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Angaben zur Veröffentlichung / Publication details:

Neuendorf, Nathalie L., Katharina Angermayr, and Sebastian Scherr. 2026. "Trade-offs in mental health support: preferred patient-centered communication attributes across AI chatbots, telemedicine, online health communities, and in-person clinicians." *Social Science & Medicine* 403: 119431. https://doi.org/10.1016/j.socscimed.2026.119431.

Social Science & Medicine 403 (2026) 119431

Contents lists available at ScienceDirect

Social Science & Medicine

journal homepage: www.elsevier.com/locate/socscimed

Trade-offs in mental health support: Preferred patient-centered communication attributes across AI chatbots, telemedicine, online health communities, and in-person clinicians

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ARTICLE INFO

Keywords:
Patient-centered communication (PCC)
Online health communities
Discrete choice experiment (DCE)
Best–worst scaling (BWS)
Thriving through relationships

ABSTRACT

Mental health support now extends beyond in-person clinicians, search engines, and medical websites to interactive healthcare providers (IHPs), including AI chatbots, telemedicine (i.e., digital clinicians), and online health communities. Two preregistered U.S. studies examined how patient-centered communication (PCC) attributes shape preferences for mental health support. Study 1 (N = 414, U.S. *quota* sample, fielded August – September 2025) used Best–Worst Scaling (BWS) to rank eight attributes in each of three domains (informational, interpersonal, and community-based), selecting the top two per domain for Study 2. Study 2 (N = 1,011, U.S. representative sample, fielded September 2025) used a Discrete Choice Experiment (DCE) testing these six attributes in trade-off decisions. Study 2 revealed provider-specific preferences. *Extended support beyond the consultation* and *multi-symptom assessment capabilities* were most salient for in-person clinicians. *Multi-symptom assessment capabilities* and *reflective attentiveness and listening skills* stood out for IHPs. We also tested for the moderating effects of faith-based thriving as it gains relevance in patient-centered mental health communication. Moderation analyses indicated a provider-specific pattern: higher faith-based thriving was associated with a stronger preference for *scope and help provided* when using AI chatbots and a stronger preference for *community-based assistance* when talking to a digital clinician. Taken together, these findings suggest a complementary care model: those designing and delivering mental health support through IHPs should prioritize robust multi-symptom assessment and reflective listening, while in-person clinicians should prioritize support beyond the consultation. Faith-based thriving findings further highlight the need for group-sensitive mental health communication.

Search engines, medical websites, and in-person clinicians remain key sources of mental health support, but interactive healthcare providers (IHPs), such as AI chatbots, digital clinicians, and online health communities (OHCs), are rapidly gaining ground (e.g., Yun and Bickmore, 2025). AI chatbots offer usability, speed, and 24/7 availability of health information (Clark and Bailey, 2024), digital clinicians are valued for accessibility and engagement with their patients (Greenwood et al., 2022), and OHCs foster peer support where users share experiences, receive emotional support, and may build self-efficacy that encourages further help-seeking beyond the platform (Prescott et al., 2020). Each IHP evokes distinct user expectations: AI systems are expected to be accessible, anonymous, and easy to understand (Laymouna et al., 2024;Angermayr et al., 2025); digital clinicians are expected to listen actively, communicate clearly, and support shared decision-making (Chen et al., 2025); and OHCs depend on effective moderation to sustain emotional support (Treadgold et al., 2025). These developments challenge traditional models of patient-centered communication (PCC; Epstein and Street, 2007). Strong PCC supports mental health by reducing stress (Gong et al., 2025). While PCC research has historically focused on face-to-face care (Clarke et al., 2022), recent work examines how PCC elements translate to telehealth or AI-based systems (Liu et al., 2025).

The authors have no known conflicts of interest to disclose.

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https://doi.org/10.1016/j.socscimed.2026.119431
Received 20 November 2025; Received in revised form 14 May 2026; Accepted 21 May 2026
Available online 22 May 2026

Within PCC, spiritual and faith-based dimensions have gained relevance (Austin et al., 2017), particularly through the lens of "thriving" (Feeney and Collins, 2015)—the ability to grow through adversity with emotional and social support. For many individuals, religious networks provide the belonging and resilience that enable thriving (Neuendorf and Scherr, 2025). IHPs can support or hinder this process depending on how well they address users' relational and community needs. We therefore test whether faith-based thriving moderates the effects of PCC attributes on evaluations and preferences for IHPs.

Across two preregistered studies [weblink], we examined preferences for AI chatbots, digital clinicians, OHCs, and in-person clinicians across three mental health scenarios (depression, anxiety, bipolar disorder). Study 1, a Best–Worst Scaling (BWS; $N = 414$; U.*S. quota* sample) study, began with a large attribute pool derived from prior PCC literature and identified the main attributes that shape these preferences. Study 2, a Discrete Choice Experiment (DCE; $N = 1011$; U.S. representative sample), assessed trade-offs among the top six attributes from Study 1 in the same scenarios and tested whether faith-based thriving moderates the resulting preference structures.

1. Interactive healthcare providers (IHPs) for mental health care

While search engines and health websites continue to be the most common starting points for searching health information (Yun and Bickmore, 2025), alongside in-person clinicians, these classic channels are limited when individuals need tailored conversation, meaning-making, and just-in-time guidance (von Lützow et al., 2025; Esmaeilzadeh et al., 2025). Hence, digital and interactive channels are becoming increasingly important in health information seeking and PCC (Alma Taya and Chuang, 2025).

In this study, we define IHPs, including AI chatbots, digital clinicians, and OHCs, as digital care formats that allow patients to actively engage in two-way exchanges. Importantly, these formats differ in whether communication is provided by humans through digital channels (i.e., digital clinicians and OHCs) or a non-human AI system (i.e., AI chatbots). What unites these formats is their responsive and user-driven communication: patients can ask questions, receive tailored feedback, and participate in ongoing interactions rather than passively consuming information (e.g., Van Oerle et al., 2018). We next discuss each format's strengths, limitations, and user expectations in detail.

1.1. AI chatbots for mental health care

AI chatbots have shown promising effects in reducing symptoms of depression and anxiety in mental health contexts (Zhong et al., 2024). They can complement clinicians (Esmaeilzadeh et al., 2025), reduce stigma by personalizing pathways to care, and offer anonymous and low-cost support (Zhong et al., 2024). However, AI chatbots still face significant limitations, including repetitive dialogue, constrained functionality, and limited novelty (Boucher et al., 2021). Responses may remain generic, with insufficient probing or recommendations that should instead involve trained professionals (Scholich et al., 2025).

1.2. Telemedicine in mental health care

Meanwhile, telemedicine (i.e., digital clinicians) is increasingly accepted. In 2024, 44% of patients in the United States reported using virtual consultations, and 94% said they would do so again (Dutta et al., 2024). In the mental health domain, online therapy (i.e., one-on-one therapeutic counseling conducted via the Internet) reduces social barriers to care, with growing evidence for effectiveness (Schlemper and Urano, 2025). Studies find outcomes comparable to face-to-face therapy, with no differences in patient satisfaction (Mazziotti and Rutigliano, 2021). A recent meta-analysis reinforces equivalence: across 12 randomized controlled trials, teletherapy and in-person therapy did not differ in symptom reduction, functioning, overall improvement, therapeutic alliance, or patient satisfaction (Greenwood et al., 2022).

1.3. Online health communities (OHCs) for mental health care

Online health communities (OHCs) provide peer-to-peer support and information exchange for individuals with mental health conditions (Liu and Kong, 2021). OHCs are Internet-based platforms for health information exchange and discussion (Chen, 2023). They facilitate peer-to-peer informational and emotional support, enabling users to share and hear experiences (Prescott et al., 2020), thereby helping address care-oriented needs that healthcare professionals often leave unmet (Van Oerle et al., 2018). OHCs also allow anonymity, which is particularly important for stigmatized conditions such as mental illness (Yan and Tan, 2014). However, exposure to others' struggles can heighten anxiety for some users (Mills et al., 2025).

Overall, IHPs offer interactive digital pathways to mental health support. Because IHPs differ in communication, responsiveness, and relational tone, understanding their role requires specifying quality in conversational interaction from a patient-centered perspective.

2. Patient-centered communication (PCC) in IHPs

Much of the foundational PCC literature focuses on patient–clinician communication in face-to-face clinical care (Epstein and Street, 2007). Despite the rapid expansion of IHPs, their broader role in mental health care remains underexplored. U.S. research often relies on convenience samples (e.g., Yun and Bickmore, 2025) or focuses narrowly on virtual visits with human clinicians (e.g., Dutta et al., 2024), leaving other IHP formats underexamined and limiting what we know about which qualities people prioritize when seeking mental health support from IHPs.

In these contexts, conversational quality is central: interactions must be responsive, respectful, and attuned to users' concerns, not merely informational. This aligns with patient-centered communication (PCC), which emphasizes empathy, shared understanding, and coordination of care around patients' concerns and preferences (Epstein and Street, 2007). Its principles largely carry over to digital clinicians (Niu et al., 2025) and can inform communication practices in OHCs. In human–AI conversations, however, PCC must be realized through wording and conversational design rather than nonverbal behavior (Angermayr et al., 2025): empathy, personalization, and shared decision-making are conveyed via language.

On this basis, PCC specifies quality criteria—hereafter attributes—whose practical meaning is grounded in what patients actually value. Decision-makers therefore need to understand how patients prioritize these attributes (Hollin et al., 2022). Preference studies show that relational elements fostering reassurance and adherence are often valued more than time or consultation mode, and that technical quality and clinical competence typically outweigh convenience (e.g., Cheraghi-Sohi et al., 2008; Tinelli et al., 2015; Whitaker et al., 2017). Logistical attributes (e.g., booking ease, waiting time, consultation length) are generally secondary, valued mainly insofar as they enable unhurried, high-quality interaction and a strong clinical conversation (Whitaker et al., 2017).

However, these insights largely stem from in-person clinician settings and do not clarify how PCC-related attributes are prioritized across the broader spectrum of IHPs. We lack comparative, attribute-level evidence on which features people value most across AI chatbots, digital clinicians, and OHCs in mental health care, or how these priorities shift by format. Such comparisons matter because users may, for example, accept weaker relational cues in exchange for faster responses or greater anonymity, or prioritize active listening over breadth of information when disclosing sensitive concerns. To address this gap, we examine preferences for key IHP attributes in U.S. mental health care and propose the following first research question.

RQ1: Which patient-centered communication attributes do U.S. individuals consider most important across different interactive healthcare providers in mental health contexts?

However, identifying which attributes matter does not reveal how individuals choose in practice. In real decision settings, people weigh relational qualities (e.g., *listening skills*) against informational qualities (e.g., *symptom assessment capabilities*), often accepting less of one to secure more of another (e.g., Tinelli et al., 2015). Understanding how these trade-offs are negotiated is essential for explaining preferences across IHPs. Accordingly, the second research question is.

RQ2: Which attributes reflecting key dimensions of patient-centered communication do U.S. individuals prioritize when engaging with different interactive healthcare providers (i.e., AI chatbots, digital clinicians, and online health communities) compared to in-person clinicians in mental health contexts?

3. Faith-based thriving as a moderator of PCC-attribute preferences in IHPs

Interactive healthcare providers (IHPs) can create emotionally and socially supportive environments that foster identification, trust, and improved mental health outcomes. In clinician-delivered teletherapy, therapeutic alliances form at levels comparable to in-person care, indicating that empathic bonds and collaborative work can be sustained online (Seuling et al., 2024). In OHCs, users' support-seeking and venting behaviors, together with prosocial community responses, suggest that community ties can foster supportive interaction and sustained engagement (Morini et al., 2025). With AI chatbots, relationship-like bonds can also emerge when conversational design consistently conveys empathy and responsiveness (Wu et al., 2025).

From a positive psychology perspective, the *thriving through relationships* framework (Feeney and Collins, 2015) explains how supportive relational bonds promote psychological growth and resilience by regulating distress, enabling adaptive meaning-making, and strengthening efficacy and agency, thereby supporting mental health. The framework specifies two core relational functions: a "safe haven" that provides comfort and support during distress, and a "secure base" that offers stability for goal pursuit and growth. Originally articulated for offline human relationships, this study extends *thriving through relationships* to digitally mediated care by specifying how safe-haven and secure-base functions can be instantiated through IHP interactions—via linguistic validation, timely availability, tailored guidance, continuity of contact, and community norms in IHP exchanges. Applied to digital care, these functions yield modality-specific expressions of thriving: with AI chatbots, through emotional safety, nonjudgmental availability, and anonymous disclosure with consistent validation (Zhong et al., 2024), with digital clinicians, through attuned therapeutic presence and collaborative meaning-making that provide reassurance and encourage growth (Greenwood et al., 2022; Niu et al., 2025), and in OHCs, by focusing on peers' needs (other-referencing), which stimulates care-related value co-creation and varies with community experience (Van Oerle et al., 2018). In this study, thriving is conceptualized as a proximal relational capacity linked to PCC that can condition how individuals evaluate specific IHP attributes.

For faith-oriented individuals, belonging and support are particularly salient, often yielding relational thriving characterized by shared identity, mutual care, and emotionally supportive ties (Schafer and Upenieks, 2016). Faith-based environments provide coping resources and growth opportunities that benefit mental health and well-being. Because we assume that thriving is typically strong in religious networks, where belonging, meaning, and mutual care are institutionalized, we examine *faith-based thriving* as the moderating capacity that conditions how individuals value IHP attributes. As thriving is rooted in relational support, individuals who experience strong relational thriving within their faith-based communities may place greater value on relational PCC attributes (e.g., *community-based assistance*) over informational attributes (e.g., *explanation about medicine*). We therefore hypothesize.

H1: Higher faith-based thriving is associated with greater preference for community-oriented (relational PCC) attributes and reduced preference for informational attributes when engaging with different interactive healthcare providers (i.e., AI chatbots, digital clinicians, and online health communities) compared to in-person clinicians in mental health contexts.

4. Study 1: Identifying preferred Attributes for IHPs

The aim of Study 1 was to determine which attributes reflecting key dimensions of PCC U.S. individuals consider most important across different IHPs in mental health contexts (RQ1). In this preregistered study, we applied Best–Worst Scaling (BWS; Marley and Louviere, 2005), in which respondents repeatedly chose the most and least important attributes from randomized subsets of a larger attribute pool (Schuster et al., 2024). The method reliably identifies preferred attributes with comparatively low response or cultural bias (Cheung et al., 2019).

5. Method

5.1. Sample and procedure

The university IRB approved both studies (IRB number: IRB-A-2025-x101). We recruited $N = 461$ U.S. adults ($\geq$18 years) via *Prolific* between August and September 2025. Participants were compensated through the platform. The sample included quotas for sex, age, and religious affiliation (approximately 25% Christian, Muslim, Jewish, and non-affiliated respondents) to ensure diversity of identified PCC attributes. For data quality, two attention checks were included. A total of $n = 47$ individuals failed at least one and were excluded, yielding a final sample of $N = 414$, which matched the sample size required based on our power analysis.[1] Individuals were between 19 and 80 years old ($M = 39.83$; $SD = 13.59$). The sample included $n = 207$ women (50.0%) and $n = 207$ men (50.0%). An overview of sample demographics is shown in Table A1. After providing informed consent, receiving BWS instructions, and being assigned to one of three mental health scenarios (depression, anxiety, bipolar disorder; Figure B1), respondents completed 18 BWS tasks (see Figure B2 for an example; full task wording in Appendix C) evaluating 24 attributes in total.

5.2. Study design: Best–Worst Scaling (BWS)

Attribute Identification. When a topic is new or rapidly evolving, BWS attributes are typically derived from literature reviews and refined through qualitative interviews and/or focus groups (Hollin et al., 2022). However, as preferences for patient–provider interactions had already been well established in systematic reviews (e.g., Pratiwi et al., 2023), we consolidated attributes into a single list based on comprehensive reviews of empirical and conceptual work on doctor–patient communication, PCC, and digital health interactions (see Table A2). Attribute consolidation followed three criteria: Attributes had to be conceptually distinct (i.e., no conceptual overlap), non–mode-specific (e.g., excluding

[1] The required sample size was determined via an a priori power analysis using the *pwr* package in R (4.5.0). Based on an empirically grounded effect size estimate of $d = .68$ based on comparable effects reported in Burton et al. (2021), a significance level of $\alpha = .05$, and desired power of $1–\beta = .95$, the analysis indicated that approximately $N = 414$ participants were needed to detect a medium-to-large effect in between-group comparisons.

opening hours, which are not applicable to AI chatbots), and similar in wording to ensure comparability across formats. Attributes were then grouped thematically. We additionally incorporated underexplored aspects of PCC, including medical jargon and patient engagement, and explicitly included cultural and spiritual dimensions based on existing studies (Puchalski et al., 2014).

The final set was organized into three domains: (1) medical quality and information, (2) patient interaction and support, and (3) community and cultural considerations, each comprising eight attributes. Two authors who are experts in health communication consolidated and categorized the attributes iteratively; disagreement was resolved through discussion with a third co-author.

Mental Health Scenarios as BWS-Context. To ensure contextual relevance, each BWS task was embedded in a mental health scenario. As the three most frequently searched mental health conditions on Google are anxiety, depression, and bipolar disorder (Minn et al., 2025), we used these conditions as scenarios in the study. Individuals were randomly assigned to one of the three scenarios, in which mental health symptoms and motivations for seeking advice from an IHP were described. The scenarios were not analyzed as an experimental factor; rather, they were included to enhance ecological validity and the generalizability of the findings.

5.3. Measures

BWS Attribute Preferences. In each of the 18 BWS tasks, respondents viewed four attributes (with brief descriptions) and indicated the most and least important attribute for seeking medical advice; the same attribute could not be selected for both. Responses were coded $+1$ for the most important attribute, -1 for the least important attribute, and 0 for non-chosen attributes. Each attribute appeared in three choice sets per respondent, approximating real-world medical consultations in which multiple communication preferences are weighed simultaneously. An incomplete-block design with balanced attribute exposure ensured that each attribute appeared equally often across the BWS tasks, while providing broad pairwise comparisons and keeping cognitive load manageable (Schuster et al., 2024).

5.4. Data analysis

BWS attribute ratings were analyzed using three approaches (Cheung et al., 2019). First, a count analysis computed how often each attribute was chosen as "best" or "worst," with scores standardized to -1 to $+1$ (higher values indicating stronger preference). Second, a multinomial logit model (MNL) estimated relative preference parameters (β) for each attribute. Third, a mixed logit model (MIXL) incorporated randomly distributed parameters and their standard deviations (η) to capture preference heterogeneity, with significant η indicating greater variability in preferences across respondents. MNL and MIXL were estimated using the package *mlogit* in R (4.5.0).

6. Results and discussion

To answer RQ1, we applied a preregistered selection rule retaining the two highest-ranked attributes within each of the three topic domains to ensure balanced coverage of PCC attributes while keeping the subsequent DCE cognitively manageable. Attribute selection was based on combined information from all three data analytic approaches (i.e., count analysis, MNL, and MIXL; Table 1). In the topic domain "medical quality & information," the attributes *explanation about medicine* and *symptom assessment capabilities* were most preferred. In the topic domain "patient interaction & support", *attentiveness and listening skills* as well as *scope and help provided* were the most preferred attributes.[2] In the domain "community & cultural considerations," *extended support beyond the consultation* and *community-based assistance* were most preferred. All retained attributes showed positive BWS scores and model-based coefficients; in the MIXL model, all were statistically significant and showed meaningful preference heterogeneity.[3]

As a robustness check, a pooled count analysis across all 24 attributes identified the same six preferred attributes (Table A3), confirming the relative attribute importance (see Marley and Louviere, 2005).

Study 1 identified preferred attributes across three core domains of patient–provider communication when interacting with IHPs (AI chatbots, OHCs, digital clinicians). We applied Best–Worst Scaling (Marley and Louviere, 2005) as an established method for assessments of this sort. From the pool of 24 attributes for effective patient–provider communication, we identified six as most relevant for IHP interactions.

7. Study 2: prioritizing Attributes for interactions with IHPs

The goal of Study 2 was to address RQ2: When not all desirable qualities can be provided simultaneously, which features of AI chatbots, digital clinicians, or online health communities, compared to in-person clinicians are valued most? This study therefore provides a contribution to understanding how users navigate relational versus informational trade-offs across different healthcare providers when seeking mental health information and guidance. We also test if faith-based thriving moderates the preference for community-oriented (relational PCC) vs. informational attributes when engaging with IHPs vs. in-person clinicians in mental health contexts (H1). Study 2 is a preregistered Discrete Choice Experiment (DCE; Carson and Louviere, 2011).

8. Method

8.1. Sample and procedure

We determined a minimum required sample size of $N = 756$ based on the Johnson and Orme (2003) rule of thumb.[4] We recruited $N = 1440$ U.S. adults via *Prolific* in September 2025 to ensure that the final analytic sample would remain above this minimum after data-quality exclusions. The sample was quota-matched to national benchmarks for sex, age, and ethnicity. Religious affiliation was measured but not quota-controlled, as the DCE aimed to estimate population-relevant preference trade-offs. Participants received monetary compensation. Data quality

[2] Although *scope and help provided* ranked third in the MNL model, it emerged as the second-most important attribute in the count analysis and as the highest-ranked attribute in the MIXL model. Following BWS best practice (e.g., Schuster et al., 2024), we base attribute retention on the count analysis and use model-based results as robustness checks. Accordingly, *scope and help provided* was retained as a focal attribute.

[3] Scenario-based robustness checks showed no systematic differences in BWS attribute preferences across anxiety, depression, and bipolar disorder scenarios (Table A6). Table A7 provides the corresponding scenario-specific coefficients for descriptive transparency.

[4] The sample size calculation was based on the "rule-of-thumb" (Johnson and Orme, 2003; see also Szinay et al., 2021) according to the following equation:

$N > 500c/(t \times a)$ (1)

In equation (1), N represents the sample size, t the number of tasks per participant (=8), a the number of alternatives in each choice task (=2), and c the number of analysis cells (=2, as this is the largest number of levels across attributes). Thus, the equation suggests a minimum sample size of $n = 63$ participants per group. Since participants were randomly assigned to 12 groups in total, we need a minimum total sample size of $N = 756$ participants (12×63).

Table 1

Ranking of most important patient-centered communication Attributes for mental health consultations with AI chatbots, telemedicine, and online health communities (study 1, BWS).

Attributes	Count analysis				MNL		MIXL		Het.
	Rank	*Best count*	*Worst count*	*BWS score*	*Rank*	*β*	*Rank*	*β*	$\|\eta\|$
				Medical quality & information					
Explanation about medicine	**1**	**631**	**65**	.46	1	2.03	1	2.83***	1.61***
Symptom assessment capabilities	**2**	**601**	**59**	.44	2	1.79*	2	2.73**	2.21***
Reputation	3	338	85	.20	4	1.02**	4	1.19***	2.14***
Extent of information provided	4	299	52	.20	3	1.44*	3	1.38***	1.34***
Financial cost	5	364	225	.11	5	.01***	5	.78***	4.18***
Length of response	6	127	445	−.26	6	−1.94***	7	−.21	1.47***
Frequency of information provided	7	97	528	−.35	7	−2.44***	6	.12	.69*
Use of medical jargon	8	27	1025	−.80	8	−4.62***	8	−8.83***	5.83***
				Patient interaction & support					
Attentiveness & listening skills	**1**	**506**	**56**	.36	1	2.44***	2	1.29***	1.64***
Scope & help provided	**2**	**504**	**205**	.24	3	.96	1	1.32***	1.96***
Shared decision making	3	404	162	.20	2	.97	5	−.12	4.65
Personalization	4	306	310	−.003	4	−.09	3	.09	1.79
Biopsychosocial care	5	283	290	−.01	5	−.10	6	−.17	1.93
Empathy & emotional support	6	269	320	−.04	6	−.27	4	−.10	2.03
Interpersonal communication style	7	110	418	−.25	7	−1.60***	7	−.88***	1.32***
Familiarity with healthcare provider	8	102	723	−.50	8	−2.31***	8	−1.45***	1.52***
				Community and cultural considerations					
Ext. support beyond consultation	**1**	**869**	**68**	.64	1	2.94***	1	3.95***	2.69***
Community-based assistance	**2**	**439**	**131**	.25	2	1.41***	2	1.45***	1.86***
Cultural competence and awareness	3	391	167	.18	3	1.00***	3	1.20***	2.22***
Community awareness	4	257	164	.07	4	.54***	4	.61***	1.60***
Family involvement	5	242	253	−.01	5	−.02***	5	.20	2.21***
Culturally sensitive language	6	89	336	−.20	6	−1.49***	7	−.55**	1.49***
Religious-based treatment recommendations	7	81	632	−.44	8	−2.32*	8	−6.40***	5.25***
Religious or spiritual guidance	8	116	733	−.50	7	−2.08*	6	−.47**	1.51***

Note. *$p < .05$, **$p < .01$, ***$p < .001$.

The table shows different rankings of eight attributes within three categories across three analysis models. Rankings are based on count analysis, Multinomial Logit (MNL) and Mixed Logit Model (MIXL) as part of a Best–Worst Scaling.

Het. ($|\eta|$) indicates the estimated standard deviation of the random coefficients in the mixed logit model, capturing preference heterogeneity across respondents (larger values = more variation).

Rank columns indicate each attribute's relative importance within a method. β coefficients represent estimated importance weights.

safeguards included three embedded attention checks (excluding $n = 36$ who failed ≥2), a manipulation check verifying correct recognition of the assigned healthcare provider condition (excluding $n = 387$), and five endline quality-control items (provided in Appendix D) that flagged additional low-quality responses (score ≥5; $n = 6$). The final sample comprised $N = 1011$ individuals and therefore remained above the prespecified minimum sample size (56.4% female; 43.6% male; age 19–83, $M = 46.37$, $SD = 15.00$; Table A1). Additional dropout analyses showed no significant differences between the final sample and respondents excluded for failed quality control (Table A4) or manipulation checks (Table A5).

After informed consent, participants completed demographic and basic health questions, were randomly assigned to one of three mental health scenarios (depression, anxiety, bipolar disorder) and one of four provider types (AI chatbot, OHC, digital human clinician, in-person clinician), and then completed a series of DCE tasks. Prior to the DCE tasks, respondents answered a separate single-item question on their provider preference (i.e., which consultation option they would be most likely to choose in the given mental health scenario). Respondents selected in-person clinicians ($n = 615$; 60.8%) most frequently, followed by digital human clinicians ($n = 219$; 21.7%), AI chatbots ($n = 124$; 12.3%), and OHCs ($n = 53$; 5.2%). Of note, the DCE tasks were explicitly framed as occurring regardless of the respondents' previous baseline provider preference ("no matter what you chose before"; Appendix D). Hence, the DCE informs us about attribute-level trade-offs within the randomly assigned provider context. The final DCE design followed Zhang et al. (2025) (see Figure B3 for an example; full task wording in Appendix D).

8.2. Study design: Discrete Choice Experiment (DCE)

DCEs help identify attribute priorities when decisions include a trade-off (Szinay et al., 2021). Typically, the DCE uses two levels for each attribute in order to create a meaningful trade-off scenario (Szinay et al., 2021). A full-profile fractional factorial design ensures that the six attributes are equally displayed between respondents, ensuring that all attributes are presented in each selection task and at two different levels. That way, the DCE balances cognitive load for each individual and maximizes efficiency for the DCE as a whole (Szinay et al., 2021). The DCE procedure includes a pretest followed by a pilot study to set up and optimize the design.

Pretest. Prior to data collection, we conducted a pretest ($n = 10$) to assess the clarity and comprehensibility of the choice tasks. As no revisions were required, the final survey instrument was used without modification.

Pilot Study. Pilot data ($N = 150$, including the pretest) were analyzed with a mixed logit model to obtain preliminary coefficients used as informative priors for the final DCE. Based on these priors, we generated and iteratively optimized a *Bayesian D-efficient design* in R (4.5.0) using *idefix* (Traets et al., 2020) with 2000 draws, maximizing efficiency while keeping choice tasks balanced. Following Szinay et al. (2021), we ensured attribute-level balance and avoided dominant alternatives. The final design achieved a Bayesian D-error of .064 (<.1 indicates high efficiency), supporting its efficiency, balance, and suitability for reliable parameter estimation.

8.3. Measures

DCE Sets. We implemented an unlabeled, fractional-factorial DCE with six attributes (A) at two levels (L). Rather than the full-factorial

$L^A = 2^6 = 64$ tasks, we used an efficient subset with eight tasks per respondent. This approach balanced respondent burden and statistical efficiency, aligning with recommendations of 7–16 sets per respondent (Szinay et al., 2021). To ensure comparability across versions, the attribute set, the order of attributes, and all attribute levels were held constant across conditions. Profiles differed on multiple communication attributes, each experimentally set at two levels representing alternative realizations of each attribute (Fig. 1).

For each choice set, respondents indicated which profile they would prefer for medical advice in their assigned scenario. Responses were coded as a binary outcome for analysis (i.e., *Option 1* (0) vs. *Option 2* (1)).

Faith-Based Thriving. To measure faith-based thriving, we used nine items of the Comprehensive Inventory of Thriving (CIT; Su et al., 2014) reflecting the social support, community, and belonging subscales, adapted to refer to one's religious/faith-based community (e.g., "there are people in my *religious* community I can depend on to help me"). Responses were given on a 7-point Likert-like scale ranging from *strongly disagree* (1) to *strongly agree* (7), with an opt-out option for respondents not identifying with any religious/faith-based community. In the final sample, $n = 735$ respondents provided valid item responses; $n = 276$ (27.3%) chose "not applicable" and were coded as zeros in the analytical sample. Given high reliability (Cronbach's $\alpha = .986$), we averaged all items to a mean score ($M = 3.35$, $SD = 2.61$), where higher values indicate stronger perceived faith-based support/thriving. For the moderation analyses, we used a z-standardized version of the faith-based thriving variable.

8.4. Data analysis

All discrete choice models were estimated in R (4.5.0; R Core Team, 2025). Each communication attribute was operationalized with two distinct levels (Fig. 1) and dummy-coded, with one level serving as the reference (0) and the alternative level coded as 1. To capture individual-level preference heterogeneity, we estimated a mixed logit (MIXL) model using the *mlogit* package (Croissant, 2025). The correlated MIXL specification provides a flexible representation of preference heterogeneity, including correlated random coefficients, which aligns with our analytic aims (e.g., Hess and Train, 2017). The model was specified without an intercept so that each coefficient represents the relative importance of the attribute level. Maximum likelihood estimation with 2000 simulation draws was performed.

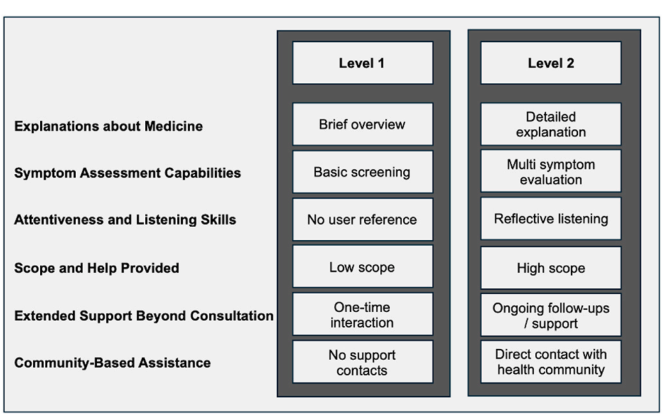

Fig. 1. *Attributes for Patient-Centered Communication at Two Levels as Operationalized in Study 2 (DCE)*
Note. PCC Attributes at two levels are depicted as shown to respondents in the Discrete Choice Experiment. Level 1 and Level 2 represent the two contrasted realizations of each attribute.

9. Results and discussion

To address RQ2, we examined provider-specific preference weights (Table 2).[5] The mixed logit analysis (Table 2) showed that *multi-symptom assessment capabilities* and *attentiveness and listening skills* emerged as the most important attributes for all IHPs. In contrast, when consulting an in-person clinician, *extended support beyond the consultation* ($\beta = 1.78$, $SE = .24$, $p < .001$) was the most valued feature, followed by *multi-symptom assessment capabilities* ($\beta = 1.51$, $SE = .22$, $p < .001$). Interestingly, *direct contact with a health-related community* ranked as the third most important attribute when interacting with an AI chatbot ($\beta = 1.09$, $SE = .17$, $p < .001$), but was among the two least important attributes for all other IHPs.

This pattern suggests that users particularly appreciate opportunities for peer or community support when engaging with AI-based tools, perhaps to compensate for the lack of human connection that typically characterizes such interactions.

Finally, we tested whether faith-based thriving moderates attribute preferences across provider types (H1) using provider-specific mixed logit models while additionally controlling for the subjective importance of religion (Table 3).[6] Again, the results indicate a provider-specific moderation pattern. For AI chatbots, higher faith-based thriving was associated with a stronger preference for *scope and help provided* ($\beta = .41$, $SE = .18$, $p = .020$). For digital clinicians, higher faith-based thriving was associated with a stronger preference for *community-based assistance* ($\beta = .63$, $SE = .23$, $p = .010$). In contrast, no thriving interaction terms were statistically significant for in-person clinicians or OHCs.

Taken together, these findings indicate a provider-specific moderation pattern and provide partial support for H1. Consistent with our expectations, higher faith-based thriving was associated with stronger preferences for relational (*scope and help provided*) and community-oriented (*community-based assistance*) attributes in two IHPs (AI chatbots and digital clinicians). However, this pattern did not generalize across all provider types, as no significant thriving interaction terms emerged for OHCs or in-person clinicians. In addition, the hypothesized reduction in preferences for informational attributes was not supported.

In our sample, 63.4% of U.S. Protestants and 55.0% of Roman Catholics scored in the high-thriving range (≥5 on a 7-point scale), and together accounted for over 85% of high-thriving individuals. Thus, the observed moderation pattern likely reflects, to a substantial extent, relational thriving as experienced within these Christian groups.

10. General discussion

This research examined how individuals evaluate and prioritize patient-centered communication (PCC; Epstein and Street, 2007) attributes when engaging with different interactive healthcare providers (IHPs) compared to in-person clinicians for mental health support. Study

[5] To address RQ2, we report provider-specific preference weights because likelihood-ratio and random-taste heterogeneity tests showed significant heterogeneity by provider type (Table A8). Mental health scenario heterogeneity was non-significant (Table A9), consistent with Study 1. Table A10 provides the corresponding scenario-specific coefficients for descriptive transparency. We additionally report exploratory scale-heterogeneity tests (Wright et al., 2018) across provider types and mental health scenarios to assess possible error-variance confounding in between-group coefficient comparisons. The results did not indicate that between-group differences were primarily driven by systematic differences in error variance (Table A8–A9).

[6] Because faith-based thriving was modeled as a continuous moderator, we tested robustness to nonlinear forms by comparing linear, quadratic, and cubic specifications. In 23 of 24 condition-by-attribute comparisons, quadratic/cubic models fit better than the linear model (*AIC/BIC*), indicating moderation is often nonlinear (Figure B4; Table A11). Crucially, the substantive pattern did not change: Nonlinear models mainly captured curvature (e.g., plateaus/turning points) rather than reversing effects.

Table 2
Trade-off ranking for patient-centered communication attributes by health provider type (study 2, DCE).

	AI chatbot				OHC				Digital clinician				In-person clinician			
	β	*SE*	*SD*	$p_{(SD)}$	β	*SE*	*SD*	$p_{(SD)}$	β	*SE*	*SD*	$p_{(SD)}$	β	*SE*	*SD*	$p_{(SD)}$
Explanation about medicine	.83***	.15	1.55***	<.001	.77***	.13	.99**	.002	.91***	.16	1.08***	<.001	1.25***	.18	1.61***	<.001
Symptom assessment capabilities	1.25***	.19	1.50***	<.001	.96***	.16	1.41***	<.001	1.48***	.23	1.66***	<.001	1.51***	.22	1.70***	<.001
Attentiveness & listening skills	1.26***	.18	1.25***	<.001	.85***	.14	.47	.191	1.31***	.19	1.25***	<.001	1.36***	.19	1.25***	<.001
Scope & help provided	.62***	.13	1.12***	<.001	.71***	.12	1.14***	<.001	.90***	.16	1.13***	<.001	.68***	.14	1.12***	<.001
Extended support beyond consultation	.87***	.16	1.63***	<.001	.46***	.13	1.49***	<.001	1.27***	.21	1.83***	<.001	1.78***	.24	2.13***	<.001
Community-based assistance	1.09***	.17	1.75***	<.001	.56***	.12	1.15***	<.001	.88***	.16	1.38***	<.001	.89***	.16	1.63***	<.001
AIC	2737.50				1917.27				2327.95				2653.75			
BIC	2764.10				2064.90				2548.00				2998.80			
RMSE	.47				.48				.48				.49			

Note. *$p < .05$, **$p < .01$, ***$p < .001$.
Mean utility coefficients (β) from a mixed logit model (MIXL) are reported. Positive β indicate a higher choice probability for that specific patient-centered communication attribute. *SD* reflects preference heterogeneity from random-effects variance–covariance matrix.

Table 3
Moderation effects of thriving through faith-based relationships by health provider type (study 2, DCE).

	AI chatbot					OHC					Digital clinician					In-person clinician				
	β	*SE*	$p_{(\beta)}$	*SD*	$p_{(SD)}$	β	*SE*	$p_{(\beta)}$	*SD*	$p_{(SD)}$	β	*SE*	$p_{(\beta)}$	*SD*	$p_{(SD)}$	β	*SE*	$p_{(\beta)}$	*SD*	$p_{(SD)}$
Explanation about medicine × thriving	−.02	.21	.920	1.57***	<.001	−.16	.20	.410	.99***	<.001	−.03	.23	.900	1.06***	<.001	.35	.21	.100	1.54***	<.001
Symptom assessment capabilities × thriving	.00	.21	.990	1.39***	<.001	.47	.24	.050	1.35***	<.001	−.25	.28	.370	1.59***	<.001	−.13	.23	.580	1.59***	<.001
Attentiveness & listening × thriving	−.29	.19	.130	1.24***	<.001	−.15	.18	.400	.40	.061	−.24	.22	.280	1.22***	<.001	−.29	.19	.130	1.14***	<.001
Scope & help provided × thriving	**.41***	**.18**	**.020**	.87***	<.001	.36	.19	.060	.80***	<.001	−.10	.21	.620	.98***	<.001	−.20	.19	.290	.90***	<.001
Ext. support beyond consultation × thriving	−.20	.22	.340	1.16***	<.001	.04	.22	.850	1.06***	<.001	.20	.26	.440	1.68***	<.001	−.08	.22	.700	1.82***	<.001
Community-based assistance × thriving	.16	.19	.400	1.52***	<.001	.17	.20	.400	.95***	<.001	**.63***	**.23**	**.010**	1.24***	<.001	−.07	.20	.720	1.22***	<.001
AIC	2547.19					1924.68					2331.00					2657.33				
BIC	2768.34					2133.43					2549.59					2882.48				
RMSE	.47					.48					.48					.50				

Note. *$p < .05$, **$p < .01$, ***$p < .001$.
Provider-specific mixed logit models (MIXL) were estimated separately for all healthcare providers. The table reports the estimated interaction coefficients (β) for attribute × faith-based thriving. All models additionally controlled for *importance of religion*. The dependent variable is the choice between two alternatives in the DCE tasks. Positive β indicates that the corresponding attribute becomes more important as thriving increases. *SD* reflects preference heterogeneity from random-effects variance–covariance matrix.

1 identified a core set of six out of 24 PCC attributes relevant across IHPs by applying a preregistered selection rule that retained the two highest-ranked attributes within each of three PCC domains, ensuring balanced coverage while keeping Study 2 cognitively manageable. Study 2 then tested how people prioritize these attributes under trade-offs and whether faith-based thriving moderates these preferences. Because provider type showed clear heterogeneity, whereas mental health scenarios did not, we focus on within-provider preference patterns in Study 2.

Compared with prior PCC and preference work from which we derived our initial attribute pool (e.g., Cheraghi-Sohi et al., 2008; Tinelli et al., 2015; Whitaker et al., 2017), Study 1 (BWS) suggests that mental health choices concentrate on a core set of interactional and informational qualities. Notably, two self-developed attributes—*community-based assistance* (based on Van Oerle et al., 2018) and *extended support beyond the consultation*—ranked among the most influential PCC attributes. Overall, the high importance of relational and informational features is broadly consistent with psychotherapy PCC research emphasizing empathy, active listening, and collaborative engagement (e.g., Niu et al., 2025) and with digital mental health preference work highlighting supportive and effective care components (e.g., Phillips et al., 2021).

In Study 2 (DCE), across the three IHPs (AI chatbots, digital clinicians, and OHCs), two attributes were consistently most important when trade-offs were required: *multi-symptom assessment capabilities* and *higher attentiveness and listening skills*. Although the importance of *attentiveness and listening skills* may seem counterintuitive for AI chatbots, in AI-mediated interactions, "listening" must be conveyed through language. It can be communicated by explicitly reflecting users' semantic content and implied meaning (e.g., through paraphrasing, thematic summarization, and contingent follow-up questions), thereby signaling understanding and helping users feel heard (Xiao et al., 2020).

In contrast, for in-person clinicians, *extended support beyond the consultation* was the top attribute, followed by *multi-symptom assessment capabilities*. This suggests that in face-to-face contexts, patients particularly value clinicians who facilitate ongoing support outside the encounter—a resource they may assume is more readily available in digital IHPs. At the same time, accurate symptom assessment remains foundational, indicating that patients still depend on clinicians for diagnostic clarity and guidance (Tinelli et al., 2015), even when broader relational needs are met elsewhere.

Drawing on the *thriving through relationships* model (Feeney and Collins, 2015), we conceptualized faith-based thriving as a relational orientation that shapes expectations for support. Thriving depends less on physical co-presence than on relational affordances such as responsiveness, continuity, or feeling "held in mind." Digital IHPs can deliver these affordances through predictability, personalization, and continuity of interaction (e.g., Niu et al., 2025). Accordingly, we conceptualize faith-based thriving as a relational moderator that shapes what kinds of support people prioritize. However, in the provider-specific MIXL models—controlling for subjective importance of religion—this moderation pattern was selective rather than general across provider types. Higher faith-based thriving was associated with a stronger preference for *scope and help provided* for AI chatbots and a stronger preference for *community-based assistance* for digital clinicians, whereas no significant thriving interactions emerged for OHCs or in-person clinicians. This pattern suggests that faith-based thriving does not uniformly increase preferences for relational attributes across all healthcare contexts. Instead, the results point to a context-dependent moderation pattern: *thriving through faith-based relationships* appears to shape preferences particularly in one-to-one digital provider settings (i.e., AI chatbots and digital clinicians), while its role is less evident in community-based or in-person contexts (i.e., OHCs and in-person clinicians), where relational or community expectations may already be more strongly defined.

Designing digital mental health tools that integrate relational cues—such as empathy or community engagement—while maintaining strong diagnostic reasoning and clear guidance (e.g., through improved AI training or low-threshold referrals to community resources within telemedicine) may help bridge the relational gap between digital and in-person care. This is especially important in mental health contexts, where connection, recognition, and belonging are central to meaningful support. Overall, our findings suggest that the most acceptable IHPs will be those that combine clinical competence with credible relational support and, where possible, connect users to the communities and continuity structures that sustain recovery beyond the immediate interaction.

11. Limitations

This study has several limitations. First, we focused on different mental health problems (depression, anxiety, bipolar disorder), limiting generalizability to other medical domains. Second, data were based on hypothetical decision situations; although DCEs approximate real preferences, they do not capture actual behavior under real-life conditions. Third, following Zhang et al. (2025), our DCE used an unlabeled, text-only, two-alternative format with two levels per attribute, which may have shaped how respondents processed trade-offs. Alternative DCE designs are also possible, such as designs with planned attribute-level overlap, which can reduce task complexity and improve choice consistency (Jonker et al., 2019). Fourth, participants were assigned to one of four healthcare providers and one of three mental health scenarios, which may have increased cognitive load and the risk of misinterpretation. To reduce this risk, both assignments were shown on separate pages in large red text, and respondents who failed the provider-context recall check were excluded. However, some misunderstanding cannot be ruled out. Fifth, because IHPs are rapidly evolving, changing capabilities may render current attribute valuations time-sensitive. Sixth, exploratory SMNL robustness tests found no statistically detectable scale heterogeneity across provider types or mental health scenarios; however, these tests cannot confirm scale invariance, and cross-group differences in coefficient magnitudes should therefore be interpreted cautiously. Seventh, despite controlling for the subjective importance of religion, coding "not applicable" as zero may conflate non-applicability with very low faith-based thriving.

12. Conclusion

The present studies show that PCC hinges on a shifting balance between informational clarity and relational depth. Across digital IHPs, choices cluster around two core signals of "good care": strong multi-symptom assessment and attentive, emotionally responsive communication. In face-to-face care, clinicians gain distinct value when support extends beyond the visit. Faith-based thriving partially moderates these preferences for two of the three digital IHPs: Higher faith-based thriving was associated with a stronger preference for *scope and help provided* for AI chatbots and a stronger preference for *community-based assistance* for digital clinicians. Health system decision-makers should incorporate relational signaling, continuity mechanisms, and diagnostic precision into digital healthcare provider tools, and, particularly in telemedicine, institutionalize low-threshold handoffs to community-based supports as a core component of mental health care.

Ethical considerations

Ethical approval for both studies was obtained from the Ethics Committee of the University of Augsburg (IRB-A-2025-x101).

Statement on privacy and informed consent

The privacy rights of all human subjects were fully respected during this study. Participation was voluntary, and informed consent was obtained from all participants prior to data collection.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT 5.2 in order to refine the language of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Funding sources

This research was supported by the University of Augsburg, the Faculty of Philosophy and Social Sciences (Grant VAF25), and the Graduate School Center.

CRediT authorship contribution statement

Nathalie Laura Neuendorf: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Katharina Angermayr:** Conceptualization, Data curation, Methodology, Writing – review & editing. **Sebastian Scherr:** Conceptualization, Data curation, Methodology, Supervision, Writing – review & editing.

Declaration of interest

The authors report there are no competing interests to declare.

Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2026.119431.

Data availability

Data will be made available on request.

References

Alma Taya, D., Chuang, Y.-C., 2025. Internet use for health information, health service utilization, and quality of care in the U.S. BMC Health Serv. Res. 25 (1), 659. https://doi.org/10.1186/s12913-025-12807-5.

Angermayr, K., Street, Jr. R.L., Scherr, S., 2025. Communication accommodation with AI-chatbots: improving patient-centered communication in times of conversational AI [conference presentation]. In: 108th Annual AEJMC Conference, San Francisco, CA.

Austin, P., Macleod, R., Siddall, P., McSherry, W., Egan, R., 2017. Spiritual care training is needed for clinical and non-clinical staff to manage patients' spiritual needs. J. Study Spiritual. 7 (1), 50–63. https://doi.org/10.1080/20440243.2017.1290031.

Boucher, E.M., Harake, N.R., Ward, H.E., Stoeckl, S.E., Vargas, J., Minkel, J., Parks, A.C., Zilca, R., 2021. Artificially intelligent chatbots in digital mental health interventions: a review. Expert Rev. Med. Dev. 18 (Suppl. 1), 37–49. https://doi.org/10.1080/17434440.2021.2013200.

Burton, N., Burton, M., Fisher, C., Peña, P.G., Rhodes, G., Ewing, L., 2021. Beyond Likert ratings: improving the robustness of developmental research measurement using best–worst scaling. Behav. Res. Methods 53 (5), 2273–2279. https://doi.org/10.3758/s13428-021-01566-w.

Carson, R.T., Louviere, J.J., 2011. A common nomenclature for stated preference elicitation approaches. Environ. Resour. Econ. 49 (4), 539–559. https://doi.org/10.1007/s10640-010-9450-x.

Chen, X., 2023. Online health communities influence people's health behaviors in the context of COVID-19. PLoS One 18 (4), e0282368. https://doi.org/10.1371/journal.pone.0282368.

Chen, L., Chu, H., Wang, H., Du, L., Gao, Y., Shen, J., 2025. Effects of communication, trust, and respect on shared decision-making: insights from healthcare providers in Chinese public hospitals. Front. Med. 12, 1577276. https://doi.org/10.3389/fmed.2025.1577276.

Cheraghi-Sohi, S., Hole, A.R., Mead, N., McDonald, R., Whalley, D., Bower, P., Roland, M., 2008. What patients want from primary care consultations: a discrete choice experiment to identify patients' priorities. Ann. Fam. Med. 6 (2), 107–115. https://doi.org/10.1370/afm.816.

Cheung, K.L., Mayer, S., Simon, J., de Vries, H., Evers, S.M.A.A., Kremer, I.E.H., Hiligsmann, M., 2019. Comparison of statistical analysis methods for object case best–worst scaling. J. Med. Econ. 22 (6), 509–515. https://doi.org/10.1080/13696998.2018.1553781.

Clark, M., Bailey, S., 2024. Chatbots in health care: connecting patients to information. Can. J. Health Technol. 4 (1), 1–22. https://doi.org/10.51731/cjht.2024.818.

Clarke, G.M., Dias, A., Wolters, A., 2022. Access to and Delivery of General Practice Services: a Study of Patients at Practices Using Digital and Online Tools. The Health Foundation. https://www.health.org.uk/reports-and-analysis/briefings/access-to-and-delivery-of-general-practice-services. (Accessed 7 May 2026).

Croissant, Y., 2025. Mlogit: Multinomial Logit Models. CRAN [software], Version 1.1-3. https://cran.r-project.org/web/packages/mlogit/index.html. (Accessed 7 May 2026).

Dutta, A., Nelson, H., Shah, U., Korenda, L., Varia, H., Wagh, M., 2024. The Growing Disconnect Between Virtual Health Availability and Consumer Demand. Deloitte Center for Health Solutions. https://www.deloitte.com/us/en/insights/industry/health-care/virtual-health-consumer-demand-and-availability.html. (Accessed 7 May 2026).

Epstein, R.M., Street, Jr. R.L., 2007. Patient-Centered Communication in Cancer Care: Promoting Healing and Reducing Suffering. National Cancer Institute, Bethesda, MD. NIH Publication No. 07-6225. https://cancercontrol.cancer.gov/sites/default/files/2020-06/pcc_monograph.pdf. (Accessed 7 May 2026).

Esmaeilzadeh, P., Maddah, M., Mirzaei, T., 2025. Using AI chatbots (e.g., CHATGPT) in seeking health-related information online: the case of a common ailment. Comput. Hum. Behav. Artif. Humans 3, 100127. https://doi.org/10.1016/j.chbah.2025.100127.

Feeney, B.C., Collins, N.L., 2015. A new look at social support: a theoretical perspective on thriving through relationships. Pers. Soc. Psychol. Rev. 19 (2), 113–147. https://doi.org/10.1177/1088868314544222.

Gong, S.A., Ao, S.H., Chen, Y.S., 2025. The influence of patient-centered communication on psychological distress: the chain mediating role of health-related self-efficacy and healthy lifestyle behaviors and the moderating role of social media use. Front. Psychiatr. 16, 1562414. https://doi.org/10.3389/fpsyt.2025.1562414.

Greenwood, H., Krzyzaniak, N., Peiris, R., Clark, J., Scott, A.M., Cardona, M., Griffith, R., Glasziou, P., 2022. Telehealth versus face-to-face psychotherapy for less common mental health conditions: systematic review and meta-analysis of randomized controlled trials. JMIR Ment. Health 9 (3), e31780. https://doi.org/10.2196/31780.

Hess, S., Train, K., 2017. Correlation and scale in mixed logit models. J. Choice Model 23, 1–8. https://doi.org/10.1016/j.jocm.2017.03.001.

Hollin, I.L., Paskett, J., Schuster, A.L.R., Crossnohere, N.L., Bridges, J.F.P., 2022. Best–worst scaling and the prioritization of objects in health: a systematic review. Pharmacoeconomics 40 (9), 883–899. https://doi.org/10.1007/s40273-022-01167-1.

Johnson, R., Orme, B., 2003. Getting the most from CBC. In: Sawtooth Software Research Paper Series, Sawtooth Software. WA, Sequim. https://sawtoothsoftware.com/resources/technical-papers/getting-the-most-from-cbc. (Accessed 7 May 2026).

Jonker, M.F., Donkers, B., de Bekker-Grob, E., Stolk, E.A., 2019. Attribute level overlap (and color coding) can reduce task complexity, improve choice consistency, and decrease the dropout rate in discrete choice experiments. Health Econ. 28 (3), 350–363. https://doi.org/10.1002/hec.3846.

Laymouna, M., Ma, Y., Lessard, D., Schuster, T., Engler, K., Lebouché, B., 2024. Roles, users, benefits, and limitations of chatbots in health care: rapid review. J. Med. Internet Res. 26 (1), e56930. https://doi.org/10.2196/56930.

Liu, Z., Zou, W., Yang, S., 2025. What drives patient preferences for AI chatbots over doctors? A survey study using the O-S-O-R model. Health Commun. 1–12. https://doi.org/10.1080/10410236.2025.2537814.

Liu, J., Kong, J., 2021. Why do users of online mental health communities get likes and reposts: a combination of text mining and empirical analysis. Healthcare 9 (9), 1133. https://doi.org/10.3390/healthcare9091133.

Marley, A.A.J., Louviere, J.J., 2005. Some probabilistic models of best, worst, and best–worst choices. J. Math. Psychol. 49 (6), 464–480. https://doi.org/10.1016/j.jmp.2005.05.003.

Mazziotti, R., Rutigliano, G., 2021. Tele–mental health for reaching out to patients in a time of pandemic: provider survey and meta-analysis of patient satisfaction. JMIR Ment. Health 8 (7), e26187. https://doi.org/10.2196/26187.

Mills, F., Drury, J., Hall, C.E., Weston, D., Symons, C., Amlôt, R., Carter, H., 2025. A mixed studies systematic review on the health and wellbeing effects, and underlying mechanisms, of online support groups for chronic conditions. Commun. Psychol. 3, 40. https://doi.org/10.1038/s44271-025-00217-6.

Minn, S.W., Tariq, D., Ndubueze, C., Paul, P.M., See, J.W., 2025. A Google trends analysis exploring public interest in common psychiatric conditions and non-pharmacological interventions. Asian J. Psychiatry 107, 104482. https://doi.org/10.1016/j.ajp.2025.104482.

Morini, V., Sansoni, M., Rossetti, G., Pedreschi, D., Castillo, C., 2025. Participant behavior and community response in online mental health communities: insights from Reddit. Comput. Hum. Behav. 165, 108544. https://doi.org/10.1016/j.chb.2024.108544.

Neuendorf, N.L., Scherr, S., 2025. The influence of religious social networks on mental health: a systematic review [conference presentation]. In: 75th Annual ICA Conference. Denver, CO.

Niu, Y., Sun, J., Zhu, K., Xu, B., Zhang, Y.-P., Peng, M., 2025. The critical role and effects of patient-centered communication in psychotherapy: a narrative review. Psychol. Res. Behav. Manag. 18, 1657–1671. https://doi.org/10.2147/PRBM.S528343.

Phillips, E.A., Himmler, S.F., Schreyögg, J., 2021. Preferences for e-mental health interventions in Germany: a discrete choice experiment. Value Health 24 (3), 421–430. https://doi.org/10.1016/j.jval.2020.09.018.

Pratiwi, A.B., Padmawati, R.S., Mulyanto, J., Willems, D.L., 2023. Patients values regarding primary health care: a systematic review of qualitative and quantitative evidence. BMC Health Serv. Res. 23 (1), 400. https://doi.org/10.1186/s12913-023-09394-8.

Prescott, J., Rathbone, A.L., Hanley, T., 2020. Online mental health communities, self-efficacy and transition to further support. Ment. Health Rev. 25 (4), 329–344. https://doi.org/10.1108/MHRJ-12-2019-0048.

Puchalski, C.M., Vitillo, R., Hull, S.K., Reller, N., 2014. Improving the spiritual dimension of whole person care: reaching national and international consensus. J. Palliat. Med. 17 (6), 642–656. https://doi.org/10.1089/jpm.2014.9427.

R Core Team, 2025. R: a Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria [software]. https://www.R-project.org/.

Schafer, M.H., Upenieks, L., 2016. Trans-congregational triadic closure: churchgoers' networks within and beyond the pews. J. Sci. Stud. Relig. 55 (3), 597–621. https://doi.org/10.1111/jssr.12281.

Schlemper, L., Urano, Y., 2025. Who prefers online therapy for mental health problems? A cross-sectional study in Japan. Comput. Hum. Behav. Rep 19, 100743. https://doi.org/10.1016/j.chbr.2025.100743.

Scholich, T., Barr, M., Stirman, S.W., Raj, S., 2025. A comparison of responses from human therapists and large language model–based chatbots to assess therapeutic communication: mixed methods study. JMIR Ment. Health 12 (1), e69709. https://doi.org/10.2196/69709.

Schuster, A.L.R., Crossnohere, N.L., Campoamor, N.B., Hollin, I.L., Bridges, J.F.P., 2024. The rise of best-worst scaling for prioritization: a transdisciplinary literature review. J. Choice Model. 50, 100466. https://doi.org/10.1016/j.jocm.2023.100466.

Seuling, P.D., Fendel, J.C., Spille, L., Göritz, A.S., Schmidt, S., 2024. Therapeutic alliance in videoconferencing psychotherapy compared to psychotherapy in person: a systematic review and meta-analysis. J. Telemed. Telecare 30 (10), 1521–1531. https://doi.org/10.1177/1357633X231161774.

Su, R., Tay, L., Diener, E., 2014. The development and validation of the comprehensive inventory of thriving (CIT) and the brief inventory of thriving (BIT). Appl. Psychol. Health Well-Being 6 (3), 251–279. https://doi.org/10.1111/aphw.12027.

Szinay, D., Cameron, R., Naughton, F., Whitty, J.A., Brown, J., Jones, A., 2021. Understanding uptake of digital health products: methodology tutorial for a discrete choice experiment using the Bayesian efficient design. J. Med. Internet Res. 23 (10), e32365. https://doi.org/10.2196/32365.

Tinelli, M., Nikoloski, Z., Kumpunen, S., Knai, C., Pribakovic Brinovec, R., Warren, E., Wittgens, K., Dickmann, P., 2015. Decision-making criteria among European patients: exploring patient preferences for primary care services. Eur. J. Publ. Health 25 (1), 3–9. https://doi.org/10.1093/eurpub/cku082.

Traets, F., Sanchez, D.G., Vandebroek, M., 2020. Generating optimal designs for discrete choice experiments in R: the idefix package. J. Stat. Software 96 (3), 1–41. https://doi.org/10.18637/jss.v096.i03.

Treadgold, B.M., Coulson, N.S., Campbell, J.L., Lambert, J., Pitchforth, E., 2025. Quality and misinformation about health conditions in online peer support groups: scoping review. J. Med. Internet Res. 27 (1), e71140. https://doi.org/10.2196/71140.

Van Oerle, S., Lievens, A., Mahr, D., 2018. Value co-creation in online healthcare communities: the impact of patients' reference frames on cure and care. Psychol. Market. 35 (9), 629–639. https://doi.org/10.1002/mar.21111.

von Lützow, U., Neuendorf, N.L., Scherr, S., 2025. Effectiveness of just-in-time adaptive interventions for improving mental health and psychological well-being: a systematic review and meta-analysis. BMJ Ment. Health 28 (1), e301641. https://doi.org/10.1136/bmjment-2025-301641.

Whitaker, K.L., Ghanouni, A., Zhou, Y., Lyratzopoulos, G., Morris, S., 2017. Patients' preferences for GP consultation for perceived cancer risk in primary care: a discrete choice experiment. Br. J. Gen. Pract. 67 (659), e388–e395. https://doi.org/10.3399/bjgp17X690905.

Wright, S.J., Vass, C.M., Sim, G., Burton, M., Fiebig, D.G., Payne, K., 2018. Accounting for scale heterogeneity in healthcare-related discrete choice experiments when comparing stated preferences: a systematic review. Patient 11 (5), 475–488. https://doi.org/10.1007/s40271-018-0304-x.

Wu, X., Liew, K., Dorahy, M.J., 2025. Trust, anxious attachment, and conversational AI adoption intentions in digital counseling: a preliminary cross-sectional questionnaire study. JMIR AI 4 (1), e68960. https://doi.org/10.2196/68960.

Xiao, Z., Zhou, M.X., Chen, W., Yang, H., Chi, C., 2020. If I hear you correctly: building and evaluating interview chatbots with active listening skills. In: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, pp. 1–14. https://doi.org/10.1145/3313831.3376131.

Yan, L., Tan, Y., 2014. Feeling blue? Go online: an empirical study of social support among patients. Inf. Syst. Res. 25 (4), 690–709. https://doi.org/10.1287/isre.2014.0538.

Yun, H.S., Bickmore, T., 2025. Online health information–seeking in the era of large language models: cross-sectional web-based survey study. J. Med. Internet Res. 27 (1), e68560. https://doi.org/10.2196/68560.

Zhang, J., Wang, J., Zhang, J., Xia, X., Zhou, Z., Zhou, X., Wu, Y., 2025. Young adult perspectives on artificial intelligence–based medication counseling in China: discrete choice experiment. J. Med. Internet Res. 27 (1), e67744. https://doi.org/10.2196/67744.

Zhong, W., Luo, J., Zhang, H., 2024. The therapeutic effectiveness of artificial intelligence-based chatbots in alleviation of depressive and anxiety symptoms in short-course treatments: a systematic review and meta-analysis. J. Affect. Disord. 356, 459–469. https://doi.org/10.1016/j.jad.2024.04.057.