Original Paper

Effect of Teledermatologist Supervision in AI Skin Cancer Apps on Patients' Trust and Adherence Intentions: Randomized Controlled Trial

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Abstract

Background: Skin cancer incidence is rising globally, increasing pressure on dermatology services and making efficient triage increasingly important. AI-driven skin cancer mobile health apps may help address this need, but their usefulness depends on whether users trust the advice and intend to follow it. Teledermatologist supervision has been proposed to combine AI efficiency with human clinical oversight, but dermatologist shortages make it critical to understand whether such supervision improves patient trust and adherence at the population level, or whether AI-only advice suffices for most users.

Objective: This study tests whether teledermatologist supervision in an AI-driven skin cancer app affects patient trust and adherence intentions, compared with AI-only advice, and whether these effects differ by motivational context and risk assessment level.

Methods: The randomized controlled, online vignette experiment with repeated measures was conducted from May to June 2025 as a single-center study among Dutch adults via an academic hospital-based patient panel. Eligible participants were adult members of the Erasmus MC Digital Patient Panel invited by email; those not completing all 4 vignette trials were excluded from the analysis. Participants completed 4 simulated mobile app scenarios varying in advice source (AI-only vs hybrid teledermatologist and AI) and risk assessment level (high vs low). The primary outcomes were trust in the advice (0-100 scale) and adherence intention (recoded 3-level ordinal scale). Mixed-effects models were used to analyze the data.

Results: Of the 2707 patient panel members, 879 participated (response rate: 32.5%). Participants were aged 18 to 93 (mean 62.5, SD 12.64) years; 50.4% (n=443) were female, and 21.4% (n=188) had a history of skin cancer. Participants were randomly allocated to motivation conditions (concern: n=438 vs curiosity: n=441). Trust was higher for hybrid advice than AI-only advice (mean 76.9, SE 0.73 vs mean 65.7, SE 0.73; estimated difference 11.98; partial η^2=0.22; P<.001). The odds of adherence were 1.7 times greater with hybrid vs AI-only (odds ratio 1/0.59=1.7, 95% CI 1.28-2.22; P<.001). High-risk assessments increased adherence (odds ratio 2.9, 95% CI 2.2-3.8; P<.001), with a moderated effect by motivation (P=.03), showing stronger adherence with concern vs curiosity. The effect of advice source on adherence was fully mediated by trust.

Conclusions: Teledermatologist supervision of AI-based advice robustly increased patient trust and adherence intentions, particularly for high-risk assessments and concerned users. Our experiment is innovative in testing teledermatologist supervision in a population-level AI skin cancer app and in examining how motivational context shapes responses to advice. Unlike studies focused on postreferral teledermatology or chatbot-based advice, this study isolates the effect of hybrid AI-human advice in a store-and-forward screening context. These findings suggest that developers and health care implementers may

consider integrating teledermatologist supervision to maximize patient trust of and adherence to advice, potentially improving triaging efficiency and safety.

Trial Registration: Open Science Framework 64pjn; https://osf.io/64pjn

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Keywords: mobile health; mHealth apps; health behavior; patient motivation; user experience; human-AI collaboration; dermatology; teledermatology; mHealth

Introduction

Background

Globally, the incidence of both melanoma [1-3] and other skin cancer [4,5] is increasing, with related deaths projected to increase by 68% from 2020 to 2040 [6]. The increased incidence compounds the already significant strain on dermatology services, causing delays in diagnosis and treatment in some regions [7]. Teledermatology [8], whereby a dermatologist makes their assessment remotely using digital technologies, has helped address this challenge by postreferral triaging [9,10], achieving improved accessibility and cost savings of 6.3% to 45.3% per patient [11,12] by potentially avoiding unnecessary appointments with the general practitioner [13]. However, widescale teledermatology is likely unrealistic, given global dermatologist shortages [14-16].

Using AI in place of teledermatology has been proposed [17-19], as experiments found AI to diagnose lesion images more accurately than both nonspecialists [20] and dermatologists [21]. Certain use cases for AI in dermatology are promising (Du-Harpur et al [22]), for example, as an aid for diagnosing [23-25] or in triaging [26]. In fact, both AI alone and AI with a dermatologist check were found to be more cost-effective in postreferral triage than face-to-face assessments or teledermatology [26]. Combining teledermatology and AI postreferral enhances care quality, streamlines processes, and reduces costs [27], and consequently, hybrid models are recommended to help expand access [28,29] and are often preferred by patients [23,24]. However, less research has been conducted on AI-teledermatology apps at the population level, which can face practical challenges, such as users not being sufficiently reassured by low-risk assessments and seeking doctor appointments anyway, as found in a Dutch study [30]. The app in the study [30] increased premalignant or malignant lesion detection by 32%, while also tripling to quadrupling benign lesion claims, indicating population-level overdiagnosis. Furthermore, patients receiving a low-risk assessment from the app had twice as many claims for benign skin lesions, suggesting that they were neither reassured by the app nor their general practitioner [30]. Therefore, adherence to low-risk advice for population-level apps needs to be high to mitigate the risk of increased health care demand. Using AI-based apps to prevent unnecessary appointments appears achievable, as a feasibility study reported that 54% of patients who visited the general practitioner with benign lesions and had low-risk app ratings would have felt reassured enough to cancel their general practitioner visit [13].

People's adherence may differ based on their reason for using the app. For highly concerned users, the perceived threat [31] of skin cancer cannot be alleviated by an algorithm [32], so they will still seek follow-up appointments regardless of the app's risk assessment. In contrast, users motivated by curiosity, which is often a reason to seek health information [33], may be less inclined to follow-up with their general practitioner even if advised by their app. How users' adherence is influenced by motivational context (ie, concern or curiosity) and risk assessment (ie, low or high risk) is unexplored, yet it is critical to understand if AI-based apps in dermatology are able to alleviate health care demand at the population level. Trust is key [34] as patients who trust their clinicians show greater confidence in clinicians' decisions [35] and better adherence [36,37], and presumably the same would apply to health apps. An online experiment [38] found that trust in advice is highest when given by a doctor, followed by human-AI collaboration, and least when offered by AI alone. However, the experiment [38] involved real-time involvement of a doctor, but in teledermatology, a store-and-forward format [39] is common, where patients upload photos [28] for later assessment. Furthermore, the experiment's [38] AI-only option was a chatbot, not an AI photo analysis.

Although population-level AI skin cancer apps have shown feasibility [13], it remains unclear whether teledermatologist supervision improves users' trust and intended adherence when advice is delivered in a patient-facing, store-and-forward format. This study aims to address this gap by assessing user responses to store-and-forward–style, AI-based dermatology apps using a vignette-based experimental design. Vignette experiments have been established as a valid, reliable, and practical method in health care research, offering strong criterion validity while bypassing the ethical and practical constraints of real-world experiments [40].

Research Question and Hypotheses

The current study poses the question: How do advice source (AI alone or hybrid) and user motivation (curiosity vs concern) shape patient trust and adherence intentions to the provided advice within the context of AI-supported teledermatology? Three preregistered hypotheses are posed:

1. H1: Trust (H1a) and adherence intentions (H1b) will be higher for hybrid advice vs AI-only (main effect of advice source on trust and adherence intentions).
2. H2: High-risk assessments will increase adherence intentions (H2a), particularly in the concern condition (H2b) (a main effect of risk assessment and an interaction of motivation and risk assessment on adherence intentions).

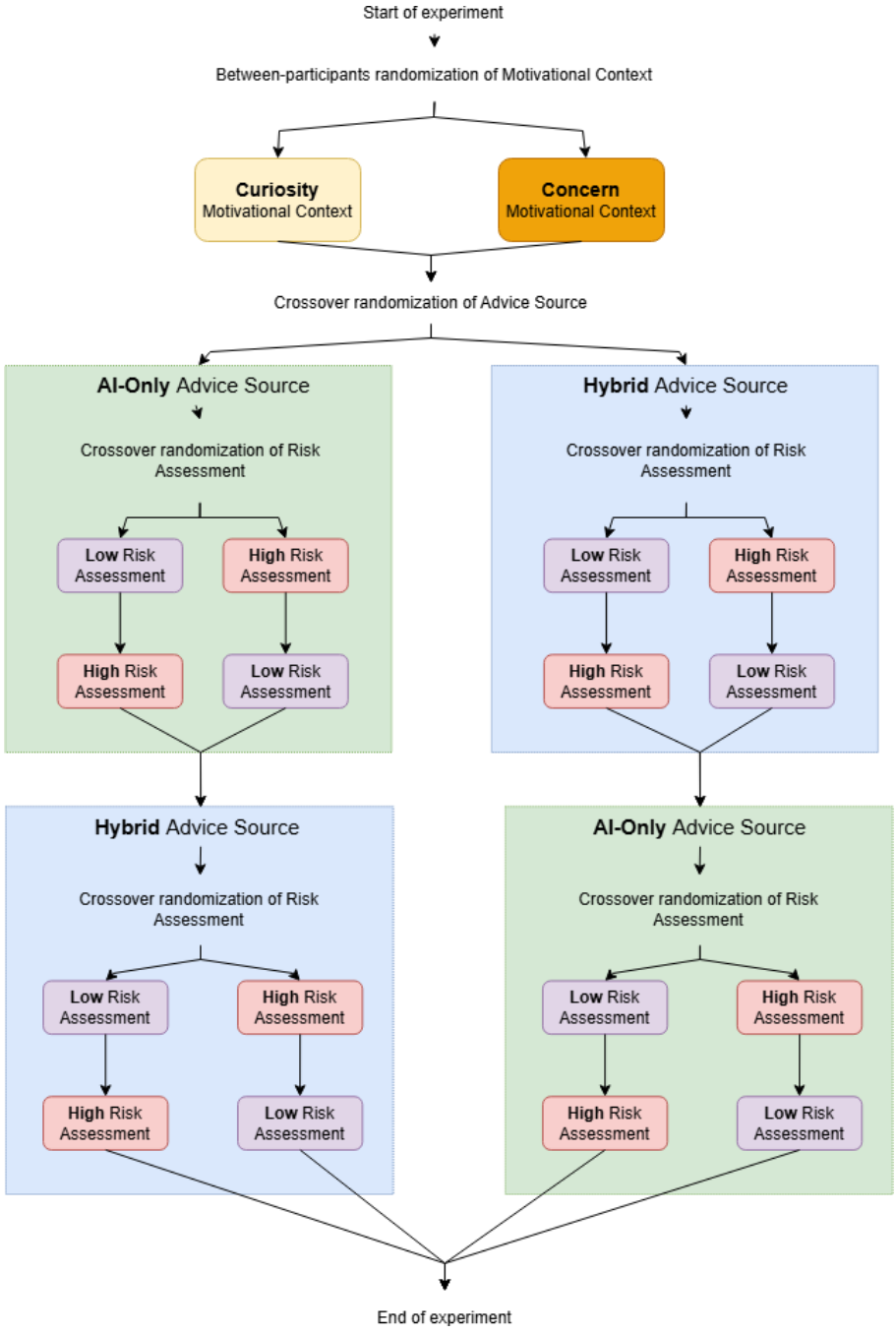
3. H3: Trust will mediate the effect of advice source on adherence intentions.

Methods

Trial Design

Our randomized controlled, online vignette experiment with repeated measures uses a 2×2×2 design, with motivational context (concern vs curiosity) as a between-participants factor and advice source (AI-only vs hybrid) and risk assessment (high vs low) as within-participants factors. The dependent variables include trust and adherence to medical advice. Figure 1 presents a study design flowchart. The public was not involved in the design, conduct, or reporting of the trial.

Figure 1. Experimental design flowchart for a 2×2×2 randomized vignette experiment among Dutch adults recruited from the Erasmus MC Patient Panel, Rotterdam, the Netherlands, May to June 2025. Participants were randomized to curiosity or concern, and then completed 4 simulated app trials varying in advice source (AI-only vs hybrid teledermatologist + AI) and risk assessment (low vs high). Participants were assigned to motivation conditions between participants, then received both advice source types and risk assessment levels in randomized order (within participants). Each completed 4 trials of risk assessments, with trust and adherence intentions measured after each trial.



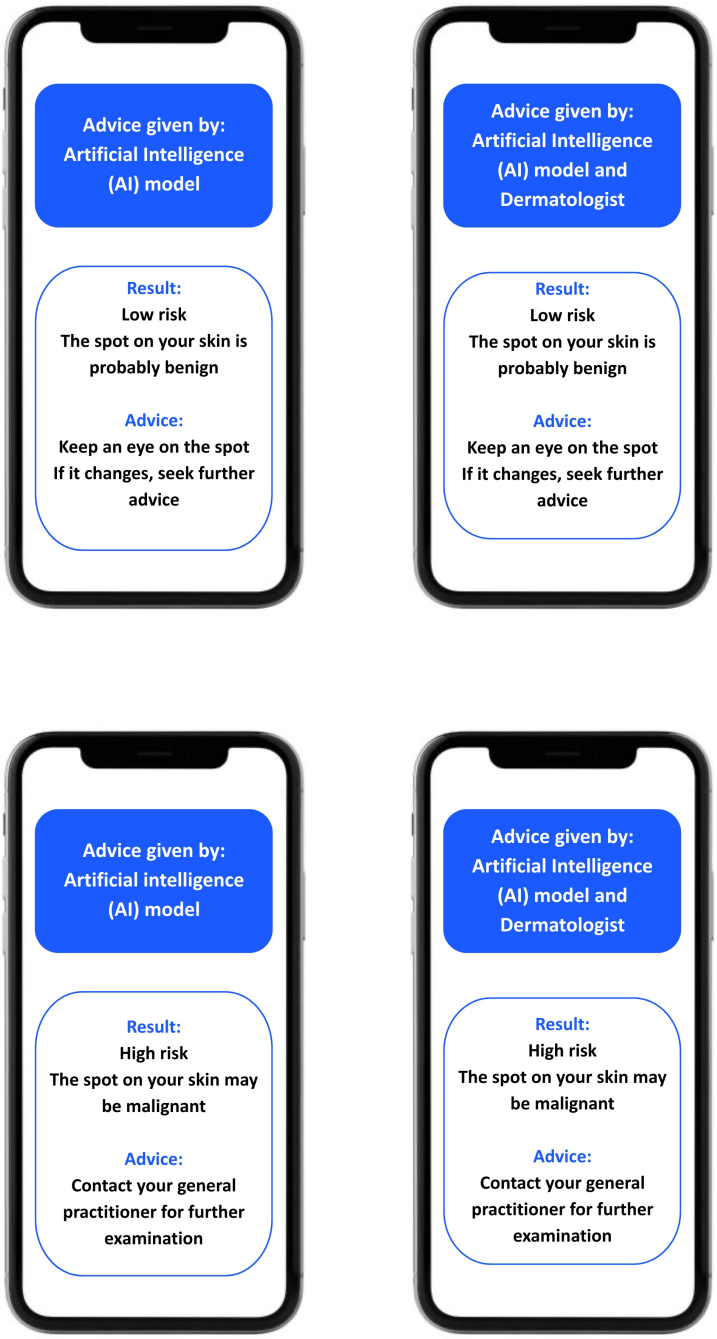
Sample Size

An a priori power analysis was conducted in G*Power 3.1.9.6 [41] for the planned within-between interaction in a repeated measures ANOVA (test family: *F* tests; statistical test: ANOVA: repeated measures, within-between interaction). Because no directly comparable prior studies were available, we conservatively assumed a small-to-medium effect size of f(V)=0.25 [42], α=.05, power=0.80, 2 groups (motivation factor), 4 measurements (2×2 within-participants factors), and nonsphericity correction (ϵ=1). This yielded a minimum total sample size of 168 [41].

Materials

The experiment was created using Qualtrics and conducted in Dutch. No personnel were required to conduct the study as it was automated and online. The experiment included an introduction to AI, experiment instructions (Multimedia Appendix 1), 2 motivation texts, and image stimuli for the motivation conditions (Multimedia Appendix 2). Additionally, 4 simulated mobile health app trials, varying in combinations between advice source and risk assessment, were included (see Figure 2 and Multimedia Appendix 3).

Figure 2. Simulated medical risk assessment outputs used in a randomized vignette experiment among Dutch adults recruited from the Erasmus MC Patient Panel, Rotterdam, the Netherlands, May to June 2025. Each risk assessment also reminds participants of the advice source and provides follow-up advice. App images were created using Canva and AI.



Ethical Considerations

This study was approved by the Medical Ethics Committee of Erasmus MC (MEC-2025-0371) and conducted in accordance with the procedures of the Erasmus MC Digital Patient Panel [43]. Informed consent was obtained through panel membership registration, by which members agree to be approached for research participation and may opt out of any individual study at any time; no separate consent procedure was required within the study itself. All data were collected anonymously through the panel infrastructure; no personally identifiable information was linked to experimental responses, ensuring participant confidentiality. Participants received no financial or material compensation for participation. No harms were posed on participants as it was an online study, and no concomitant care was provided. All efforts have been made to ensure that individual participants cannot be identified in any images of the manuscript or supplementary material.

Procedure

As this study involved a hypothetical vignette-based experiment assessing patient-reported trust and adherence intentions rather than a health-related intervention delivered to patients or a health-related outcome, prospective trial registration was not required under International Committee of Medical Journal Editors guidelines [44]. The study was nonetheless preregistered on the Open Science Framework [45] to enhance transparency of our research on May 26, 2025, after recruitment had begun but before any data inspection, cleaning, or analysis. The experiment was emailed to 2707 panel members between May 22 and June 10, 2025, with the first response being on May 22. The data collection period was defined by the panel administrators. After demographics and an AI attitudes scale, participants were randomly assigned by Qualtrics to motivation conditions (concern or curiosity; see Multimedia Appendix 2). They completed 4 trials in 2 randomized blocks, varying advice source (AI-only vs hybrid) and risk assessment (high vs. low). Each trial presented 1 advice output, followed by trust and adherence intention measures.

Consequently, each participant saw 4 assessment outputs, 1 high-risk and 1 low-risk per advice source. After each assessment, participants answered 1 item measuring trust and another measuring their intention to adhere to the advice. Finally, participants were debriefed about the aim of the study.

Outcomes

In a preexperiment questionnaire, participants answered questions on demographic data (age, gender, and skin cancer history) and their attitudes toward AI in health care, measured using a Dutch version of the validated 4-item AI Attitude Scale (AIAS-4) [46], with participants indicating their level of agreement on scales from 1 (“Not at all”) to 10 (“Completely agree”). After each trial, trust was rated on a continuous slider (0=no trust, 100=full trust) with the question “How much trust do you have in this result?” This single-item format was chosen to minimize respondent burden across 4 repeated trials. While single-item measures cannot capture all dimensions of trust, they can provide reliable and valid indicators of overall trust judgments [47].

Adherence was assessed by asking “What would you do next regarding your mole?” Participants selected 1 of 5 response options (Table 1), which were recoded, with input from a clinician, into a 3-level ordinal adherence variable for both risk assessment levels. The recoding scheme was designed to reflect medically meaningful levels of adherence. Because the clinical implications of the same response differ depending on whether the AI advice indicated high or low risk, the classification of the responses varied by risk condition.

Table 1. Recoding of postvignette adherence intention responses into a 3-level ordinal outcome in a randomized vignette experiment on an AI-supported skin cancer app among Dutch adults recruited from the Erasmus MC Patient Panel, Rotterdam, the Netherlands, May to June 2025[a].

Response option	High-risk advice	Low-risk advice	Justification
“I would make an appointment with my GP the same day.”	High adherence	Neglect	It is high adherence for high risk because there is same-day intention to make an appointment. Conversely, it is neglect for low risk because an appointment is made.
“I would make an appointment within a week.”	Moderate adherence	Neglect	For high risk, this option is moderate adherence because an appointment is still made but with suboptimal urgency. Conversely, it is neglect for low risk because an appointment is made.
“I would make an appointment when I have time; I am not immediately worried.”	Neglect	Moderate adherence	For high risk, this option is clearly neglect because there is a lack of clear intention to make a doctor’s appointment. For low risk, it is moderate adherence because they might make an appointment but there is not a clear intention.
“I would monitor the mole and only make an appointment if it changes.”	Neglect	High adherence	For high risk, this option is considered neglect because the user intends to wait for further signs before making an appointment. In contrast, for low risk, it is desirable that an appointment is not made, unless the mole changes.
“I would not seek any further medical assessment.”	Neglect	High adherence	For high risk, this decision is clear neglect because no intention to make an appointment is present. In contrast, for low risk, it is high adherence because there is no sign that the user intends to make an appointment.

[a]Participants were asked “What would you do next regarding your mole?”

Statistical Methods

Analyses were conducted using both SPSS (version: 28.0.1.0(142); IBM Statistics) and RStudio (2025.05.1 Build 513). For H1, a linear mixed-effects model (LMM) was used with trust as the continuous outcome, advice source and risk assessment as within-participants factors, motivation as a between-participants covariate, and participant as a random intercept. Although the Shapiro-Wilk test was significant, the residuals appeared normally distributed and no other assumptions were violated, and we proceeded with the LMM. Effect size was calculated using the following equation: $\eta_p^2 = \frac{F \times dfeffect}{F \times dfeffect + dferror}$.

For H1b and H2, a cumulative link mixed model (CLMM) [48,49] was used given the ordinal nature of adherence intentions. Category counts were sufficient. Logit plots supported proportional odds assumption for advice source and motivation, but risk assessment violated it. To address this, 2 binary generalized linear mixed model sensitivity analyses were conducted: 1 contrasting high adherence vs moderate adherence/neglect combined and 1 contrasting neglect vs high/moderate adherence combined. The latter reflects the theoretically motivated distinction between engagement (high and moderate adherence) and complete disengagement (neglect). The results of both sensitivity analyses are reported alongside the primary CLMM findings. A CLMM was conducted with adherence intentions, predicted by the independent variables: advice source, risk assessment, motivation, and their interactions, with a random intercept for participant ID.

For H3, the main effects of trust, advice source, and their interaction on adherence intentions were tested using a CLMM, with no proportional odds assumption violations for any predictor. A mediation analysis was conducted to test the indirect effect of advice source on adherence intentions via trust as the product of 2 paths: source → trust and trust → adherence intentions, assessed through a Monte Carlo simulation with 10,000 draws. To obtain unbiased estimates, both the CLMM for trust's effect on adherence intentions (path b) and the LMM for source's effect on trust (path a) were rerun without any interaction terms.

Reporting Guidelines

We reported this randomized vignette experiment in accordance with [50] the CONSORT (Consolidated Standards of Reporting Trials) abstract extension [51], CONSORT-EHEALTH (Consolidated Standards of Reporting Trials of Electronic and Mobile Health Applications and Online Telehealth) guidelines (Checklist 1) [52], and TIDieR (Template for Intervention Description and Replication) guidelines [53].

Changes to Trial Protocol

We made the following four changes compared to the preregistration [45]:

1. A wording clarification for H2
2. Substitution of mixed-factor ANOVA with LMM for trust
3. Substitution of mixed-factor ANOVA with CLMM for adherence
4. Replacement of the regression-based mediation with Monte Carlo mediation using mixed-model path estimates

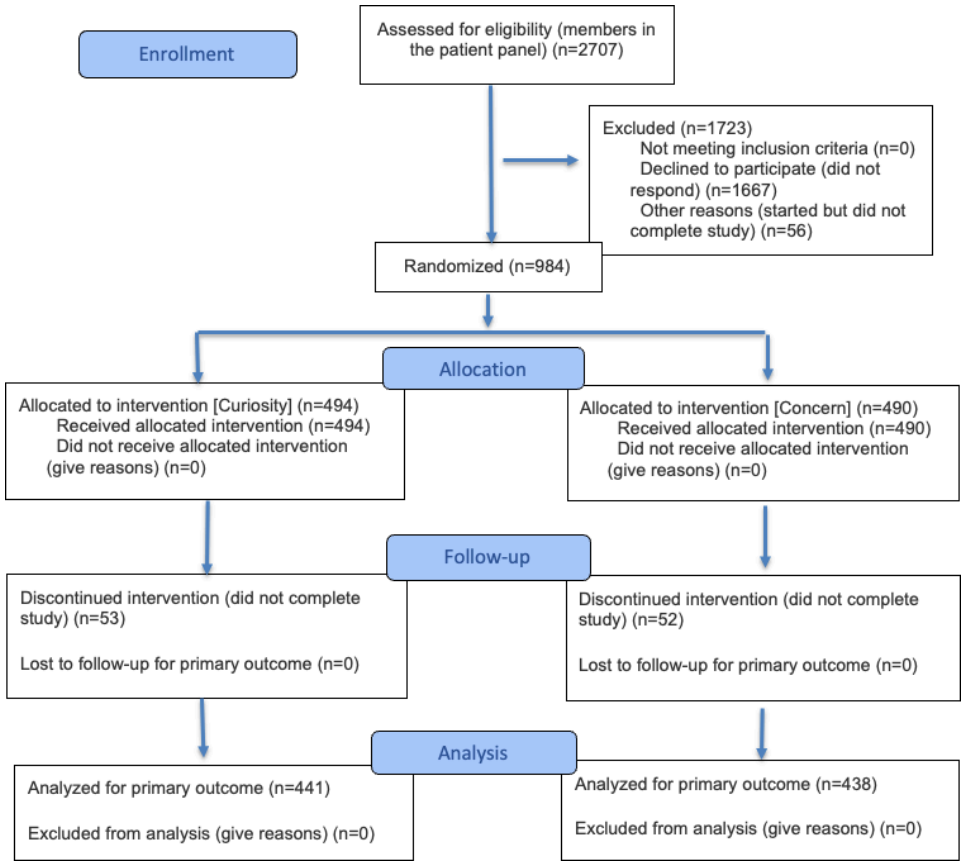
Points 2 and 3 allow for random intercepts for each participant, enhancing the modeling of individual variability [54]. A full account of deviations from the preregistration, including justification for each change, is documented in a Transparent Changes file on the OSF project page [45] and in Multimedia Appendix 4.

Results

Participant Flow

The study received 1040 responses in total. Of the 2707 patient panel members, there were 879 full completions, resulting in a response rate of 32.5% (Figure 3).

Figure 3. CONSORT (Consolidated Standards of Reporting Trials) flow diagram of participant screening, randomization, exclusions, and analysis in the randomized vignette experiment among Dutch adults recruited from the Erasmus MC Patient Panel, Rotterdam, the Netherlands, May to June 2025.



Excluded participants were slightly older than included participants (mean 64.9, SD 12.31 y vs mean 62.5, SD 12.62 y; t_{1030}=2.19, d=0.19; P=.03). There were no statistically significant differences in baseline AI attitudes (mean 5.95, SD 2.33 vs mean 6.17, SD 2.08; P=.30), gender distribution (P=.22), personal skin cancer history (P=.82), or motivation assignment (P=.95).

Baseline Data

The median completion time was 4 minutes 56 seconds (IQR 2:55-3:45; range 1:28-175:26). Participants had a mean age of 62.5 (SD 12.64, range 18-93) years with balanced gender distribution (female: n=443, 50.4%; male: n=433, 49.3%). A total of 188 (21%) reported a prior skin cancer diagnosis. The average AIAS-4 score was 6.17 (SD 2.08; n=879), indicating a slightly positive attitude toward AI.

Effects on Primary Outcomes of Trust and Adherence Intentions

H1a Influence of Advice Source on Trust

The LMM revealed a significant main effect of advice source on trust ($F_{1,2643}$=758.50; P<.001); trust was higher for hybrid (estimated marginal mean 76.88, SE 0.73) than AI-only (estimated marginal mean 65.68, SE 0.73), with an estimated difference of 11.98 (95% CI 10.39-13.58). This relatively narrow interval indicates a precise estimate of the source effect on trust. Advice source's effect size was large (partial η^2=0.22), supporting hypothesis H1a that participants trust hybrid-based assessments more than AI-only assessments. Table S1 in Multimedia Appendix 5 shows the tests of fixed effects, while Table S2 in Multimedia Appendix 5 shows the estimates of fixed effects.

H1b and H2: Influence of Advice Source, Risk Assessment, and Motivational Context on Adherence Intentions

In all CLMMs, odds ratios (ORs) reflect the cumulative odds of being in a higher adherence intention category, with values greater than 1 indicating increased odds of stronger adherence intentions. The CLMM found a significant main effect of advice source (b=–0.52, SE 0.14; z=–3.84; P<.001) on adherence intentions (see the full table in Multimedia Appendix 6). The OR for hybrid compared to AI was approximately 0.59 (OR 1/0.59=1.7, 95% CI 1.28-2.22; P<.001), indicating that participants were about 1.7 times more likely to be in a higher adherence intention category under the hybrid advice source condition compared to the AI-only advice, supporting hypothesis H1b. The CI suggests a reasonably precise estimate of this effect.

The CLMM also found a significant main effect of risk assessment on adherence intentions (b=–1.07, SE =0.14; z=–7.86; P<.001). Because lower scores indicate stronger adherence intentions, this means that participants who received a high-risk assessment were about 3 times more likely (OR 2.9, 95% CI 2.2-3.8) to report higher adherence intentions compared to those with low-risk diagnoses. The

relatively narrow CI indicates a precise estimate of the risk effect.

Importantly, a significant interaction between risk and motivation was found (*riskHigh × motivationCuriosity; b*=0.40, SE =0.19; *z*=2.13; *P*=.03). This indicates that the boost in adherence intentions associated with high risk was weaker among curiosity-motivated participants compared to those motivated by concern, which can also be seen in Table 2.

Table 2. Distribution of adherence intention responses by motivation condition, advice source, and risk assessment in a randomized vignette experiment among Dutch adults recruited from the Erasmus MC Patient Panel, Rotterdam, the Netherlands, May to June 2025[a].

Motivation	Source	Risk	Total, n	High adherence intention, n (%)	Moderate adherence intention, n (%)	Neglect, n (%)
Concern	AI	High	438	264 (60.3)	142 (32.4)	32 (7.3)
Concern	AI	Low	438	192 (43.8)	89 (20.3)	157 (35.8)
Concern	Hybrid	High	438	297 (67.8)	120 (27.4)	21 (4.8)
Concern	Hybrid	Low	438	246 (56.2)	65 (14.8)	127 (29)
Curiosity	AI	High	441	247 (56)	141 (32)	53 (12)
Curiosity	AI	Low	441	206 (46.7)	94 (21.3)	141 (32)
Curiosity	Hybrid	High	441	281 (63.7)	130 (29.5)	30 (6.8)
Curiosity	Hybrid	Low	441	255 (57.8)	64 (14.5)	122 (27.7)

[a]Percentages were calculated within each motivation × source × risk condition.

In practical terms, individuals driven by concern showed a larger increase in adherence intentions when receiving a high-risk assessment than those driven by curiosity.

Sensitivity Analysis

Overview

To address the proportional odds assumption violation for risk assessment, 2 binary generalized linear mixed model sensitivity analyses were conducted with the same predictors and participant random intercepts. The first contrasted high adherence intentions vs moderate/neglect; the second contrasted neglect vs high/moderate adherence, reflecting the theoretically motivated distinction between engagement (high and moderate) and disengagement (neglect).

Main effects replicated across both models: hybrid source increased odds of high adherence intentions (OR 1.45, 95% CI 1.08-1.94; *P*=.01), and high-risk assessment strongly reduced odds of neglect (OR 9.40, 95% CI 6.04-14.63; *P*<.001). Critically, the risk × motivation interaction replicated in the neglect model (OR 0.44, 95% CI 0.25-0.78; *P*=.005), confirming that concern-motivated participants were significantly less likely to neglect a high-risk assessment compared to curiosity-motivated participants—consistent with the CLMM finding that the boost in adherence intentions from high risk was larger for concern than curiosity. The interaction did not reach significance in the high adherence intentions model (*P*=.11), indicating that the effect is specifically concentrated at the disengagement threshold rather than the high engagement threshold. These analyses confirm that the CLMM findings are robust to the proportional odds violation. The relatively narrow CIs indicate that these effects were estimated with good precision.

H3: Trust Will Mediate the Effect of Advice Source on Adherence Intentions

CLMM on Adherence Intentions by Trust and Advice Source

The CLMM—with participant as a random intercept—showed that greater trust significantly increased odds of stronger adherence intentions. Advice source had no main (*P*=.29) or interaction effect (*P*=.17), indicating trust's influence on adherence intentions was consistent across sources (see Multimedia Appendix 7). These results suggest that trust mediates advice source's effect on adherence intentions, supporting hypothesis H3, contrasting with H1b where advice source affected adherence when trust was not accounted for.

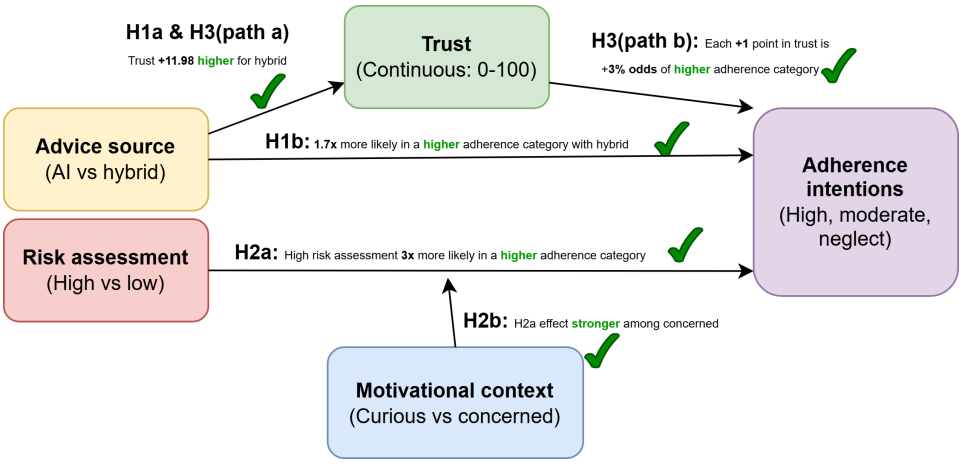
Mediation Analyses via Monte Carlo Simulation

The indirect effect of advice source on adherence intentions via trust was estimated as the product of 2 paths: source → trust and trust → adherence intentions, assessed through a Monte Carlo simulation with 10,000 draws. To obtain unbiased estimates, both CLMM for trust's effect on adherence (path b) and LMM for source's effect on trust (path a) were rerun without any interaction terms. The CLMM showed a statistically significant negative effect of trust on adherence intentions (estimate=–0.030, SE =0.002; *P*<.001), indicating that higher trust predicted better adherence. The LMM revealed a highly significant and negative effect of AI source compared to the reference hybrid source (estimate=–11.20, SE =0.41; *P*<.001), indicating lower trust under AI-only advice. Combining these path coefficients, the indirect effect was estimated as 0.34 with a 95% CI (0.29-0.39), excluding zero and indicating good precision as well as full mediation (H3). The relatively narrow CI indicates that this mediated effect was estimated with good precision. This positive indirect effect suggests that hybrid

advice sources increase adherence intentions by enhancing trust.

Figure 4 provides an overview of the results of the main hypothesis tests.

Figure 4. Summary of preregistered hypotheses and main results from the randomized vignette experiment among Dutch adults recruited from the Erasmus MC Patient Panel, Rotterdam, the Netherlands, May to June 2025. Ticks (✔) indicate hypotheses supported by the evidence.



Discussion

Principal Findings

This randomized controlled, vignette experiment aimed to answer the question "How do advice source (AI alone or Hybrid) and user motivation (curiosity vs concern) shape patient trust and adherence intentions to the provided advice within the context of AI-supported teledermatology?" The 879 participating adults reported trusting risk assessments from a hybrid source (AI plus a teledermatologist) more than AI-only assessments and reported higher intentions to follow the advice. Mediation analysis showed that trust fully explained this effect, meaning that hybrid advice increased adherence intentions by increasing the participants' trust. A high risk of a malignancy (rather than a low risk) further strengthened the intention to follow the advice, particularly among participants who use the app out of concern rather than out of curiosity. Notably, the sensitivity analysis revealed that the interaction between motivational context and risk assessment level was specific to the disengagement threshold: concern-motivated participants were significantly less likely to neglect a high-risk assessment compared to curiosity-motivated participants, while the 2 groups did not differ substantially in rates of high adherence intentions. This suggests that users motivated by curiosity are more likely to neglect when receiving high-risk assessments, compared to users who are already concerned. From a health behavior perspective, this is consistent with protection motivation theory [55], which posits that threat appraisal motivates protective behavior most strongly when perceived vulnerability is high and personally relevant. Curiosity-driven users—who may perceive themselves as less personally at risk—may be more prone to dismissing unexpected high-risk findings as a false alarm.

The results also identified trust as the central mechanism through which hybrid advice improves adherence intentions, highlighting the value of integrating teledermatologist supervision into AI-driven skin cancer apps to maximize triaging efficiency. An overview of the main results can be found in Figure 4. Our findings differ slightly from those of Soellner and Koenigstorfer [56], who found that the mediators between increased patient compliance and human physician supplementing AI were perceived social presence and innovativeness, suggesting multiple mediating factors are induced by human clinician presence. Similarly, Reis et al [57] found patients preferred human-only chat responses for reliability, empathy, and willingness to follow advice, compared with an AI chatbot or a hybrid chat. Soellner and Koenigstorfer [56] presented AI in a positive manner and communicated a clear purpose, mentioning AI's capability in diagnosing skin lesion photos. In contrast, Reis et al [57] used chatbot transcripts without clarifying AI's role, possibly explaining the preference for human-only advice rather than hybrid. These findings suggest hybrid advice works best when users understand the AI's purpose, not as a full substitute for human care [58]. Therefore, it is recommended to ensure patients understand the purpose of AI's involvement, alleviating patients' concerns about losing human involvement in health care [59], and for making human-AI collaboration more effective.

Practical Implications

Although including a human teledermatologist was found to increase the likelihood of higher adherence intentions by a factor of 1.7, and users' trust in the assessment from 66% to 77%, always including human teledermatologist supervision may be increasing workload too much [26]. Both AI-alone and hybrid models are more cost-effective postreferral than face-to-face assessments without AI [26], but only offering teledermatology to cases where the AI assessment is high risk, or shifting the usage of AI to postreferral by a primary health care provider, may be an effective compromise, depending on the intervention requirements and goals. This is particularly relevant given that Smak Gregoor et al [30] found that low-risk app assessments failed to prevent unnecessary appointments, tripling benign lesion claims.

Offering teledermatology review to concerned users with low-risk assessments may be a strategy to prevent in-person appointments, depending on the health care system. To avoid users neglecting high-risk assessments, strategies are required to ensure that those who use the app out of curiosity take the assessment seriously. High-risk assessments may require tailored messaging for users who do not present with preexisting concern, to prevent disengagement in precisely the cases where action is most warranted.

Strengths and Limitations

Our study provides insights on intended adherence to low-risk/benign assessments—reflecting most real-world cases—rather than comparing stage 0 skin cancer with stage 2 as did Soellner and Koenigstorfer [56], which represents the minority of cases. Thus, our results provide insights into drivers of patients' adherence intentions prior to triaging, which is crucial for avoiding overdiagnosis [9,30]. It is worthy of noting that the vignettes in our study altered the motivation (curiosity vs concern), which is intertwined with perceived lesion risk. This was done intentionally to create credible vignettes. However, it is plausible that a user of an app has low perceived lesion risk and is not curious but is using the app for other reasons. Further research could investigate whether using the app because it was encouraged by a family doctor, or family member, or for any other reason influences adherence to the app's advice.

Our study did not consider costs of teledermatology integration, so AI-only solutions may be more cost-effective despite lower adherence intentions and trust although hybrid solutions appear to be most effective postreferral [26]. The study sample was drawn from the Erasmus MC Patient Panel, representing highly engaged health care users with typically higher digital literacy and education levels than in the general population, which may limit generalizability.

The vignette-based experiment involved participants experiencing hypothetical scenarios, and stated trust and adherence intentions may not fully reflect behavior during actual app use. The use of predetermined simulated app outputs rather than participant-uploaded images prioritizes internal validity by isolating the effects of advice source and risk level, though it may reduce perceived personal relevance compared to a real app scenario. However, vignette responses have been shown to correspond closely with real clinical behavior [60], and relative comparisons between conditions are generally robust to hypothetical bias [61,62]. The mixed design—with motivational context as a between-participants factor and advice source and risk level as within-participants factors—allowed for controlled manipulation of key variables while accounting for individual differences. The crossover design used randomized trial order, meaning each condition appeared first equally often across participants, so any contrast effects would be unsystematic and unlikely to bias results in a particular direction. Nonetheless, the possibility that participants compared conditions rather than evaluating each independently remains a limitation inherent to within-participants designs, and trust and adherence may further differ when participants submit an actual image and perceive the assessment as personally relevant to their own lesion. Trust was measured using a single-item slider, which, while practical for repeated trial-level measurement, cannot capture the multidimensional nature of trust. Although single-item trust measures have been shown to produce reliable and valid results comparable to multi-item scales [47], a validated instrument such as the 11-item Trust in Physician Scale by Thom et al [63] may have revealed differential effects of advice source on specific facets of trust—such as perceived competence or benevolence—rather than on overall trust judgments alone [34]. Administering such a scale after each of 4 trials would, however, have imposed considerable respondent burden. Future research could use multi-item trust scales in a between-participants design to examine this more comprehensively.

Conclusions

The findings of this preregistered online experiment support the hypothesis that adding hybrid (teledermatologist and AI) advice increases trust, which, in turn, improves intended adherence, particularly for high-risk assessments and concerned users. This study is innovative in testing teledermatologist supervision in a population-level AI skin cancer app and in examining how motivational context shapes responses to advice. It differs from existing studies focused on postreferral teledermatology [26] or chatbot-based advice [38] by isolating the effect of hybrid AI-human advice in a store-and-forward screening context. These findings can inform the design of AI-based health care apps such that maximal triaging efficiency is achieved. Practically, these results support consideration of teledermatologist supervision in AI-based triage systems where maximizing trust, adherence, and safe follow-through are priorities.

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Generative AI Use

According to the GAIDeT taxonomy (2025), the following tasks were delegated to GenAI tools under full human supervision: code generation, code optimization, data cleaning, data curation and organization, data analysis, visualization, proofreading and editing, formulation of conclusions, and translation. The GenAI tool used was Perplexity, which uses a variety of models, and ChatGPT 5.6 Terra. Responsibility for the final manuscript lies entirely with the authors. GenAI tools are not listed as authors and do not bear responsibility for the final outcomes. Declaration submitted by RS, MM

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Data Availability

Data used in this study are available upon request—please contact secretariaat.mgz@erasmusmc.nl. The available data include (1) the Qualtrics printout PDF, (2) R and SPSS analysis codes, and (3) the anonymized dataset.

Authors' Contributions

Conceptualization: RS, MM, LZ
Data curation: RS, MM
Formal analysis: RS, MM
Funding acquisition: LZ
Methodology: RS, MM, LZ
Project administration: ND, EB
Resources: ND, EB
Supervision: JS, MW, LZ
Visualization: RS
Writing – original draft: RS, MM
Writing – review & editing: RS, JS, MW, LZ

Conflicts of Interest

The Department of Dermatology of the Erasmus MC Cancer Institute, where MW is affiliated, has received an unrestricted research grant from SkinVision. The remaining authors declare no conflicts of interest.

Multimedia Appendix 1

Instruction before starting the main experiment.
[DOCX File (Microsoft Word File), 28 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Motivation condition stimuli.
[DOCX File (Microsoft Word File), 340 KB-Multimedia Appendix 2]

Multimedia Appendix 3

Loading pages of the mobile health app.
[DOCX File (Microsoft Word File), 150 KB-Multimedia Appendix 3]

Multimedia Appendix 4

Document of changes to preregistration.
[DOCX File (Microsoft Word File), 16 KB-Multimedia Appendix 4]

Multimedia Appendix 5

Tests and estimates of fixed effects.
[DOCX File (Microsoft Word File), 21 KB-Multimedia Appendix 5]

Multimedia Appendix 6

Coefficients from the cumulative link mixed model examining advice source, risk assessment, and motivational context.
[DOCX File (Microsoft Word File), 16 KB-Multimedia Appendix 6]

Multimedia Appendix 7

Coefficients from the cumulative link mixed model examining trust and advice source.
[DOCX File (Microsoft Word File), 15 KB-Multimedia Appendix 7]

Checklist 1

CONSORT-EHEALTH checklist.
[PDF File (Adobe File), 3812 KB-Checklist 1]

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Abbreviations

AIAS-4: 4-item AI Attitude Scale
CLMM: cumulative link mixed model
CONSORT: Consolidated Standards of Reporting Trials
CONSORT-EHEALTH: Consolidated Standards of Reporting Trials of Electronic and Mobile Health Applications and Online Telehealth
LMM: linear mixed-effect model

OR: odds ratio
TIDieR: Template for Intervention Description and Replication

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