Osteopathy Educators' and Researchers' Perspectives on Artificial Intelligence in Academia: A Cross-Sectional Study

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ABSTRACT

Background: Artificial intelligence (AI) is increasingly being integrated into healthcare education and research, yet little is known about how AI is perceived within osteopathy. To the best of our knowledge, this is the first cross-sectional study to examine AI perspectives specifically among osteopathic educators and researchers, providing fresh insights into technology adoption within this healthcare discipline.

Methods: A cross-sectional survey was conducted between December 2023 and February 2024 among osteopathic educators and/or researchers through snowball sampling. The survey collected data on AI-related knowledge, usage in educational and research contexts, attitudes toward AI, perceived risks, and necessities challenges. Principal Component Analysis (PCA) was used to validate the structure of the survey. Demographic factors such as age, gender, occupation, and academic qualifications were analysed in relation to scores.

Results: 190 respondents from 18 countries completed the survey. Participants demonstrated positive attitudes toward the role of AI in education and research, but acknowledged limited proficiency in its use. Usage of AI was higher among younger, male participants, with AI primarily used for personal organisation and research. Concerns about AI included risks of bias, over-reliance on technology, and potential replacement of human judgment. Participants with educational roles expressed fewer concerns about AI's risks compared to those outside of education. Knowledge of AI was not correlated with demographic factors, but attitudes and concerns about risks varied with age.

Conclusion: Osteopathic educators and researchers view AI as a beneficial tool for teaching and research, but face challenges in its effective implementation due to concerns about technology replacing human expertise and biases. Training, institutional support, and ethical guidelines are essential to foster the responsible integration of AI in osteopathy.

KEYWORDS : ARTIFICIAL INTELLIGENCE, EDUCATION, RESEARCH, OSTEOPATHIC MEDICINE

1. Introduction

Artificial intelligence (AI) is transforming the landscape of education and research, challenging established methodologies while opening up new and innovative avenues for innovation. AI is defined as "*the behaviours by computer software that are designed to mimic and extend human rational thinking and actions*" [1]. The term AI, first coined by John McCarthy in 1955 [2], has found widespread application in a number of different fields. For example, it is employed in the automotive, finance and economics sectors [3], medicine [4,5] and education including medical education, as well as in Google's search engine [6].

In the field of medical education, AI can be used for a number of different purposes. Notably, it has the ability to provide student feedback, offering personalised assessments and recommendations [7]. Furthermore, AI can facilitate a guided learning pathway, which refers to an adaptive curriculum that adjusts based on a student's progress and learning style [8]. Additionally, the implementation of AI systems has the potential to decrease the costs associated with traditional educational methods [9].

Health research has begun to explore the risks and opportunities of generative AI for scientific publishing [10], including pain research [11,12], clinical decision support [13], medical imaging analysis [14], and the development of medical educational content [15]. Such opportunities include the potential to improve readability for diverse audiences, assist non-native English speakers, and increase productivity [16]. The potential risks associated with the use of AI in scientific publishing include the perpetuation of bias, the generation of false information, and the potential flooding of databases with AI-generated papers [17]. Guidelines for the use of AI in research are emerging. It is recommended that researchers explicitly acknowledge the use of AI tools in manuscripts, remain aware of the limitations of AI, and carefully review AI-generated content [18].

In healthcare, AI is already being employed to improve diagnostic accuracy, facilitate the automation of administrative procedures, and optimise educational practices [19,20]. In pain management, AI is already used to predict medication and dose response; to predict acute and chronic pain; to predict opioid misuse; and to support treatment decisions, real-time treatment tailoring, and self-management [21]. Existing research on AI in healthcare education suggests that while there is enthusiasm for its potential [22], concerns remain about ethical considerations, data security, and the risk of over-reliance on technology persist [23]. Moreover, educators often highlight the need for specific training to effectively incorporate AI tools into curricula [24,25]. Students have reported deficiencies in their information literacy, particularly in distinguishing AI-generated content, and have expressed a need for critical evaluation of references and accuracy [26]. Rather than advocating for a complete ban on AI, students have called for the establishment of clear regulatory frameworks that delineate the boundaries of its use and provide sector-wide guidelines for its implementation in education [24,27].

Despite this growing trend, the integration of AI into osteopathic education and research remains underexplored. The use of AI-driven tools, including predictive modelling, machine learning algorithms and virtual simulation platforms, offers significant potential for advancing the field [28]. However, in order for these innovations to be effectively implemented, it is essential to gain knowledge about the perspectives amongst osteopathic educators and researchers to adopt such technologies. This encompasses their understanding of AI, current patterns of use, attitudes towards its integration, and perceived obstacles or risks associated with its implementation. This study offers a novel contribution by examining AI adoption specifically within osteopathic education and research, building upon previous work in medical education while providing the first comprehensive analysis of AI integration challenges unique to osteopathy.

This cross-sectional survey aims to quantify how osteopaths involved in osteopathic education and/or research perceive their knowledge, use, attitudes, concerns, risks and needs related to the integration of AI. Additionally, it examines potential associations between participants' perceptions of AI integration and factors such as national regulatory frameworks, age, gender, academic qualifications, and time allocated to practice, research, or education. This research could be a starting point for informing institutional policies and educational practices in osteopathic education globally, particularly as the profession grapples with AI integration. The findings could provide insight into how osteopathic educators approach technology adoption and establish benchmarks for AI implementation in manual therapy education more broadly.

2. Methods

2.1. Study design, ethics and registration

An online cross-sectional questionnaire-based survey was conducted between December 2023 and February 2024.

Approval for the research project was granted by the Institut d'Ostéopathie de Rennes-Bretagne (IO-RB) Scientific Committee on December 12, 2023, and the study adhered to the ethical guidelines of the Declaration of Helsinki for research involving human subjects [29] and to the guidelines set out in the European Code of Conduct for Research Integrity [30].

The study protocol was prospectively registered online with the Open Science Framework on November 29, 2023 (Registration DOI: https://doi.org/10.17605/OSF.IO/QEYWG). The study did not collect any personal information and the survey design precluded the possibility of linking participants to their responses. This study is reported in line with the The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidance for cross-sectional studies [31].

2.2 Setting

To ensure methodological rigour, we followed a systematic approach to participant recruitment and data collection. The sample size, while not predetermined, achieved adequate statistical power for the primary analyses (detailed in the statistical analysis section).

Recruitment

The respondents were invited to participate in the survey through an electronic-based campaign to reach educators and researchers in osteopathy: a combined social media and targeted email strategy was implemented. AI generated videos were posted on three social media platforms (Facebook, Instagram, and LinkedIn) and reposted once a week by the authors during the recruitment campaign. At the same time, the authors sent emails with a link to the survey to all their professional networks, including osteopathic educational institutions (OEIs), professional associations and research networks in Europe, Oceania, North and South America. Follow-up reminders were not issued to professional organisations. However, snowball sampling was encouraged among participants as existing participants were suggested to assist in recruiting new subjects for the study.

Data collection procedure

Data was gathered via an online survey using Framaforms software [32]. The platform processes data in line with the General Data Protection Regulation requirements, ensuring user privacy and data protection. By recognising the user's IP address, this online platform limited multiple responses from the same participant. The online link to the survey was active between 13/12/2023 and 13/02/2024. Since the global number of osteopathy educators and/or researchers is unknown, no a priori sample size was determined for the questionnaire, and further research is needed to establish an optimal sample size for future studies and psychometric evaluations.

Pilot testing

An initial survey underwent pilot testing with a purposive sample of five osteopaths that were currently involved in research or education from different European countries. Pilot testing assessed the electronic survey's accessibility, survey completion time, and comprehensibility. Following slight adjustments and misspellings correction based on the pilot testing feedback, the survey was deemed finalised.

2.3 Participants

Prospective participants had to meet specific inclusion criteria, namely being osteopaths actively involved in research and/or educational activities in the field of osteopathy (whether at an undergraduate or postgraduate level), and having the ability to understand and respond to the questionnaire in English. The informed consent process was explicitly communicated in the online survey presentation and participants confirmed their understanding and agreement with this condition by proceeding to the survey page.

2.4 Description of survey and variables

The questionnaire is a 68-items questionnaire designed to describe knowledge, attitudes, use, perceived risks and necessities of AI among physiotherapy educators and researchers [33]. The questionnaire was developed by one of the European Network of Physiotherapy in Higher Education (ENPHE) working groups to address key areas in physiotherapy education and practice [34]. Permission for use of the questionnaire was requested by the authors and granted by António Alves Lopes, PT, MSc. No psychometric data are currently available for this questionnaire. The survey comprises six constructs: *perceived knowledge* (7 items, rated using a 5-point scale ranging from “Strongly Agree” to “Strongly Disagree”), *use* (10 items for education, 5 for research, and 6 for self productivity, rated using a 5-point scale ranging from “Daily” to “Never”), *attitudes and perceptions* (9 items for education and 5 for research, rated using a 5-point scale ranging from “Strongly Agree” to “Strongly Disagree”), *concerns and risks* (10 items, rated using a 5-point scale ranging from “Strongly Agree” to “Strongly Disagree”), *necessities* (8 items, rated using a 5-point scale ranging from “Strongly Agree” to “Strongly Disagree”), and *socio-demographics* (7 multiple-choice items). Socio-demographic questions included age, gender, country of residence, weekly time dedicated to practice, research and education, and qualification. The questionnaire was adapted to the osteopathic field only by replacing the word *‘physiotherapy’* by *‘osteopathy’*.

2.5 Statistical analysis

The analytical approach demonstrated rigour through systematic validation of questionnaire constructs using Principal Component Analysis (PCA), rigorous handling of missing data, careful consideration of potential confounding variables, and conservative interpretation of statistical findings. An audit trail was maintained throughout the analysis process.

Principal component analysis

To build scores on knowledge, usage, attitudes and perception, concerns and risks, it was first necessary to validate the construct of the questions. This was done by applying PCA for each subset of the questionnaire. PCA identifies patterns in data by reducing variables into components that explain shared variance. Eigenvalues indicate the variance explained by each component, while uniqueness reflects how much of a variable's variance is not explained by the components. Bartlett's test for sphericity and the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy (MSA) were computed for the model before proceeding to the PCA analysis in which KMO measure of sampling adequacy for each included variable was expected to have a KMO > 0.5. If lower values were found, the corresponding loaded variables were eliminated stepwise from the lowest to the highest till all variables have a KMO (MSA) > 0.5. Horn's parallel analysis was used to define the number of components to be retained. Once this was done, the uniqueness of the PCA analysis was measured and should not exceed 0.5 for each loaded factor. Factors higher than 0.5 were eliminated and the process was repeated. Finally, a VARIMAX-rotated component analysis of the retained factors was then done. Factor loading still needed to show a uniqueness ≤0.5 and the absence of cross-loading across multiple factors. If these factors were not met, the corresponding variables were eliminated and the entire process was run again. KMO and Crohnbach's Alpha were used to quantify the internal validity of each construct. Scores were calculated by adding the individual scores from the Likert scales.

Modelling knowledge, usage, attitudes and perceptions, concerns and risks, and necessities by demographic profile

Association between scores for knowledge, usage, attitudes and perception, concerns and risks and country regulation type, age, gender, academic qualifications, and time devoted to practice, research or education were measured using linear regression. R-squared (R^2) value was to define the strength of the association. Significant variables were used in a multivariate linear regression analysis to adjust each factor by the others. To avoid collinearity, only one of cofactors with correlation coefficients of more than 0.7 (Pearson's r) was retained. The one with the highest correlation coefficient with AI was retained.

3. Results

3.1 Participants characteristics

A total of 190 questionnaire responses were received. However, five responses were excluded from the analysis, as the participants reported having no hours dedicated to research or teaching in osteopathy. Thus, a total of 185 responses were included for analysis. The majority of participants (64%) were aged between 30 and 50 years, with 27% over 50 and 9% under 30. Two thirds of participants identified as men. The majority of respondents were European (89%), including 57% from France, 17% from the United Kingdom, 13.5% from Italy, and 13% from Spain. Respondents held a position in education (n=167; 90.3%), as practising osteopaths (n=169; 91.3%), and/or in research (n=153; 82.7%). Nearly half (46.5%) held a Master's degree, while 18.4% had a PhD/doctoral degree. Details on participants' sociodemographic characteristics are provided in Table 1.

Table 1.

Characteristic	Frequency, n (%)
Age	
Less than 30	16 (9)
30-39 years	52 (28)
40-49 years	67 (36)
50-59 years	35 (19)
60-69 years	12 (6)
70+ years	3 (2)
Gender identity	
Man	124 (67)
Woman	57 (31)
Non-binary	1 (1)
Prefer not to answer	3 (2)
Highest qualification	
Diploma/bachelor in osteopathy	65 (35)
Master	86 (46)
PhD	34 (18)
Hours per week in (clinical) osteopathic practice	
0 h	16 (9)
1-5 h	17 (9)
6-10 h	24 (13)
11-15 h	17 (9)
16-20 h	24 (13)
21-25 h	21 (11)
26-30 h	22 (12)
31-35 h	18 (10)
36-40 h	17 (9)
41-45 h	5 (3)
46-50 h	3 (2)
50+ h	1 (1)
Hours per week participating in research	
0 h	32 (17)
1-5 h	96 (52)
6-10 h	14 (8)
11-15 h	19 (10)
16-20 h	8 (4)
21-25 h	7 (4)
26-30 h	4 (2)
31-35 h	2 (1)
36-40 h	2 (1)
41-50+ h	1 (1)
Hours per week working in the higher education sector	
0 h	18 (10)
1-5 h	68 (37)
6-10 h	15 (8)
11-15 h	41 (22)
16-20 h	19 (10)
21-25 h	9 (5)
26-30 h	4 (2)
31-35 h	7 (4)
36-40 h	3 (2)
41-50+ h	1 (1)
Country of respondants	
Australia	6 (3)
Belgium	1 (1)
Brazil	8 (4)
Canada	4 (2)
Denmark	1 (1)
Finland	3 (2)
France	57 (31)
Germany	6 (3)
Ireland {Republic}	1 (1)
Italy	25 (14)
New Zealand	1 (1)
Norway	1 (1)
Portugal	4 (2)
Spain	24 (13)
Sweden	3 (2)
Switzerland	7 (4)
United Kingdom	32 (17)
United States of America	1 (1)

3.2 Validation the construct of the questions and defining scores

PCA revealed the question structure to be relevant (Table 2). Correlations among key questionnaire constructs are reported in Table 3. Each dimension (i.e. Knowledge, Usage, Attitudes and perceptions, Concerns and risks, Necessities) was investigated for uniqueness and internal consistency. The questions related to "Knowledge" defined a single factor. The eighth question (QA8) had a uniqueness value > 0.5 and was not accounted for when measuring a score for knowledge. Three distinct factors were revealed in the "Usage" dimension, each corresponding to personal organisation, education or research. The analysis for "Attitudes and perceptions" was run omitting QC5 as answers from this question were not collected on the online survey. The analysis without QC5 did not reveal two separate dimensions (i.e. Education, Research). A unique dimension was retained with nine of the initial 15 questions. QC1, QC2, QC3, QC8, and QC12 all had an Eigenvalues > 0.5. Questions related to "Concerns and Risks" revealed two separate factors: the first corresponds to AI concerns for validity including data security, biases, integrity and validity of findings, and over-reliance on technologies. The second corresponds to concerns about being replaced by AI. QD1 was removed due to an Eigenvalue > 0.5, leaving nine questions, seven for the first factor (validity) and two for the second (replacement). Two questions (QE5, QE8) for "Necessities" had Uniqueness > 0.5 and were suppressed leaving six questions.

Dimensions	Number of items and score	KMO	Cronbach's alpha	Adjusted Eigenvalue*
Knowledge	6 [-12 to 12]	0.861	0.872	3.489
Usage	21 [0 to 84]	0.903	0.947	–
Personal organisation	6 [0 to 24]	–	–	1.860
Education	10 [0 to 40]	–	–	10.074
Research	5 [0 to 20]	–	–	1.361
Attitudes and perception†	9 [-18 to 18]	0.908	0.905	4.847
Concerns and risks	9 [-18 to 18]	0.773	0.842	–
Validity	7 [-14 to 14]	–	–	3.947
Replacement	2 [-4 to 4]	–	–	1.106
Integration	6 [-12 to 12]	0.813	0.862	3.287

Table 2. Validation of the construct of the questions * Horn's parallel Analysis for principal components.
† QC5 was not collected and omitted from the analysis. KMO = Kaiser-Meyer-Olkin measure of sampling adequacy

Score	Knowledge	Usage (education)	Usage (personal)	Usage (research)	Attitude	Risk (validity)	Risk (replacement)	Integration
Knowledge	1							
Usage (education)	0.3592**	1						
Usage (personal)	0.4453**	0.61**	1					
Usage (research)	0.3264**	0.489**	0.5163**	1				
Attitude	0.4581**	0.182	0.2812*	0.224*	1			
Risk (validity)	0.162	0.014	-0.016	0.001	0.016	1		
Risk (replacement)	0.13	0.082	0.096	0.02	0.073	0.34	1	
Integration	0.2863*	0.113	0.113	0.172	0.5557**	0.2957*	0.04	1

Table 3. Correlation matrix of key questionnaire constructs (significance: ** : < 0.001 ; * : < 0.01)

3.3 Quantification of knowledge, usage, attitudes and perceptions, concerns and risks, and necessities of AI among osteopath educators and researchers

Knowledge

"Knowledge" included six questions with an overall score ranging from -12 to 12. Higher scores reflected greater perceived knowledge of AI . The average score from the 185 respondents was of 2.7 (SD=4.7; median=3). Half of the respondents had a score ranging from 1 to 6. Slightly over half of osteopaths reported they were familiar with the basic concept of AI (58%) without necessarily being aware of advancement in AI technologies (69%). Details on knowledge are provided in Figure 1A.

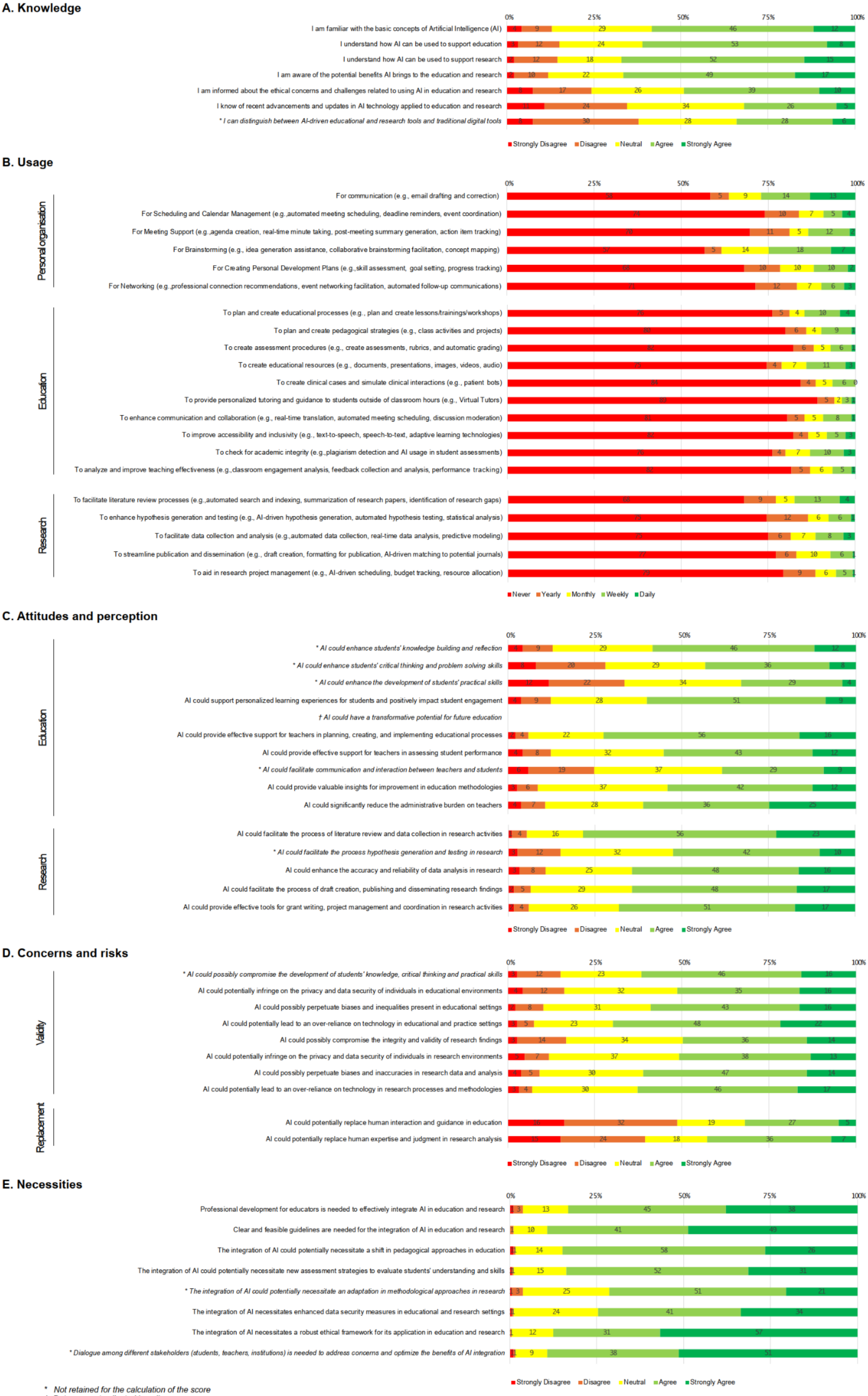
Usage

"Usage" included 21 questions (score ranging from 0 to 84); 10 for education, 6 for personal organisation, and 5 for research (Figure 1B). Lower scores indicated lower levels of AI usage. The average usage score was 11.9 (SD=15.8; median=5). AI was never used by 40.5% of participants, including 49.7% who never used it for personal organization, 67.6% for education, and 63.8% for research.

Osteopaths reported using AI in the context of personal organisation essentially for communication (27% used it weekly or daily) and brainstorming (25 % used it weekly or daily). In education, AI was mostly used to plan and create educational processes (14%), create educational resources (14%), and to check for academic integrity/plagiarism (13%). In research, AI was mostly used to facilitate the literature review process (17%).

Figure 1

3



* Not retained for the calculation of the score
† Data was not collected in online survey

Attitudes and perceptions

"Attitudes and perceptions" included 9 questions (score ranging from -18 to 18) in a single dimension combining those related to education and research. Higher scores were associated with a more favourable view of AI. The average score was 5.5 (SD=5.4; median=6). Most participants did not believe that AI enhances practical skills (67%), problem-solving skills (56%), or facilitates communication (52%). Respondents showed a positive attitude in its usefulness for planning, creating, and implementing educational processes (72%), and for facilitating literature review (79%). Further details are provided in Figure 1C.

Concerns and risks

"Concerns and risks" included 9 questions (score ranging from -18 to 18) with 2 dimensions: validity (seven questions) and fear of replacement (two questions). Higher scores reflected greater concerns about AI. Average concern score was 3.8 (SD=6.1; median=4). Participants manifested little concern of being replaced (-0.3; SD=2.1; median=0). The main concern was for over-relying on technologies (70%). Details for other concerns can be found in Figure 1D.

Necessities

"Necessities" included 6 questions (score ranging from -12 to 12). Lower scores were associated with lower perceived necessities. Participants had elevated scores for needs (7.2; SD=3.5; Median=7) with 75% of them scoring 5 or above. Disagreement about necessities was very low for all of the questions (Figure 1E) ranging from 1-4%.

3.4 Associations of assimilation scores with demographic profile

Age was independently associated with AI assimilation, with older respondents using AI less frequently for research. Use decreased by 0.7 points (95% CI: 0.04 to 1.2; $p = 0.035$) for every ten-year increase in age. Furthermore, older respondents were less engaged with AI as 'Attitudes and Perceptions' scores diminished each 10 years of age (-1.6, CI95% 0.8 to 2.4; $p<0.001$) .

Gender was independently associated with assimilation. Men reported using AI for research more frequently than women (1.8 points, CI95% 0.4 to 3.1; p=0.010).

Occupation was independently associated with AI assimilation. Respondents working more than 15 hours a week in research were also more likely to use AI for research (1.9 points; CI95% 0.03 to 3.8; p=0.046). Furthermore, educators were less concerned by risks than others (-3.5 points; CI95% -6.4 to -0.5; p=0.021). However, respondents with longer education and/or research time per week were concerned by the validity of AI-based content (-2.8 points; CI9% -5.2 to 0.4; p=0.024) rather than the fear of being replaced by AI (-0.7 points; CI95% -1.7 to 0.4; p=0.207).

AI assimilation was not associated with respondents' academic qualifications nor with their countries' educational regulation standards in osteopathy. "Knowledge" and "Necessities" scores were not associated with age, gender, occupation, nor any other studied demographic variables.

4. Discussion

4.1 Summary of findings and contextual setting

This was the first cross-sectional study assessing osteopathic educators' and researchers' perspectives on AI. This study aimed to quantify how osteopaths involved in education and/or research perceive their knowledge, use, attitudes and perceptions, concerns, risks and needs related to AI integration. Our findings revealed five distinct dimensions of AI assimilation: knowledge, usage, attitudes and perception, concerns and risks, and necessities. The dimension ''*attitudes and perceptions*' assessed participants' overall orientation toward AI—both their level of acceptance and their understanding of AI's potential roles in academic and research settings. This was treated as a single evaluative dimension. In contrast, the 'concerns' construct focused specifically on potential risks or negative implications of AI use, such as misinformation or ethical ambiguity. Despite limited reported skills in AI use, participants showed predominantly positive attitudes toward AI's role in education and research. Key demographic factors influenced AI assimilation patterns: men reported higher

AI usage than women, particularly in research and personal organisation. Age emerged as a significant factor, with older participants showing decreased AI use, less positive attitudes, and increased concerns about risks. Those spending more time in education and research reported fewer concerns about AI validity but maintained consistent levels of concern about potential replacement by AI. Notably, neither academic qualifications nor country-specific regulatory frameworks appeared to influence AI assimilation patterns. These findings provide the first comprehensive picture of AI adoption patterns among osteopathic educators and researchers, highlighting both opportunities for integration and areas requiring targeted support.

Our findings that 40.5% of respondents had never used AI are consistent with data from the pain management field. A recent systematic review of 197 articles on the use of AI in pain management identified limited provider understanding of AI as one of the six most common barriers to AI implementation [21]. Our survey identified several areas of limited implementation of AI, including personal organisation, education and research. The implications of these findings are discussed below.

Our finding that educators showed less concern about AI risks than their non-educator colleagues is particularly interesting. This contrasts with general anxiety about AI in healthcare education noted by Alser and Waisberg (2023), who found widespread concerns about AI's impact on academic integrity and learning. The lower level of concern among educators in our study might reflect their practical experience with educational technologies and clearer understanding of AI's potential role as a complementary tool rather than a replacement for core teaching activities, a perspective similarly observed in a recent study involving medical educators [35]. Further research could explore the lower level of concern among osteopathic educators.

The lack of association between academic qualifications and AI adoption patterns challenges assumptions about formal education's role in technology acceptance. This suggests that other factors - such as institutional culture, practical experience, and individual attitudes - may be more influential in shaping AI acceptance in osteopathic education than academic credentials alone.

4.3 Strengths and limitations

This study's rigour is demonstrated through several key strengths. First, we ensured transparent reporting by strictly adhering to STROBE guidelines for cross-sectional studies, with comprehensive documentation of all methodological decisions throughout the research process. The statistical analyses were robust, employing appropriate validation techniques including Principal Component Analysis with clear criteria for factor retention and elimination. The study also benefits from broad geographical coverage across multiple countries, capturing diverse experiences in practice, research and education. The survey questions demonstrated strong construct validity in targeting dimensions related to AI assimilation in education and research.

Despite these strengths, several limitations warrant consideration. The sample size constrains our ability to adequately model interactions between socio-demographic factors and AI assimilation. The questionnaire lacks face validity for AI assimilation dimensions in a health context, suggesting other important dimensions may not have been captured. This may limit the interpretation of certain constructs and should be considered when generalising the findings. Additionally, variations in cultural background and English proficiency may have affected question interpretation, as no cross-cultural validation was performed.

Response biases are among the limitations of our study. The questionnaire was adapted to the osteopathic field only by replacing the word 'physiotherapy' with 'osteopathy'. The use of snowball sampling strategies may have introduced selection bias. Furthermore, without knowing the total population of eligible osteopathic educators and researchers, we cannot determine a response rate. The questionnaire's psychometric properties remain unknown as it has not been validated.

Geographical representation was limited primarily to Europe (with nearly a third of participants from France), with no responses from Africa and Asia. Whilst there are fewer osteopathic educational providers in these continents, our results reflect only limited geographical areas. These results may affect the generalisability of the findings to other cultural and regulatory contexts where attitudes toward AI may differ.

Finally, common questionnaire-based survey biases may have affected our findings, as outlined by Choi and Pak (2004). Social desirability bias might have led respondents to provide perceived acceptable answers. Confirmation bias could have shaped responses based on pre-existing beliefs. Self-selection bias may have resulted in a sample with higher AI affinity, potentially limiting representativeness of the global osteopathy educators and researchers community.

4.4 Practical implications

These findings are particularly significant as they establish, for the first time, baseline data about AI adoption patterns in osteopathic education, potentially benefiting curriculum development across all osteopathic educational institutions. The timing is crucial as educational institutions worldwide are actively developing AI policies. Our findings suggest some implications for osteopathic education and research that require careful consideration and evidence-based implementation:

Institutional Level: The high scores in 'necessities' across all demographics (7.2/12) suggest institutional policy development should be prioritised. With only 1-4% of participants disagreeing about necessities, there appears to be strong consensus for institutional action. This could include (1) development of clear guidelines for AI use in teaching and assessment, particularly given that 14% of respondents reported already using AI for educational resource creation, (2) creation of support structures addressing the age and gender differences identified in our study, (3) implementation of AI literacy programmes that acknowledge varying levels of current usage (40.5% reporting no AI use versus 27% using AI weekly/daily for communication).

Educational Practice: With 67.6% of respondents reporting no current AI use in education despite positive attitudes, there appears to be a gap between interest and implementation. Priority areas include supporting educators in areas where AI showed highest current adoption: planning educational processes (14%), creating resources (14%), and checking academic integrity (13%); and addressing the identified age-related differences in attitudes and usage through targeted support.

Research Applications: Given that 17% of respondents already use AI for literature reviews, but overall research usage remains low (63.8% reporting no use); opportunities exist to (1) develop guidelines for appropriate AI integration in research methodology, (2) create frameworks for maintaining research integrity while leveraging AI tools, and (3) support researchers across age groups and genders in ethical AI implementation.

5. **Conclusion**

This study reveals both enthusiasm and apprehension regarding the integration of AI into education and research, and provides valuable insights into the perceptions of AI among osteopathic educators and researchers. While AI is largely viewed as a beneficial tool, its effective implementation is hindered by concerns about bias, technological over-reliance, and the potential erosion of human expertise. In particular, demographic factors influenced AI use and attitudes, with younger, male participants showing greater engagement with AI tools. The findings highlight the need for structured training programmes, institutional support and robust ethical frameworks to ensure the responsible use of AI in osteopathy.

As AI continues to evolve at an unprecedented pace, shaping policy and redefining its role in healthcare, ongoing adaptation will be key. Perceptions of educators and researchers may evolve as AI capabilities expand and ethical considerations mature. Now is a pivotal moment to stimulate informed discussion, proactive education and ethical integration - to ensure that AI enhances, rather than disrupts, the core values of osteopathic education and research. The future of AI in osteopathy is not just about keeping up with change, but leading it in both clinical practice and academia with wisdom, integrity and purpose, while ensuring that those seeking care are always at the centre of these developments.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used AI technology in order to improve language and readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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