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Patient preferences for the use of AI in chest X-ray result processing and communication

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A B S T R A C T

Introduction: Artificial Intelligence (AI) tools are increasingly used in imaging such as X-rays, but there is limited evidence about how patients view the use of AI in the diagnostic process.
Methods: Using the Technology Acceptance Model (TAM) to select attributes and the Health Belief Model (HBM) to interpret between-group differences this study evaluates patients' preferences regarding the use of AI in processing and communication of chest X-ray (CXR) results in the context of the NHS in the UK. A choice-based conjoint experimental (CBC) design was employed to examine various attributes influencing patient preferences across three samples 1) respondents with lung cancer diagnosis, 2) respondents who have had chest X-rays for any reason and 3) respondents with no recent CXRs. Furthermore, word–emotion association analysis was used to assess and compare the emotions levels in the open-text responses across the samples.
Results: A total of 440 respondents completed the study. Overall, respondents expressed support for using AI in X-ray processing, believing it would reduce waiting times. Waiting time and the decision on the next step of the care pathway accounted for the largest share of preference with a combined relative importance; the share of choice variation attributable to these attributes, of ~67% in Samples 1 and 2 and 60% in Sample 3. Lung cancer patients (Sample 1) significantly favoured combined Human and AI processing (mean part-worth $+13.3$, $p < 0.001$), whereas Samples 2 and 3 favoured Human-only to Human and AI (mean part-worth -5.7, $p = 0.008$ and -12.0, $p < 0.001$ respectively for the attribute level Human and AI).
Conclusion: Overall, patients welcome the supplementary use of AI in their care, with lung cancer patients having higher acceptance.
Implications for practice: Understanding patient preferences can inform healthcare providers about optimising the diagnostic pathway, improving patient experiences, and potentially alleviating patient anxiety.

Introduction

The integration of Artificial Intelligence (AI) into medical diagnostics, particularly in the detection of cancers from chest X-rays (CXRs), marks a transformative shift in healthcare that holds immense promise for enhancing diagnostic accuracy, expediting treatment planning, and ultimately improving patient outcomes yet it also introduces a complex interplay of patient perceptions, trust, and acceptance.[1–3] Evidence shows that the successful implementation of these technologies' hinges not only on their technical capabilities but also on the willingness of patients to embrace them.[4]

Screening for lung cancer with low-dose CT has been proven to improve lung cancer mortality.[5] However, not all patients diagnosed with lung cancer will be eligible for screening or accept the

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invitation to attend. Therefore, there is still a need to improve the symptomatic diagnosis pathway for lung cancer patients. CXRs are often the first test for suspected lung cancer, for patients referred from primary care/general practice.[6] Rapid, early and accurate diagnosis of lung cancer is needed to improve outcomes, with 44% of lung cancer patients with a T-stage upgrade during the radiology diagnostic period.[7] Evidence suggests that immediate reporting of CXRs referred from primary care and same-day CT when suspicious of lung cancer can shorten the time to diagnosis of lung cancer.[8] However, the number of CXRs is high, and they are performed for a wide range of reasons and symptoms.[6] Therefore, it may not be feasible to provide an immediate report for all primary care CXRs. AI technologies may help identify CXRs that require urgent review. Patient and public attitudes are central to whether such tools can be adopted. Systematic reviews report broadly cautious acceptance of clinical AI, conditional on retained human oversight and on trust in clinicians and the tools they use,[15,21,23,25] yet evidence on preferences specific to the processing and communication of CXR results is lacking. This study addresses that gap.

Building on the Technology Acceptance Model (TAM) and the Health Belief Model (HBM) we create a design to identify how different patient groups value attributes such as waiting times, communication methods, and the integration of AI in result processing. TAM was selected because acceptance hinges on perceived usefulness and ease of use, which we mapped to the processing-agent and communication attributes[9]; HBM was selected because perceived susceptibility and severity plausibly differ between lung cancer patients and comparison groups.[10-13]

An important component of an accelerated lung cancer pathway is communicating results with patients and arranging the next test/steps on the pathway. The communication of diagnostic results is a critical aspect of patient care, particularly in time-sensitive conditions such as lung cancer. The communication location and strategies may differ, occurring within the radiology department rather than with the referrer, and at the time of examination rather than after the event.[8,14] With the increasing use of AI in imaging, it is essential to understand patient preferences regarding the processing and communication of chest X-ray results. Understanding these preferences can inform healthcare providers about optimising the diagnostic pathway, improving patient experiences, and potentially alleviating patient anxiety. This study aims to quantify patients' preferences for the processing and communication of chest X-ray results specifically, including the use of AI, and to compare these across lung cancer patients and two comparison samples.

Methods

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To evaluate how patients value the advantages and disadvantages of various attributes of using AI in chest X-ray result processing and communications when referred by their GP/Primary care doctor, a Choice-Based Conjoint (CBC) experiment was conducted. A CBC design, by its nature, determines how respondents value different attributes and the utility they assign to various levels of these attributes. Unlike a conventional survey, a CBC requires respondents to make a series of discrete choices, simulating real-life decisions and trade-offs a patient would make. Due to these methodological advantages, discrete-choice experiments, specifically CBC designs, are commonly used in healthcare research that inherently involves decisions based on trade-offs.[15,16]

An initial design was created with attributes and levels based on current NHS England practices and median waiting times.[17] Specifically, the waiting-time and care-pathway levels were taken from the National Optimal Lung Cancer Pathway and the median times for England in the NHS England Diagnostic Imaging Dataset, supporting their content validity. This design was then validated and updated with feedback from a pilot with a convenience sample of 8 people that involved lay-people without a background in research, experts in public health, cancer patients and clinicians. The feedback was used to refine the wording of the processing-agent and communication levels and to confirm that respondents understood the attributes and could complete the task within the target time. Table 1 presents the final set of attributes and levels used in the design. These attributes and levels were utilised to generate orthogonal choice sets, each containing three options, with eight choice sets per respondent. Eight tasks were chosen to balance statistical efficiency against respondent burden in a patient sample and to keep completion within the ~10-min target. In each choice set, respondents were asked to select the 'most preferred' option from the three presented. This follows a standard choice-based conjoint design. The design was created using the CBC software, Sawtooth. Fig. 1 shows an example of a choice set that was presented to respondents. In addition to the CBC, the survey included consent and attention checks, questions related to awareness, open-text questions on attitudes towards AI, and demographic questions about the respondents.

Three UK-based samples were identified for the study, and data was collected from May to July 2024. Sample 1 consists of lung cancer patients identified via various cancer patient groups such as Roy Castle Lung Cancer Foundation (via Health unlocked), CRAF (formerly NCRI consumer forum), and other lung cancer patients involved in research from across the UK. Participation was voluntary and the respondents received no financial or non-financial incentive to participate. In Sample 1, we collected 56 valid responses after excluding 20 records of which 16 were incomplete and 4 failed the attention check. Sample 2 consists of respondents who have had a chest x-ray in the past 6 months. This sample was identified using Prolific, an online research survey platform. There were 171 valid responses in sample 2 after excluding 29 records of which 24 were incomplete and 5 failed the attention check; Sample 3 consists of respondents who have not had a CXR in the past 6 months. These respondents were also identified using Prolific. There were 213 valid responses in sample 3 after dropping 39 records of which 27 were incomplete and 12 failed the attention check. Participation was voluntary and respondents for samples 2 and 3 were paid £2 each to respond to the survey. Consent and attention checks were applied prior to analysis. The demographic data in Table 2 shows the distribution of respondents across the three final samples.

Part-worth utilities were estimated by Hierarchical Bayes in Sawtooth (10,000 iterations; 10,000 draws per respondent) and reported as zero-centred differences. Attribute importance was computed for each respondent as the range of utilities within an attribute divided by the sum of ranges across attributes, then averaged. Using the sampling rule for conjoint designs $n \geq 500c/(t \times a)$ (largest level count $c = 4$, $t = 8$ tasks, $a = 3$ alternatives ~ 84 for stable aggregate estimates), Samples 2 and 3 exceed the threshold while Sample 1 ($n = 56$) falls below it. This is mitigated by Hierarchical Bayes individual-level estimation and is acknowledged as a limitation.

It is worth highlighting two observations in our sample distribution. First, our sample of lung cancer patients was predominantly white (95% for lung cancer patients, i.e., Sample 1 v. 75% in the Prolific general-public comparison sample without a recent chest X-ray, i.e., Sample 3) and second, the median and mode for

Table 1
Attributes and levels used in the CBC design.

	Processing agent	Waiting time for results	Decision on the next step of the care pathway	Medium of communication of results
Level 1	Human only	Immediate	Immediately	A letter and in-person discussion with your GP
Level 2	Human and AI	Next day	3 days	A letter and telephone discussion with your GP
Level 3		2 days	15 days	A letter only (Default communication at 3 weeks via app, on the NHS website/portal, or post)
Level 4		12 days	28 days	A letter and in-person discussion at radiology (the department where the X-ray imaging was done)

lung cancer patients (Sample 1) is 60 and 69 years, compared to 30 and 39 years in the Prolific general-public comparison sample (Sample 3). Therefore, the preferences in communication methods and acceptance of AI may not be generalisable across the entire spectrum of patients. Lung cancer incidence data shows that lung cancer is more common in white and older patients and therefore the older age of Sample 1 (lung cancer patients) reflects the prevalence of lung cancer in older patients.[18]

Open-text responses were collected to assess the motivations and attitudes towards AI for the choices in the discrete choice experiments. A word–emotion association analysis was performed using the NRC Word–Emotion Association Lexicon,[19] a technique

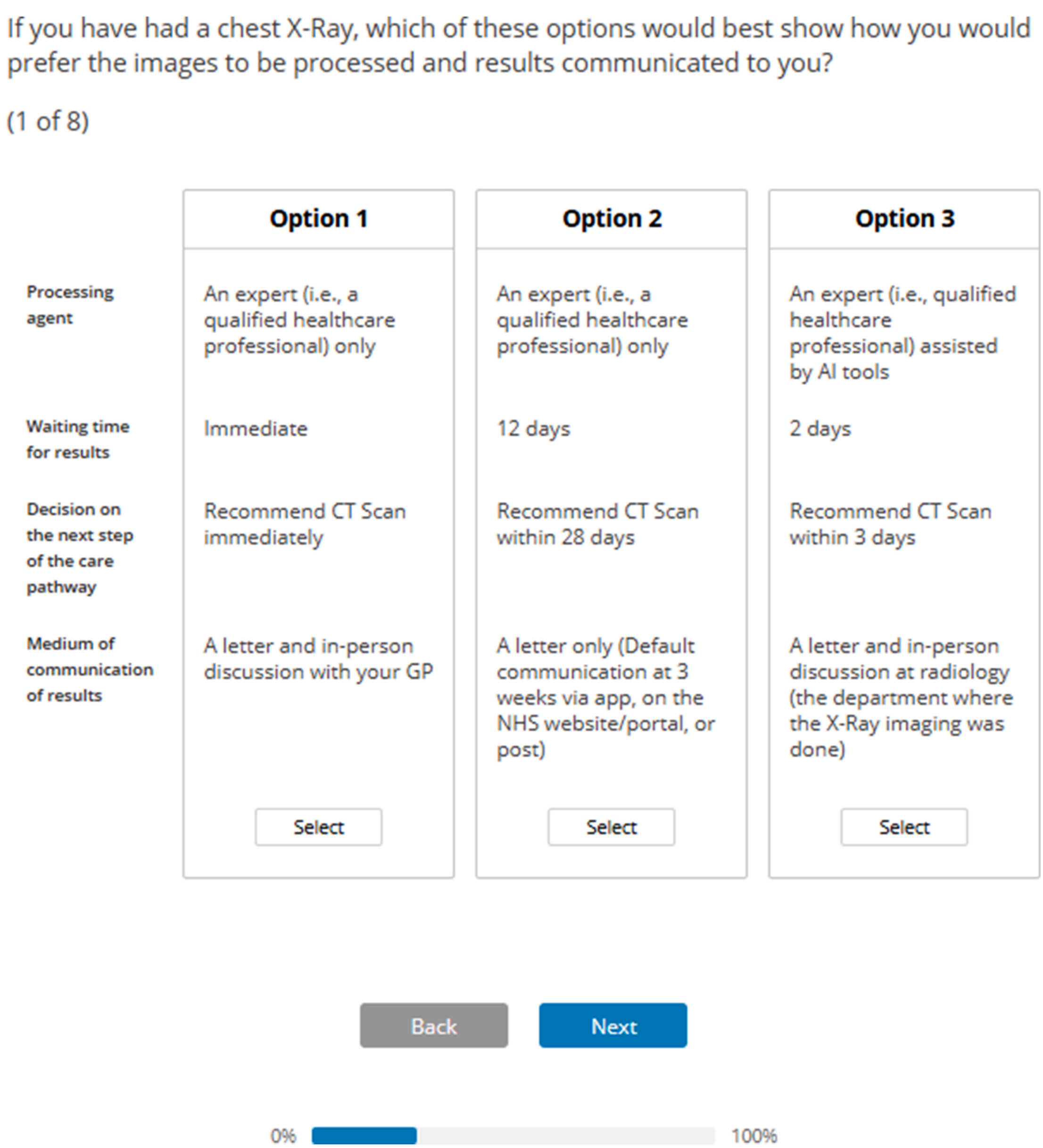

Figure 1. Example of a choice set.

Table 2
Demographic profile of samples.

Age	Sample 1	Sample 2	Sample 3
	n = 56	n = 171	n = 213
Less than 20 years	0%	1%	3%
20–29 years	0%	18%	23%
30–39 years	2%	27%	27%
40–49 years	2%	18%	21%
50–59 years	23%	21%	17%
60–69 years	45%	12%	8%
70 or more	27%	5%	2%
Prefer not to answer	2%	0%	0%
Total	100%	100%	100%
Gender	**Sample 1**	**Sample 2**	**Sample 3**
Male	34%	47%	48%
Female	64%	51%	51%
Transgender	0%	1%	1%
Non-binary	0%	1%	0%
Other	2%	0%	0%
Prefer not to answer	0%	0%	0%
Total	100%	100%	100%
Ethnicity	**Sample 1**	**Sample 2**	**Sample 3**
White/Caucasian	95%	87%	75%
Asian/Asian British	0%	6%	11%
Black/African/Caribbean/Black British	2%	2%	8%
Mixed/Multiple ethnic groups	2%	2%	5%
Other ethnic group	2%	1%	1%
Prefer not to answer	0%	2%	0%
Total	100%	100%	100%
Education	**Sample 1**	**Sample 2**	**Sample 3**
Post-graduate degree (Master's/PhD)	20%	16%	18%
Undergraduate degree (Bachelor's)	32%	32%	39%
Higher education certificate (CertHE) or (HNC)/ further ed	21%	11%	6%
A level/Advanced apprenticeship	5%	25%	21%
GCSE - grades 9, 8, 7, 6, 5, 4 or A*, A, B, C/In. Apprenticeship	11%	12%	11%
GCSE - grades 3, 2, 1 or grades D, E, F, G/First certificate	4%	2%	3%
Other	4%	3%	0%
Prefer not to answer	4%	1%	1%
Total	100%	100%	100%

that has been used to assess and compare the anxiety levels of patients from their statements, was performed.[20] In this technique, tokens are matched to eight emotions, counts are normalised by the respondent's word count, and scores are aggregated by sample. Underlying values are provided in the supplementary material. Open-text responses were analysed thematically. Responses were coded by the lead author, and codes were grouped into themes and reconciled by discussion with all authors to support reliability.

Results

Conjoint analysis

The relative importance of each attribute (Table 3) is a measure of its relative impact on the total utility. The part-worth utilities (Table 3) were calculated using a Hierarchical Bayes estimation model. The values are scaled to an arbitrary additive constant within each attribute so that the sum of the utilities is zero for that attribute. Together, these help understand the relative importance of each attribute and level on the respondent's decision to accept an offer.[21]

Overall, similar patterns were found across all the three samples; 'Waiting for results' and 'Decision on the next step of the care pathway' account for two-thirds of the value that respondents associate with the four attributes presented in this choice. This is followed by the 'Medium of communication' and finally 'Processing agent' received the least importance.

The part-worth utilities from Table 3 demonstrate how the respondents value the different levels in an attribute. This analysis reveals respondents in sample 1 (lung cancer survivors) value the use of Human and AI as processing agents more than Human only. This is different from the preferences shown in sample 3 (no recent chest X-ray), which value Human only more than Human and AI while respondents in sample 2 (recent X-ray no cancer), appear to be indifferent and in between the preferences indicated by samples 1 and 3.

Between-sample comparisons (individual-level estimates; Kruskal–Wallis with pairwise Mann–Whitney; full values and 95% CIs are in Supplementary Table S1–S2) showed that attribute importance differed across samples for all four attributes (care pathway, waiting time and medium $p \leq 0.001$; processing agent $p = 0.019$). For the processing agent specifically, Sample 1 significantly favoured combined Human and AI over Human-only (mean part-worth +13.3, 95% CI 6.0 to 20.5; $p < 0.001$; 75% of respondents favoured AI), whereas Sample 3 favoured Human-only (−12.0, 95% CI −16.9 to −7.1; $p < 0.001$) and Sample 2 was intermediate (−5.7, 95% CI −9.9 to −1.5; $p = 0.008$). Sample 1 differed significantly from both Sample 2 and Sample 3 (both $p < 0.001$), while Samples 2 and 3 did not differ significantly ($p = 0.06$).

On average, respondents in sample 1 associate greater value with 'Next day' results for the attribute 'Waiting time for results'. A similar pattern is observed for the attribute 'Decision on the next step of the care pathway' where the average utility associated with responses from sample 1 is higher for '3 days' as opposed to 'Immediately'. These estimates carry wide individual-level dispersion (reflected in the standard deviations in Table 3 and the confidence intervals in the supplementary tables), indicating substantial heterogeneity within each sample rather than a uniform view; Hierarchical Bayes individual estimates reveal meaningful preference segments. For the other attributes and levels, we find similar patterns across the three samples.

Analysis of responses to open text questions

Analysis of the open-text comments provides a deeper understanding of the motivations behind these choices. Similar patterns were found across the three samples, with key themes with one representative quote in Table 4.

The word–emotion association analysis reports the relative comparison of emotion expressed by each sample (Fig. 2; underlying values in Supplementary Table S3). Sample 1 showed the highest scores for the anxiety-related emotions fear and sadness; this was significantly higher than Sample 2 (fear $p = 0.030$; sadness $p = 0.024$; combined $p = 0.025$), although the overall three-group comparison (fear $p = 0.107$; sadness $p = 0.078$; combined $p = 0.083$) and the Sample 1 vs Sample 3 contrast (combined $p = 0.067$) did not reach conventional significance. Given Sample 1's small size, this finding should be read as indicative.

Discussion

Results of the CBC found waiting time for X-ray results and the subsequent decision on the next step of the care pathway are the

Table 3
Average importance of attributes and average part-worth utility for each level by samples.

	Sample 1		Sample 2		Sample 3	
	n = 56		n = 171		n = 213	
Average importances of attributes	Average importances	Standard deviation	Average importances	Standard deviation	Average importances	Standard deviation
Processing agent	11.06	10.18	10.1	10.05	13.69	13.1
Waiting time for results	32.04	7.84	35.89	9.56	31.96	10.61
Decision on the next step of the care pathway	35.35	10.87	31.14	9.93	28.15	11.65
Medium of communication of results	21.55	9.69	22.87	11.89	26.2	12.2

Attribute	Level	Average utilities	Standard deviation	Average utilities	Standard deviation	Average utilities	Standard deviation
Processing agent	Human only	−13.29	27.08	5.72	27.95	11.99	36
	Human and AI	13.29	27.08	−5.72	27.95	−11.99	36
Waiting time for results	Immediate	25.07	31.88	46.13	17.05	39.98	25.84
	Next day	37.01	24.9	37.3	12.65	34.07	21.45
	2 days	10.62	19.97	11.13	13.34	1.71	16.24
	12 days	−72.7	33.38	−94.56	26.58	−75.76	30.55
Decision on the next step of the care pathway	Immediately	42.05	33.11	49.72	28.16	47.56	28.39
	3 days	56.6	26.54	37.13	14.09	31.22	24.51
	15 days	−26.56	19.82	−21.98	14.4	−25.26	20.07
	28 days	−72.09	39.4	−64.86	28.15	−53.51	35.98
Medium of communication of results	A letter and in-person discussion with your GP	16.99	30.58	15.48	23.04	23.38	24.13
	A letter and telephone discussion with your GP	9.36	23	16.15	18.99	11.86	20.55
	A letter only (Default communication at 3 weeks via app, on the NHS website/portal, or post)	−42.2	31.1	−51.93	34.01	−53.73	41.05
	A letter and in-person discussion at radiology (the department where the X-ray imaging was done)	15.85	23.93	20.3	25.11	18.49	37.14

Note: Average utilities calculated as zero-centred differences.

most valued attributes, collectively representing two-thirds of the overall value assigned by respondents, in line with prior work on patients' concerns with waiting times along the diagnosis and treatment journey.[22] A central and arguably headline finding is the consistency of attribute importance across three distinct samples: all groups prioritised the same attributes in the same order. This is also in line with prior work that shows both patients and the general public have similar attitudes towards the use of AI in medical diagnosis.[23]

However, notable variation was found between the preferences of lung cancer patients, who exhibited a stronger inclination towards combined Human and AI processing. One hypothesis, consistent with but not demonstrated by the data is that this group, having experienced higher anxiety while waiting for results (as reflected in their open-text comments), perceives combined processing as likely to expedite results and reduce stress, as well as potentially being more accurate.[24] However, patient engagement workshops have emphasised the impact of delayed diagnosis of lung cancer has on patient anxiety.[14] The open-text comments highlighted key themes such as the speed of results, anxiety related to waiting, the perceived accuracy and speed benefits of AI, the importance of personal interactions, and clear communication. These insights triangulate with the quantitative importances and part-worths i.e., speed-related attributes dominating, and a desire for human contact in the communication attribute.[25] The observed preference for speedy, in-person face-to-face discussion of CXR results in radiology or at the GP, mirrors work from the USA where patients preferred rapid access to results (7520 of 7859; 95.7%) and discussion where their results were not normal (2337 of 2453; 9.3%).[26]

Demographic differences between the samples warrant caution when interpreting these comparisons. Sample 1 was older and predominantly White; while this mirrors lung cancer epidemiology, it may independently shape both communication preferences and attitudes to AI, and limits generalisability.

When applied to the context of AI adoption among cancer patients, the HBM highlights several considerations.[10] These constructs map onto our results: higher perceived susceptibility/severity in lung cancer patients is consistent with their greater acceptance of AI-assisted processing and their higher weighting of pathway speed, while perceived benefits align with the speed-related themes in the open text. Perceived susceptibility refers to a patient's belief about their risk of experiencing adverse outcomes related to their cancer, such as disease progression, treatment side effects, or recurrence. If patients do not perceive themselves as being particularly vulnerable to these risks, they may be less motivated to adopt AI-driven tools designed to mitigate them. Perceived severity, on the other hand, encompasses the patient's assessment of the seriousness of these potential outcomes, including their impact on physical health, emotional well-being, and overall quality of life.[11,12] Patients who perceive cancer and its associated challenges as highly severe are more likely to seek out and utilise technological solutions that promise to improve their prognosis or alleviate their suffering.

The perceived benefits of adopting AI technology play a crucial role in influencing patient behaviour, with patients weighing the potential advantages against the perceived barriers.[23,27-29] For instance, AI-powered diagnostic tools may offer the promise of earlier and more accurate detection of cancer recurrence, while AI-driven treatment planning systems could lead to more personalized and effective therapies. However, patients must believe that these benefits are tangible and outweigh the potential drawbacks, such as concerns about data privacy, algorithmic bias, or the impersonal nature of AI-driven care.[13,30] If patients do not understand the benefits of AI or find it difficult to use, they may be less likely to adopt it, regardless of their perceptions of susceptibility and severity.[31]

Acceptance is also shaped by concerns this study did not measure directly. Algorithmic bias, accountability and oversight, explainability, and equitable access may all temper patient acceptance, and

Table 4
Thematic analysis of motivations and attitudes towards AI with prevalence scores.

Theme	Sample 1 n (%)	Sample 2 n (%)	Sample 3 n (%)	Representative quote (sample, respondent)
Question: "Could you please explain what influenced your preferences for the processing and communication of chest X-ray results?"				
Speed of processing results	37 (67%)	87 (51%)	105 (49%)	*"For me speed is the main driver - I'm not fussed who gives me the results so long as somebody explains the terminology …"* **(S1, 8)**
Importance of clear communication	31 (56%)	63 (37%)	77 (36%)	*"… some form of communication explaining what was happening next."* **(S1, 41)**
Importance of personal interaction	18 (33%)	65 (38%)	66 (31%)	*"I would prefer a conversation with a real person at the earliest point possible in the process."* **(S2, 81)**
Role of AI in improving speed and accuracy	13 (24%)	36 (21%)	29 (14%)	*"… I feel that AI + a human expert working together will provide the most accurate results."* **(S1, 13)**
Anxiety about waiting	11 (20%)	14 (8%)	27 (13%)	*"I prefer results as soon as possible as the waiting can make me anxious."* **(S1, 35)**
Question: "Do you have any views on the use of AI tools to assist the processing of chest X-rays? Please explain"				
AI can support humans	24 (43%)	56 (33%)	76 (36%)	*"… the AI may identify issues that the human might not."* **(S1, 13)**
AI is good for speed	15 (27%)	25 (15%)	35 (17%)	*"Anything that can assist and expedite the processing of results has to be a good thing!"* **(S3, 71)**
Accuracy of AI	10 (18%)	20 (12%)	16 (8%)	*"… the results could give false positives which would be an unnecessary time of anxiety."* **(S1, 12)**
Hesitation in fully relying on AI	3 (5%)	14 (8%)	17 (8%)	*"I would be uncomfortable at the thought of AI on its own processing results …"* **(S3, 45)**
Concern about oversight	1 (2%)	8 (5%)	17 (8%)	*"… experts over rely on the AI results and sift out or miss areas of concern."* **(S2, 155)**

Note: Prevalence = number (percentage) of respondents expressing each theme. Themes for the first question were coded from the relevant open-text (denominators: S1 n = 55, S2 n = 171, S3 n = 213); themes for the second question from the AI-views open-text (denominators: S1 n = 56, S2 n = 168, S3 n = 212). Respondents could express more than one theme, so percentages do not sum to 100%.

are consistent with the strong preference for human oversight observed here.[27-29,32,33] It is important to distinguish AI-assisted decision support, which our respondents endorsed, from autonomous AI, which they did not; current UK regulation prohibits autonomous AI evaluation of chest X-rays, so assisted interpretation is the relevant near-term scenario. The analysis of attitudes towards AI indicated general support for its use, particularly for speeding up results. Fast and accurate results were reported as important by

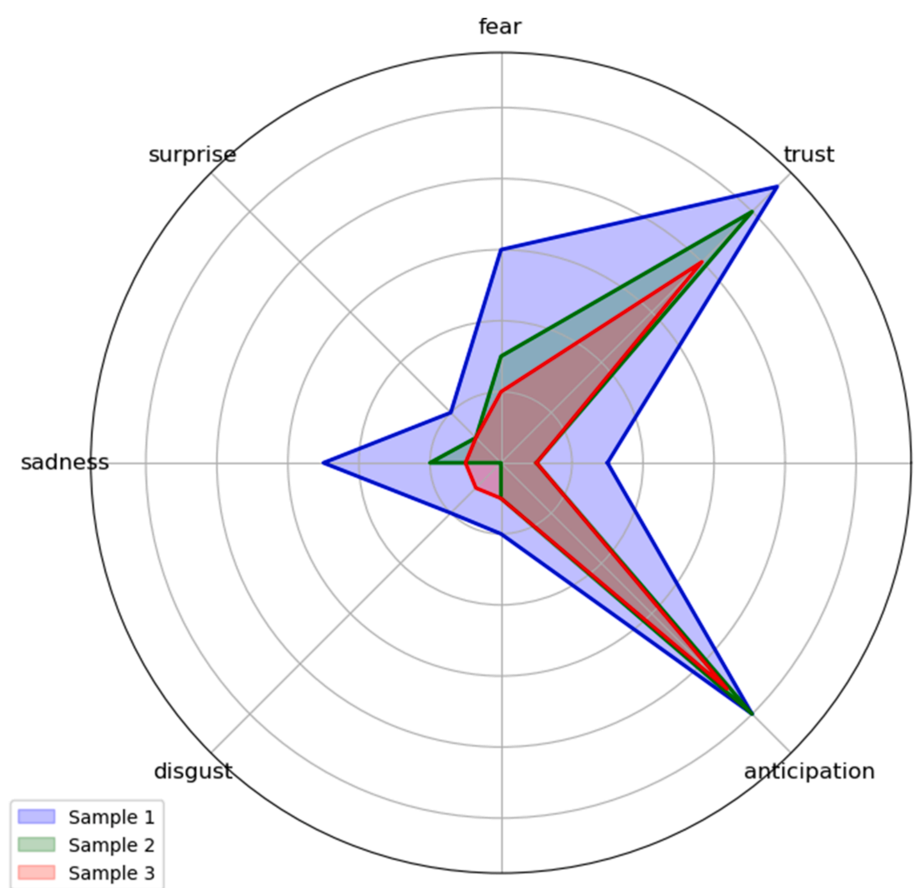

Figure 2. Word-emotion analysis of open-text comments for three samples.

patients in the work of Kelly et al., who also reported patient need for personal connection with the healthcare provider sharing the results.[34] However, some respondents expressed reservations about fully relying on AI without human oversight, underscoring the importance of a balanced approach that leverages AI's strengths while maintaining expert supervision[27,32]. Lennartz et al., also found a human supervision of AI was a strong patient preference, especially when compared to AI alone/autonomous diagnoses,[33] mirroring concerns identified by Richardson et al. for AI safety and patient choice.[28]

Healthcare providers must understand how AI algorithms generate recommendations, the underlying evidence supporting those recommendations, and the limitations and uncertainties inherent in AI-driven predictions.[35] Patient trust in clinicians includes trust in the clinical tools they choose, and in the selection of AI-based tools.[29] If the patient sees the use of AI in their care management plan as impeding their ability to act as a partner with their doctor, it will become vital for the physician to right the dynamic back to a stable equilibrium through discussions, education, and reconfirmed consent.[36] Current UK legislation prohibits autonomous AI clinical evaluation of chest X-rays, but patient preference for assisted interpretation is an important consideration for any future work.

Several limitations should be noted. The lung cancer cohort was small (n = 56), below the sampling rule benchmark for aggregate CBC estimation, though Hierarchical Bayes mitigates this. Recruitment differed across samples (patient/research networks for Sample 1; Prolific for Samples 2 and 3), which may introduce selection and motivation differences, and the samples differed in age and ethnicity. The communication attribute deliberately bundled medium, professional and location to keep the task realistic, so the effect of each component cannot be isolated. No ‘none/opt-out’ alternative was offered, which may inflate apparent engagement; this is a design choice rather than an inherent feature of CBC. The descriptors ‘expert’ and ‘qualified healthcare professional’ may carry positive framing, though wording was held constant across options. Finally, respondents evaluated hypothetical scenarios, which may not fully predict behaviour under real-world implementation.

Conclusion

Patients in this study consistently valued speed above all: waiting time for results and the decision on the next step of the care pathway together accounted for the largest share of their preferences across all three samples, with timely and personal communication also valued. We find support for AI as an assistive tool working alongside qualified professionals rather than as a replacement, consistent with current UK regulation, which prohibits autonomous AI evaluation of chest X-rays. This preference for assisted AI was most marked among lung cancer patients, who have lived experience of the diagnostic pathway and associated waiting. The study assessed patient preferences and perceptions rather than the diagnostic accuracy or performance of AI. For practice, these findings suggest prioritising reductions in waiting time and clear, personal communication, positioning AI as a transparent aid under human oversight, and supporting patients' informed, active involvement in decisions about how AI is used in their care. Realising these benefits will require communicating the current evidence base including its uncertainties, to patients and the public.

Ethics approval and consent to participate

This study has been approved by City St. George's, University of London, Bayes Business School, Research Ethics Committee. REC reference number ETH2324-1961.

Availability of data

The data that support the findings of this study are available from the corresponding author [author initials], upon reasonable request.

Author contributions

AB: Conceptualisation, methodology, investigation, data curation, writing – original draft and review/editing, visualisation.

JR: methodology, investigation, writing – original draft and review/editing,

DRB: Conceptualisation, methodology, investigation, writing – original draft and review/editing, supervision, funding acquisition.

NW: Conceptualisation, methodology, investigation, writing – original draft and review/editing, supervision, funding acquisition.

Generative AI use

Statement: During the preparation of this work the authors used Grammarly, Microsoft's AI Assistant, and Chat GPT to improve the grammar and readability of the text. After using these tool/service, the authors reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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Conflict of interest statement

NW: Nick Woznitza declares consultancy fees from InHealth, Apollo Radiology (UK) and SMR Health & Tech unrelated to the current study, travel grant from Qure. ai Technologies to attend ECR 2023.

All other authors: no conflicts to declare.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.radi.2026.103554.

References

1. Farina E, Nabhen JJ, Dacoregio MI, Batalini F, Moraes FY. An overview of artificial intelligence in oncology. *Future Sci OA*. 2022;8(4):Fso787. https://doi.org/10.2144/fsoa-2021-0074.
2. Huang S, Yang J, Fong S, Zhao Qi. Artificial intelligence in cancer diagnosis and prognosis: opportunities and challenges. *Cancer Lett*. 2020;471:61–71. https://doi.org/10.1016/j.canlet.2019.12.007.
3. Kann BH, Thompson R, Thomas Jr CR, Dicker A, Aneja S. Artificial intelligence in oncology: current applications and future directions. *Oncology (Williston Park)*. 2019;33(2):46–53.
4. Dixon D, Sattar H, Moros N, Kesireddy SR, Ahsan H, Lakkimsetti M, et al. Unveiling the influence of AI predictive analytics on patient outcomes: a

comprehensive narrative review. *Cureus*. 2024;16(5):e59954. https://doi.org/10.7759/cureus.59954.

5. Field JK, Baldwin D, Brain K, Devaraj A, Eisen T, Duffy SW, et al. CT screening for lung cancer in the UK: position statement by UKLS investigators following the NLST report. *Thorax*. 2011;66(8):736–737. https://doi.org/10.1136/thoraxjnl-2011-200351.
6. Bradley SH, Baldwin D, Bhartia BSK, Black GB, Callister MEJ, Clayton K, et al. Achieving earlier diagnosis of symptomatic lung cancer. *Br J Gen Pract*. 2025;75(750):40–43. https://doi.org/10.3399/bjgp25X740493.
7. Mullin ML, Verghese P, Khaw CR, Creamer AW, Bhamani A, Prendecki R, et al. Stage shift in lung cancers found during a screening study: early detection is only half the battle. *Lung Cancer*. 2025;200:108309. https://doi.org/10.1016/j.lungcan.2025.108309.
8. Woznitza N, Ghimire B, Devaraj A, Janes S, Piper K, Rowe S, et al. Impact of radiographer immediate reporting of chest X-rays from general practice on the lung cancer pathway(radioX): a randomised controlled trial. *Thorax*. 2023;78:890–894. https://doi.org/10.1136/thorax-2022-219210.
9. Ismatullaev UVU, Kim SH. Review of the factors affecting acceptance of AI-Infused systems. *Hum Factors*. 2024;66(1):126–144. https://doi.org/10.1177/00187208211064707.
10. Al-Ani A, Hammouri M, Sultan H, Al-Huneidy L, Mansour A, Al-Hussaini M. Factors affecting cervical screening using the health belief model during the last decade: a systematic review and meta-analysis. *Psychooncology*. 2024;33(1):e6275. https://doi.org/10.1002/pon.6275.
11. Champion VL, Skinner CS. The health belief model. In: Glanz K, Rimer BK, Viswanath K, eds. *Health behavior and health education: theory, research, and practice*. 4th ed. ed. San Fransisco: Jossey-Bass; 2008:45–65.
12. Janz NK, Becker MH. The Health Belief Model: a decade later. *Health Educ Q*. 1984;11(1):1–47. https://doi.org/10.1177/109019818401100101.
13. Hilbers D, Nekain N, Bates A, Nunez J-J. Patient attitudes toward artificial intelligence in cancer care: scoping review. *JMIR Cancer*. 2025;11:e74010. https://doi.org/10.2196/74010. e10.
14. Stavropoulou C, Scarbrough H, Rawlinson J, Cui M, Baldwin D, Woznitza N. Implementing AI innovation in radiology departments in the English NHS: a qualitative study on the experiences of professionals, patient groups and innovators. *Front Digit Health*. 2026;8. https://doi.org/10.3389/fdgth.2026.1736911.
15. Ghosh A, Acar OA, Banerjee A, Wiertz C. Moving towards people-centred healthcare systems: using discrete choice experiments to improve leadership decision making. *BMJ Lead*. 2023;7(4):294–297. https://doi.org/10.1136/leader-2022-000727.
16. Viswanathan VS, Toro P, Corredor G, Mukhopadhyay S, Madabhushi A. The state of the art for artificial intelligence in lung digital pathology. *J Pathol*. 2022;257(4):413–429. https://doi.org/10.1002/path.5966 [published Online First: 20220620].
17. NHS England. *Diagnostic imaging dataset annual statistical release 2024/25*. London: NHS England; 2025.
18. Cancer Research UK. *Lung cancer statistics*. Cancer Research UK; 2026.
19. Mohammad SM, Turney PD. Crowdsourcing a word–emotion association lexicon. *Comput Intell*. 2013;29(3):436–465. https://doi.org/10.1111/j.1467-8640.2012.00460.x.
20. Chichua M, Filipponi C, Mazzoni D, Pravettoni G. The emotional side of taking part in a cancer clinical trial. *PLoS One*. 2023;18(4):e0284268. https://doi.org/10.1371/journal.pone.0284268.
21. Hair JF, Black WC, Babin BJ, Anderson RE. In: *Multivariate data analysis*. 7th New International Edition. London: Pearson; 2013.
22. Paul C, Carey M, Anderson A, Mackenzie L, Sanson-Fisher R, Courtney R, et al. Cancer patients' concerns regarding access to cancer care: perceived impact of waiting times along the diagnosis and treatment journey. *Eur J Cancer Care*. 2012;21(3):321–329. https://doi.org/10.1111/j.1365-2354.2011.01311.x.
23. Young AT, Amara D, Bhattacharya A, Wei Maria L. Patient and general public attitudes towards clinical artificial intelligence: a mixed methods systematic review. *Lancet Digit Health*. 2021;3(9):e599–e611. https://doi.org/10.1016/s2589-7500(21)00132-1.
24. Eckerling A, Ricon-Becker I, Sorski L, Sandbank E, Ben-Eliyahu S. Stress and cancer: mechanisms, significance and future directions. *Nat Rev Cancer*. 2021;21(12):767–785. https://doi.org/10.1038/s41568-021-00395-5.
25. Hardardottir H, Aspelund T, Zhu J, Fall K, Hauksdottir A, Fang F, et al. Optimal communication associated with lower risk of acute traumatic stress after lung cancer diagnosis. *Support Care Cancer*. 2022;30(1):259–269. https://doi.org/10.1007/s00520-021-06138-4.
26. Steitz BD, Turer RW, Lin C-T, MacDonald S, Salmi L, Wright A, et al. Perspectives of patients about immediate access to test results through an online patient portal. *JAMA Netw Open*. 2023;6(3):e233572. https://doi.org/10.1001/jamanetworkopen.2023.3572. e72.
27. Vo V, Chen G, Aquino YSJ, Carter SM, Do QN, Woode ME. Multi-stakeholder preferences for the use of artificial intelligence in healthcare: a systematic review and thematic analysis. *Soc Sci Med*. 2023;338:116357. https://doi.org/10.1016/j.socscimed.2023.116357.
28. Richardson JP, Smith C, Curtis S, Watson S, Zhu X, Barry B, et al. Patient apprehensions about the use of artificial intelligence in healthcare. *npj Digit Med*. 2021;4(1). https://doi.org/10.1038/s41746-021-00509-1.
29. Reddy S, Allan S, Coghlan S, Cooper P. A governance model for the application of AI in health care. *J Am Med Inform Assoc*. 2020;27(3):491–497. https://doi.org/10.1093/jamia/ocz192.
30. Erul E, Aktekin Y, Danışman FB, Gümüştaş Ş, Aktekin A, Yekedüz BS, et al. Perceptions, attitudes, and concerns on artificial intelligence applications in patients with cancer. *Cancer Control*. 2025;32. https://doi.org/10.1177/10732748251343245, 1073274825134
3245.
31. Rosenstock IM, Strecher VJ, Becker MH. Social learning theory and the Health Belief Model. *Health Educ Q*. 1988;15(2):175–183. https://doi.org/10.1177/109019818801500203.
32. Rojahn J, Palu A, Skiena S, Jones JJ. American public opinion on artificial intelligence in healthcare. *PLoS One*. 2023;18(11):e0294028. https://doi.org/10.1371/journal.pone.0294028.
33. Lennartz S, Dratsch T, Zopfs D, Persigehl T, Maintz D, Große Hokamp N, et al. Use and control of artificial intelligence in patients across the medical workflow: Single-Center questionnaire study of patient perspectives. *J Med Internet Res*. 2021;23(2):e24221. https://doi.org/10.2196/24221.
34. Kelly BS, Kirwan A, Quinn MS, Kelly AM, Mathur P, Lawlor A, et al. The ethical matrix as a method for involving people living with disease and the wider public (PPI) in near-term artificial intelligence research. *Radiography*. 2023;29(Suppl 1):S103. https://doi.org/10.1016/j.radi.2023.03.009. s11.
35. Elhaddad M, Hamam S. AI-Driven clinical decision support systems: an ongoing pursuit of potential. *Cureus*. 2024;16(4):e57728. https://doi.org/10.7759/cureus.57728.
36. LaRosa E, Danks D. Impacts on trust of healthcare AI. In: *Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society*. New York: AIES '18; 2018.