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Exploring the impact of patients' risk-benefit and knowledge perceptions on trust and intention to use AI-based medical imaging tools in radiology

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ABSTRACT

The integration of artificial intelligence (AI) with medical imaging tools has enabled faster and more accurate diagnostic processes, transforming radiology into a more precise, efficient, and data-driven medical discipline. However, the successful implementation of AI-based medical imaging tools in emotionally sensitive, life-critical domains such as radiology depends heavily on public trust and acceptance. This study examines how value perceptions and trust shape behavioral intentions to adopt AI-based tools in radiology by extending Esmaeilzadeh's Value-Based Model, which is conceptually aligned with Privacy Calculus Theory. To enhance the model's explanatory power, additional variables were incorporated, including perceived knowledge as a predictor and trust as a mediating factor.

A cross-sectional online survey (N = 961) was conducted, and data was analyzed through structural equation modeling. The findings indicate that perceived risk, perceived benefit, and perceived knowledge significantly influence trust perception. Importantly, trust served as a key mediating variable, partially mediating the effects of these factors on the intention to use AI-based medical imaging tools. The inclusion of trust increased the model's explanatory power from $R^2 = 0.68$ to $R^2 = 0.74$. Multigroup analysis based on gender, age, and education level revealed significant differences in certain pathways; however, the effect sizes were small. These findings highlight the importance of developing inclusive and targeted strategies that address both technical and emotional concerns, enhance perceived benefits, foster public trust, and strengthen the intention to use AI-based tools in radiology.

1. Introduction

Human intelligence is broadly defined as the ability to mentally represent information, reason, learn, solve problems, and adapt across diverse contexts (Haier et al., 2023; Mackintosh, 2011). In contrast, artificial intelligence (AI) broadly refers to machine-based, logical, and data-driven systems that are designed to mimic aspects of human intelligence by following predefined rules to solve specialized tasks (Collins et al., 2021; Korteling et al., 2021). While effective in narrow domains, this specificity limits AI's ability to reflect key features of human intelligence, such as lack of generalizable reasoning (Helm et al., 2020). Recent research proposed a unified definition of intelligence as "the ability to achieve complex goals" bridging both biological and artificial systems (Legg & Hutter, 2007). This perspective suggests that AI's strengths, such as consistency, speed, and large-scale data processing, should be developed to complement and compensate for human cognitive limitations, including restricted working memory, slower processing speed, limited attention, and susceptibility to bias, rather than replicating or replacing human intelligence (Korteling et al., 2021).

Additionally, advances in generative AI, including generative adversarial networks, diffusion models, variational autoencoders, and large language models, have expanded opportunities for innovation in medical imaging by learning complex patterns and generating new data that enhance diagnostic performance (Jung et al., 2024; Kim et al., 2024). These developments have further improved diagnostic accuracy, efficiency, and workflow performance within medical imaging (Bera et al., 2022; Bi et al., 2019; Lång et al., 2023; Portik et al., 2024; Sahiner et al., 2019; van Leeuwen et al., 2022).

Despite these benefits, public skepticism toward AI-based medical

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imaging tools can hinder adoption, delay diagnoses, and exacerbate health disparities. Concerns often stem from uncertainty about how AI systems generate outputs, leading to questions about accuracy, fairness, privacy, accountability, and the extent of human oversight that highlight the essential need for trust between users and AI systems (Baghdadi et al., 2024; Richardson et al., 2021).

While public perception and confidence remain decisive for the successful clinical implementation of AI, users' general familiarity and understanding of AI-based medical imaging tools play a crucial role in shaping their perceptions of risk, benefit, and trust, which, in turn, influence their intention to adopt such technologies (Esmaeilzadeh, 2020; Huo et al., 2022; Odle, 2020; Yakar et al., 2022). Achieving effective integration of AI into medical imaging, therefore, requires a clear understanding of patients' attitudes and perceptions toward these tools (Hua et al., 2024; Romero-Brufau et al., 2020; Zhang et al., 2021). If users perceive AI-based tools as unreliable or impersonal, they may be reluctant to engage with them, leaving much of their potential unrealized (Beets et al., 2023). Despite growing interest in public attitudes toward healthcare AI, radiology continues to lack empirically grounded, value-based, and trust-centered models capable of explaining how the public evaluates AI-based imaging technologies (Hemphill et al., 2023). Moreover, few empirical studies investigate patients' perceptions of risk and benefit within the radiology context or examine how these perceptions, together with AI literacy, shape trust and intention to adopt AI-based medical imaging tools. This gap limits current understanding of the factors that influence public acceptance of AI-based tools in radiology.

To address this gap, the present study extends Esmaeilzadeh's (2020) VBM of risk and benefit, which is conceptually aligned with privacy calculus theory (Dinev & Hart, 2006). First, we adapted this model to the radiology context, where diagnostic autonomy and the emotional sensitivity of context introduce unique contextual considerations. Second, we designed our study to include user's AI knowledge and trust perception as additional constructions particularly relevant to AI-based medical imaging adoption. This study contributes to research and practice by clarifying how users' perceptions of risk and benefit are formed within the context of radiology, and how these perceptions together with AI knowledge influence trust and adoption intentions for AI-based medical imaging tools. In addition, the findings offer insights that may support efforts to enhance user trust and inform the responsible implementation of AI-enabled imaging technologies. Furthermore, recognizing that demographic characteristics often moderate technology acceptance relationships, we explored whether these structural paths differ across gender, age, education, and employment status (Esmaeilzadeh, 2020; Gursoy et al., 2019), using multigroup analysis. To ensure generalizability and analytical robustness, we surveyed members of the public ($N = 961$), and estimated the model using SEM with 5000 bootstrap resamples for indirect effects and measurement-invariance checks (Almaiah et al., 2023; Liu & Tao, 2022; Park et al., 2019; Sun & Medaglia, 2019).

2. Theoretical background

This study draws on established theories of technology adoption and decision-making to examine individuals' acceptance of AI-based medical imaging tools in radiology. Prior research has proposed multiple theoretical perspectives to explain how attitudes and behavioral intentions toward new technologies are formed (Ajzen, 1991; Davis, 1989; Venkatesh et al., 2003).

In high-risk healthcare contexts characterized by uncertainty, ethical concerns, and data sensitivity, adoption decisions are more accurately explained through value-based cognitive evaluations in which perceived benefits are weighed against perceived risks (Lee et al., 2025; Sohn & Kwon, 2020). In such settings, value-based perspectives conceptualize adoption as the outcome of risk–benefit evaluations and therefore provide a more suitable lens for understanding AI acceptance in sensitive clinical domains (Esmaeilzadeh, 2020; Kim et al., 2007). The Privacy Calculus framework similarly emphasizes trade-offs between perceived benefits and potential harms in data-intensive environments (Dinev & Hart, 2006). Building on these perspectives, this study adopts the Value-Based Model (VBM) as its primary theoretical framework for explaining individuals' acceptance of AI-based medical imaging tools in radiology.

2.1. AI in healthcare and radiology

AI has demonstrated significant value in healthcare by enhancing diagnostic precision, information processing, and clinical decision-making (Dreyer & Allen, 2018; Sunarti et al., 2021). Radiology is particularly well suited for AI advancement due to its high volume of digital imaging data and the demand for efficient diagnostic and prognostic workflows (Aerts, 2018; Jiang et al., 2025; Najjar, 2023). Moreover, radiology represents an emotionally sensitive clinical domain in which diagnostic autonomy and imaging-based judgments play a central role in guiding critical medical decisions. These characteristics position radiology as a highly impactful and consequential context for AI integration (Bergquist et al., 2024; Pesapane et al., 2024). AI in radiology can independently analyze complex imaging data, enabling automated diagnostic support with minimal human input (Bi et al., 2019; Najjar, 2023). At the same time, medical imaging supports critical clinical decisions across disciplines, from diagnosis to treatment planning (Bergquist et al., 2024; Odle, 2020) and often involves emotionally charged scenarios, such as cancer screening, where human empathetic communication is vital (Bergquist et al., 2024; Pesapane et al., 2023). These contextual features suggest that perceptions of AI may develop differently in radiology than in less sensitive or lower-risk healthcare settings.

Accordingly, AI has been widely applied across radiological imaging modalities, including mammography, CT, and MRI, for lesion detection, segmentation, reconstruction, and report generation (Kim et al., 2024; Topol, 2019; van Leeuwen et al., 2022). Examples include breast-cancer detection in screening (Anaby et al., 2023), lung cancer detection (Ardila et al., 2019), imaging workflow optimization (van Leeuwen et al., 2022), and tumor segmentation and response assessment (Kim et al., 2024). Beyond traditional discriminative models, generative AI can synthesize missing MRI sequences (Zhong & Xie, 2024), enhance image quality, and produce privacy-preserving synthetic data that strengthens downstream detection and segmentation across modalities (Jung et al., 2024; Kim et al., 2024).

Given radiology's central role in early disease detection and treatment planning, the reliability of AI-based imaging tools is critical for healthcare delivery (Odle, 2020; Pesapane et al., 2024). As Bergquist (2024) notes, building stakeholder confidence is essential for the ethical and equitable use of AI in these high-stakes settings. Understanding how the public interprets their value becomes increasingly important. For instance, AI may help detect early signs of breast cancer during mammography, yet patients may still seek human confirmation due to uncertainty about the system's accuracy or decision process (van Leeuwen et al., 2022). Together, these characteristics make radiology a context in which value-based evaluations of benefits and risks, as well as trust formation, are particularly salient.

2.2. Technology acceptance models

To better understand the determinants of AI acceptance, prior research has applied various technology adoption models in healthcare contexts, including the Robot Acceptance Model for Care (RAM-care) (Turja et al., 2020), TAM (Liu & Tao, 2022), the Theory of Reasoned Action (TRA) (Dwivedi et al., 2019), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Kwak et al., 2022). These models have contributed valuable insights into how attitudes and intentions toward new technologies are formed. However, empirical evidence suggests that such models offer limited explanatory power in high-risk healthcare settings, where ethical concerns, uncertainty, perceived risk, and trust play a more central role in shaping adoption decisions (Lee et al., 2025; Sohn & Kwon, 2020). While TAM and related theories are grounded in a strong tradition of psychological research and provide parsimonious, testable causal structures (Ajzen, 1991), recent studies emphasize the need to extend these models by incorporating additional factors such as trust, training, clinical relevance, and value-based considerations to better capture the complexities of AI adoption in healthcare (Gursoy et al., 2019; Lambert et al., 2023; Ratta et al., 2025). Consequently, while technology acceptance models inform the broader adoption literature, they do not fully capture the value-based and trust-centered mechanisms relevant to AI-based medical imaging in radiology and therefore serve as conceptual background rather than the primary framework of the present study.

2.3. Privacy calculus theory (PCT)

The PCT explains technology-related decision-making as a comparison between perceived benefits and perceived risks, particularly those related to data privacy and potential misuse (Dinev & Hart, 2006), according to this perspective, individuals are more likely to engage with a system when they believe that its benefits outweigh its potential harms. This logic has been empirically supported across various digital and data-intensive contexts. In data-intensive and privacy-sensitive domains, prior research shows that perceived benefits and privacy risks shape trust and individuals' willingness to engage with intelligent systems. For example, Kim et al. (2019) extended this framework to the Internet of Things (IoT) domain, showing that perceived benefits and perceived risks affect users' trust and willingness to engage with intelligent systems. Similarly, Jozani et al. (2020) found that both institutional privacy risks and perceived social benefits influenced trust and engagement in social media–enabled apps. Together, these findings underscore the relevance of risk–benefit trade-offs in data-sensitive environments, including AI-based medical imaging.

2.4. Value-based model and core constructs

The Value-Based Model (VBM) conceptualizes technology adoption as the outcome of individuals' evaluations of perceived benefits relative to perceived risks, which together form the central mechanism driving perceived value (Kim et al., 2007). Within this framework, adoption decisions arise from a cognitive appraisal process in which expected gains are weighed against potential negative consequences. Prior research has demonstrated the applicability of this value-based logic in healthcare contexts, where decision-making is often characterized by uncertainty and potentially severe outcomes (Esmaeilzadeh, 2020).

In the context of AI-based medical imaging in radiology, Perceived risk is defined as individuals' assessment of the potential negative outcomes, the possibility of unexpected problems, and the uncertainty associated with the use of AI-based tools (Melazzini et al., 2025). Perceived benefit refers to the clinical and operational advantages of AI-based medical imaging tools, including enhanced diagnostic accuracy, support for care planning and treatment decisions, improved healthcare outcomes, greater efficiency, cost reduction, and improved transparency and interpretability of medical imaging data (Esmaeilzadeh, 2020; Shevtsova et al., 2024). Together, perceived risk and perceived benefit constitute the core components of value appraisal within the VBM.

In high-stakes clinical domains such as radiology, value appraisals are closely linked to trust, which plays a central role in translating value perceptions into behavioral intention toward AI-based tools (Bergquist et al., 2024; Reddy et al., 2020). Moreover, individuals' knowledge of AI-based medical imaging tools influences how risks and benefits are interpreted and evaluated, thereby shaping the value appraisal process itself (Longoni et al., 2019; Shevtsova et al., 2024).

Knowledge of AI-based medical imaging tools is defined as general AI literacy, encompassing individuals' awareness and self-assessed understanding of AI concepts, diagnostic applications in radiology, and the potential benefits and limitations of these tools. Rather than representing an evaluative judgment, knowledge shapes how value-related information is interpreted in the adoption process (Afroogh et al., 2024; Longoni et al., 2019; Shevtsova et al., 2024). Trust refers to individuals' confidence in the accuracy, reliability, and suitability of AI-based medical imaging tools and functions as a key mediating mechanism through which value perceptions are translated into behavioral intention (Reddy et al., 2020; Shevtsova et al., 2024). Together, these constructs form a coherent, theory-driven framework in which value appraisal constitutes the central decision mechanism, knowledge shapes evaluative interpretations, and trust links value perceptions to individuals' behavioral intentions toward AI-based medical imaging tools in radiology.

3. Hypothesis development

This section outlines the hypothesized relationships among key variables, grounded in PCT, which holds that individuals weigh perceived risks against benefits when deciding to engage with a technology (Dinev & Hart, 2006). In the context of healthcare, and radiology in particular, this evaluative process interacts with users' knowledge of AI and leads to trust, which subsequently shapes their behavioral intention to adopt AI-based tools (Esmaeilzadeh, 2020; Longoni et al., 2019; Shevtsova et al., 2024). The emotionally sensitive nature of radiology, where diagnostic decisions often carry substantial psychological and clinical implications, may influence individuals' interpretation of the risks and benefits of AI-based tools in radiology in different ways.

Accordingly, this study's conceptual framework integrates users' knowledge of AI, perceived risk, and perceived benefit to examine how these perceptions are formed within the radiological context and how they influence individuals' behavioral intention to use AI-based medical imaging tools, with trust serving as a mediating variable. An overview of the proposed relationships is presented in Fig. 1.

3.1. Perceived risk

Prior studies identify numerous concerns associated with AI-based diagnostic tools, including issues related to accuracy, fairness, bias, safety, and loss of human oversight (Esmaeilzadeh, 2020; Melazzini et al., 2025; Schwesig et al., 2023; von Eschenbach, 2021). While these specific concerns provide important contextual grounding, the present study conceptualizes perceived risk more broadly as individuals' overall assessment of the severity of potential negative outcomes, the likelihood of adverse consequences, the possibility of unexpected problems, and the degree of uncertainty arising from the use of AI-based medical imaging tools. For instance, patients may fear that AI might miss subtle malignant findings, misclassify benign lesions as suspicious, or process sensitive imaging data in ways that compromise confidentiality. Such concerns are especially salient in emotionally charged diagnostic contexts, such as cancer screening, where erroneous or opaque decisions can have profound psychological and clinical consequences (Bergquist et al., 2024; Pesapane et al., 2024).

Consistent with the VBM and conceptually aligned with the risk–benefit logic described in PCT, perceived risk decreases perceived value and weakens trust in technology. Empirical evidence in healthcare and radiology indicates that elevated risk perceptions are associated with lower trust and diminished intention to adopt AI systems (Esmaeilzadeh, 2020; Hemphill et al., 2023). Accordingly, perceived risk is expected to exert a negative effect on both trust and behavioral intention regarding the use of AI-based medical imaging tools. Thus, the following hypotheses are proposed:

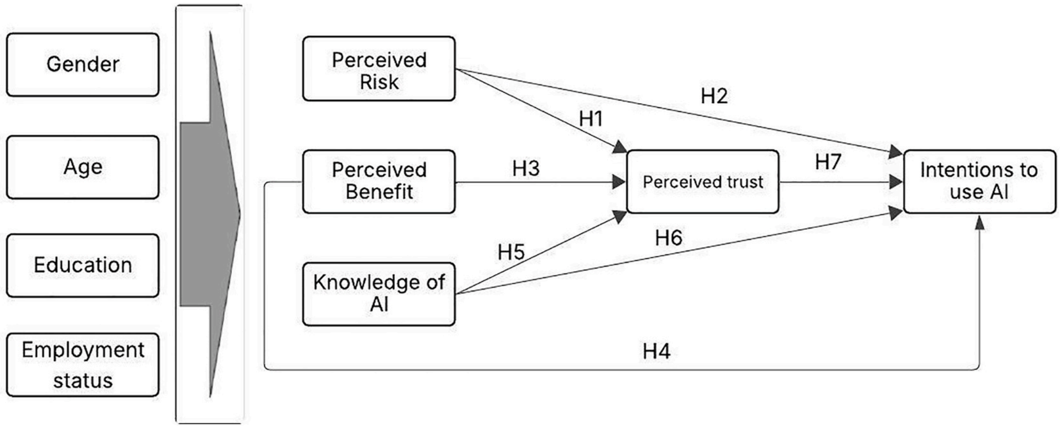

Fig. 1. Proposed conceptual framework illustrating hypothesized relationships among perceived knowledge, risk, benefit, trust, and behavioral intention in AI-based medical imaging. Demographic factors (gender, age, education, and employment status) are included as control variables.

H1. Perceived risk is negatively associated with perceived trust in AI-based medical imaging tools.

H2. Perceived risk is negatively associated with intention to use AI-based medical imaging tools.

3.2. Perceived benefit

In radiology, perceived benefit reflects users' beliefs about the clinical and operational value of AI-based medical imaging tools. This includes improved diagnostic accuracy, more reliable treatment recommendations, enhanced early disease detection, better healthcare outcomes, increased transparency, and potential cost reductions (Esmaeilzadeh, 2020; Kim et al., 2024; Shevtsova et al., 2024; van Leeuwen et al., 2022). For example, patients may feel reassured when AI is perceived as providing an additional "second reader" in mammography, increasing the likelihood of early cancer detection and reducing missed lesions. These dimensions align with our measurement, which captures perceived improvements in care planning, diagnostic and predictive performance, outcome quality, cost efficiency, and interpretability.

Consistent with the VBM and conceptually aligned with PCT, salient benefits enhance the perceived value of AI-based tools, strengthen trust, and may offset perceived risks, thereby increasing the intention to use AI-based tools (Dinev & Hart, 2006; Esmaeilzadeh, 2020). In emotionally sensitive contexts, such as radiology, visible clinical gains such as reduced waiting times for results or more confident diagnoses are particularly influential in shaping users' trust and adoption intentions (Pesapane et al., 2024; Shevtsova et al., 2024). Therefore, we propose the following hypotheses:

H3. Perceived benefit is positively associated with perceived trust in AI-based medical imaging tools.

H4. Perceived benefit is positively associated with intention to use AI-based medical imaging tools.

3.3. Knowledge of AI-based medical imaging tools

This study defines knowledge of AI-based medical imaging tools as individuals' awareness and conceptual understanding of how AI operates, its diagnostic applications, and its benefits and limitations (Longoni et al., 2019; Shevtsova et al., 2024). This conceptualization aligns with established frameworks of AI literacy, which describe foundational knowledge as familiarity with AI principles, capabilities, constraints, and implications for decision-making, without requiring technical insight into internal algorithmic processes (Ng et al., 2021). Accordingly, some knowledge items are designed to capture cognitive understanding rather than value-based appraisal. In contrast to perceived risk and perceived benefit, which assess individuals' subjective evaluations of potential harm and utility, the knowledge construct reflects respondents' self-assessed familiarity with AI capabilities and constraints. This distinction aligns with AI literacy frameworks that treat awareness of benefits and limitations as foundational knowledge rather than as evaluative perceptions.

Prior research indicates that limited user understanding of AI-based medical imaging tools can act as a barrier to trust in healthcare settings (Bergquist et al., 2024). Such limitations in understanding may contribute to a misalignment between how AI systems are intended to be used in clinical practice and how users perceive and interpret their role in diagnostic decision-making. Conversely, greater general knowledge of AI can reduce uncertainty and support more informed evaluations of AI-based medical imaging tools, thereby strengthening trust and willingness to adopt such technologies in radiology, particularly when users understand AI as a clinically validated support tool rather than a replacement for human radiologists (Dhagarra et al., 2020; Ongena et al., 2020; Shevtsova et al., 2024). This clearer understanding of how AI tools are intended to be used may also reduce perceived uncertainty and support more balanced interpretations of AI's advantages and limitations (Afroogh et al., 2024; Xu & Shuttleworth, 2024).

Although PCT focuses on risk–benefit evaluation, knowledge can function as an enabling factor by shaping how individuals perceive and interpret these risks and benefits. By clarifying the purpose, capabilities, and limitations of AI-based medical imaging tools, greater knowledge is expected to promote trust and strengthen individuals' intention to adopt such technologies. Therefore, we hypothesize the following:

H5. Knowledge of AI is positively associated with perceived trust in AI-based medical imaging tools.

H6. Knowledge of AI is positively associated with intention to use AI-based medical imaging tools.

3.4. Perceived trust

Trust has been identified as an important factor influencing individuals' willingness to use AI-based tools in healthcare, particularly when they evaluate the risks, benefits, and understandability of such systems (Huo et al., 2022; Liu & Tao, 2022). In radiology, where diagnostic decisions carry substantial emotional and clinical consequences and patients often have limited direct interaction with radiologists, trust becomes a decisive determinant of whether clinicians and patients are willing to rely on AI-assisted imaging (Bergquist et al., 2024; Pesapane et al., 2024). Prior research indicates that trust is shaped by users' perceptions of AI systems' accuracy, consistency, and alignment with clinical reasoning, and that trust declines when systems are perceived as unreliable or unpredictable (Richardson et al., 2021; Xu & Shuttleworth, 2024). More broadly, trust judgments in radiology are influenced by how individuals evaluate the potential risks, benefits, and limitations of AI-based imaging tools, which collectively shape their acceptance of AI-supported diagnostic technologies (Shevtsova et al., 2024).

Despite the growing recognition of trust as a central component in AI acceptance, its mediating role in linking perceived risk, perceived benefit, and knowledge to behavioral intention remains underexplored in the radiology domain. Therefore, the following hypothesis is proposed:

H7. Perceived trust is positively associated with intention to use AI-based medical imaging tools.

4. Methods

4.1. Study sample

Participants aged 18 years or older were eligible for this study. Participants' attention was assessed using instructed response and nonsense items (Gummer et al., 2021; Meade & Craig, 2012). Participants who failed these checks were excluded. According to participants' answers to attention check items, and excluding any failed or incomplete responses, 39 participants were excluded. CloudResearch reports a typical rejection rate of 1 %–5 % for online surveys on their platform. In our study, 39 out of 1000 participants were rejected (3.9 %), which falls within this range (Litman & Robinson, 2020).This study was reviewed and approved by the Research Ethics Committee at the Western Norway University of Applied Sciences on 10 January 2025. All participants provided informed consent prior to participation.

4.2. Instruments

The questionnaire used in this study consisted of two main sections. The first section included questions about demographic information, such as age, gender, education, and employment status. The second section covered five constructs related to the study variables: perceived risk (5 items), perceived benefit (7 items), perceived trust (5 items), and intention to use AI-based medical imaging tools (5 items), all adapted from Esmaeilzadeh's (2020) study, tshe perceived knowledge construct (5 items) was adapted from the studies by Ongena et al. (2020) and Sur et al. (2020). All items were measured using a 6-point Likert scale ranging from 1 to 6. A complete list of questionnaire items is available in Appendix A.

All items were adapted to explicitly reference AI-based medical imaging tools to enhance clarity and relevance for participants. In the perceived risk and perceived benefit sections, we included information about AI-based medical imaging tools in the questions to increase their relevance and comprehensibility for participants. In the intention of using section, we identified clinicians as the main users of AI-based medical imaging tools in radiology. We assessed users' intentions to use these tools based on their willingness to give clinicians permission to image them. Additionally, our knowledge items were modified to include a broader scope of AI-based medical imaging applications and to assess both technical comprehension of AI concepts and the understanding of the risks and benefits of AI in medical imaging.

4.3. Procedures

4.3.1. Preliminary evaluation of study materials

Before conducting the main study, we performed a preliminary evaluation to validate the suitability of the questionnaire for AI-based medical imaging tools. Feedback was obtained from six lecturers and researchers in the Radiography Department at the Western Norway University of Applied Sciences. This step ensured that the questionnaire items were clear, relevant, and appropriate, accurately capturing the required data for medical imaging tools within a radiology setting.

4.4. Pilot test

A pilot study involving 50 participants was conducted using the CloudResearch Connect platform to test the feasibility and effectiveness of the research methodology and data collection procedures. Based on this, we refined the terminology and resolved technical issues to make the questions more accessible to the public (Tsang et al., 2017). The CloudResearch Connect platform is a web-based tool that offers efficient access to a large, diverse participant pool and supports the collection of high-quality data (Center, 2024; Hartman et al., 2023).

4.5. Data analysis

Our sample size was informed by the maximum necessary sample for the different paths in the mediation analyses, based on simulation-based power analyses using the semPower package (Moshagen & Bader, 2024). We anticipated the planned minimum number of indicator/manifest variables per latent variable ($i = 5$), high power of 99 %, and a low alpha level ($\alpha = 0.01$). We chose conservative loadings on each latent factor (0.7), which were lower than those reported in the original article (>0.8) (Esmaeilzadeh, 2020). The estimates for the slopes/effects were set to be all equal at a relatively low $\beta = 0.2$. The resulting minimum sample size for the model structure was $N = 867$. To enhance the strength, robustness, and generalizability of the findings, and to allow for potential exclusions or data loss, we sampled a total of $N = 1000$ participants.

We examined the normality of every construct within the model by checking its skewness and kurtosis values, ensuring they were within ± 2 for skewness and ± 7 for kurtosis (Kline, 2023). Multicollinearity was assessed by checking the Variance Inflation Factor (VIF) and tolerance values, where VIF values less than 5 and tolerance values greater than 0.1 were used as proxies for the absence of severe multicollinearity (Hair et al., 2019).

Confirmatory Factor Analysis (CFA) was conducted to assess the measurement model, evaluating internal consistency, convergent validity, and discriminant validity. Cronbach's alpha and Composite Reliability (CR) were used to assess internal consistency, with values above 0.70 considered acceptable for reliability. For convergent validity, constructs were considered valid if their factor loadings were above 0.70 and the Average Variance Extracted (AVE) was greater than 0.50, confirming that the indicators effectively represented their respective constructs (Fornell & Larcker, 1981). Discriminant validity was evaluated by ensuring that the square root of the AVE for each construct was greater than 0.7 and larger than its correlations with other constructs (Cheung & Wang, 2017).

We examined the standardized path coefficients (β) for all seven hypothesized paths to evaluate the significance of the associations between latent variables, as well as the mediating effect of trust on the intention to use AI-based medical imaging tools. This analysis was performed using 5000 bootstrap resamples, and 95 % confidence intervals (CIs) were derived from unstandardized bootstrap estimates. Additionally, the coefficient of determination (R^2) was calculated for the endogenous variables to assess the proportion of variance explained by the exogenous variables. This analysis was conducted in Jamovi using the *lavaan* package (Rosseel, 2012), providing insight into the predictive power and significance of the structural model. Furthermore, a multigroup analysis was conducted to examine whether relationships between constructs varied based on demographic variables such as sex, age, education, and employment status (Gursoy et al., 2019; Hair et al., 2019).

5. Results

After exclusions, we obtained a sample of N = 961 see Table 1 for detailed descriptive statistics). Approximately 29.1 %% of the participants were in the 30–39 age group, and 26.3 % were in the 40–49 age group. About 44.24%had a bachelor's degree. Most participants were employed-full time (67.2 %) of whom (38.1 %) were male and (29.1 %) were female.

All VIF values ranged from 1.29 to 3.84, which were within acceptable limits (<5). Similarly, all tolerance values ranged from 0.261 to 0.858, clearly above the recommended minimum threshold of 0.10. Collectively, these results indicate that multicollinearity was not a concern in the analysis (Hair et al., 2011). Additionally, we evaluated the data for normality. The skewness values varied between −0.356 and 0.387, and the kurtosis values ranged from −0.967 to −0.107. These figures fall well within the acceptable thresholds of ±2 for skewness and ±7 for kurtosis (Kline, 2023). While formal normality tests (Shapiro-Wilk, Kolmogorov-Smirnov, and Anderson-Darling) were all statistically significant ($p < .001$) (Razali & Wah, 2011). Visual inspections of histograms and Q-Q plots further confirmed that, while not perfectly normal, the distributions were approximately normal, with only minor tail deviations. Overall, the combined evidence from both the statistical and visual assessments indicated that the distributions, despite minor deviations in some constructs like intention and knowledge, are reasonably close to normal. See Appendix B for the detailed results.

5.1. Measurement model assessment

Table 2 (Correlation Matrix) and 3 (Convergent Validity) summarize the mean values, standard deviations (SD), z-values, factor loadings, composite reliability (CR), average variance extracted (AVE), Cronbach's alpha values, and square roots of AVE. Factor loadings were generally high (above 0.80), with the exception of two items (KN_2 in the knowledge construct and PB_6 in the perceived benefit construct), which exhibited slightly lower loadings (0.64 and 0.595, respectively) but remained acceptable given the strong CR and AVE values of their respective constructs. All CR values (0.87–0.96) and AVE values (0.62–0.83) exceeded recommended thresholds, indicating strong convergent validity. Cronbach's alpha values (>0.86) demonstrated excellent internal consistency reliability. Discriminant validity was supported, as the square root of AVE for each construct (0.79–0.91) exceeded its correlations with other constructs. To assess potential construct overlaps, alternative CFA models were estimated in which Knowledge was combined with perceived risk and perceived benefit. Both models showed substantial deterioration in fit (Knowledge–Risk: CFI = 0.51, RMSEA = 0.24; Knowledge–Benefit: CFI = 0.86, RMSEA = 0.14), indicating severe misspecification. In the Knowledge–Risk model, indicators loaded in opposite directions, while in the Knowledge–Benefit model, Knowledge items exhibited substantially weaker loadings than Benefit indicators. Together, these results provide empirical evidence that Knowledge is a distinct construct and should not be collapsed with perceived risk or perceived benefit (see Table 3).

Table 1
Study sample characteristics.

Variable	Categories	N	Percent
Gender	Male	489	50.9 %
	Female	472	49.1 %
Age Group	<20 years	6	0.6 %
	20–29 years	148	15.4 %
	30–39 years	280	29.1 %
	40–49 years	253	26.3 %
	50–59 years	156	16.2 %
	60–69 years	93	9.7 %
	≥70 years	25	%2.6 %
Educational	Less than high school	4	0.4 %
	High school graduate	99	10.3 %
	Some college education	164	17.1 %
	Associate degree (2-year)	105	10.9 %
	Bachelor's degree	425	44.2 %
	Master's degree	128	13.3 %
	Doctorate degree	34	3.5 %
	Other	2	0.2 %
Employment Status	Employed (full-time)	646	67.2 %
	Employed (part-time)	128	13.3 %
	Unemployed	108	11.2 %
	Retired	60	6.2 %
	Student	19	2 %

5.2. Structural model assessment

Model refinement was done by both exploratory and confirmatory factor analyses. The first item (KN_1) in the Knowledge construct was removed due to a low loading, which improved the overall model fit and strengthened the factor structure. Full details of the model diagnostics and adjustments are provided in Appendix C, Supplementary Note, Model Sanity Checks.

We evaluated the structural model fit using multiple indices. The chi-square test ($\chi^2/df = 2.69$, $p < .001$) was within the acceptable range (<3), indicating a reasonable fit. Given the sensitivity of chi-square to large sample sizes, we also examined additional fit indices. According to Byrne (2001), evaluating SEM model fit involves multiple indices to capture different aspects of model performance. In the present study, the RMSEA was 0.06, well below the recommended threshold of 0.08, indicating a good fit. Similarly, the SRMR value of 0.029 was substantially below the accepted cutoff of 0.08. Both the CFI and TLI were 0.999, exceeding the recommended threshold of 0.95, and thus demonstrated excellent incremental fit (Byrne, 2001). As noted by Mulaik et al. (1989), the Parsimony Normed Fit Index (PNFI) accounts for model complexity in evaluating fitness. In the present study, the PNFI value of 0.888 suggests an optimal balance between model fit and parsimony. Taken together, these indices provide strong evidence of an excellent model fit to the data. The structural model analysis confirmed all seven hypothesized relationships, providing strong empirical support for the proposed framework. Specifically, the model supported the direct effects of risk, benefit, and knowledge on intention, as well as the significant mediating role of trust on the intention to use AI-based medical imaging tools. Our results support all proposed hypotheses. Perceived risk had a significant negative effect on both trust ($\beta = -0.25$, $p < 0.001$; H1) and the intention to use AI-based medical imaging tools ($\beta = -0.13$, $p < 0.001$; H2). Perceived benefit positively influenced trust ($\beta = 0.64$, $p < 0.001$; H3) and intention to use ($\beta = 0.28$, $p < 0.001$; H4). Knowledge also showed a positive impact on trust ($\beta = 0.17$, $p < 0.001$; H5) and intention ($\beta = 0.10$, $p < 0.001$; H6). Finally, trust significantly and positively influenced the intention to use AI-based medical imaging tools ($\beta = 0.49$, $p < 0.001$; H7). These findings align with the proposed structural relationships, indicating that perceived risk, benefit, and knowledge collectively explain 73.9 % of the variance in trust and 68 % of the variance in individuals' intention to use AI-based medical imaging tools, demonstrating the strong explanatory power of the model. The results of the structural model and hypothesis testing are summarized in Table 4 and illustrated in Fig. 2.

5.3. Mediation effect of trust

The mediation analysis revealed that trust partially mediates the relationships between behavioral intention and the constructs of risk, benefit, and knowledge. According to Nitzl et al.'s (2016) mediation framework, trust partially mediates the relationship between perceived risk and intention, indicating that while risk directly influences intention, part of its effect operates through trust. Similarly, trust partially mediates the relationships between perceived benefit and intention, as well as knowledge and intention, highlighting its pivotal role in shaping individuals' decisions to adopt AI-based medical imaging tools. By

Table 2
Correlation Matrix and square roots of average variance extracted (diagonal values).

Spearman's correlation	Mean	SD	Risk	Benefit	Knowledge	Trust	Intention
Risk	3.59	1.15	**0.89**				
Benefit	3.97	1.04	−0.458	**0.83**			
Knowledge	2.70	1.12	−0.072	0.349	**0.79**		
Trust	3.33	1.20	−0.536	0.808	0.417	**0.91**	
Intention	3.21	1.40	−0.536	0.785	0.418	0.837	**0.91**

Table 3
Convergent validity result. Mean, standard deviation (SD), Z-value, p-value, standardized estimate, composite reliability (CR), average variance extracted (AVE), and Cronbach's alpha of the constructs.

Factor	indicators	mean	SD	Z value	P value	Standard. estimate	CR	AVE	Cronbach 's alpha
Risk	pr_1	3.55	1.27	37.1	<0.001	0.918	**0.95**	**0.80**	**0.952**
	pr_2	3.50	1.23	37.4	<0.001	0.923			
	pr_3	3.63	1.27	34.6	<0.001	0.882			
	pr_4	3.49	1.27	37.2	<0.001	0.920			
	pr_5	3.75	1.24	31.1	<0.001	0.826			
Benefit	pb_1	4.04	1.17	34.1	<0.001	0.875	**0.94**	**0.68**	**0.931**
	pb_2	4.22	1.18	31.6	<0.001	0.835			
	pb_3	3.95	1.23	30.2	<0.001	0.811			
	pb_4	3.84	1.21	33.4	<0.001	0.864			
	pb_5	3.85	1.21	33.0	<0.001	0.858			
	pb_6	3.85	1.42	19.9	<0.001	0.595			
	pb_7	4.03	1.22	35.7	<0.001	0.900			
Knowledge	kn_2	2.87	1.36	21.1	<0.001	0.640	**0.87**	**0.62**	**0.86**
	kn_3	2.34	1.25	31.2	<0.001	0.850			
	kn_4	2.60	1.34	30.4	<0.001	0.835			
	kn_5	2.99	1.40	28.9	<0.001	0.807			
Trust	pt_1	3.37	1.29	39.0	<0.001	0.942	**0.96**	**0.83**	**0.958**
	pt_2	3.32	1.27	38.0	<0.001	0.929			
	pt_3	3.40	1.28	37.8	<0.001	0.927			
	pt_4	3.33	1.29	37.9	<0.001	0.927			
	pt_5	3.21	1.34	30.6	<0.001	0.815			
Intention	int_1	3.39	1.56	37.0	<0.001	0.916	**0.96**	**0.82**	**0.959**
	int_2	2.98	1.46	37.5	<0.001	0.924			
	int_3	3.16	1.51	39.2	<0.001	0.946			
	int_4	3.22	1.50	32.2	<0.001	0.842			
	int_5	3.32	1.53	36.6	<0.001	0.910			

Table 4
Summary of hypothesis testing results.

Hypothesis	Path	Standardized coefficient	SE	95 % CI	z-value	P value	supported
H1	Risk ⇒ Trust	−0.25	0.02	−0.30 to −0.21	−12.85	<0.001	Yes
H2	Risk ⇒ Intention	−0.13	0.03	−0.21 to −0.10	−6.18	<0.001	Yes
H3	Benefit ⇒ Trust	0.64	0.02	0.68 to 0.79	31.34	<0.001	Yes
H4	Benefit⇒ Intention	0.28	0.04	0.29 to 0.46	9.54	<0.001	Yes
H5	Knowledge ⇒ Trust	0.17	0.02	0.14 to 0.22	9.39	<0.001	Yes
H6	Knowledge ⇒ Intention	0.10	0.02	0.07 to 0.17	5.37	<0.001	Yes
H7	Trust ⇒ Intention	0.49	0.04	0.50 to 0.66	15.26	<0.001	Yes

incorporating trust as a mediator, the model's explanatory power improved significantly, increasing the explained variance in intention from $R^2 = 0.68$ % to $R^2 = 0.74$ %. This increase underscores the critical role of trust in predicting individuals' behavioral intentions to use AI-based medical imaging tools. See Table 5 for details on the mediation effect of trust on intention to use AI-based medical imaging tools.

5.4. Multigroup analysis

5.4.1. Gender

A multigroup SEM analysis was conducted to examine gender differences. The only significant difference was found in the path from benefit to intention ($\Delta\beta = -0.056$, $p = .018$), indicating a slightly stronger relationship for females. All other path differences were not statistically significant ($p > .05$; see Table 6).

5.4.2. Age

Among the tested structural paths based on age, only the path from knowledge to trust showed a significant difference across age groups. Specifically, significant differences were observed between participants aged 20–29 and 30–39 (χ^2 (1) = 7.35, $p = .007$), as well as between those aged 20–29 and 50–59 (χ^2 (1) = 6.57, $p = .010$). No other path differences across age groups reached statistical significance, as shown in Table 7.

5.4.3. Employment status

The multigroup SEM analysis found no statistically significant differences in the structural paths across employment status groups.

5.4.4. Education

A multigroup analysis based on education level revealed significant differences in three hypothesized paths. The effect of risk on intention (H2) differed significantly between high school graduates and those

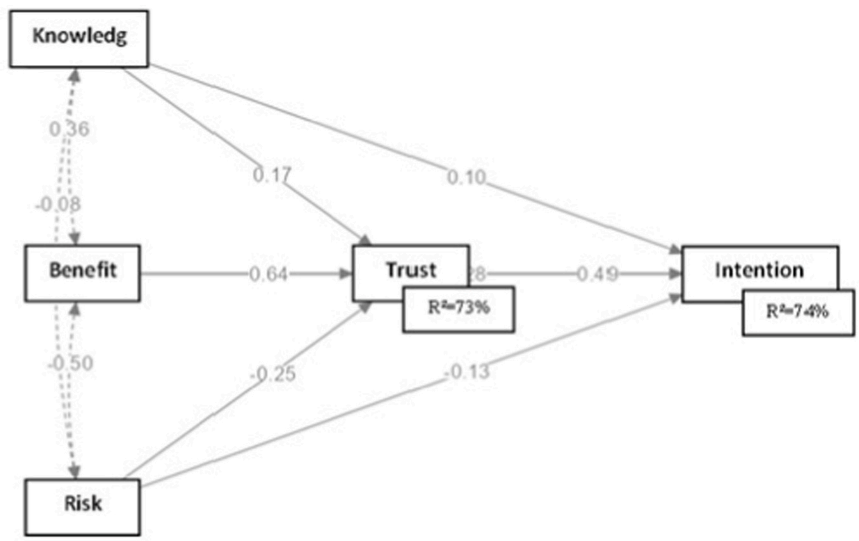

Fig. 2. Results of the structural equation model. Solid arrows represent hypothesized paths, while dashed arrows indicate covariances between predictor variables.

Table 5
Mediation effect of trust.

Direct effect	Path coefficient	P value	Indirect effect	Path coefficient	P value	Mediation effect of trust Result
Risk ⇒ Intention	−0.13	<0.001	Risk ⇒ Trust ⇒ Intention	−0.12	<0.001	Partial mediation
Benefit⇒ Intention	0.28	<0.001	Benefit ⇒ Trust ⇒ Intention	0.32	<0.001	Partial mediation
Knowledge ⇒ Intention	0.1	<0.001	Knowledge ⇒ Trust ⇒ Intention	0.08	<0.001	Partial mediation

Table 6
Multivariate analysis based on gender differences.

Hypothesis	Path	Male β [95 % CI]	Female β [95 % CI]	Male–Female (Δβ)	p-value (Gender difference)
H1	Risk ⇒ Trust	−0.2519[−0.294, −0.216]	−0.2400[−0.294, −0.216]	−0.0119	0.915
H2	Risk ⇒ Intention	−0.1280[−0.199, −0.101]	−0.1201[−0.199, −0.101]	−0.0079	0.886
H3	Benefit ⇒ Trust	0.6306[0.691, 0.784]	0.6529[0.691, 0.784]	−0.0223	0.792
H4	Benefit⇒ Intention	0.2784[0.300, 0.453]	0.2840[0.300, 0.453]	−0.0056	0.018
H5	Knowledge ⇒ Trust	0.1656[0.139, 0.214]	0.1657[0.139, 0.214]	−0.0001	0.667
H6	Knowledge ⇒ Intention	0.0958[0.073, 0.163]	0.0945[0.073, 0.163]	0.0013	0.386
H7	Trust ⇒ Intention	0.4954[0.499, 0.646]	0.4881[0.499, 0.646]	0.0073	0.190

with some college education (χ^2 (1) = 4.18, p = .041). Additionally, the effect of knowledge on intention (H6) showed a significant difference between high school graduates and bachelor's degree holders (χ^2 (1) = 5.88, p = .015). For the path from knowledge to trust (H5), significant differences were found between high school graduates and those with some college education (χ^2 (1) = 7.97, p = .005), as well as between high school graduates and bachelor's degree holders (χ^2 (1) = 7.04, p = .008). As indicated in Table 8, no significant differences were observed across education levels for the remaining hypothesized paths (H1, H3, H4, and H7).

As summarized in Table 9, statistically significant, but small differences were observed across gender, age, and education levels. Specifically, females showed a slightly stronger relationship between perceived benefit and behavioral intention (H4). Age-based differences were evident in the effect of knowledge on trust (H5), suggesting that perceptions of knowledge influence trust differently across age groups. Education level influenced three key paths: risk to intention (H2), knowledge to trust (H5), and knowledge to intention (H6). Participants with higher educational attainment demonstrated stronger associations between knowledge and both trust and intention. In contrast, those with incomplete college education appeared more sensitive to AI-related risk and reported lower trust. No significant differences were found based on employment status, indicating that occupational background had no substantial effect on behavioral intentions in this context.

6. Discussion

In this study, we examined public trust and behavioral intentions toward adopting AI-based medical imaging tools by extending Esmaeilzadeh's VBM (Esmaeilzadeh, 2020) and aligning it with the core principles of the PCT (Dinev & Hart, 2006), to explain technology adoption decisions. In this extended model, perceived knowledge was introduced as an additional determinant, and trust was positioned as a key mediating variable linking perceptions of benefit, risk, and

Table 7
Multivariate analysis based on age differences.

hypotheses	Path	Age Group 1	β [95 % CI]	Age Group 2	β [95 % CI]	Group 1 – Group 2 (Δβ)	p-value
H5	Knowledge ⇒ Trust	20–29	0.159 [0.119, 0.199]	30–39	0.175 [0.134, 0.215]	−0.016	0.007
H5	Knowledge ⇒ Trust	20–29	0.159 [0.119, 0.199]	50–59	0.150 [0.113, 0.187]	0.009	0.01

Table 8
Multivariate analysis based on education.

Hypothesis	Path	Education Group 1	β [95 % CI]	Education Group 2	β [95 % CI]	Group 1 – Group 2 (Δβ)	p-value
H2	Risk—Intention	High school	−0.125(0.1671 to −0.0823)	Some college	−0.131(-0.1731 to −0.0879)	0.006	0.041
H6	Knowledge ⇒ Intention	High school	0.084(0.05–0.1176)	Bachelor	0.106(0.0663–0.1465)	−0.022	0.015
H5	Knowledge ⇒ Trust	High school	0.147(0.1084–0.1854)	Some college	0.136(0.1025–0.1686)	0.011	0.005
H5	Knowledge ⇒ Trust	High school	0.147(0.1084–0.1854)	Bachelor	0.182(0.1424–0.2211)	−0.035	0.008

knowledge to behavioral intention. Consistent with prior research, this model highlights that individuals' evaluations of AI-based medical imaging tools are shaped by their familiarity with the technology, along with AI-specific contextual concerns related to safety and the continued need for human involvement in diagnostic decision-making (Dhagarra et al., 2020; Pesapane et al., 2024; Richardson et al., 2021). Within the extended model, trust emerges as a pivotal mechanism that links users' perceptions of benefit and risk to their behavioral intention to adopt AI-based medical imaging tools (Almaiah et al., 2023; Park et al., 2019; Sarkar et al., 2020).

Applying this framework to radiology a high-stakes clinical domain where diagnostic accuracy and human oversight are particularly salient (Bergquist et al., 2024; Pesapane et al., 2024), allowed us to examine AI-based tools adoption in a context where trust considerations are especially pronounced. Using a large and demographically diverse sample (N = 961), the model explained 74 % of the variance in behavioral intention to adopt AI-based medical imaging tools. These results provide both theoretical and practical insights into how cognitive, effective, and knowledge-based factors jointly shape trust and intention behavior in healthcare AI.

6.1. Principal findings

The results indicate that trust functions as a partial mediator between value perceptions and behavioral intention. Although perceived risk, perceived benefit, and user knowledge directly affected the adoption of AI-based medical imaging tools, the incorporating of trust significantly enhanced the model's explanatory power, increasing R^2 from 0.68 to 0.74. These findings underscore the central role of trust in translating value-based evaluations into intention behavior, consistent with prior research identifying trust as a critical determinant of technology acceptance in healthcare context (Jermutus et al., 2022; Liu & Tao, 2022; Shevtsova et al., 2024; Zhang et al., 2021).

Among the value-related constructions, perceived benefit emerged as the strongest predictor of both trust and behavioral intention. This finding suggests that users are more likely to trust and adopt AI-based medical imaging tools when they perceive clear clinical and operational advantages, such as improved diagnostic accuracy, enhanced care planning, increased efficiency, and better health outcomes. This result aligns with prior studies demonstrating that perceived usefulness and performance-related benefits are primary drivers of AI adoption in medical contexts, particularly in high-stakes domains such as radiology (Esmaeilzadeh, 2020; Jermutus et al., 2022; Liu & Tao, 2022; Tran et al., 2019). The strong effect of perceived benefit indicates that favorable evaluations of AI's practical value play a decisive role in fostering trust and supporting adoption intentions.

Perceived risk demonstrated a significant negative effect on both trust and intention to use AI-based medical imaging tools. This finding is consistent with prior evidence showing that concerns related to safety, reliability, and potential adverse outcomes negatively influence trust and acceptance of AI-based imaging tools in radiology (Hemphill et al., 2023; Lai et al., 2020; Richardson et al., 2021). In the radiology context, where diagnostic decisions can have substantial clinical implications, heightened sensitivity to potential negative outcomes appears to amplify the influence of perceived risk on trust formation and intention behavior. These results reinforce the importance of addressing perceived risks to support public acceptance of AI-based imaging tools.

Knowledge of AI-based medical imaging tools positively influenced

Table 9
Summary of main multigroup SEM outcomes across key demographic subgroups; Effect sizes are reported as Δβ (difference in standardized path coefficients) for significant pairwise group comparisons based on multigroup SEM.

Moderator	Significant Differences	Paths Affected	Effect Size	Interpretation
Gender	Yes	Benefit-intention (H4)	Δβ = −0.0056 (Female vs. Male), p = .018	Females showed slightly higher benefit–intention link.
Age	Yes	Knowledge-Trust (H5)	Δβ = −0.016 (20–29 vs. 30–39), p = .007 Δβ = +0.009 (20–29 vs. 50–59), p = .010	Knowledge perception effect on trust varied across different age groups
Education	Yes	Risk–Intention (H2) Knowledge-Trust (H5) Knowledge–Intention (H6)	Δβ = 0.006 (High School vs. Some College), p = .041 (H2)Δβ = −0.022 (High School vs. Bachelor), p = .015 (H6)Δβ = 0.011 (High School vs. Some College), p = .005 (H5)Δβ = −0.035 (High School vs. Bachelor), p = .008 (H5)	Participants with higher education levels showed stronger trust and intention. Those with incomplete college education were more sensitive to AI-related risk and less trusting.
Employment status	No	None	–	No significant differences were observed across employment status groups.

both trust and behavioral intention, indicating that individuals with greater general AI literacy were more inclined to trust and consider using AI-based medical imaging tools. The observed weak negative covariation between knowledge and perceived risk, alongside a stronger positive covariation with perceived benefit, suggests that knowledge primarily enhances perceptions of the clinical and operational advantages of AI-based medical imaging tools rather than substantially reducing perceived risk. In this respect, knowledge appears to function as an enabling factor that supports benefit-oriented evaluations, which in turn facilitate trust formation and intention behavior. This interpretation is consistent with prior research indicating that general AI literacy promotes more informed evaluations of technology and supports trust and acceptance in healthcare contexts (Dhagarra et al., 2020; Ongena et al., 2020; Shevtsova et al., 2024).

Together, the findings indicate that trust serves as a central mechanism through which value-based evaluations influence behavioral intention to adopt AI-based medical imaging tools. Perceived benefit emerged as the dominant driver of both trust and intention, whereas perceived risk exerted a constraining effect on these relationships. Perceived knowledge, operationalized as general AI literacy, played a supportive role by amplifying benefit-oriented evaluations rather than by substantially attenuating risk perceptions. Collectively, these results underscore the importance of value-based assessments in shaping trust and adoption intentions in the context of healthcare AI.

6.2. Theoretical contributions for medical imaging and AI development

This study advances theoretical understanding of trust and technology adoption by extending Esmaeilzadeh's VBM (2020) in the context of radiology. While conceptually aligned with the risk–benefit logic articulated in PCT (Dinev & Hart, 2006). By integrating perceived knowledge and trust alongside perceived risk and perceived benefit, this study provides a more comprehensive explanation of how individuals evaluate and form adoption intentions toward AI-based medical imaging tools.

This study strengthens and contextualizes the VBM by clarifying the relative roles of perceived benefit and perceived risk in shaping trust and adoption intentions within the radiology context. Consistent with prior research, benefit-oriented evaluations emerge as the dominant drivers of both trust and behavioral intention, whereas perceived risk functions primarily as a constraining influence within the evaluative process rather than as a principal motivator of adoption (Hemphill et al., 2023; Pesapane et al., 2024; Richardson et al., 2021). The findings support and extend prior VBM-based research in healthcare and align with recent empirical evidence demonstrating that benefit perceptions are central to trust formation and acceptance of medical AI systems (Jermutus et al., 2022; Liu & Tao, 2022; Shevtsova et al., 2024). By articulating the differentiated influence of perceived benefit and perceived risk within a unified value-based framework, this study refines theoretical understanding of how value appraisals translate into trust formation and behavioral intention in high-stakes clinical domains such as radiology.

The inclusion of perceived knowledge provides an important theoretical extension to the VBM by positioning general AI literacy as an enabling cognitive mechanism that shapes value perceptions rather than merely attaining perceived risk. This study conceptualizes perceived knowledge as a cognitive resource that shapes how individuals interpret and weigh value-related information when evaluating AI-based medical tools. This reframing refines existing VBM (Esmaeilzadeh, 2020) and PCT (Dinev & Hart, 2006), perspectives by demonstrating that knowledge contributes to behavioral intention predominantly through benefit-oriented evaluations and trust formation, rather than by directly resolving uncertainty or concerns related to AI-associated risks. Consistent with prior research on AI literacy and medical AI acceptance, which emphasizes the role of general understanding in supporting informed evaluation and trust (Charow et al., 2021; Dhagarra et al., 2020; Ongena et al., 2020; Shevtsova et al., 2024). This study advances a theoretical view of perceived knowledge as an integral component of value-based reasoning rather than as a narrowly defined risk-management factor in AI-enabled medical imaging.

Taken together, these contributions advance theory by demonstrating that adoption of AI-based medical imaging tools is best explained through a value-based evaluative process in which perceived benefit, perceived risk, and knowledge jointly shape trust and behavioral intention. By empirically integrating these constructs within the VBM, the study provides a more precise and theoretically grounded explanation of AI adoption in radiology and underscores the importance of trust-centered, value-based frameworks for understanding public acceptance of AI in high-stakes healthcare domains.

6.3. Demographic differences and equity considerations

A multigroup analysis was conducted to examine potential differences in structural path relationships across demographic subgroups gender, age, employment status, and education level to explore whether public perceptions of AI-based medical imaging tools differ across population segments and whether these patterns reflect broader equity concerns related to digital access, literacy, and inclusion.

Gender-based differences were minimal. The only statistically significant difference was observed in the path from perceived benefit to behavioral intention (H4), with a slightly stronger effect among female participants. This may reflect women's more frequent exposure to imaging technologies through routine screenings such as mammography and prenatal ultrasounds, which can foster greater familiarity and positive perceptions of AI in radiology (Kauttonen et al., 2025; Tran et al., 2019). Although the magnitude of the difference was small, it supports prior findings suggesting subtle gender-based variation in health technology adoption (Kelly-Hedrick et al., 2023; Pesapane et al., 2023).

Significant differences were observed in the path from Knowledge to Trust (H5) across age groups. Participants aged 30–39 demonstrated a stronger relationship compared with those aged 20–29 and 50–59. This pattern supports previous evidence that middle-aged adults rely more heavily on knowledge when forming trust, likely due to greater professional experience and balanced exposure to digital systems (Wong et al., 2025). In contrast, older adults may exhibit lower trust because of limited familiarity and heightened safety concerns, while younger adults may lack sufficient experience to translate knowledge into trust. These findings suggest that trust formation depends on both knowledge and lived experience, aligning with recent theoretical developments in the Privacy Calculus framework, which emphasize that individuals' ability to weigh risks and benefits is shaped by their understanding and familiarity with the technology (Dienlin, 2023; Sah & Jun 2024).

Employment status revealed no statistically significant differences across any of the proposed structural relationships. This finding contrasts with the study by Esmaeilzadeh (2020), which reported a significant effect of employment status, particularly noting that individuals with higher educational and professional engagement were more inclined to adopt AI-based tools. One possible explanation for the lack of significant differences in the present study could be the composition of the sample. A substantial majority of participants were either employed full-time (67 %) or part-time (13 %), which may have resulted in limited variability in employment status, thereby reducing the potential to detect meaningful differences.

Education level, however, produced several significant moderating effects, particularly involving perceived risk and knowledge. The risk–intention (H2) and knowledge–trust (H5) paths differed between high school graduates and individuals with some college education. This suggests that those with partial exposure to higher education may have greater awareness of potential risks but insufficient conceptual depth to form robust trust. Additional differences were found between high school graduates and bachelor's degree holders for the knowledge–intention (H6) and knowledge–trust (H5) paths, indicating that higher educational attainment enhances the ability to translate knowledge into trust and intention to use. These findings align with Esmaeilzadeh's

(2020) study, which emphasized the role of education in AI acceptance.

Overall, while the effect sizes were modest, the observed age and education-related patterns reinforce the importance of digital literacy and equitable knowledge dissemination in shaping perceptions of AI-based medical imaging tools. From a theoretical standpoint, they support the Privacy Calculus view that individuals' capacity to evaluate benefits and risks depends on their understanding of technology highlighting potential disparities in trust and adoption that stem from unequal access to knowledge and digital competence.

6.4. Practical implications for medical imaging and AI development

Considering the central role of radiology in clinical care (Odle, 2020), contextual characteristics of this domain such as emotionally sensitive diagnostic settings and the increasing autonomy of AI-based imaging tools may shape how patients interpret the potential risks and benefits of AI differently than in other healthcare contexts (Bergquist et al., 2024; Bi et al., 2019; Pesapane et al., 2024). Within this context, the findings of the present study offer practical guidance for policymakers and clinicians seeking to enhance trust and support the responsible implementation of AI-based medical imaging tools.

First, the finding that perceived benefit was the strongest predictor of both trust and behavioral intention underscores the importance of clearly communicating the tangible clinical and operational advantages of AI-based medical imaging tools. These advantages include improved diagnostic accuracy, earlier disease detection, enhanced care planning, and greater workflow efficiency. Prior research indicates that emphasizing such benefits strengthens trust and acceptance of AI in healthcare settings (Liu & Tao, 2022; Shevtsova et al., 2024). Additionally, gender differences observed in the data suggest that female patients may be more responsive to perceived benefits, possibly due to more frequent encounters with imaging technologies in contexts such as mammography screening (Johansson et al., 2024), and prenatal ultrasounds (Kelly-Hedrick et al., 2023). Acknowledging and integrating women's lived experiences and familiarity with medical imaging into communication strategies could enhance trust and acceptance of AI technologies among patients.

Second, the negative effect of perceived risk on both trust and adoption underscores the importance of proactive risk communication strategies in radiology. Clinicians and healthcare institutions should therefore provide clear and accessible information regarding AI system reliability, validation procedures, the management of potential negative outcomes and unexpected errors, and the continued role of human oversight in diagnostic decision-making. Transparent communication about safeguards and accountability mechanisms may help reduce perceived risk and foster more informed, trust-based engagement with AI-supported imaging tools.

Third, the positive association between knowledge and perceived benefit, together with the positive influence on trust and behavioral intention, suggests that improving public AI literacy represents an important practical lever for enhancing acceptance of AI-based medical imaging tools. These findings indicate that educational initiatives should prioritize clear, nontechnical explanations of AI's clinical purpose, anticipated benefits, and recognized limitations. Consistent with prior research, clinician-mediated explanations and public-facing educational efforts delivered through trusted healthcare channels appear particularly effective in supporting informed evaluation and fostering trust in medical AI systems (Dhagarra et al., 2020; Ongena et al., 2020; Shevtsova et al., 2024).

Fourth, although demographic differences were modest, the observed variations across age and education levels suggest potential disparities in how individuals translate knowledge into trust and intention behavior. Individuals with lower educational attainment or limited digital familiarity may experience greater difficulty evaluating AI-based tools, potentially amplifying perceived risk. To promote equitable access to AI-enabled healthcare, implementation strategies should incorporate inclusive communication approaches tailored to diverse literacy levels and age groups. Such efforts may help reduce disparities in trust and ensure that the benefits of AI-based medical imaging are broadly accessible across population segments.

6.5. Limitations and future research directions

Despite its strengths, this study has several limitations. First, the cross-sectional survey design limits causal inference and does not capture how trust, knowledge, and adoption intentions may evolve over time as individuals gain experience with AI-based medical imaging tools. Future longitudinal or experimental research would be better suited to examine the dynamic development of these perceptions.

Second, data was collected through an online survey administered via the CloudResearch platform, which may limit representativeness, particularly for populations with restricted internet access or lower digital literacy. Moreover, the study focused on members of the U.S. public. Future research could expand the scope to include participants from developing and underdeveloped countries, as well as professional stakeholders such as radiology students, technologists, and radiologists, to provide more comprehensive and context-sensitive insights.

Although multigroup analyses identified some statistically significant demographic differences (e.g., by gender, age, and education), effect sizes were small, suggesting that these differences should be interpreted with caution and not overstated in theoretical or practical conclusions.

Finally, this study employed a parsimonious measurement approach that simplifies inherently multidimensional constructions. Trust, AI knowledge, perceived risk, and perceived benefit were measured as overall perceptions rather than distinct subdimensions. While this approach supports model simplicity and aligns with value-based adoption models, it does not capture the full complexity of these constructs. Future research should apply more detailed, multidimensional measures to better understand trust and adoption in medical AI contexts.

7. Conclusion

The rapid advancement of artificial intelligence has accelerated its integration into medical imaging, raising critical questions regarding public perceptions and behavioral intentions essential for successful implementation in radiology. By extending the value-based model, this study demonstrates that trust functions as a key psychological mechanism linking perceived risks, perceived benefits, and AI knowledge to individuals' intentions to use AI-based medical imaging tools. The findings further indicate that AI knowledge plays a central role in shaping value-based evaluations, which in turn influence trust formation and adoption-related decision-making. This study contributes to the literature on human interaction with AI-based tools by advancing a trust-centered, value-based framework for understanding public acceptance of AI-based medical imaging technologies. From a practical standpoint, the findings underscore the importance of clearly communicating tangible clinical and operational benefits while strengthening public AI literacy. Collectively, these insights position trust as a critical mechanism for fostering the responsible, sustainable, and socially accepted adoption of AI technologies in radiology.

Declaration of generative AI use

During the preparation of this work, the author(s) used ChatGPT (OpenAI) to improve the clarity and readability of the manuscript. After using this tool, the author(s) reviewed and edited the content as needed and take full responsibility for the final version of the manuscript.

CRediT authorship contribution statement

Hassan Alipanahzadeh: Writing – original draft, Validation, Methodology, Formal analysis, Conceptualization. **Eli Eikefjord:** Writing – review & editing, Visualization. **Max Korbmacher:** Writing – review & editing, Supervision, Project administration, Methodology.

Ethical approval

This study was reviewed by the Research Ethics Committee at the Faculty of Health and Social Sciences, Western Norway University of Applied Sciences (reference number 24/06416-8). All participants provided informed consent before participating in the study. Written informed consent was obtained electronically at the beginning of the online survey.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: MK has received a speakers honorarium from Merck.

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Appendix D. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chbr.2026.100936.

Appendix A. survey questionnaire items

Constracts	Items
Perceived Risk	**PR1.** I think the potential risk associated with the use of AI-based medical imaging tools is:
	PR2. Overall, I think the chance of adverse consequences associated with the use of AI-based medical imaging tools is:
	PR3. I think the likelihood of unexpected problems with the use of AI-based medical imaging tools is:
	PR4. I think the risk of using AI-based medical imaging tools is:
	PR5. I think the degree of uncertainty associated with the use of AI-based medical imaging tools is:
Perceived Benefit	**PB1**. I think AI-based medical imaging tools can suggest accurate care planning.
	PB2. Overall, I think AI-based medical imaging tools can boost healthcare outcomes.
	PB3. I think AI-based medical imaging tools can recommend reliable treatment options
	PB4. I think AI-based medical imaging tools can reduce healthcare costs.
	PB5. I think AI-based medical imaging tools can enhance correctly identifying disease states.
	PB6. I think AI-based medical imaging tools make data more accessible, increase transparency, and provide more interpretable outputs.
	PB7. I think AI-based medical imaging tools can enhance detecting disease states early.
Perceived Knowledge	**KN1**. How familiar are you with the concept of artificial intelligence (AI)?
	KN2. How well do you understand the difference between machine learning, deep learning and AI?
	KN3. How familiar are you with the various applications of AI in medical imaging diagnostic practices?
	KN4. How well do you understand the limitations and risks of using AI in medical imaging?
	KN5. How well do you understand the potential benefits of using AI to enhance medical imaging?
Perceived Trust	**PT1**. I trust in the AI-based medical imaging algorithms used in the healthcare
	PT2. I trust that AI-based medical imaging tools can adapt to specific and unforeseen medical situations.
	PT3. I trust in the AI-based medical imaging tools' predictive and diagnostic ability for treatment purposes
	PT4. I trust in the accuracy and predictive powers of current AI-based medical imaging models used in the medical context
	PT5. I trust in the AI-based medical imaging tools used for healthcare delivery.
Intention to use	**INT1**. I consent that my clinician uses AI-based medical imaging tools for clinical purposes.
	INT2.I prefer that my clinician uses AI-based medical imaging tools for healthcare purposes.
	INT3. I consent that my clinician uses recommendations provided by AI-based medical imaging tools for care planning.
	INT4. I would like my clinician to use AI-based medical imaging tools to manage my healthcare.
	INT5. I expect my clinician to use AI-based medical imaging tools for care planning, once available.

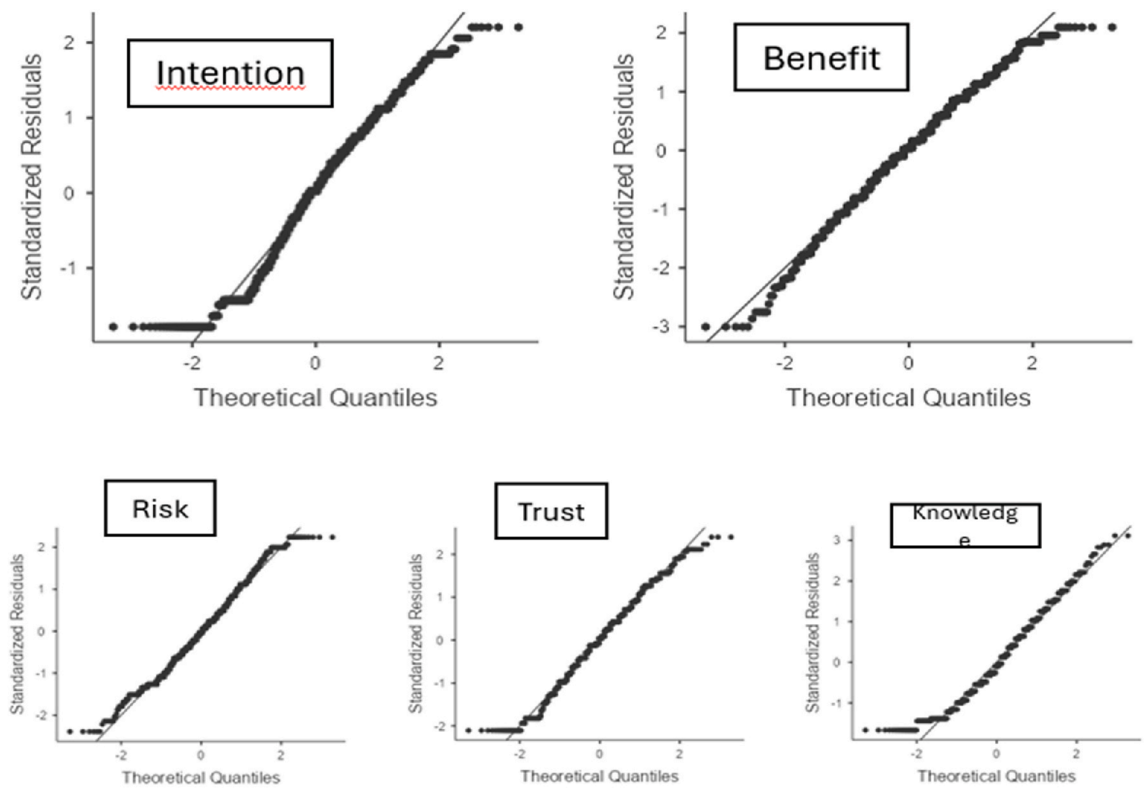
Appendix B. Results of normality testing for study variables

Normality Tests			
		statistic	p
Risk	Shapiro-Wilk	0.988	<0.001
	Kolmogorov-Smirnov	0.0429	0.058
	Anderson-Darling	2.27	<0.001
Benefit	Shapiro-Wilk	0.989	<0.001
	Kolmogorov-Smirnov	0.0510	0.013
	Anderson-Darling	2.04	<0.001
Trust	Shapiro-Wilk	0.988	<0.001
	Kolmogorov-Smirnov	0.0488	0.021
	Anderson-Darling	1.98	<0.001
Intention	Shapiro-Wilk	0.973	<0.001
	Kolmogorov-Smirnov	0.0632	<0.001

(*continued on next page*)

(*continued*)

Normality Tests			
		statistic	p
	Anderson-Darling	6.13	<0.001
Knowledge	Shapiro-Wilk	0.972	<0.001
	Kolmogorov-Smirnov	0.0888	<0.001
	Anderson-Darling	6.47	<0.001



Appendix C. Supplementary Note 1, Model sanity check

The measurement model was refined based on evidence from both Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) to enhance its validity and fit (Wong, 2025). The initial EFA identified two factors within the Knowledge construct, with the first knowledge item (kn_1) loading highly (0.997) on Factor 2, while the remaining knowledge items (kn_2 to kn_5) primarily loaded onto Factor 1, suggesting a more coherent structure. However, CFA revealed a significantly lower loading for kn_1 (0.584), falling below the recommended threshold (≥0.70), indicating weak contribution to the construction. After removing kn_1, model fit improved significantly, and the remaining indicators (kn_2, kn_3, kn_4, kn_5) exhibited stronger and acceptable loadings, confirming a more robust factor structure.

Data availability

The datasets, analysis code, and materials supporting the findings of this study are openly available in the Open Science Framework (OSF) repository at (https://osf.io/szad9/?view_only=33b6c7ce9ac94cfb88ad14bf7f7d7494):

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