and Other (3.0%).

Table 1
Demographic and Professional Characteristics of Participants (N = 135)

Characteristic	Category	n (%)
Age (years)	Mean $\pm$ SD	26.24 $\pm$ 7.64
Gender	Male	78 (57.8)
	Female	57 (42.2)
Level of training	Preclinical Students	22 (16.3)
	Clinical Students	55 (40.7)
	House Officer	15 (11.1)
	Medical Officer	7 (5.2)
	Resident Doctor	16 (11.9)
	Consultant	4 (3.0)
	Other	16 (11.9)
Geopolitical zone of Institution	North	57 (42.2)
	South	78 (57.8)
Formal AI training	Yes	31 (23.0)
	No	104 (77.0)
Previous AI workshop/course	Yes	43 (31.9)
	No	92 (68.1)
Tech-savviness	Basic	27 (20.0)
	Intermediate	75 (55.6)
	Advanced	33 (24.4)

SD = Standard Deviation.

Figure 2. Prior Exposure to AI Tools Among Participants (N = 135)

Figure 3. Primary Self-Reported Purposes for Using AI Among Participants (N = 135)

Baseline Perceptions of AI in Medical Research

Table 2 provides the baseline mean scores and the percentage of participants who endorsed each statement (i.e., selected "Agree" or "Strongly Agree") for the 35 items across the eight domains. For Perceived Knowledge, item means ranged from 2.47 ± 1.06 for "I can explain how AI algorithms are trained and validated" to 3.79 ± 0.81 for "I understand what artificial intelligence means in the context of healthcare." For Perceived Susceptibility, means ranged from 3.55 ± 0.96 to 4.02 ± 0.89 ; for Perceived Severity, from 3.50 ± 1.04 to 3.99 ± 0.79 ; for Perceived Benefits, from 4.04 ± 0.75 to 4.36 ± 0.70 ; for Perceived Barriers, from 3.05 ± 1.17 to 3.86 ± 0.92 ; for Cues to Action, from 3.04 ± 1.08 to 4.33 ± 0.70 ; for Self-Efficacy, from 3.36 ± 0.99 to 4.27 ± 0.82 ; and for Ethical Concerns, from 3.47 ± 1.16 to 4.39 ± 0.74 . Complementing these mean scores, the proportion of participants who endorsed each item (Agree/Strongly Agree) showed notable variation. The highest levels of endorsement were observed for the time-saving benefits of AI (92.6%) and the necessity of clear ethical guidelines (89.7%), while the lowest were for the ability to explain how AI algorithms are trained (16.3%) and familiarity with machine learning and deep learning techniques (30.4%).

Figure 4 illustrates the distribution of high versus low baseline perception levels across the eight domains. The proportion of participants with high scores (≥ 4) ranged from 14.1% (Perceived Knowledge) to 78.5% (Perceived Benefits). The corresponding low-score proportions were 85.9% for Knowledge, 44.4% for Susceptibility, 44.4% for Severity, 21.5% for Benefits, 68.1% for Barriers, 57.0% for Cues, 64.4% for Self-Efficacy, and 36.3% for Ethical Concerns.

Table 2
Baseline Perceptions of AI in Medical Research Across the Eight Domains (N = 135)

Statement	Domain Assessed	Mean $\pm$ SD	% Agree/Strongly Agree
I understand what artificial intelligence means in the context of healthcare.	Perceived Knowledge of AI in Medical Research	3.79 $\pm$ 0.81	70.4%
I am familiar with common AI techniques such as machine learning and deep learning.	Perceived Knowledge of AI in Medical Research	2.97 $\pm$ 1.04	30.4%
I understand how AI can be applied to medical research.	Perceived Knowledge of AI in Medical Research	3.31 $\pm$ 1.00	48.8%
I understand the limitations of current AI applications in medical research.	Perceived Knowledge of AI in Medical Research	3.27 $\pm$ 1.00	44.4%
I can explain how AI algorithms are trained and validated.	Perceived Knowledge of AI in Medical Research	2.47 $\pm$ 1.06	16.3%
If I do not learn to use AI tools, I risk falling behind my peers in medical research capabilities.	Perceived Susceptibility (Risk of not adopting AI)	4.02 $\pm$ 0.89	77.1%
Not using AI in my research will make it difficult for me to keep up with the growing volume of scientific literature.	Perceived Susceptibility (Risk of not adopting AI)	3.91 $\pm$ 0.87	77.1%
Without AI skills, I will miss opportunities to conduct high-quality research that can be published in top journals.	Perceived Susceptibility (Risk of not adopting AI)	3.55 $\pm$ 0.96	57.8%
Not being proficient in AI for research will seriously limit my career advancement opportunities.	Perceived Severity (Consequences of not adopting AI)	3.75 $\pm$ 0.88	69.6%
The inability to use AI tools will significantly reduce the quality and impact of my research output.	Perceived Severity (Consequences of not adopting AI)	3.50 $\pm$ 1.04	58.5%
If I ignore AI in research, I will be at a severe disadvantage compared to colleagues who embrace it.	Perceived Severity (Consequences of not adopting AI)	3.99 $\pm$ 0.79	79.3%
AI can greatly improve the accuracy of data analysis in my research.	Perceived Benefits (Advantages of adopting AI)	4.11 $\pm$ 0.73	85.2%
Using AI tools will make medical research more efficient by saving time and effort.	Perceived Benefits (Advantages of adopting AI)	4.36 $\pm$ 0.70	92.6%
Incorporating AI will enhance my ability to make novel discoveries in medical research.	Perceived Benefits (Advantages of adopting AI)	4.04 $\pm$ 0.75	84.4%
I lack the technical knowledge and training required to effectively use AI tools for research.	Perceived Barriers (Obstacles to adopting AI)	3.50 $\pm$ 1.01	59.3%
The high cost of AI software and hardware makes it difficult for me to access these tools.	Perceived Barriers (Obstacles to adopting AI)	3.47 $\pm$ 1.07	48.9%
Unreliable internet connectivity prevents me from using AI-based research platforms.	Perceived Barriers (Obstacles to adopting AI)	3.05 $\pm$ 1.17	41.5%
There is insufficient institutional support or training available to help me learn AI for research.	Perceived Barriers (Obstacles to adopting AI)	3.86 $\pm$ 0.92	74.8%
I worry that AI-generated research outputs may contain biases that affect the fairness of my work.	Perceived Barriers (Obstacles to adopting AI)	3.62 $\pm$ 0.92	62.2%

Statement	Domain Assessed	Mean $\pm$ SD	% Agree/Strongly Agree
Advice from senior colleagues or mentors encourages me to learn AI for research.	Cues to Action (Triggers motivating AI adoption)	3.57 $\pm$ 0.97	63.0%
Seeing my peers use AI tools in their research motivates me to do the same.	Cues to Action (Triggers motivating AI adoption)	3.79 $\pm$ 0.91	70.4%
My institution actively recommends that students and doctors acquire AI skills.	Cues to Action (Triggers motivating AI adoption)	3.04 $\pm$ 1.08	33.3%
Media and online content about AI in healthcare have raised my interest in adopting AI for research.	Cues to Action (Triggers motivating AI adoption)	3.94 $\pm$ 0.87	77.1%
Attending workshops and webinars like this one serves as a strong trigger for me to start using AI in research.	Cues to Action (Triggers motivating AI adoption)	4.33 $\pm$ 0.70	91.9%
I am confident that I can learn to use AI tools effectively for my research.	Self-Efficacy (Confidence in one's ability to use AI in research)	4.27 $\pm$ 0.82	87.4%
I am capable of identifying situations where AI would be appropriate or inappropriate in research.	Self-Efficacy (Confidence in one's ability to use AI in research)	3.70 $\pm$ 0.98	59.3%
I feel capable of critically evaluating the quality and reliability of AI-generated research outputs.	Self-Efficacy (Confidence in one's ability to use AI in research)	3.36 $\pm$ 0.99	45.2%
I can integrate AI tools into my research workflow without major difficulties.	Self-Efficacy (Confidence in one's ability to use AI in research)	3.36 $\pm$ 1.01	48.2%
I would feel comfortable teaching a colleague how to use an AI research tool.	Self-Efficacy (Confidence in one's ability to use AI in research)	3.55 $\pm$ 1.04	57.7%
I am concerned about patient data privacy when AI is used in research.	Ethical Concerns Regarding AI in Medical Research	3.95 $\pm$ 0.88	73.3%
I am concerned about fabricated information ("hallucinations") generated by AI systems.	Ethical Concerns Regarding AI in Medical Research	4.07 $\pm$ 0.90	79.3%
I am concerned that AI use in research may reduce the humanistic aspects of medicine.	Ethical Concerns Regarding AI in Medical Research	3.47 $\pm$ 1.16	54.9%
I believe there should be clear accountability for errors made by AI systems in research.	Ethical Concerns Regarding AI in Medical Research	4.20 $\pm$ 0.79	84.4%
I am concerned that AI may be used without adequate transparency ("black box" problem).	Ethical Concerns Regarding AI in Medical Research	3.90 $\pm$ 0.85	74.1%
I believe that ethical guidelines for AI use in medical research are necessary.	Ethical Concerns Regarding AI in Medical Research	4.39 $\pm$ 0.74	89.7%

SD = Standard Deviation. Note: Range of Likert Scale: 1 (Strongly Disagree) to 5 (Strongly Agree).

Figure 4. Distribution of Baseline AI Perception Levels (High vs Low) Across the Eight Domains

Reliability of the Perception Scales

Table 3 reports Cronbach's α at pre- and post-webinar. At pre-webinar, α values were: Perceived Knowledge 0.789, Susceptibility 0.718, Severity 0.768, Benefits 0.850, Barriers 0.701, Cues 0.732, Self-Efficacy 0.800, and Ethical Concerns

0.795. At post-webinar, the values were: Knowledge 0.751, Susceptibility 0.860, Severity 0.772, Benefits 0.717, Barriers 0.665, Cues 0.600, Self-Efficacy 0.849, and Ethical Concerns 0.708.

Table 3
Internal Consistency (Cronbach's α) of the Perception Scales at Pre- and Post-Webinar (N = 135)

Domain	Number of Items	Pre-Webinar α	Post-Webinar α
Perceived Knowledge	5	0.789	0.751
Perceived Susceptibility	3	0.718	0.860
Perceived Severity	3	0.768	0.772
Perceived Benefits	3	0.850	0.717
Perceived Barriers	5	0.701	0.665
Cues to Action	5	0.732	0.600
Self-Efficacy	5	0.800	0.849
Ethical Concerns	6	0.795	0.708

Immediate Impact of the AI Training Intervention

Figure 5A and 5B present the radar charts of baseline and post-intervention mean scores for each domain. Shapiro–Wilk test was conducted to check the normality of each of the change scores; all eight change variables deviated significantly from normality ($p < 0.05$). Accordingly, Table 4 reports the results of the Wilcoxon signed-rank tests. For Perceived Knowledge, the pre-intervention mean was 3.16 ± 0.73 and post-intervention mean was 4.18 ± 0.50 ; the median change was 1.00 (IQR: 0.60–1.40), with a statistically significant increase ($Z = -9.787$, $p < 0.001$, $r = 0.84$). For Perceived Susceptibility, mean increased from 3.83 ± 0.72 to 4.18 ± 0.72 , median change = 0.33 (IQR: 0.00–1.00), $Z = -5.022$, $p < 0.001$, $r = 0.43$. For Perceived Severity, mean increased from 3.75 ± 0.75 to 4.04 ± 0.72 , median change = 0.33 (IQR: 0.00–0.67), $Z = -4.540$, $p < 0.001$, $r = 0.39$. For Perceived Benefits, mean increased from 4.17 ± 0.64 to 4.33 ± 0.53 , median change = 0.00 (IQR: -0.33–0.67), $Z = -2.654$, $p = 0.008$, $r = 0.23$. For Perceived Barriers, mean decreased from 3.50 ± 0.69 to 3.15 ± 0.71 , median change = -0.40 (IQR: -1.00–0.00), $Z = -5.147$, $p < 0.001$, $r = 0.44$. For Cues to Action, means increased from 3.73 ± 0.63 to 4.08 ± 0.50 , median change = 0.20 (IQR: 0.00–0.60), $Z = -6.153$, $p < 0.001$, $r = 0.53$. For Self-Efficacy, mean increased from 3.65 ± 0.72 to 4.11 ± 0.51 , median change = 0.40 (IQR: 0.00–1.00), $Z = -6.194$, $p < 0.001$, $r = 0.53$. For Ethical Concerns, the means were 4.00 ± 0.63 pre- and 3.99 ± 0.57 post-intervention, with a median change of 0.00 (IQR: -0.33–0.33), which was not statistically significant ($Z = -0.559$, $p = 0.576$, $r = 0.05$).

Figure 5: Baseline and Post-Intervention Perceptions of AI in Medical Research Across the Eight Domains (N = 135)

Table 4
Impact of the AI Training Intervention: Pre vs Post Intervention Perception Scores (N = 135)

Domain	Pre Intervention Mean $\pm$ SD	Post Intervention Mean $\pm$ SD	Median Change (Post – Pre) [IQR]	Z	p value	r
Perceived Knowledge	3.16 $\pm$ 0.73	4.18 $\pm$ 0.50	1.00 [0.60–1.40]	-9.787	< 0.001*	0.84
Perceived Susceptibility	3.83 $\pm$ 0.72	4.18 $\pm$ 0.72	0.33 [0.00–1.00]	-5.022	< 0.001*	0.43
Perceived Severity	3.75 $\pm$ 0.75	4.04 $\pm$ 0.72	0.33 [0.00–0.67]	-4.540	< 0.001*	0.39
Perceived Benefits	4.17 $\pm$ 0.64	4.33 $\pm$ 0.53	0.00 [-0.33–0.67]	-2.654	0.008*	0.23
Perceived Barriers	3.50 $\pm$ 0.69	3.15 $\pm$ 0.71	-0.40 [-1.00–0.00]	-5.147	< 0.001*	0.44
Cues to Action	3.73 $\pm$ 0.63	4.08 $\pm$ 0.50	0.20 [0.00–0.60]	-6.153	< 0.001*	0.53
Self Efficacy	3.65 $\pm$ 0.72	4.11 $\pm$ 0.51	0.40 [0.00–1.00]	-6.194	< 0.001*	0.53
Ethical Concerns	4.00 $\pm$ 0.63	3.99 $\pm$ 0.57	0.00 [-0.33–0.33]	-0.559	0.576	0.05

SD = Standard Deviation; IQR = Interquartile Range; Z = Wilcoxon Test statistic; r = Effect size. *Statistically significant at $p < 0.05$.

Subgroup Differences in Intervention Effects (Bivariate Associations)

For Perceived Knowledge, Perceived Susceptibility, Perceived Severity, Perceived Barriers, Cues to Action, and Ethical Concerns, no characteristic showed a statistically significant association. For Perceived Benefits, tech-savviness was significantly associated ($H = 11.987$, $p = 0.002$, $\epsilon^2 = 0.076$), while gender, training level, geopolitical zone, and formal AI training were not. For Self-Efficacy, geopolitical zone ($U = 1728.000$, $p = 0.027$, $r = -0.19$) and tech-savviness ($H = 7.568$, $p = 0.023$, $\epsilon^2 = 0.043$) were significantly associated, whereas gender, training level, and formal AI training were not. Post-hoc pairwise comparisons were conducted for tech-savviness levels to determine the statistically significant domains. For Perceived Benefits, the advanced-intermediate comparison was significant ($Z = 3.458$, adjusted $p = 0.002$), while advanced-basic ($Z = 1.793$, adjusted $p = 0.219$) and basic-intermediate ($Z = -1.145$, adjusted $p = 0.757$) were not. For Self-Efficacy, the advanced-intermediate comparison was significant ($Z = 2.751$, adjusted $p = 0.018$), whereas advanced-basic ($Z = 1.558$, adjusted $p = 0.357$) and basic-intermediate ($Z = -0.759$, adjusted $p = 1.000$) were not. An additional file shows this subgroup analysis in more detail [see **Additional file 2**].

Correlation between Domain Change Scores

Figure 6 displays a heatmap of Pearson correlation coefficients between change scores for the eight domains. Statistically significant correlations ($p < 0.05$) are indicated with asterisks. The heatmap shows a cluster of positive correlations among Perceived Knowledge, Perceived Severity, Perceived Benefits, Perceived Barriers, Cues to Action, and Self-Efficacy, with coefficients ranging from moderate to strong. Perceived Knowledge was negatively correlated with Ethical Concerns.

Figure 6: Heatmap of Pearson correlation coefficients (r) between change scores for the eight domains.

Predictors of Change in AI Perception Scores (Multiple Linear Regression)

Table 5 presents the standardized coefficients (β) from multiple linear regression models for each domain. The model R^2 values were: Perceived Knowledge ($R^2 = 0.080$, adjusted $R^2 = -0.019$), Susceptibility ($R^2 = 0.153$, adjusted $R^2 = 0.062$),

Severity ($R^2 = 0.094$, adjusted $R^2 = -0.003$), Benefits ($R^2 = 0.166$, adjusted $R^2 = 0.077$), Barriers ($R^2 = 0.100$, adjusted $R^2 = 0.003$), Cues ($R^2 = 0.084$, adjusted $R^2 = -0.014$), Self-Efficacy ($R^2 = 0.223$, adjusted $R^2 = 0.140$), and Ethical Concerns ($R^2 = 0.056$, adjusted $R^2 = -0.046$). In the Self-Efficacy model, the “Other” training category ($\beta = 0.249$, $p < 0.05$) and geopolitical zone (North vs South, $\beta = 0.297$, $p < 0.01$) were statistically significant predictors. In the Barriers model, previous AI workshop attendance (Yes vs No, $\beta = 0.195$, $p < 0.05$) was a significant predictor.

Table 5
Multiple Linear Regression: Predictors of Change in AI Perception Scores Across the Eight Domains

Predictor	Perceived Knowledge	Perceived Susceptibility	Perceived Severity	Perceived Benefits	Perceived Barriers	Cues to Action	Self Efficacy	Ethical Concerns
Age (years)	−.111	−.206	−.181	−.210	−.226	−.238	.027	−.049
Gender								
Female (ref)	–	–	–	–	–	–	–	–
Male	−.065	−.022	.018	−.102	.085	−.056	.007	−.028
Level								
Preclinical Student (ref)	–	–	–	–	–	–	–	–
Clinical Student	.185	.157	−.100	−.027	−.096	−.015	.036	.046
House Officer	.154	−.131	−.117	−.080	.053	−.037	−.062	.098
Medical Officer	.020	.064	−.030	.001	.051	−.012	.133	.012
Resident Doctor	.253	.275	.140	.188	.065	.184	.217	.164
Consultant	.134	.186	.099	.146	.082	.223	.170	−.027
Other	.130	−.098	−.157	.014	.034	−.019	.249*	.089
Geopolitical Zone								
South (ref)	–	–	–	–	–	–	–	–
North	.079	.138	.092	.069	−.085	.106	.297**	−.016
Formal AI Training								
No (ref)	–	–	–	–	–	–	–	–
Yes	−.062	−.016	−.076	−.091	.030	.015	−.051	.038
Tech savviness								
Basic (ref)	–	–	–	–	–	–	–	–
Intermediate	.034	.177	.135	.200	.067	.031	.154	.104
Advanced	−.061	.156	.068	−.181	.138	−.133	−.100	.151
Previous AI Workshop								
No (ref)	–	–	–	–	–	–	–	–
Yes	−.114	−.100	.099	−.025	.195*	−.036	−.087	.093
Note. Values are standardized coefficients (β). *p < .05; **p < .01; ***p < .001.								

Predictor	Perceived Knowledge	Perceived Susceptibility	Perceived Severity	Perceived Benefits	Perceived Barriers	Cues to Action	Self Efficacy	Ethical Concerns
Model R²	.080	.153	.094	.166	.100	.084	.223	.056
Adjusted R²	-.019	.062	-.003	.077	.003	-.014	.140	-.046
Note. Values are standardized coefficients (β). * $p < .05$; ** $p < .01$; *** $p < .001$.								

Table 5: Multiple Linear Regression: Predictors of Change in AI Perception Scores Across the Eight Domains

Webinar Feedback and Participant Satisfaction

Table 6 summarizes the post-webinar feedback. Mean scores ranged from 4.35 ± 0.684 for “The webinar was well organized and easy to follow” to 4.61 ± 0.635 for “The webinar increased my interest in using AI for medical research.” The remaining items scored: “The webinar content was relevant and useful to my needs” (mean $\pm$ SD = 4.50 ± 0.621), “The webinar improved my understanding of the role of AI in medical research” (mean $\pm$ SD = 4.48 ± 0.571), and “I would recommend this webinar to a colleague” (mean $\pm$ SD = 4.57 ± 0.664). The proportion of participants who endorsed each statement (agree/strongly agree) ranged from 93.3% (for organization) to 97.1% (for relevance), reflecting a uniformly high level of satisfaction and perceived utility of the program. All items used a 1–5 Likert scale. All items used a 1–5 Likert scale.

Table 6
Post Webinar Feedback on the Training Program (N = 135)

Statement	Score Mean $\pm$ SD	% Agree/Strongly Agree
The webinar content was relevant and useful to my needs.	4.50 ± 0.621	97.1%
The webinar was well organized and easy to follow.	4.35 ± 0.684	93.3%
The webinar increased my interest in using AI for medical research.	4.61 ± 0.635	95.5%
The webinar improved my understanding of the role of AI in medical research.	4.48 ± 0.571	96.3%
I would recommend this webinar to a colleague.	4.57 ± 0.664	95.6%
Note. Likert scale: 1 (Strongly Disagree) to 5 (Strongly Agree).		

Discussion

Of the 160 medical students and doctors who attended the AI in Medical Research training webinar, 135 (84.4%) the post-webinar assessments and formed the analytic sample. Participants were predominantly clinical-level trainees (40.7%) and pre-clinical students (16.3%), with a mean age of 26.2 years, and only 23.0% had received any prior formal AI training. At baseline, perceptions were uneven across the eight Health Belief Model (HBM) domain. Perceived Knowledge was the weakest area, with only 14.1% of participants scoring high and just 16.3% agreeing they could explain how AI algorithms are trained, while Perceived Benefits was the strongest, with 78.5% scoring high and 92.6% agreeing that AI saves time in research. Ethical Concerns were also high at baseline (89.7%), indicating the need for ethical guidelines for AI use.

Following the four-session intervention, statistically significant improvements were observed in seven of the eight domains; Perceived Knowledge showed the largest shift, followed by moderate-to-large gains in Cues to Action, Self-Efficacy, Perceived Barriers; which fell significantly as expected, then Perceived Susceptibility and Perceived Severity. Perceived Benefits improved only marginally, consistent with its already-high baseline, while Ethical Concerns showed no significant change. Analysis showed that change scores were largely uniform across gender, level of training, and formal AI training

status. The exceptions were tech-savviness, which was associated with differential gains in Perceived Benefits, Self-Efficacy (advanced users improving more than intermediate users), and geopolitical zone which was associated with Self-Efficacy change. Satisfaction with the webinar was uniformly high, with 93–97% of participants endorsing its relevance, organization, and impact on their interest in AI.

The low baseline knowledge scores observed echo a consistent pattern across Nigerian and wider literature; a cross-sectional study of 342 students at a Nigerian university similarly found only moderate knowledge and formal AI training in just 20.8% of respondents,¹⁹ while a ten-university, six-geopolitical-zone Nigerian survey of 1003 students and lecturers found average knowledge levels and prior AI training in fewer than 5% of participants.²⁴ This gap is not unique to Nigeria, a nine-country Arab study of 4492 students in which 92.4% had received no formal AI training and 87.1% exhibited a low knowledge of AI and deep learning,²⁵ both describes the same combination of high awareness but low technical understanding seen in the present cohort's baseline scores. The magnitude of the knowledge gain produced by the single structured weekend is striking, though not without precedent as a paired pre–post interventional study of 600 first-year MBBS students in Maharashtra reported knowledge scores rising from 41.2 ± 7.4 to 72.5 ± 8.8 out of 100 after one awareness session,²⁶ and a four-week, hands-on AI-literacy programme for pre-medical students in the United States reported rising values across knowledge domains.²⁷ Together these findings suggest that even brief, well-structured exposure can produce large, immediate shifts in self-reported and tested AI knowledge among learners starting from a low baseline.

The comparatively small change observed for Perceived Benefits mirrors a ceiling effect reported elsewhere in which a paired pre–post study of an AI-focused radiology panel in London similarly found that domains with already-favorable baseline attitudes showed the smallest post-session movement, while domains reflecting factual understanding shifted the most.²⁸ A similar favorable baseline Perceived Benefit of AI in medical research was also reported in a cross-sectional study conducted among Nigerian medical doctors.²³

The absence of a training-level, gender, or prior-AI-training effect on change scores is a notable differentiator from a cross-sectional literature, in which utilization and perception of AI varied by level favoring clinical students and by gender.¹⁹ It may indicate that, unlike passive exposure or self-selected use, a structured intervention narrows preexisting knowledge gaps regardless of a participant's starting point. Tech-savviness however, retained an independent association with gains in Benefits and Self-Efficacy, consistent with evidence that prior technical confidence, rather than clinical seniority alone, shapes how much new information translates into applied confidence.²⁹ Perhaps the most consequential finding is that Ethical Concerns was the highest-scoring domain at baseline in this study and is the only domain that failed to change following the intervention, which could be due to the fact that ethical concern is an aspect that requires more than a 2-day structured session to see significant improvement. In this current study, it shows that most participants are aware of the ethical aspect of AI use, especially in the necessity of guidelines in research and the clear accountability for errors made with the use of AI in research which could be explained as because of the healthcare profession ethical training. It was also observed that participants' baseline AI exposure was heavily skewed towards general-purpose tools such as ChatGPT (97.8%) while there was low exposure in research focused AI tools such as Consensus (12.6%), Elicit (5.2%), and Scite (2.2%) and this distinction is echoed in the item-level knowledge data, where 70.4% of participants agreed they understood what AI means in healthcare generally, but only 48.8% agreed they understood how AI applies specifically to medical research. Together, these patterns suggest that the baseline knowledge deficit identified in this study was more of a specific gap between broad AI familiarity and research-oriented AI literacy, a distinction with direct curricular implication which is that subsequent training should assume general tool familiarity and focus more time on research-specific applications rather than general AI orientation.

The overall pattern of change broadly supports the applicability of the Health Belief Model to AI adoption in a medical research context; knowledge, susceptibility, severity, cues to action, self-efficacy and barriers all moved in the theoretically predicted direction following a structured educational input, consistent with HBM-based interventions in other clinical

education settings.³⁰ The large shift in Knowledge, paired with parallel gains in Susceptibility and Severity, suggests that in this context, knowledge functioned as an upstream driver that re-calibrated participants' risk perception of not adopting AI. Participants who left the webinar understanding AI better also appeared to more clearly appreciate what they stood to lose by not engaging with it. Perceived Knowledge showed the largest post-intervention gain of the eight domains, which is consistent with the combination of a low starting point and direct curricular targeting; three of the webinar's four sessions delivered explicit AI content, and studies of similarly structured short, information-dense sessions have reported comparably large knowledge gains from a low baseline, including a hands-on AI-literacy programme for pre-medical students.²⁷ Cues to Action also responded greatly to the intervention which fits the construct itself as this domain prompts individuals to adopt AI use, resources and guidance and a live session that names specific platforms and demonstrates them, functions as a direct behavioral cue. Self-Efficacy also showed a large gain, and this is best explained by the applied hands-on structure of the later sessions rather than passive delivery alone. Evidence from medical education broadly supports this, a randomized cross-over trial comparing active, interactive large group sessions with passive lecture delivery found significantly greater learning gains in the active condition.³¹

Strengths

The sample was national, with 135 matched participants drawn from all six geopolitical zones of Nigeria, with Northern (42.2%) and Southern (57.8%) representation including over 40 universities and 30 hospital/health institutions, spanning training levels from preclinical students through to consultants. The questionnaire was not constructed from scratch but grounded in the Health Belief Model, a behavioral framework with decades of application in health education research. Structuring the instrument around an established theory, rather than assembling items intuitively, gave the eight domains a principled basis and makes the findings more directly comparable to future studies working within the same framework.

Of the 160 participants who attended the webinar workshop, 135 returned matched postwebinar data, representing a retention rate of 84.4%. For context, a similar study by Sirajudeen et al. worked with 40 participants at a single symposium,²⁸ and Hopson et al. flagged sample size as a limitation that may have inflated their effect estimates.²⁷ 135 participants drawn from across the country for this study, is a stronger foundation.

On the analytic side, the team made careful, deliberate methodological choices. Before running the main analysis, Shapiro-Wilk tests confirmed that all eight change score distributions deviated significantly from normality ($p < 0.05$ for all domains) prompting the use of non-parametric tests. The measurement instrument also performed reliably, with prewebinar Cronbach's α values ranging from 0.701 to 0.850 across all eight domains, reflecting acceptable to good internal consistency throughout.

Limitations

The most significant limitation of this study was that there was no control group. Sirajudeen et al. faced the same limitation.²⁸ It is a recurring problem in short-format AI education research, not unique to this study. Another major limitation was the convenience sampling utilized in the present study. Participation was open beyond any single network and drew from broader channels, but attendance was entirely voluntary. That self-selection matters. People who choose to spend a weekend at a structured AI training webinar are not representative of Nigerian medical students and doctors as a whole; they are, by definition, the curious and motivated subset of that group. The fact that 77.0% had no prior formal AI training does not resolve this. Oluwadiya et al. reported similar limitation as their survey was voluntary and they acknowledged the sample likely skewed toward people already interested in AI.²⁴ Two Nigerian studies arriving independently at the same concern is worth noting. It suggests the problem is structural, not incidental, and that future research in this space needs to think more carefully about how participants are identified and recruited.

Online delivery enabled the study's national reach, but it also created barriers that deserve honest acknowledgment. Reliable internet access and a compatible device were prerequisites for full participation, none of which are equally

distributed across Nigeria. This was not an abstract structural concern. Participants reported it directly. One could not fully follow a session because of poor network on his side. Another recommended that future programs be made physical, stating that "online connectivity is a sole problem", on the grounds that Nigerian infrastructure does not reliably support high-fidelity streaming at scale. This dimension of the limitation is notably absent from comparable studies conducted in high-income settings, where internet access is largely assumed, and represents a contextually specific challenge that research on AI education in sub-Saharan Africa must take more seriously. On top of connectivity issues, Microsoft Teams itself was flagged as confusing and unfamiliar by multiple respondents, who recommended switching to Zoom or Google Meet. Attendance was also self-reported with no independent verification, a gap that participants noticed themselves, with several calling for automatic tracking systems in future programs.

The Ethical Concerns domain deserves special attention. It was the only one of eight that failed to show a significant change ($Z = -0.559$, $p = 0.576$, $r = 0.05$), and that finding raises a question. Ethics is not a knowledge deficit that can be corrected with two days of instructions. The questions this domain encompasses, including accountability when AI makes errors, algorithmic bias, data privacy, and transparency, are genuinely contested and resistant to quick resolution. What makes the finding more nuanced is that ethics content was not ignored by participants; several named it among the most valuable things they encountered. One respondent said the webinar finally answered a question they had long held about who bears responsibility when AI makes a mistake. The content landed for those who engaged with it. The issue is likely duration.

Recommendations

The findings of the present study offer directions for integrating AI training into medical education. First, the scale of the knowledge and self-efficacy gains achieved through a single intervention of 4 sessions supports embedding short, intensive, practically oriented AI modules at both the undergraduate and postgraduate level, rather than relying on incidental exposure.

Second, because Perceived Barriers, while significantly reduced, remained moderately high post-intervention and because infrastructural constraints such as unreliable connectivity and limited institutional support were the most persistently endorsed obstacles at baseline, institutional investment in stable internet access, shared computing resources, and dedicated AI-training time is a necessary complement to curricular reform, particularly given the documented digital-literacy and infrastructure gaps affecting AI adoption across sub-Saharan African medical education more broadly.³²

Third, the reach achieved through this webinar, drawing 135 matched participants across both Northern and Southern Nigeria through a single professional association, illustrates the practical value of medical student and professional bodies such as IMGN in bridging the national training gap previously documented, in which fewer than 5% of surveyed students and lecturers across ten Nigerian universities had received prior formal AI training.²⁴ Such organizations are well placed to standardize content, reach trainees outside major teaching hospitals and sustain training pipelines where formal curricular reform is slower to implement.

Finally, curriculum development should emphasize practical-skills content, which this intervention shows can be taught and absorbed rapidly, and ethical-awareness content, which the unchanged Ethical Concerns domain suggests needs a different approach and recommended strategies include case-based discussion, structured ethics committees, stressing on the ethical aspect in future interventions and revisited content across the training continuum rather than a single session, in line with published recommendations for embedding transparency, accountability, bias-awareness, and data-protection principles throughout medical AI curricula.³³

Conclusions

This study demonstrates that Nigerian medical students and doctors generally enter formal AI training with a specific and identifiable knowledge gap; not an absence of AI familiarity, but a deficit in research-oriented AI literacy. A structured, two-day intervention was sufficient to produce significant improvements across most perception domains, suggesting that targeted, practically oriented training can rapidly close this gap even in resource-limited settings. These findings carry direct implications for medical education policy in Nigeria and across sub-Saharan Africa. Professional bodies such as IMGN have demonstrated their capacity to reach trainees at national scale through extracurricular channels, and this model offers a practical interim solution while formal curricular reform is pursued. However, future interventions should place greater emphasis on the ethical aspect which requires more sustained approaches.

Abbreviations

AI
Artificial Intelligence
DL
Deep Learning
GPT
3-Generative Pre-trained Transformer 3
HBM
Health Belief Model
IQR
Interquartile Range
IMGN
Internal Medicine Interest Group of Nigeria
LLMs
Large Language Models
ML
Machine Learning
NLP
Natural Language Processing
SD
Standard Deviation
SPSS
Statistical Package for the Social Sciences
UK
United Kingdom

Declarations

Ethics approval and consent to participate

Ethical approval was obtained from the Research Ethics Committee of Usmanu Danfodiyo University Teaching Hospital on the 13th of June 2026 (Assigned Number: UDUTH/HREC/2026/1765/V1), and the study was conducted in accordance with the Nigerian National Code for Health Research Ethics and the Declaration of Helsinki. Informed consent was obtained electronically from all participants. All data were anonymized and stored securely, with identifiable information collected solely for matching pre and post test responses and issuing certificates of participation. All identifiable information were stored separately from the main dataset and were not included in the final analysis file.

Consent for publication

Not applicable.

Availability of data and materials

All data obtained and analyzed are available in the manuscript. The main dataset generated during the current study is available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

A.Y. and S.O. conceptualized the study and validated the research questionnaire. U.K., H.U., O.D., and J.O. oversaw the pilot testing of the questionnaire, and implemented all necessary changes. A.Y. drafted the initial draft of the research proposal. S.O. and A.P. finalized the research proposal. All authors contributed to obtaining ethical approval and participated in data collection. A.Y., A.P., U.K., E.O., O.D., J.O., and D.G. implemented the intervention. A.Y. performed data cleaning, coding and conducted the data analysis and also prepared all the tables and figures. A.Y., J.C., H.U., C.N., and J.O. prepared the original manuscript draft. S.O., U.K., O.D., and D.G. critically reviewed and edited the manuscript. All authors read and approved the final manuscript and agree to be accountable for all aspects of the work.

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Figures

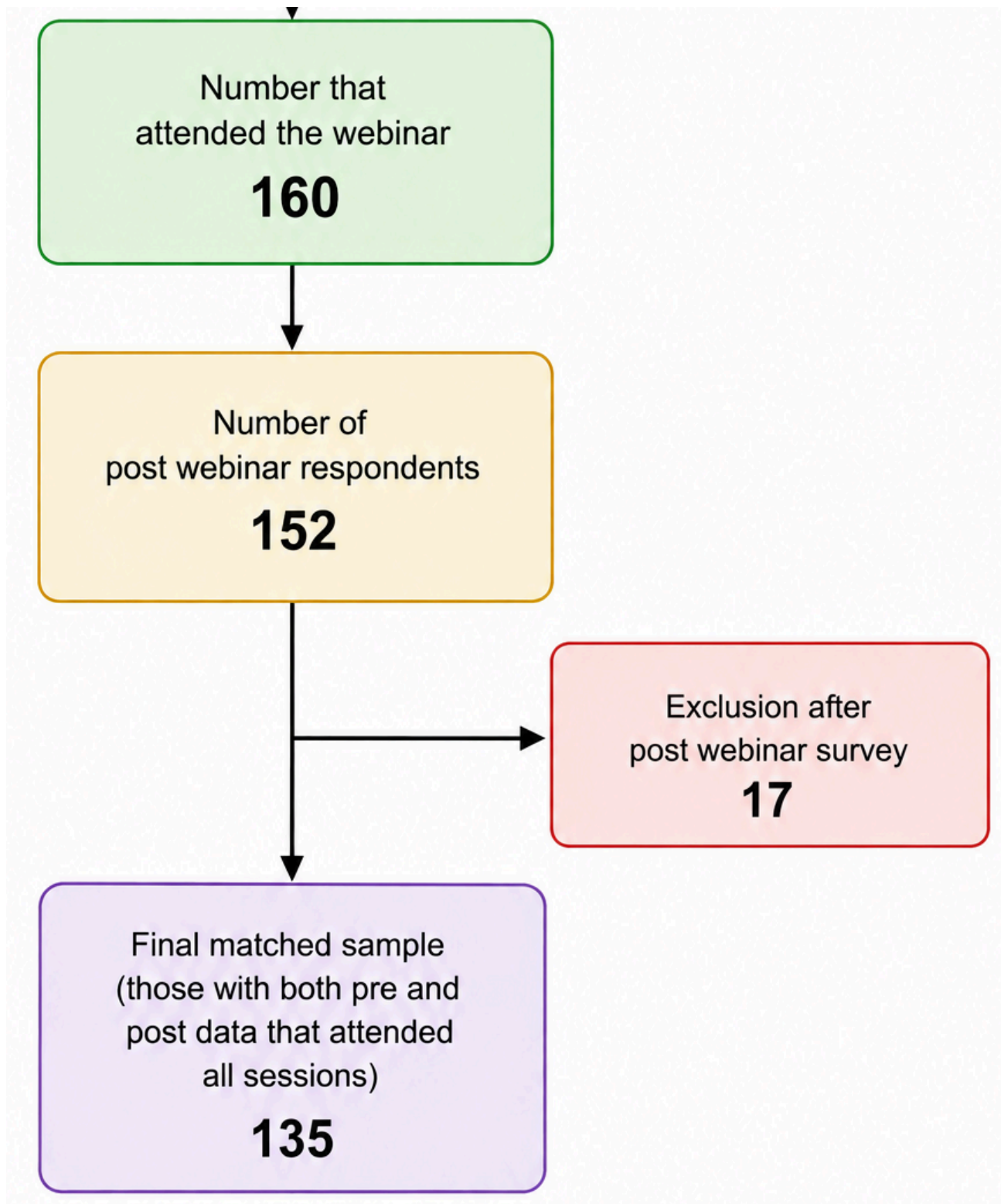


Figure 1

Participant Flow Diagram for the AI in Medical Research Training Program

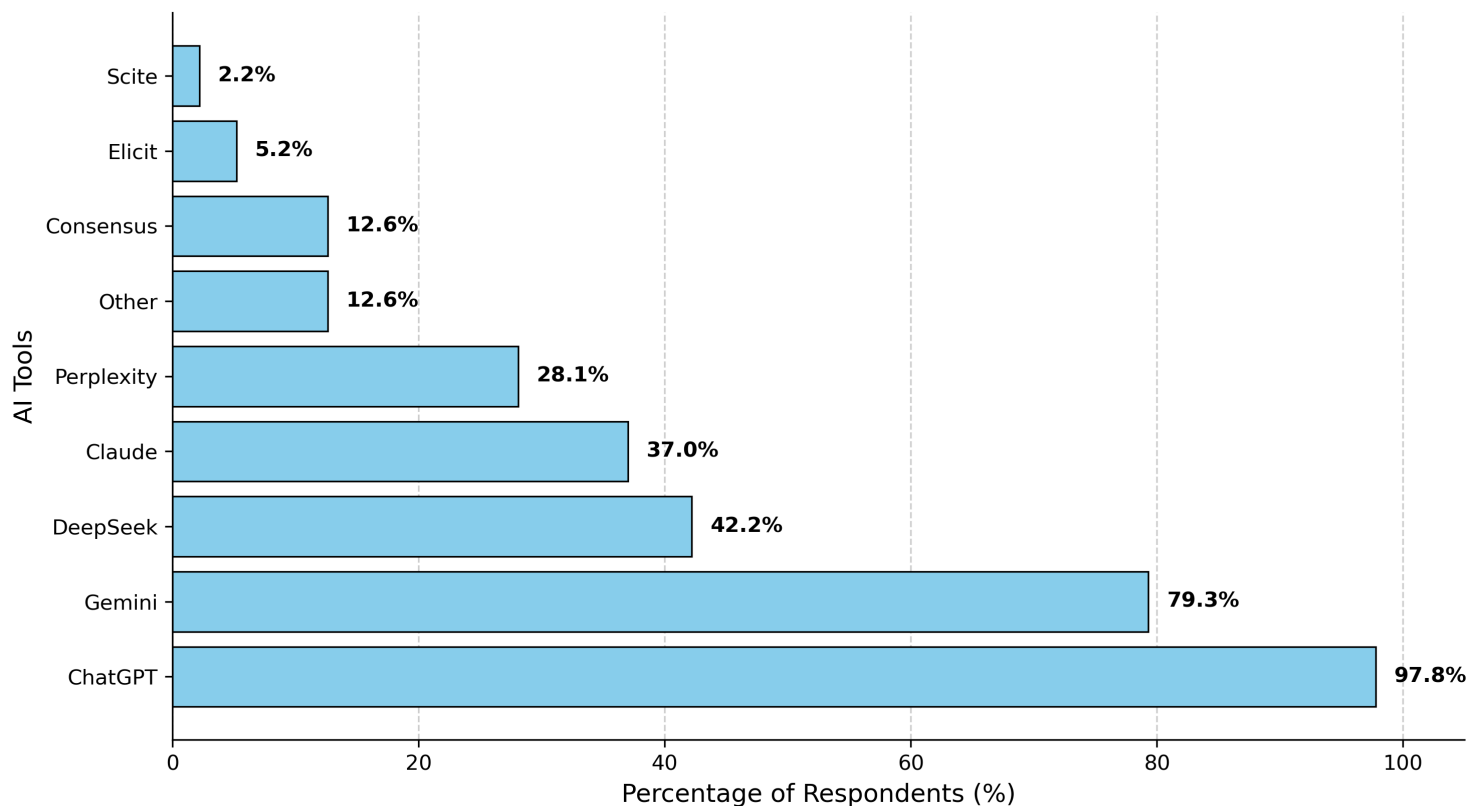


Figure 2

Prior Exposure to AI Tools Among Participants (N = 135)

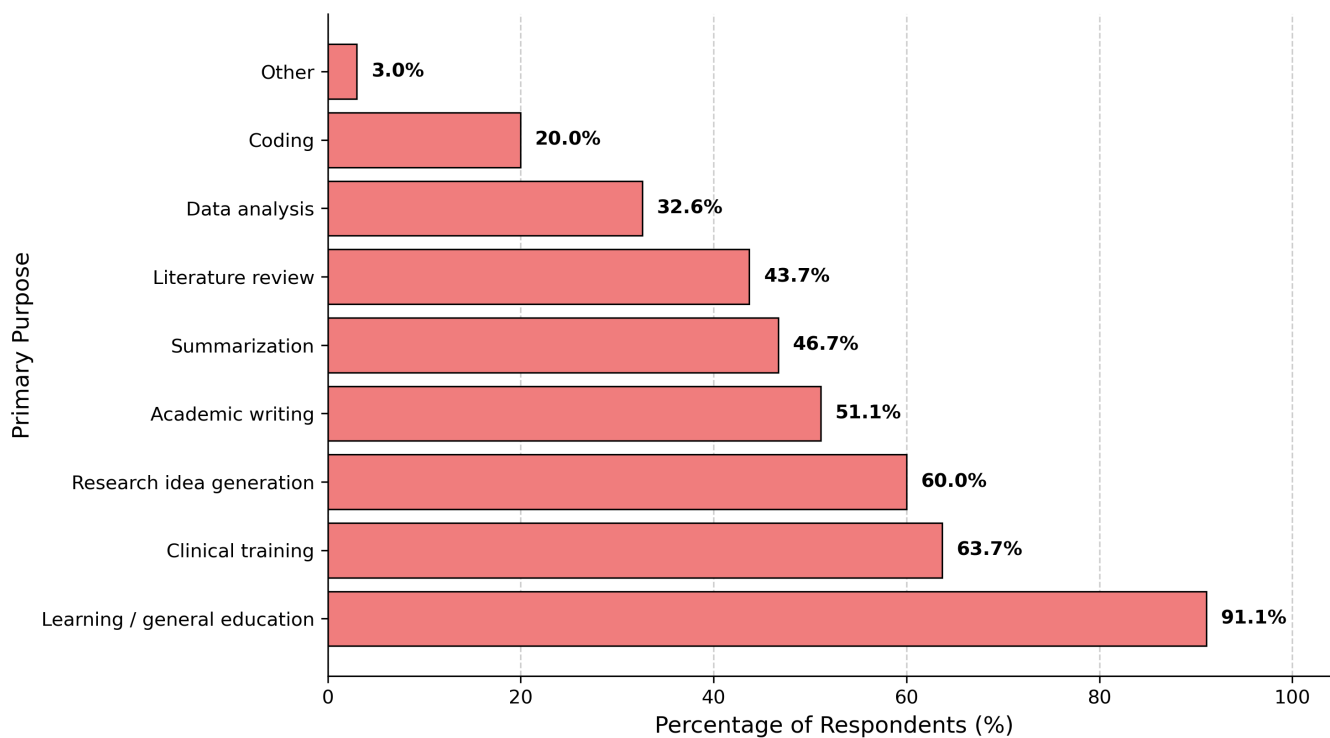


Figure 3

Primary Self-Reported Purposes for Using AI Among Participants (N = 135)

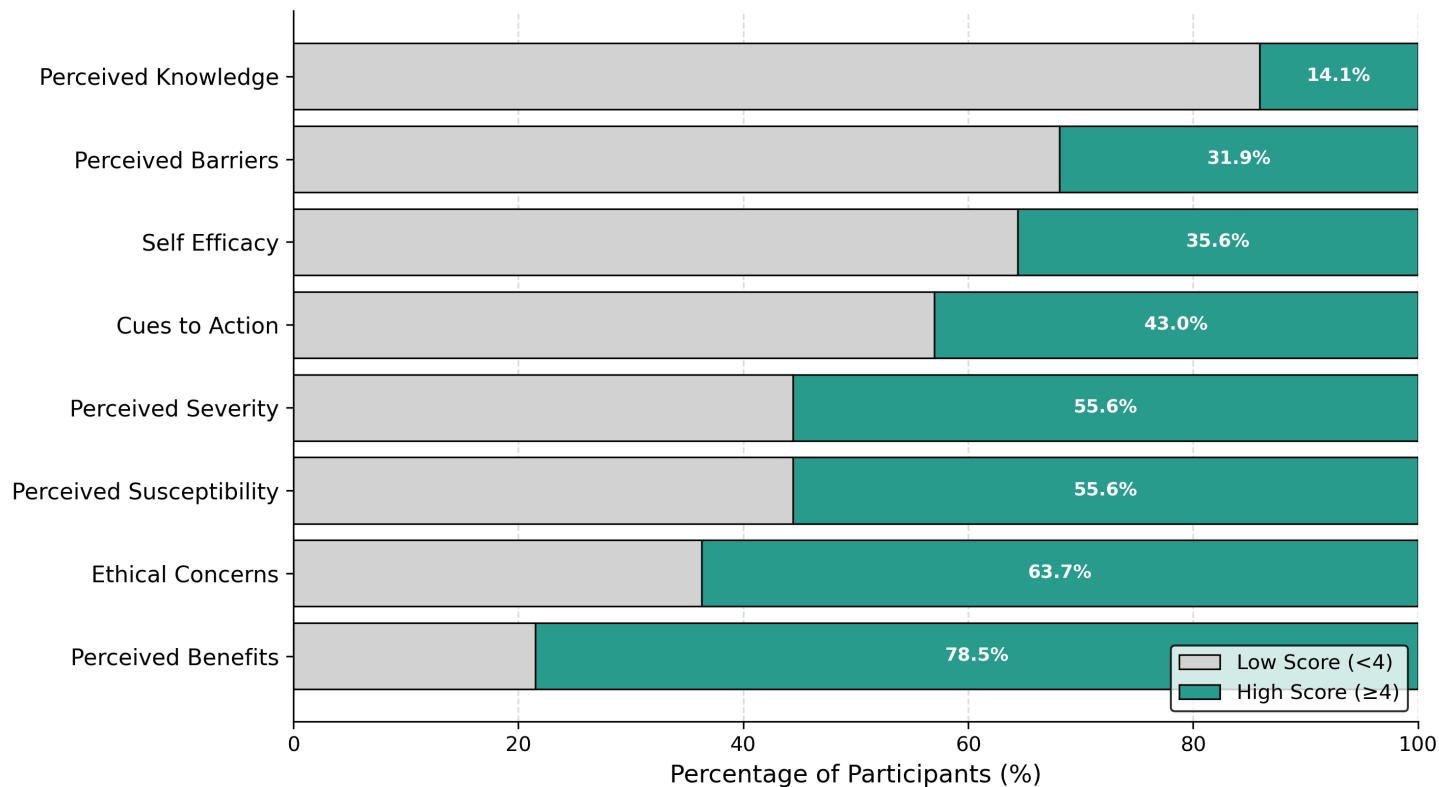


Figure 4

Distribution of Baseline AI Perception Levels (High vs Low) Across the Eight Domains

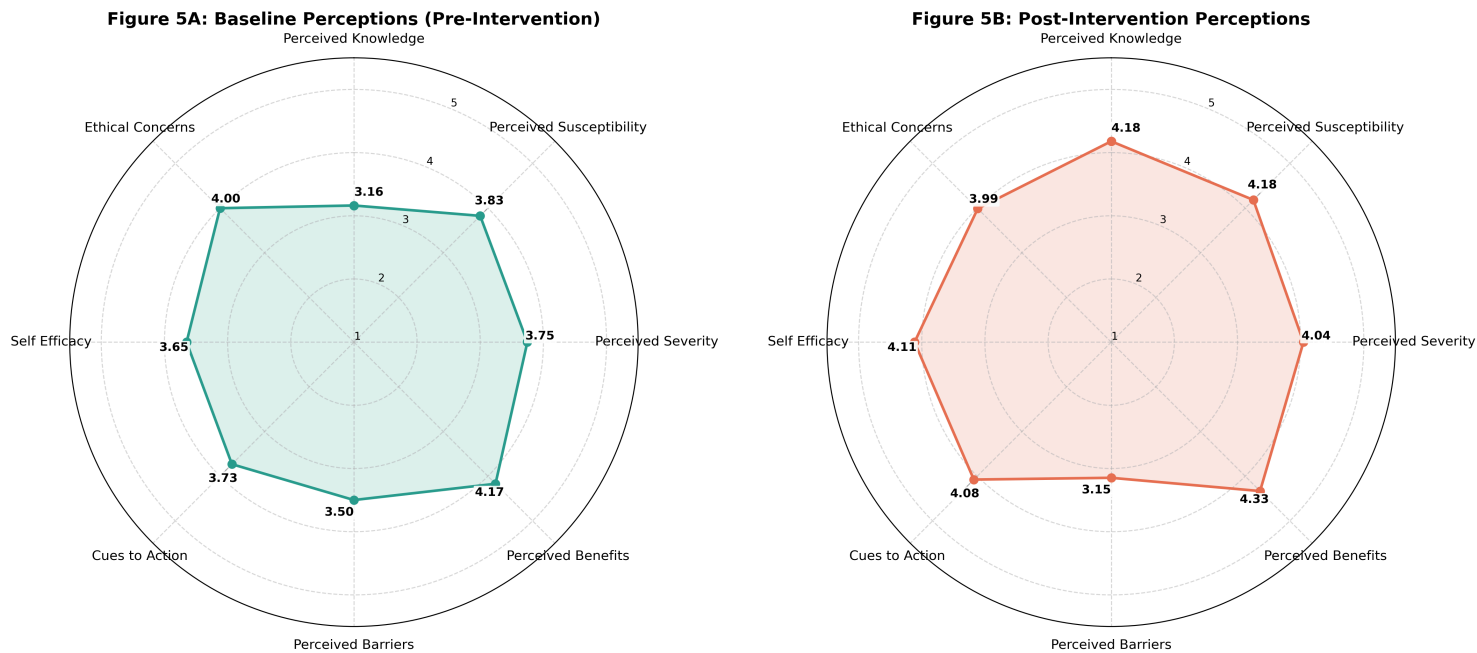


Figure 5

Baseline and Post-Intervention Perceptions of AI in Medical Research Across the Eight Domains (N = 135)

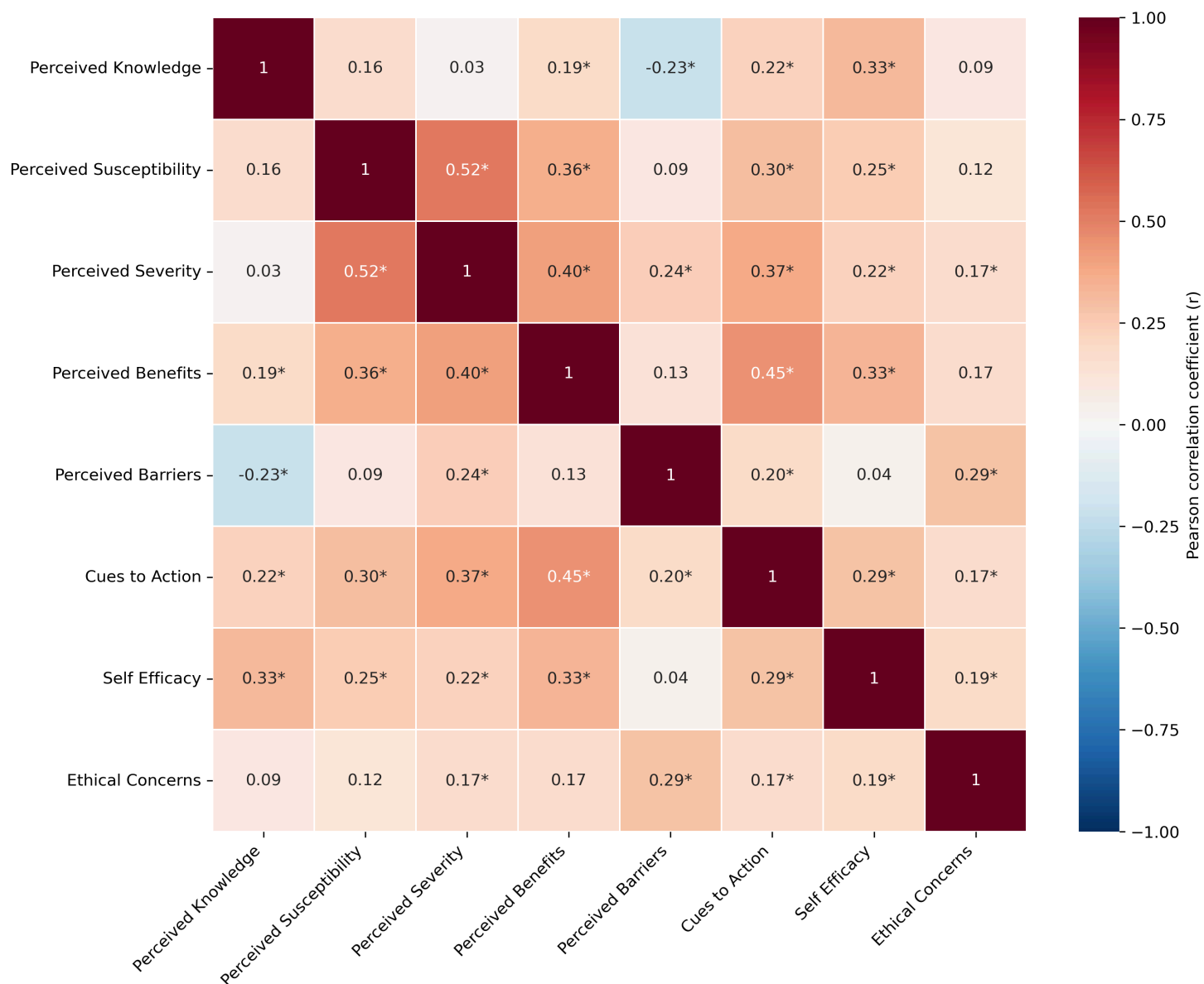


Figure 6

Heatmap of Pearson correlation coefficients (r) between change scores for the eight domains.

Supplementary Files

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