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Original Article

Artificial Intelligence in Oral and Maxillofacial Surgery: A Cross-Sectional Study of Knowledge, Attitudes, and Clinical Adoption among Surgeons and Trainees

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ABSTRACT

To investigate how oral and maxillofacial surgery (OMS) clinicians and trainees perceive and apply artificial intelligence (AI), examining their familiarity, viewpoints, and behaviors regarding its role in OMS clinical care and education. A cross-sectional questionnaire-based investigation was undertaken among OMS specialists and trainees in Singapore to gather their opinions on AI in OMS. The instrument contained 25 items, organized into five parts, and was distributed via an online survey platform. 48 individuals filled in the questionnaire, of whom 37 were specialists, and 11 were trainees. A sound grasp of AI was lacking among 60.4% of those surveyed; 52.1% were uninformed about AI's applications in OMS; and 81.3% had never received any AI-related instruction. A large majority considered AI likely to be useful for diagnosis and treatment planning (72.9%), for boosting patient outcomes (75.0%), and believed it ought to be embedded in OMS training (68.8%). Although gender-based differences were absent, younger individuals showed a tendency toward more favorable perspectives ($P < 0.05$). Worries highlighted by respondents included erroneous diagnoses or plans (77.1%), excessive reliance (70.8%), confidentiality and data safety risks (41.7%), and elevated healthcare expenditure (41.7%). Even though most respondents (68.8%) indicated using AI in everyday life and recognized that AI made executing tasks simpler (62.5%), the majority had yet to incorporate AI into their clinical workflow (62.5%). It felt insufficiently trained or resourced for that step (79.2% and 58.3%, respectively). OMS specialists and trainees in Singapore predominantly harbor optimistic attitudes toward AI, with younger subjects leaning toward more positive views. Both knowledge and practical application present scope for growth.

Keywords: Artificial intelligence, Surgery, Oral, Health knowledge, Attitudes, Practice

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Introduction

Technologies grounded in artificial intelligence (AI) have steadily surfaced across the healthcare domain over recent years. Within academia, the output of AI-related medical papers has grown at a consistent annual rate of 28.4% [1]. The specialty of oral and maxillofacial surgery (OMS) mirrors these developments, with AI-powered systems being formulated to assist in both diagnostic processes and operative treatment strategies [2]. Prominent technology firms such as Google have correspondingly amplified these initiatives, devising tools like MedLM to address medical inquiries and AI-driven solutions to identify pathology [3]. In the sphere of health professions education, a host of prospective uses for enriching learning have been put forward, including serving as instructional aids, platforms for autonomous study, and elements within automated evaluation [4]. While industry pushes ahead with embedding AI into health services and training, the ground-level willingness of practitioners, teachers, and learners to adopt these innovations in their daily work remains comparatively uncharted. Investigations into knowledge, attitudes, and practices (KAP) have secured broad recognition across the health sciences as a means of capturing foundational perspectives on particular subjects before refining and improving programs [5].

With specific reference to AI, several KAP surveys targeting researchers, educators, students, and health professionals have appeared within the last three years [6–8]. Within the dental field, KAP inquiries among dental undergraduates and qualified dentists have revealed inconsistent levels of awareness, alongside predominantly positive attitudes toward integrating AI into dental curricula and clinical workflows [9]. To date, however, no research has focused specifically on OMS clinicians, and studies of East or Southeast Asian cohorts are scarce or nonexistent. Beyond leveraging AI to advance oral healthcare delivery, OMS stands out for its blend of medical and surgical disciplines, expanding dentistry's reach to encompass the hard and soft tissues of the face. It is consequently unclear whether the awareness and outlook of an OMS clinician mirror those of a general dental practitioner.

Accordingly, this study aims to appraise the knowledge, attitudes, and current practices of OMS specialists and trainees regarding the application of AI in clinical practice and professional education.

Materials and Methods

A cross-sectional questionnaire investigation was conducted among OMS clinicians from both public and private settings in Singapore between October 7, 2024, and November 15, 2024. The questionnaire was designed following the Checklist for Reporting Results of Internet E-Surveys (CHERRIES) [10]. Individuals recruited for the research comprised OMS specialists and trainees; OMS specialists referred to practitioners formally registered as OMS specialists with the Singapore Dental Council, whereas OMS trainees encompassed residents currently undertaking the National University of Singapore (NUS) Master of Dental Surgery (OMS) programme (which constitutes the sole OMS residency programme in Singapore), along with clinicians who have finished an OMS residency programme and are presently working in Singapore without specialist registration. An exemption from the National University of Singapore Institutional Review Board (IRB) was obtained before data collection (NUS-IRB-2024-892).

Survey development, testing, and validation

An online questionnaire tool (Qualtrics XM, USA) was employed for survey hosting and data gathering. The questionnaire items were developed following deliberation among the research group **(Table 1).** The questionnaire was organized into five parts: Part 1 collected respondents' demographic details (age, gender, duration of clinical experience); Parts 2, 3, and 4 examined respondents' knowledge, attitudes, and practices, respectively; and Part 5 was open-ended for any further remarks. A mixture of single-answer, multiple-choice, Likert-type, and free-text questions was included.

Table 1. Survey sections and questions.

Section 1: demographics	**Answer options**			
Q1: What is your age?	_______________			
Q2: What is your gender?	Male	Female		
Q3: Are you an accredited specialist in OMS?	Yes	No		
Q4: How many years have you practiced OMS?	0–5	6–15	>15	
Section 2: Knowledge	**Answer options**			
Q1: I have a good level of understanding of artificial intelligence (AI), e.g., machine learning, large language models	Strongly agree	Somewhat agree	Somewhat disagree	Strongly disagree
Q2: I am aware of the uses of AI in OMS practice and education	Strongly agree	Somewhat agree	Somewhat disagree	Strongly disagree
Q3: I have attended courses, lectures, or any other form of training in AI	Strongly agree	Somewhat agree	Somewhat disagree	Strongly disagree

Q4: Please list any AI technologies you are familiar with (within or outside OMS)	_____________				
Section 3: Attitudes	**Answer options**				
Q1: AI is or can be beneficial in enhancing patient outcomes in OMS	Strongly Agree	Somewhat agree	Unsure	Somewhat disagree	Strongly disagree
Q2: AI should be integrated into clinical practice for diagnosis and treatment planning	Strongly agree	Somewhat agree	Unsure	Somewhat disagree	Strongly disagree
Q3: AI should be a part of OMS training	Strongly agree	Somewhat agree	Unsure	Somewhat disagree	Strongly disagree
Q4: AI may replace OMS surgeons in the future	Strongly agree	Somewhat agree	Unsure	Somewhat disagree	Strongly disagree
Q5: Overuse of AI may cause surgeons to lose certain clinical skills	Strongly agree	Somewhat agree	Unsure	Somewhat disagree	Strongly disagree
Q6: What do you think are some advantages of AI in OMS practice and education? (You may select more than one option)	• Increased clinical efficiency • Reduced workload for clinicians, educators, or trainees • Increased accessibility and personalization for patients/students • I do not think there are any advantages • Others: _______________				
Q7: What are your concerns regarding using AI in clinical practice? (You may select more than one option)	• Privacy and security concerns • Inaccurate diagnosis or treatment • Clinician overreliance and eventually becoming obsolete • Increased healthcare costs • Others: _______________				
Section 4: Practices	**Answer options**				
Q1: I have used AI technologies in any field/other times in life outside of work	Strongly agree	Somewhat agree	Unsure	Somewhat disagree	Strongly disagree
Q2: I have used AI technologies in my practice of OMS	Strongly agree	Somewhat agree	Unsure	Somewhat disagree	Strongly disagree
Q3: I have used or considered using AI for the following purposes: (you may select more than one option)	• Diagnosis (radiographic, histopathologic, clinical) • Patient or student education • Self-directed learning • Treatment planning • Intraoperative as an adjunct • I have not used or considered using AI in my practice • Others: _______________				

Q4: I have used or considered using AI in the diagnosis or treatment planning for the following OMS subspecialties: (you may select more than one option)	• Dentofacial deformities • Dentoalveolar surgery • Surgical pathology (including surgical oncology) • Maxillofacial trauma • Implant and preprosthetic surgery • TMJ surgery • I have not used or considered using AI in my practice				
Q5: AI makes the completion of my work easier	Strongly agree	Somewhat agree	Unsure	Somewhat disagree	Strongly disagree
Q6: I feel adequately trained to use AI tools	Strongly agree	Somewhat agree	Unsure	Somewhat disagree	Strongly disagree
Q7: My clinic or institution is equipped to incorporate AI into clinical practice	Strongly agree	Somewhat agree	Unsure	Somewhat disagree	Strongly disagree
Q8: What resources do you think are necessary for better integration of AI in your practice?	____________________				
Section 5: Other comments	**Answer options**				
Q1: Do you have any other comments?	____				

A sample size computation was undertaken before survey rollout, yielding a target sample of 52 with a 95% confidence interval and an 8% margin of error.

The sampling strategy was intended to rely on convenience sampling. Before circulation, a qualitative review of the questionnaire was conducted to confirm its validity. Content validity was assessed by a panel of three experts in OMS and AI, who evaluated the questionnaire items. These authorities scrutinized the items and provided input on the questionnaire's relevance and scope. Subsequently, face validity was assessed via a pilot study with 6 individuals (equivalent to 10% of the target sample). This step formed part of the questionnaire refinement to ensure item clarity, ease of understanding, and relevance. The internal consistency of Parts 2, 3, and 4 (Knowledge, Attitudes, and Practices, respectively) was appraised via Cronbach's alpha, treating a figure exceeding 0.7 as an acceptable threshold of internal consistency.

Survey administration

The questionnaire was sent to prospective respondents by email through local professional bodies (the Association of Oral and Maxillofacial Surgeons Singapore, AOMSS) and educational establishments (NUS). The questionnaire remained accessible, with no password required. Respondents were briefed on the study's objectives, the research team members, and the estimated time required to complete the questionnaire, and consent was obtained upon beginning the questionnaire. Involvement was entirely optional, and respondents could opt out at any moment. All replies were kept confidential, and respondents were not requested to supply identifying information. No rewards were offered to those who completed the questionnaire.

Information gathered through the questionnaire platform was exported to an Excel spreadsheet. In addition to the questionnaire responses, the number of distinct users was calculated using IP addresses and cookies to filter out duplicate entries. Timestamps were also noted to flag questionnaires completed in less than 20 seconds and those left incomplete, indicating improper completion and warranting exclusion.

Data analysis

Descriptive statistics (counts and percentages) were generated for each questionnaire item. Beyond this, statistical testing was conducted to examine relationships between demographic characteristics (gender, age, and years of experience) and questionnaire responses. For Likert-type items, favorable replies ("Strongly Agree" and "Somewhat Agree") were merged into a single category labeled "Agree". In contrast, unfavorable replies ("Strongly Disagree" and "Somewhat Disagree") were merged into a single category labeled "Disagree". Items using a five-point Likert scale included an extra response option, "Unsure," which was retained as a third category. Fisher's exact test was then applied to examine relationships between replies and demographic characteristics. Likewise, for items permitting multiple replies, each choice was handled as a separate binary variable (chosen vs. not chosen), and Fisher's exact test was subsequently used to ascertain whether the proportion of each choice varied across any demographic subgroups. All statistical work was performed with R Statistical Software, adopting a significance threshold of $p < 0.05$.

Finally, members of the research group undertook thematic analysis of the free-text replies to the open-ended items in Parts 4 and 5 in stages, commencing with data familiarisation and then coding. The coded material was thereafter grouped into themes deemed suitable for investigating how to more effectively embed AI into practice.

Results and Discussion

55 replies were received by the set closing date of November 15 2024. Seven of these replies were incomplete and were consequently discarded, leaving 48 valid replies for analysis. Respondents required a mean time of 2.43 min to finish the questionnaire. The mean age of the respondents was 40.8 years, with 35 (72.9%) identifying as male and 13 (27.1%) as female. Respondents were distributed relatively evenly among the three bands of practice duration: 15 (31.3%) had been in practice for 5 years or fewer (i.e., trainees), 17 (35.4%) had practiced for 6–15 years (new or junior specialists), and 16 (33.3%) had done so for over 15 years (senior specialists).

Knowledge

In general, most respondents acknowledged a deficiency in their grasp of AI as it relates to OMS **(Table 2)**. Specifically, 60.4% of those surveyed disagreed (by choosing "Strongly Disagree" or "Somewhat Disagree") that they possessed a solid general understanding of AI, and 52.1% responded in the same manner regarding their familiarity with AI's applications within OMS. A small minority of just 18.8% had ever participated in any form of AI-related instruction. Responses did not vary meaningfully according to gender ($P = 0.741$–1.000), age ($P = 0.153$–1.000), or length of clinical experience ($P = 0.222$–1.000) **(Table 3).** The internal reliability of the knowledge domain was acceptable, with a Cronbach's alpha of 0.76 **(Table 4).**

Table 2. Summary of responses to questions utilizing the Likert scale.

Question	Strongly disagree	Somewhat disagree	Unsure	Somewhat agree	Strongly agree
Section 2: Knowledge					
Q1: My understanding of AI is strong	10 (20.8%)	19 (39.6%)	NA	17 (35.4%)	2 (4.2%)
Q2: I know how AI is applied in OMS	6 (12.5%)	19 (39.6%)	NA	19 (39.6%)	4 (8.3%)
Q3: I have taken part in AI education	17 (35.4%)	17 (35.4%)	NA	8 (16.7%)	1 (2.1%)
Section 3: Attitudes					
Q1: AI presently does or could enhance patient results in OMS	1 (2.1%)	1 (2.1%)	10 (20.8%)	19 (39.6%)	17 (35.4%)
Q2: AI ought to be brought into everyday practice for diagnosis and treatment planning	2 (4.2%)	2 (4.2%)	9 (18.8%)	20 (41.6%)	15 (31.3%)
Q3: AI ought to form part of OMS education	2 (4.2%)	4 (8.3%)	9 (18.8%)	19 (39.6%)	14 (29.2%)
Q4: AI might one day take the place of OMS surgeons	24 (50.0%)	14 (29.2%)	7 (14.6%)	3 (6.3%)	0 (0%)
Q5: Too much reliance on AI could lead to loss of clinical skills among surgeons	4 (8.3%)	11 (22.9%)	5 (10.4%)	22 (45.8%)	6 (12.5%)
Section 4: Practices					
Q1: I have employed AI tools in other areas of life	5 (10.4%)	8 (16.7%)	2 (4.2%)	23 (47.9%)	10 (20.8%)
Q2: I have applied AI tools within my OMS work	15 (31.3%)	15 (31.3%)	6 (12.5%)	12 (25.0%)	0 (0%)

Q5: AI simplifies getting my tasks done	2 (4.2%)	3 (6.3%)	13 (27.1%)	22 (45.8%)	8 (16.7%)
Q6: I believe I have enough training to operate AI tools	19 (39.6%)	19 (39.6%)	4 (8.3%)	6 (12.5%)	0 (0%)
Q7: My workplace has the means to adopt AI clinically	16 (33.3%)	12 (25.0%)	9 (18.8%)	10 (20.8%)	0 (0%)

Table 3. Associations between demographic factors (gender, age, and years of practice) and responses to Likert-scale survey questions.

Question	**P-value**	**> 15 years of practice**	**6–15 years of practice**	**1–5 years of practice**	**P-value**	**Age > 40 years**	**Age ≤ 40 years**	**P-value**	**Male**	**Female**
Section 2: Knowledge										
Q1: My understanding of AI is strong	1.000				0.770			0.741		
Disagree		10 (62.5%)	10 (58.8%)	9 (60.0%)		12 (57.1%)	17 (63.0%)		22 (62.9%)	7 (53.8%)
Agree		6 (37.5%)	7 (41.2%)	6 (40.0%)		9 (42.9%)	10 (37.0%)		13 (37.1%)	6 (46.2%)
Q2: I know how AI is applied in OMS	0.393				1.000			0.335		
Disagree		8 (50.0%)	11 (64.7%)	6 (40.0%)		11 (52.4%)	14 (51.9%)		20 (57.1%)	5 (38.5%)
Agree		8 (50.0%)	6 (35.3%)	9 (60.0%)		10 (47.6%)	13 (48.1%)		15 (42.9%)	8 (61.5%)
Q3: I have taken part in AI education	0.222				0.153			1.000		
Disagree		11 (68.8%)	14 (82.4%)	14 (93.3%)		15 (71.4%)	24 (88.9%)		28 (80.0%)	11 (84.6%)
Agree		5 (31.2%)	3 (17.6%)	1 (6.7%)		6 (28.6%)	3 (11.1%)		7 (20.0%)	2 (15.4%)
Section 3: Attitudes										
Q1: AI presently does or could enhance patient results	<0.001*				0.004*			1.000		
Disagree		2 (12.5%)	0 (0.0%)	0 (0.0%)		2 (9.5%)	0 (0.0%)		2 (5.7%)	0 (0.0%)
Unsure		8 (50.0%)	1 (5.9%)	1 (6.7%)		8 (38.1%)	2 (7.4%)		7 (20.0%)	3 (23.1%)
Agree		6 (37.5%)	16 (94.1%)	14 (93.3%)		11 (52.4%)	25 (92.6%)		26 (74.3%)	10 (76.9%)
Q2: AI ought to be brought into clinical practice for diagnosis and treatment planning	0.024*				0.009*			0.251		
Disagree		4 (25.0%)	0 (0.0%)	0 (0.0%)		4 (19.0%)	0 (0.0%)		4 (11.4%)	0 (0.0%)
Unsure		4 (25.0%)	4 (23.5%)	1 (6.7%)		6 (28.6%)	3 (11.1%)		5 (14.3%)	4 (30.8%)
Agree		8 (50.0%)	13 (76.5%)	14 (93.3%)		11 (52.4%)	24 (88.9%)		26 (74.3%)	9 (69.2%)
Q3: AI ought to form part of OMS education	0.146				0.122			0.478		
Disagree		4 (25.0%)	1 (5.9%)	1 (6.7%)		4 (19.0%)	2 (7.4%)		5 (14.3%)	1 (7.7%)

Unsure		5 (31.2%)	2 (11.8%)	2 (13.3%)		6 (28.6%)	3 (11.1%)		8 (22.9%)	1 (7.7%)
Agree		7 (43.8%)	14 (82.4%)	12 (80.0%)		11 (52.4%)	22 (81.5%)		22 (62.9%)	11 (84.6%)
Q4: AI might one day take the place of OMS surgeons	0.415				0.865			0.846		
Disagree		13 (81.2%)	14 (82.4%)	11 (73.3%)		16 (76.2%)	22 (81.5%)		27 (77.1%)	11 (84.6%)
Unsure		2 (12.5%)	1 (5.9%)	4 (26.7%)		3 (14.3%)	4 (14.8%)		6 (17.1%)	1 (7.7%)
Agree		1 (6.2%)	2 (11.8%)	0 (0.0%)		2 (9.5%)	1 (3.7%)		2 (5.7%)	1 (7.7%)
Q5: Too much reliance on AI could lead to loss of clinical skills among surgeons	0.545				0.828			0.078		
Disagree		5 (31.2%)	3 (17.6%)	7 (46.7%)		6 (28.6%)	9 (33.3%)		13 (37.1%)	2 (15.4%)
Unsure		2 (12.5%)	2 (11.8%)	1 (6.7%)		3 (14.3%)	2 (7.4%)		5 (14.3%)	0 (0.0%)
Agree		9 (56.2%)	12 (70.6%)	7 (46.7%)		12 (57.1%)	16 (59.3%)		17 (48.6%)	11 (84.6%)
Section 4: Practices										
Q1: I have employed AI tools in other areas of life	0.075				0.290			0.606		
Disagree		7 (43.8%)	5 (29.4%)	1 (6.7%)		8 (38.1%)	5 (18.5%)		9 (25.7%)	4 (30.8%)
Unsure		1 (6.2%)	0 (0.0%)	1 (6.7%)		1 (4.8%)	1 (3.7%)		1 (2.9%)	1 (7.7%)
Agree		8 (50.0%)	12 (70.6%)	13 (86.7%)		12 (57.1%)	21 (77.8%)		25 (71.4%)	8 (61.5%)
Q2: I have applied AI tools within my OMS work	0.880				0.335			0.448		
Disagree		11 (68.8%)	10 (58.8%)	9 (60.0%)		15 (71.4%)	15 (55.6%)		23 (65.7%)	7 (53.8%)
Unsure		1 (6.2%)	2 (11.8%)	3 (20.0%)		1 (4.8%)	5 (18.5%)		3 (8.6%)	3 (23.1%)
Agree		4 (25.0%)	5 (29.4%)	3 (20.0%)		5 (23.8%)	7 (25.9%)		9 (25.7%)	3 (23.1%)
Q5: AI simplifies getting my tasks done	0.656				0.379			0.785		
Disagree		3 (18.8%)	1 (5.9%)	1 (6.7%)		3 (14.3%)	2 (7.4%)		3 (8.6%)	2 (15.4%)
Unsure		5 (31.2%)	5 (29.4%)	3 (20.0%)		7 (33.3%)	6 (22.2%)		10 (28.6%)	3 (23.1%)
Agree		8 (50.0%)	11 (64.7%)	11 (73.3%)		11 (52.4%)	19 (70.4%)		22 (62.9%)	8 (61.5%)
Q6: I believe I have enough training to operate AI tools	0.810				0.880			0.437		
Disagree		13 (81.2%)	14 (82.4%)	11 (73.3%)		17 (81.0%)	21 (77.8%)		29 (82.9%)	9 (69.2%)
Unsure		2 (12.5%)	1 (5.9%)	1 (6.7%)		2 (9.5%)	2 (7.4%)		2 (5.7%)	2 (15.4%)
Agree		1 (6.2%)	2 (11.8%)	3 (20.0%)		2 (9.5%)	4 (14.8%)		4 (11.4%)	2 (15.4%)
Q7: My workplace has the means to	0.905				0.720			1.000		

adopt AI clinically										
Disagree		11 (68.8%)	10 (58.8%)	8 (53.3%)		14 (66.7%)	15 (55.6%)		21 (60.0%)	8 (61.5%)
Unsure		2 (12.5%)	4 (23.5%)	3 (20.0%)		3 (14.3%)	6 (22.2%)		7 (20.0%)	2 (15.4%)
Agree		3 (18.8%)	3 (17.6%)	4 (26.7%)		4 (19.0%)	6 (22.2%)		7 (20.0%)	3 (23.1%)

Indicates statistically significant.

Table 4. Cronbach's alpha for sections 2–3 of the survey.

Section	Cronbach's alpha
2 (Knowledge)	0.76
3 (Attitudes)	0.71
4 (Practices)	0.78

When asked to name existing AI technologies, 25 respondents (52.1%) specified at least one relevant to OMS; of these, 15 were linked to examination and diagnosis, 7 to treatment planning, and 3 to other purposes. Looking beyond OMS, 24 participants (50.0%) could name a large language model, 5 (10.4%) brought up robotics, and 5 (10.4%) mentioned speech-to-text or text-to-speech tools. Twelve respondents (25.0%) were unable to name any AI technology.

Attitudes

The findings revealed that the prevailing sentiment towards AI in OMS was favorable **(Table 2).** Broad agreement was recorded for the statements that AI can elevate patient outcomes (75.0%), that it should be woven into clinical workflows (72.9%), and that it ought to form part of OMS training (68.8%). Only a very slim minority (ranging from 4.2% to 12.5%) registered disagreement with these same statements. In contrast, 79.2% of participants rejected the idea that AI could one day replace surgeons, and 58.3% endorsed the view that overusing AI might lead to a deterioration of clinical skills. While gender showed no significant bearing on responses ($P = 0.078–1.000$), a considerably larger share of participants aged 40 years or younger expressed agreement that AI can improve patient outcomes ($P = 0.004$) and that it should be incorporated into clinical practice ($P = 0.009$) **(Table 3).** In parallel, significant differences in agreement proportions were detected across the three tiers of clinical experience: 5 years or fewer, 6–15 years, and more than 15 years ($P < 0.001$ and $P = 0.024$, respectively). The attitudes domain demonstrated acceptable internal consistency, with a Cronbach's alpha of 0.71 **(Table 4).**

Turning to the perceived benefits and potential risks of AI in OMS, 83.3% highlighted greater efficiency as an advantage, 72.9% pointed to a reduction in workload, 45.8% identified increased personalization, and 6.3% believed AI conferred no advantages whatsoever. Responses were largely uniform across demographic groupings, although a notably greater proportion of those aged 40 or under recognized increased personalization as a benefit ($P = 0.013$), and the percentage viewing efficiency gains as an advantage differed significantly by years of clinical experience ($P = 0.010$) **(Table 5).** Apprehensions regarding inaccurate diagnoses or management plans were expressed by 77.1% of participants; 70.8% worried about over-dependence, and both privacy/security issues and rising healthcare costs were each cited by 41.7%. These patterns held steady across demographic segments **(Table 5).**

Table 5. Associations between demographic factors (gender, age, and years of practice) and responses to multi-response survey questions.

Question	P	> 15 years	6–15 years	1–5 years	P	Age > 40 years	Age ≤ 40 years	P	Male	Female
Section 3: Attitudes										
Q6: Perceived advantages										
Greater clinical efficiency	0.010*	10 (62.5%)	17 (100%)	13 (86.7%)	1.000	31 (83.8%)	9 (81.8%)	1.000	29 (82.9%)	11 (84.6%)
Lower workload	0.355	11 (68.8%)	11 (64.7%)	13 (86.7%)	0.246	25 (67.6%)	10 (90.9%)	0.466	24 (68.6%)	11 (84.6%)
Better personalisation	0.050	5 (31.2%)	6 (35.3%)	11 (73.3%)	0.013*	13 (35.1%)	9 (81.8%)	0.210	14 (40.0%)	8 (61.5%)
No benefits	0.059	3 (18.8%)	0 (0.0%)	0 (0.0%)	1.000	3 (8.1%)	0 (0.0%)	0.553	3 (8.6%)	0 (0.0%)

Q7: Worries										
Privacy and data safety	0.555	6 (37.5%)	9 (52.9%)	5 (33.3%)	0.741	16 (43.2%)	4 (36.4%)	1.000	15 (42.9%)	5 (38.5%)
Wrong diagnoses or treatment	0.755	13 (81.2%)	12 (70.6%)	12 (80.0%)	0.246	30 (81.1%)	7 (63.6%)	0.458	28 (80.0%)	9 (69.2%)
Over-dependence on AI	0.445	13 (81.2%)	11 (64.7%)	9 (60.0%)	0.720	26 (70.3%)	7 (63.6%)	0.512	16 (45.7%)	4 (30.8%)
Rising healthcare costs	0.175	8 (50.0%)	4 (23.5%)	8 (53.3%)	0.741	16 (43.2%)	4 (36.4%)	0.182	22 (62.9%)	11 (84.6%)
Section 4: Practices										
Q3: Applications in OMS										
Diagnosis	0.020*	3 (18.8%)	9 (52.9%)	10 (66.7%)	0.732	16 (43.2%)	6 (54.5%)	0.746	17 (48.6%)	5 (38.5%)
Education	0.091	3 (18.8%)	9 (52.9%)	8 (53.3%)	0.488	14 (37.8%)	6 (54.5%)	0.750	14 (40.0%)	6 (46.2%)
Personal study and learning	0.341	5 (31.2%)	5 (29.4%)	8 (53.3%)	0.288	12 (32.4%)	6 (54.5%)	0.740	14 (40.0%)	4 (30.8%)
Treatment planning	0.934	6 (37.5%)	7 (41.2%)	5 (33.3%)	1.000	14 (37.8%)	4 (36.4%)	0.317	15 (42.9%)	3 (23.1%)
Support during surgery	0.227	2 (12.5%)	1 (5.9%)	4 (26.7%)	0.653	5 (13.5%)	2 (18.2%)	0.656	6 (17.1%)	1 (7.7%)
Have not / will not use	0.009*	7 (43.8%)	3 (17.6%)	0 (0.0%)	0.089	10 (27.0%)	0 (0.0%)	1.000	7 (20.0%)	3 (23.1%)
Q4: Use by subspecialty										
Dentofacial deformities	0.594	6 (37.5%)	9 (52.9%)	8 (57.1%)	1.000	18 (48.6%)	5 (50.0%)	0.740	18 (51.4%)	5 (41.7%)
Dentoalveolar surgery	0.358	2 (12.5%)	4 (23.5%)	5 (35.7%)	1.000	9 (24.3%)	2 (20.0%)	0.065	7 (20.0%)	6 (50.0%)
Surgical pathology	0.800	5 (31.2%)	7 (41.2%)	4 (28.6%)	1.000	13 (35.1%)	3 (30.0%)	0.703	9 (25.7%)	2 (16.7%)
Maxillofacial trauma	1.000	4 (25.0%)	4 (23.5%)	4 (28.6%)	1.000	10 (27.0%)	2 (20.0%)	0.505	13 (37.1%)	3 (25.0%)
Implant and preprosthetic surgery	0.357	7 (43.8%)	8 (47.1%)	3 (21.4%)	0.065	17 (45.9%)	1 (10.0%)	0.703	10 (28.6%)	2 (16.7%)
TMJ surgery	0.519	3 (18.8%)	1 (5.9%)	1 (7.1%)	0.569	5 (13.5%)	0 (0.0%)	0.324	15 (42.9%)	3 (25.0%)
Have not / will not use	0.225	7 (43.8%)	3 (17.6%)	3 (21.4%)	1.000	10 (27.0%)	3 (30.0%)	1.000	4 (11.4%)	1 (8.3%)

Indicates statistically significant.

Practices

Although a clear majority (68.8%) reported using AI outside their professional lives, only a quarter (25.0%) had done so within the specialty of OMS. Despite 62.5% agreeing that AI could facilitate their work, most felt they were insufficiently trained to apply it (79.2%) and that their clinical settings lacked the necessary equipment (58.3%) **(Table 2).** No significant differences emerged for these items based on gender (P = 0.437–1.000), age (P = 0.290–0.880), or years in practice (P = 0.075–0.905) **(Table 3).** The practices domain yielded a Cronbach's alpha of 0.78, indicating acceptable internal consistency **(Table 4).**

Regarding specific potential uses, respondents reported either using or contemplating using AI most commonly for diagnosis (45.8%), followed by patient or student education (41.7%), self-directed learning (37.5%), treatment planning (37.5%), and intraoperative assistance (16.7%). The only statistically significant divergence by years of clinical practice was in considering AI for diagnosis (P = 0.020) **(Table 5).** Eleven respondents (22.9%) admitted they had never utilized or considered utilizing AI in clinical practice; this stance was significantly more prevalent among clinicians with over 15 years of experience (P = 0.009). The subspecialty most frequently earmarked for AI integration was dentofacial deformities (50.0%), ahead of implant surgery (39.6%) and surgical pathology (35.4%). No demographic influences were detected on preferences for any subspecialty ($P > 0.05$).

Thematic analysis

From the open-ended item exploring what resources would be required to better weave AI into OMS, four themes were distilled. These comprised: [1] Training accessibility, [2] systematization, [3] financial resourcing, and [4] technical advancement. Under the first theme of training accessibility, 10 remarks (20.8%) noted that clinicians would benefit from organized educational initiatives, dedicated coursework, and access to relevant software. Five individuals (10.4%) addressed the second theme, underscoring the need for superior systematization and workflow design to enable a frictionless implementation. Within this category, participants noted the prospective value of refining institutional and departmental processes, as well as resolving regulatory issues related to consent and data protection, before any large-scale deployment.

Regarding the third theme, financial resourcing, a further 5 (10.4%) responses highlighted the need for stronger fiscal backing—such as state or institutional funding—to overcome initial adoption obstacles. Lastly, 2 (4.2%) participants addressed the fourth theme of technical advancement. One contribution advocated establishing a population-specific national database to hone AI algorithms for greater local relevance, while the other expressed reluctance to embrace AI systems until they deliver demonstrably stronger outcomes.

A broad consensus exists that AI can meaningfully contribute to diagnosis, prognosis, treatment strategizing, and even intraoperative decision-making for surgical cases [11]. Keeping pace with the rapid evolution of medical technologies, therefore, demands an appreciation of the current landscape and the hurdles OMS practitioners face to lower the barriers to AI assimilation.

The knowledge portion of the survey revealed that no more than half of the respondents were familiar with AI's applicability within OMS. In step with this, only half successfully named an AI technology usable in a clinical setting, and a full quarter could not cite any AI technology whatsoever. These figures align with findings from parallel studies among other cadres of health workers and health sciences students [7, 12, 13]. Given that no distinctions emerged among demographic segments in the present work, the modest state of knowledge may stem from a shortage of structured learning channels through which clinicians can deepen their understanding of AI and its possibilities; over 80% of the sample had never undertaken any AI-oriented instruction. This pattern does not seem exclusive to OMS—a survey of radiologists indicated that almost 70% lacked any AI-related training [14]. Notwithstanding the sharp uptick in published literature detailing AI model development in surgery [15], awareness of these novel developments appears not to be permeating a sizeable segment of the clinician community in our context.

Responses from the attitudes segment were largely hopeful concerning the future role AI might play in OMS. A preponderance of participants endorsed by selecting "strongly agree" or "agree"—the view that AI stands to boost patient outcomes and merits incorporation into both clinical environments and educational frameworks. Similar outlooks emerged in earlier published investigations of nursing professionals and other health workers, in which most saw AI as a valuable adjunct to diagnosis and treatment formulation and regarded it as integral to medicine and nursing [12, 16]. Diverging from those studies, however—where roughly half of subjects voiced unease about AI displacing their positions—only 6.3% of the current cohort expressed such a worry. While there is a sense of assurance that the OMS professional remit will not be assumed by AI imminently, over half the participants nonetheless sounded a note of caution about excessive reliance, which they felt could precipitate a deterioration in hands-on clinical competencies.

Those falling below the mean age of 40.8 years, as well as respondents with briefer clinical tenures, were more likely to hold sanguine perspectives on AI in OMS. Although statistical significance was reached only for the statements "AI can enhance patient outcomes" and "AI should be integrated into practice," numerous non-significant comparisons nonetheless showed that younger, less experienced participants had higher proportions of favorable attitudes. To illustrate, the statement "AI should be a part of OMS training" struck a chord with 81.5% of those aged 40 or younger and 80% of those with 1–5 years of practice, but only with 52.4% of those above 40 and 43.8% of those with over 15 years in practice. Moreover, a substantially larger share of those who had practiced for more than 15 years indicated that they had not and would not deploy AI clinically. Given that younger respondents have fewer years of experience, this pattern mirrors the well-documented tendency for younger age groups to be more accepting of technologies such as AI [17].

Within the practice segment, a considerable number of participants stressed the twin themes of insufficient training and inadequate hands-on experience. While close to two-thirds acknowledged that AI could ease their workload, most had not attempted to apply it professionally and felt they lacked the requisite capabilities to embed it into routine practice—a view shared across every demographic slice examined. Along the same lines, a combined 30% of respondents called for expanded access to training and more tangible workflow frameworks to accelerate AI's uptake in clinical settings. Analogous challenges and perceptions are evident elsewhere in medicine, with medical schools frequently lacking the faculty expertise to integrate AI into teaching, and health professionals advocating for collaborative ventures with software engineers and the launch of awareness-raising efforts about AI's utility [14, 18]. Looking ahead, the pathway to integrating AI into OMS might profitably begin with its insertion into postgraduate—or even undergraduate—training syllabi, so that clinicians grow accustomed to AI from an early stage and the adoption barrier rooted in unfamiliarity is effectively lowered.

Outstanding concerns

The other legitimate worries raised by participants in this investigation can be grouped into three overarching categories: unease about erroneous diagnoses and treatment strategies, apprehensions surrounding privacy and data security, and fears of escalating healthcare expenditure. The four recommendations put forth by respondents—enhancing training accessibility, streamlining implementation workflows, boosting financial support, and further refining and optimizing AI tools—directly address the perceived challenges of deploying AI in OMS.

The specter of incorrect diagnoses and management plans emerged as the most prevalent worry among those surveyed, with a small subset even urging greater development and refinement of AI systems before they are adopted clinically. The capacity of AI to accurately field OMS-related queries remains suboptimal; one investigation into large language models reported a mean performance of merely 62.5%, equating to a B grade, on OMS examination items [19]. That said, a growing body of work demonstrates the promising diagnostic precision of AI algorithms in identifying pathology from clinical notes, photographs, radiographs, or histopathological specimens, as well as in forecasting the course of oral diseases [20–23]. Even so, the consequences of a mistaken diagnosis have prompted some voices to advocate for strict validation protocols before implementation [24]. On balance, addressing this concern requires progress on two fronts: advancing AI models to maximize their accuracy and fostering broader recognition that AI is intended not to supplant the clinician but to serve as a supportive instrument in their duties.

Worries about data security and violations of patient confidentiality were expressed by nearly half of the respondents. This represents a substantial issue, given that vast quantities of information are supplied to and processed by AI models during their training and validation phases. Breaches of patient privacy can occur at both model construction and deployment stages, since regulatory frameworks such as the Health Insurance Portability and Accountability Act (HIPAA) currently lack clearly delineated provisions that address AI-related technologies [25]. Apprehensions that large technology corporations like Google could re-identify ostensibly de-identified data through cross-referencing with other datasets are likewise not unfounded, as successful re-identification has been demonstrated previously [26, 27], and legal action stemming from this has been initiated [28]. Rectifying this matter calls for a twofold approach. Firstly, thought could be given to building future AI systems using realistic synthetic patient data generated by generative models rather than actual patient records [29], thereby circumventing the need for genuine patient data wherever feasible. Secondly, regulations governing patient information require revisiting and sharpening to strengthen privacy legislation tailored specifically to AI applications in healthcare.

Along related lines, although no participant in our study mentioned other ethical dimensions of embedding AI into OMS, this remains a potential topic worth discussing. As much as AI carries the promise of improving patient outcomes, training, and research, its deployment must still preserve transparency, the informed consent of the individuals whose data are used, and patient autonomy in deciding whether to disclose their health details and in making choices about their care [30]. Professional integrity should be upheld through openly declaring AI usage in practice and research to both patients and colleagues. Moreover, it is essential to recognize that, in its current state, AI should act as a complement rather than a substitute for the human element that remains indispensable in patient care, teaching, and investigation. A review by Rokshad and colleagues outlined a framework that could be adopted in the ongoing refinement of AI tools in dental practice and research; this framework tackles ethical challenges anchored in eleven ethical pillars—transparency, diversity, wellness, respect for autonomy, privacy, accountability, equity, prudence, sustainability, solidarity, and governance—and serves as a sound reference for understanding how best to safeguard our patients' interests as AI becomes more embedded [31]. Finally, nearly half of the study's participants raised concerns about potentially inflated healthcare costs. This finding was notably at odds with a comparable inquiry among nurses, in which the prevailing sentiment was that AI could actually reduce healthcare spending [16]. While there are misgivings that the expense of developing AI technologies might be passed on to the patient's bill, a 2022 review encompassing 200 studies has instead shown that weaving AI into healthcare yields considerable cost reductions [32]. This can be credited to reduced time spent on diagnosis and treatment and to greater efficiency that grows with each year of application. Although no cost-effectiveness analyses specific to OMS have appeared in print, the aforementioned financial savings have been documented in other branches of dentistry, including its use for dental caries detection and the early detection of oral mucosal lesions [33, 34]. To guard against inflated individual patient expenses, governments and institutions may be in the interest of funding model development. Additional avenues for curbing healthcare costs include trimming models to remove superfluous components and crafting explainable AI systems that incorporate feedback loops to enhance their practicality and long-term viability [32].

This cross-sectional investigation marks the first attempt to gauge the knowledge, attitudes, and practices of OMS specialists and trainees. While the views uncovered align with those of other healthcare professionals, understanding the outlooks and reservations of colleagues within our own specialty enables us to devise concrete responses to lingering issues. The study, nonetheless, carries limitations. To begin with, the small number of OMS practitioners in Singapore may make the investigation underpowered. Though 55 responses were initially logged, the final sample count fell shy of our target of 52, as 7 entries were incomplete and had to be discarded. With only a single postgraduate training pathway nationwide, trainees' perspectives may be somewhat homogeneous, potentially limiting the transferability of their views across settings. Consequently, the small sample may yield results that are less generalizable and less robust. Overcoming this shortcoming would require multi-center rollouts across several countries in the region to increase future sample sizes.

Convenience sampling was employed in this study due to the limited human resources available to implement more elaborate sampling approaches (e.g., systematic or stratified sampling). While convenience sampling is straightforward to carry out, it can introduce a bias favoring individuals who engage more regularly with technologies such as social media, thereby tilting findings towards technologies such as AI. Reassuringly, the compact OMS community and the high level of digital literacy in Singapore meant that circulation via email and the social media channels of local professional bodies was likely to have reached the overwhelming majority of OMS clinicians in the country.

Additionally, the perspectives reported here pertain specifically to our cohort, which consists chiefly of clinicians of Southern Chinese ethnicity. They may reflect varying degrees of receptiveness to AI compared with Caucasian, African, or other ethnic populations [35]. It is also important to recognize that the study's findings capture only the current sentiments of OMS practitioners. The views held by clinicians a decade from now could diverge considerably, shaped by the probable continued evolution of AI systems and by possible legislative reforms and institutional pivots towards AI-driven care that could render its acceptance far more commonplace.

Conclusion

Although OMS specialists and trainees in Singapore hold broadly favorable views of AI, their levels of knowledge and practical engagement still show considerable scope for improvement. The input gathered on possible areas for development underscores the need for further technological and policy maturation before the inescapable incorporation of AI into everyday clinical work and education.

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