ORIGINAL ARTICLE

Self-Reported Practice of Nigerian Ophthalmologists on Artificial Intelligence

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Abstract

Background: Artificial Intelligence (AI) is revolutionising human endeavours, particularly in health care, including ophthalmology. The use of AI by ophthalmologists needs to be established as a baseline and used to optimise AI benefits.

Objective: This study investigates current AI practices among Nigerian ophthalmologists and identifies predictors of AI use among them.

Methods: This was an online cross-sectional survey of Nigerian ophthalmologists on AI use in practice. Each participant completed a questionnaire *via* the KoboToolbox form. The questionnaire link was shared on the Ophthalmological Society of Nigeria (OSN) group WhatsApp and the prospective participants' phones. 10 reminders were sent to the group WhatsApp and to prospective participants' phones for 1 month (June 2024).

Results: There were 115 ophthalmologists; 60 (52.2%) females, 55 (47.8%) males, mean age 47.1±11.6 (range: 27–74) years. Most were public servants (73.0%) working in urban facilities (74.8%). The majority engaged in comprehensive ophthalmology (79.2%), of whom (70.3%) also practiced other specialties. The majority reported poor use of AI (81.7%). Respondents reported using AI-based devices/software for research (42.6%), teaching 36 (31.3%), testing (27.8%), diagnosis (24.3%), treatment (11.3%), administration (11.3%), and outreach (9.6%). Most had practiced for≥10 years (67.8%) from the start of training, and many (45.2%) had practiced for> 10 years after qualifying (p=0.015). No associations were found between specialty areas and AI use. Longer practice duration predicted AI use: 20–29 years (AOR=14.0, 95% CI: 1.6-126.2, p=0.019) and 30-40 years (AOR=17.3, 95% CI: 1.630-184.364, p=0.018).

Conclusion: Ophthalmologists reported poor use of AI in practice. Longer duration of eye care practice increased the likelihood of AI use.

Keywords: *Artificial intelligence, ophthalmology, physicians, ophthalmologists, practice patterns, surveys and questionnaires, health care surveys, Nigeria, West Africa.*

INTRODUCTION

The advent of artificial intelligence (AI) in healthcare has opened significant opportunities for enhancing medical practice, particularly in ophthalmology [1]. AI systems are now widely used for diagnosing [2] and managing ophthalmic diseases [3], such as diabetic retinopathy [4], age-related macular degeneration [5], and glaucoma [6], offering clinicians tools to improve diagnostic accuracy and efficiency [7]. These systems process large volumes of data, learn from patterns, and may ease the burden on ophthalmologists by handling routine tasks [8, 9].

Ophthalmology is a leading field in Deep Learning (DL) adoption, with AI especially suited for automated screening in diabetic retinopathy and glaucoma. In resource-limited or high-volume settings like Nigeria, AI can assist clinicians. A systematic review by Liu *et al*. showed that DL's diagnostic performance often matches or exceeds that of human professionals. DL systems demonstrated a pooled sensitivity of 87.0% and a specificity of 92.5%, compared to 86.4% and 90.5% for health professionals [9].

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Ophthalmologists perform diverse roles, including clinical care, education, research, and administration, all of which can benefit from AI's speed, precision, and consistency. AI is now used for diagnosing Diabetic Retinopathy (DR), Age-related Macular Degeneration (AMD), glaucoma, and Retinopathy of Prematurity (ROP), with growing applications in retinal imaging, disease prediction, and tele-ophthalmology [10]. AI's potential also extends to patient triage, surgical assistance, and personalized treatment planning [10].

Despite its promise, AI adoption in clinical practice remains challenged by safety concerns [11], reliability [12], and ethical concerns [13]. Also, barriers such as a lack of regulation, data privacy concerns, limited diversity in datasets, legal ambiguities, and clinician skepticism persist [14].

Meanwhile, a global study (APPRAISE) by Gunasekeran *et al*. found that 88.1% of 1,176 ophthalmologists across 70 countries were willing to use AI as an assistive tool, with 80.9% noting that COVID-19 accelerated adoption [15]. However, the readiness of Nigerian

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ophthalmologists remains underexplored. This study investigates current AI practices among Nigerian ophthalmologists and identifies predictors of AI use among respondents.

METHODS

This study employed a cross-sectional survey design administered remotely *via* an online survey among Nigerian ophthalmologists who are members of the Ophthalmological Society of Nigeria (OSN), including ophthalmic fellows, diplomates, and trainees. The online survey was conducted over one month (June 2024), with the authors using remote collaboration tools such as Zoom, WhatsApp, and phone calls. Ethical Approval for the study was officially secured from the Health Research Ethics Committee (HREC) of the University of Nigeria Teaching Hospital, Enugu (NHREC/05/01/2008B-FWA00002458-1RB00002323). The survey was self-administered, and the questionnaire included specific statements with each respondent affirming willingness to participate in the study.

The target population for this survey comprised all ophthalmic fellows, diplomates, and trainee ophthalmologists registered with the OSN. A nonprobability sampling technique was used, reaching potential participants *via* various WhatsApp platforms associated with the OSN, as well as through text messages and phone calls.

For an infinite or large population of Nigerian Ophthalmologists, the required sample size (n) was calculated using the formula $n = [Z^2.p.(1-p)]/e^2$. Substituting z =z-value (standard deviation) corresponding to desired confidence level (1.96 for 95% confidence), p = proportion of Nigerian ophthalmologists expected to use AI (50% or 0.5), and e = margin of error (desired precision 5% or 0.05). n = 384.16.

However, for the finite population of Nigerian ophthalmologists (N = 600), the adjusted sample size (n_f) was calculated using the finite population correction formula: $n_f = n/(1+ (n-1/N)$. Substituting n=384.16 and N=600 yielded n_f =234.44 (rounded to 235). Thus, 235 ophthalmologists were targeted to complete the online survey questionnaire. In total, 115 participated—the maximum number of real-time responses recorded. No further responses were received after the 115th (indicating saturation), despite repeated messages and calls to individual ophthalmologists.

Meanwhile, some of the ophthalmologists had emigrated outside Nigeria, some were aged, and some were unreachable and therefore excluded from the online survey. Remarkably, the response rate was optimal within the first 48 hours of sharing the questionnaire on the group/individual WhatsApp, and the response thinned out thereafter and eventually stopped, even with repeated reminders at intervals. The total number of respondents after a month was 115.

Data collection was conducted *via* a self-administered online survey in KoboToolbox. This method ensured the entire process was conducted digitally and was not a face-to-face survey. Potential participants received the survey link and related communications through the Ophthalmological Society of Nigeria's (OSN) official/individual WhatsApp groups. Direct text messages and phone calls were employed to encourage participation.

The primary study tool used was a 16-item self-reported questionnaire. The questionnaire was designed to investigate participants' knowledge and use of Artificial Intelligence (AI) across clinical services, research, and training, and to collect standard socio-demographic and professional profile information. The scoring schema, adapted from Swed *et al*. [16], assigned a maximum of 1 point per item, yielding a total score of 0-16. Good AI practice was defined as a total score of 8 or above, while a score less than 8 was categorized as poor AI practice. Responses to specific items were scored accordingly, for instance, by assigning 1 mark to a positive response ("Yes" or frequency responses like "Always," "Often," or "Sometimes") and 0 marks to negative or neutral responses.

The collected data underwent initial cleaning and preparation using both Microsoft Excel and the Statistical Package for the Social Sciences (SPSS) version 20. The analysis involved summarizing the data into descriptive statistics, including proportions, percentages, charts, and graphics. For inferential statistics, the primary tests performed were the Chi-square test and the calculation of the Adjusted Odds Ratio (AOR). The Chi-square test on the use of AI in ophthalmologists' practice was analysed with variables (age, gender, professional designation, years of eye care practice, and place of practice). A multivariable logistic regression analysis was conducted on the variable (predictor) that was statistically significant in the univariate analysis (years of eye care practice since completion of residency training). The level of statistical significance for all analyses was predetermined at $p <0.05$.

RESULTS

Socio-demography and Association with Artificial Intelligence Practice

The respondents were 115 ophthalmologists, including 60 (52.2%) females and 55 (47.8%) males, with a mean age of 47.1±11.6 (range: 27-74) years. They were ophthalmic fellows (77, 67.0%), diplomates (2, 1.7%), and trainee ophthalmologists (36, 31.3%) (**Table 1**). The majority (84, 73.0%) were public servants, practiced in urban locations (86, 74.8%), and engaged in comprehensive ophthalmology 91 (79.2%), of whom 64/91 (70.3%) also practiced other ophthalmic specialties (**Table 2**). Many 22 (19.1%) engaged only in specified specialties, and 2/115 (0.02%) were not engaged in active eye care practice. Most had practiced for at least 10 years (78/115, 67.8%) from the time of starting ophthalmic training, and many (52/115, 45.2%) after qualifying as ophthalmologists (p=0.015).

Most were engaged in clinical ophthalmology 110 (95.7%), of whom 77 (70%) also engaged in training and research. There were no associations between specialty areas and AI use in ophthalmic practice (**Table 3**).

Years of Eye Care Practice as a Predictor of the Use of Artificial Intelligence

Overall, only 21 respondents (18.3%, n=115) had good AI practice (**Table 2**). Respondents between 20-29 years of eye care practice were statistically significant but had a highly uncertain effect (AOR14, 95% CI: 1.6-126.2, p=0.019). In addition, respondents aged 30-40 years with eye care practice showed a statistically significant but highly uncertain effect (AO=17, 95% CI: 1.6-184.4, p=0.018) (**Table 4**).

Grading of Self-reported Use of Artificial Intelligence among the Respondents

Overall, only 21 respondents (18.3%, n=115) had good AI practice (**Table 2**). The grading of the self-reported use of AI by the respondents indicated that a few, 21 (18.3%) had been making good use of AI in their practice while the majority were not, 94 (81.7%) (**Fig. 1**). The respondents use AI-based devices or software in their practice for mainly among others research 49 (42.6%), teaching 36 (31.3%), testing 32 (27.8%), and diagnosis 28 (24.3%). Others were treatment 13 (11.3%), administration 13 (11.3%), and community outreach 11 (9.6%) (**Fig. 2**).

Most respondents admitted they never used AI-based devices or software in their practice. However, many respondents affirmed their use for research, teaching, diagnosis, treatment, community outreach, testing, and administration, at frequencies ranging from rarely to always (**Fig. 3**).

Table 1: The participants' socio-demographic profile.

Variables	Frequency	Percentage
Age group (Years)		
20-29	5	4.3
30-39	33	28.7
40-49	27	23.5
50-59	32	27.8
≥60	18	15.7
Mean±SD; range	47.1±11.6; 27-74	
Gender		
Female	60	52.2
Male	55	47.8
Current designation		
Diplomate	2	1.7
Junior registrar	17	14.8
Senior registrar	19	16.5
Ophthalmologist (fellow)	77	67.0
Place of practice		
Public	84	73.0
Public and private	23	20.0
Private	7	6.1
Retired	1	0.9
Location of practice		
Urban	86	74.8
Semi-urban	27	23.5
Rural	2	1.7
Years of practice since completion of residency training		
None	27	23.5
1-9	36	31.3
10-19	22	19.1
20-29	20	17.4
30-40	10	8.7
Area of practice		
Comprehensive ophthalmology and other specialties	64	55.7
Comprehensive ophthalmology only	27	23.5
Public health ophthalmology	7	6.1
Pediatric ophthalmology & strabismus only	4	3.5
Glaucoma only	4	3.5
Oculoplastic surgery only	3	2.6
Retina only	3	2.6
Currently not engaged in active eye care practice	2	1.7
Cornea & Anterior segment only	1	0.9

Table 2: Respondents' demographic association with the practice of artificial intelligence.

Variables	Respondents' AI practices Good n (%)	Poor n (%)	χ2 Statistics	p-value
Age group (Years)				
20-29	0(0.0)	5(5.3)	8.287	0.082
30-39	4(19.0)	29(30.9)		
40-49	3(14.3)	24(25.5)		
50-59	7(33.3)	25(26.6)		
≤60	7(33.3)	11(11.7)		
Gender				
Female	11(52.4)	49(52.1)	0.000	0.983
Male	10(47.6)	45(47.9)		
Years of eye care practice from the time of starting residency training				
1-9	4(19.0)	33(35.1)	4.986	0.289
10-19	4(19.0)	27(28.7)		
20-29	5(23.9)	15(16.0)		
30-39	7(33.3)	16(17.0)		
≥40	1(4.8)	3(3.2)		
Years of eye care practice from the time of completion of residency training				
None	1(4.8)	26(27.7)	12.281	0.015*
1-9	4(19.0)	32(34.0)		
10-19	5(23.8)	17(18.1)		
20-29	7(33.3)	13(13.8)		
30-40	4(19.0)	6(6.4)		
Current designation				
Diplomate	1(4.8)	1(1.1)	4.733	0.192
Junior Registrar	2(9.4)	15(16.0)		
Ophthalmologist	17(81.0)	60(63.8)		
Senior Registrar	1(4.8)	18(19.1)		
Place of Practice				
Public	14(66.7)	70(74.4)	3.215	0.360
Public and Private	4(19.0)	19(20.2)		
Private	3(14.3)	4(4.3)		
Retired	0(0.0)	1(1.1)		

*AI: Artificial intelligence, *Significant at 95%.*

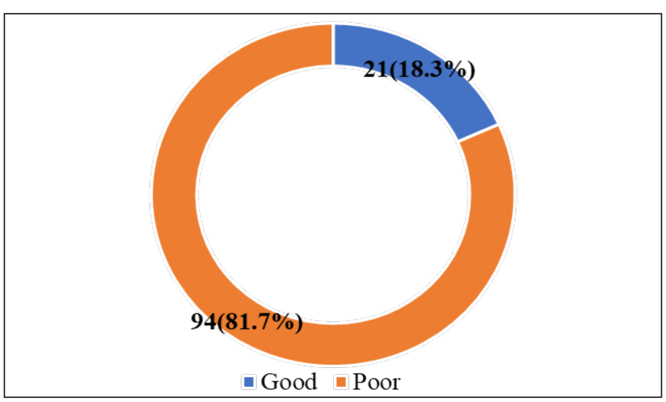

Fig. (1): Grading of self-reported use of artificial intelligence in ophthalmic practice.

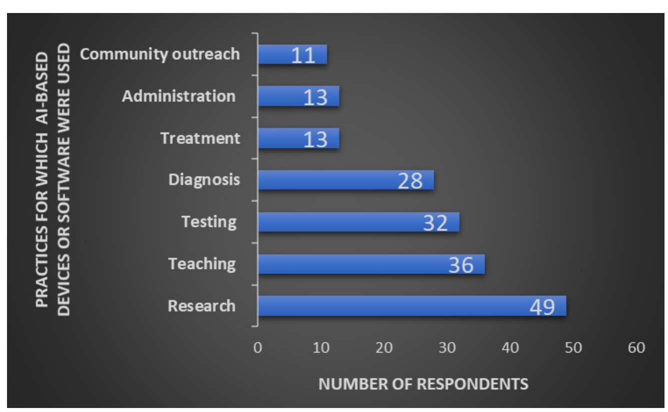

Fig. (2): Respondents' use of AI-based devices or software for practices.

Table 3: The respondents' specialties associated with the practice of artificial intelligence.

Variables	Respondent's AI practices		χ^2 Statistics	p-value
	Good n(%)	Poor n(%)		
Specialist areas				
Comprehensive ophthalmology and other specialties	10 (47.6)	54 (57.4)	5.177	0.739
Comprehensive ophthalmology only	5 (23.8)	22 (23.4)		
Cornea and anterior segment only	0 (0.0)	1 (1.1)		
Currently not engaged in active eye care practice	0 (0.0)	2 (2.1)		
Glaucoma only	1 (4.8)	3 (3.2)		
Oculoplastic surgery only	0 (0.0)	3 (3.2)		
Pediatric ophthalmology and strabismus only	1 (4.8)	3 (3.2)		
Public health ophthalmology	3 (14.3)	4 (4.3)		
Retina only	1 (4.8)	2 (2.1)		
Predominant engagement in the last 6 months				
Administration only	1 (4.8)	3 (3.2)	0.636	0.888
Clinical practice	5 (23.8)	28 (29.8)		
Clinical practice + Training + Research	15 (71.4)	62 (66.0)		
Community work	0 (0.0)	1 (1.1)		
Place of practice				
Rural	0 (0.0)	2 (2.1)	0.455	0.797
Semi-urban	5 (23.8)	22 (23.4)		
Urban	16 (76.2)	70 (74.5)		

*AI: Artificial intelligence, *Significant at 95%.*

Table 4: Predictors of use of AI among the respondents.

Factor	Odds Ratio	95% Confidence Interval		p-value
		Lower	Upper	
Years of eye care practice after completing training				
None [RC]	-	-	-	-
1-9	3.250	0.342	30.884	0.305
10-19	7.647	0.820	71.285	0.074
20-29	14.000	1.554	126.163	0.019*
30-40	17.333	1.630	184.364	0.018*

*RC: Reference Category, *Significant at 95%.*

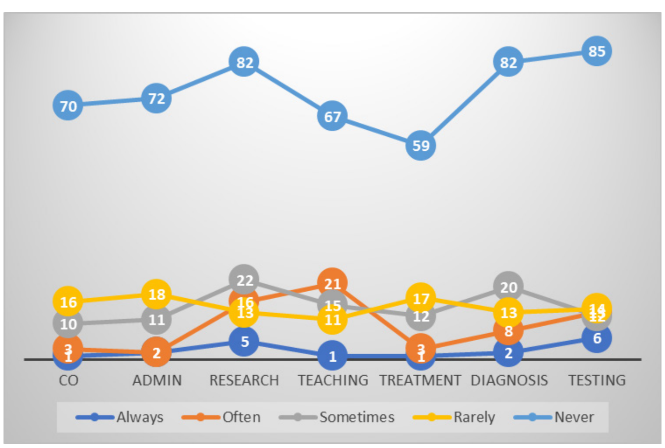

Fig. (3): Respondents' frequency of use of AI in selected activities.

CO: community outreach

Regulation of the Use of Artificial Intelligence (n=115)

The spectrum of respondents' views on regulated use of artificial intelligence in ophthalmic practice was not at all 3 (2.6%), minimally 7 (6.1%), moderately 42 (36.5%), strictly 43 (37.4%), and very strictly 20 (17.4%).

Named Used AI Devices or Software among the Respondents (n=40)

The respondents listed their commonly used AI-based devices or software as ChatGPT 20 (50%), central visual field analyser 7 (17.5%), spectra-domain optical coherence tomography (SD-OCT) 3 (7.5%), meta-AI 2 (5%), and handheld gonioscope 2 (5%). Also listed by a respondent (2.5%) for each of peak acuity, blockade laboratory, open AI, perplexity, electronic health records (EHR), and autokeratometer.

DISCUSSION

This study investigated the AI practices among Nigerian ophthalmologists and identified areas for targeted interventions.

The surveyed ophthalmologists show a relatively balanced gender distribution and a mean age of 47.1, indicating an experienced cohort with many years in practice. The majority (67.8%) of respondents had over 10 years of experience in eye care, which aligns with previous studies suggesting that senior healthcare professionals are more likely to integrate advanced technologies, such as AI, into their practices, especially after gaining confidence through experience and exposure to technological advancements in healthcare [17]. However, only 18.3% reported good AI use, suggesting a gap between the availability of AI technologies and their practical adoption in ophthalmology.

Interestingly, while age was not statistically significant in predicting AI adoption (p=0.082), a trend was observed: older ophthalmologists, particularly those aged 50-59 and above, were more likely to use AI. This contrasts with some studies, such as Erickson *et al*., which reported that younger practitioners adopted AI more readily [18]. One possible explanation for this trend is that older practitioners in this cohort may have had greater access to advanced technologies through involvement in high-level decision-making roles or management positions in urban hospitals.

Years of practice after residency emerged as a significant predictor of AI adoption (p=0.015). Those with 20–40 years of post-residency experience showed a statistically significant, but highly uncertain, effect in AI use compared to their less experienced counterparts. This finding echoes results from other studies showing that the more seasoned the clinician, the greater the likelihood of engaging with sophisticated diagnostic tools [1]. Moreover, this finding, where practice of AI use was statistically significant in respondents with years of eye care practice between 20 and 40 years compared to other categories of respondents, is very similar to a study by Syria [16] and a multi-national study [15]. Furthermore, the adoption of AI in ophthalmology has been linked with years of professional experience, as senior clinicians often encounter more complex cases where AI tools can provide valuable diagnostic or decision-making support [19]. This correlation might also indicate that these ophthalmologists have had the time to observe the evolution of AI and have developed a comfort level with its integration into practice.

No significant association was found between ophthalmic subspecialties and AI use (p=0.739), suggesting that AI adoption is not limited to specific ophthalmic subspecialties. However, comprehensive ophthalmologists, particularly those engaged in multiple subspecialties, were more likely to use AI (47.6%). This is consistent with findings from studies showing that AI adoption often occurs in general or comprehensive practices where the volume of patient data and the range of clinical activities allow for broader integration of AI tools [1].

Despite AI's potential to transform ophthalmic practice, only 21 respondents (18.3%) reported using AI effectively in their clinical settings. This mirrors findings from other studies, such as Li *et al*., which found that AI adoption in ophthalmology remained slow, particularly in low- and middle-income settings due to infrastructure challenges and limited training [20]. In this study, while AI was mainly used for research (42.6%) and teaching (31.3%), its application in direct patient care, such as diagnosis (24.3%) and treatment (11.3%), was limited. This is indicative of a broader global trend in which AI is still predominantly viewed as an academic tool rather than a clinical necessity [21].

Regarding regulation, most respondents supported moderate to strict regulation (73.9%), consistent with the global call for stringent oversight of AI use in healthcare to ensure patient safety and ethical standards [22].

Artificial intelligence (AI) tools, such as ChatGPT, were frequently used by respondents, reflecting the growing influence of natural language processing in medical research and education [23]. ChatGPT is a generative AI chatbot developed by OpenAI, a San Francisco-based AI research organization [24]. Aside, Meta AI is an AI assistant integrated into Meta's platforms like Facebook and WhatsApp, with recent 2026 updates enhancing multimodal capabilities, real-time voice in 48 languages, and ad optimization features; it's developed by Meta Platforms [25]. Also, Perplexity (Perplexity AI) is a conversational search engine using large language models for cited answers, founded in 2022 by Perplexity AI, Inc., headquartered in San Francisco (no specific version noted; last app release v3.2.0 in 2024) [26]. Currently, there are many AI tools in the market, and many are being developed with viable applications for ophthalmic services.

Meanwhile, the study cohort reported experience with clinical AI tools, such as the Central Visual

Field (CVF) analyzer and Spectral-Domain Optical Coherence Tomography (SD-OCT). These medical devices are widely recognized for their diagnostic utility in ophthalmology, consistent with other studies that highlight the role of AI in enhancing diagnostic precision [27]. Besides, the cohort of ophthalmologists listed handheld gonioscope, peak acuity (Peek Acuity), and autokeratometer as AI tools (medical devices). The CVF is a device like the Henson 9000 perimeter, a compact tool for detecting visual field changes in ~3 minutes per eye; manufactured by Topcon Healthcare (acquired from Elektron Eye Technology) [28]. SD-OCT is an imaging technology for high-resolution eye scans, with leading devices from companies such as Carl Zeiss Meditec (Cirrus HD-OCT), Topcon (3D OCT-1000), and Heidelberg Engineering (Spectralis) [29]. The handheld gonioscope includes models such as Viewlight Ocular Sussman (four-mirror for angle viewing, 9mm contact) and NIDEK GS-1 (automated goniophotography), produced by Viewlight USA and NIDEK [30]. The peak acuity (Peek Acuity) is a free Android app (version 3.8.1 as of October 2025) for measuring visual acuity using smartphones, developed by Peek Vision for eye screening [31]. Autokeratometer devices measure corneal curvature; top models include Topcon (KR-1, KR-800 with rotary prism tech), NIDEK, and Carl Zeiss Meditec [32].

Furthermore, the cohort of ophthalmologists reported Blockade Labs and electronic health records (EHR) software as AI tools. The Blockade Labs offers Skybox AI (latest Model 3.1 as of January 2025), a generative AI for 360° environments and 3D assets from text prompts; Indianapolis-based, founded 2018 [33]. Finally, the cohort's reported Electronic Health Records (EHRs) are digital patient record systems for managing patient health information, with core functionalities including clinical documentation, order entry, and support across varied healthcare settings [34].

LIMITATIONS

This study has limitations that may warrant caution in interpreting its findings. The calculated required sample size of 235 with a 5% margin of error was reduced to a final sample of 115 respondents with an increased margin of error 8.3%. This necessarily reduces the precision of point estimates, such as the exact percentage of AI adopters. This was the reality during the survey. Notwithstanding, a post hoc justification supports the adequacy of the sample for the primary analysis. The goal was exploratory: to identify factors associated with AI adoption and barriers within this experienced cohort, rather than to estimate population prevalence precisely. For such analyses (focused on trends, hypotheses, and effect sizes), a sample of 115 suffices when effects are meaningful. Statistically significant associations and clear barrier themes were detected, indicating sufficient power. Subtle effects would likely have gone undetected, so the findings' robustness within the sample engenders confidence that they are not artifacts, even if there is caution against overinterpreting adoption rate magnitudes. Moreover, a cursory appraisal of the results might suggest limited AI adoption among an "experienced cohort," potentially leading to non-response bias. The 115 respondents might not fully represent the 600-member population, especially if high-volume, busy specialists (the most experienced clinicians) skipped the survey due to time constraints, over-representing those with lighter loads or semi-retired status. The 115 ophthalmologists, including 60 (52.2%) females and 55 (47.8%) males, with a mean age of 47.1±11.6 (range 27-74) years, had good representation across gender and experience divides. Most of the 115 respondents (67.8%) had practiced for at least 10 years from the time of starting ophthalmic training, and many (45.2%) had practiced for at least 10 years after qualifying as ophthalmologists (p=0.015).

CONCLUSION

The study observes that despite an experienced cohort, their adoption of AI in ophthalmic practice remains limited. Years of practice post-residency strongly predict AI use, and while technology is predominantly applied in research and teaching, its use in patient care remains underutilized. These findings underscore the need for further training, infrastructure improvements, and regulatory frameworks to enhance AI adoption in ophthalmology.

ETHICAL APPROVAL

Ethical Approval was obtained from the Health Research Ethics Committee (HREC) of the University of Nigeria Teaching Hospital, Enugu (REF letter No. NHREC/05/01/2008B-FWA00002458-1RB00002323). All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/ or national research committee and the Helsinki Declaration.

CONSENT FOR PUBLICATION

Written informed consent was taken from the participants.

AVAILABILITY OF DATA

The data set may be acquired from the corresponding author upon a reasonable request.

FUNDING

None.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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AUTHORS' CONTRIBUTION

Conception and Design (AAA, OO, JFO, AOM) Questionnaire drafting and Administration (AAA, AA, OO, JFO, AOM), Data Analysis (AAA, AA), Manuscript Drafting and Critical Review (AAA, AA, OO, JFO, AOM), and Approval for submission for publication (AAA, AA, OO, JFO, AOM).

GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the author(s) used ChatGPT (GPT-4, OpenAI) sparingly to generate language suggestions and perform minor proofreading in some parts of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the published article.

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