Stigma Reduces AI Aversion:

A Tradeoff between Judgment and Misinformation Concerns

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February 22, 2026

Abstract

Information acquisition is a critical input into health and welfare-relevant decision-making, yet individuals often under-seek information in stigmatized domains. This paper studies how stigma shapes demand for information from artificial intelligence (AI) relative to human experts. We examine whether generative AI chatbots, by offering anonymous and non-judgmental interactions, alter information-seeking behavior when social stigma is salient. We present evidence from a series of online randomized controlled experiments and a field experiment that causally manipulate stigma and information environments. Across settings, higher perceived stigma increases individuals' propensity to seek information from AI chatbots relative to human experts, reversing the well-documented pattern of algorithm aversion in advice-taking. The effect is economically meaningful and robust across domains involving sensitive health and personal concerns. We identify two mechanisms underlying this shift in demand. First, stigma increases concern about social judgment, raising the relative utility of interacting with non-human information sources. Second, stigma attenuates concerns about misinformation, lowering resistance to algorithmic advice. Together, these forces generate a substitution toward AI-based information channels in stigmatized contexts. We provide causal evidence on both stated preferences and revealed information-seeking behavior. Our findings contribute to the literature on information frictions, technology adoption, and algorithm aversion by introducing stigma as a context-specific determinant of

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demand for algorithmic advice. From a welfare and policy perspective, AI chatbots may expand access to information in settings where stigma suppresses engagement with traditional providers, but this expansion may come with increased exposure to misinformation. We discuss implications for the design and regulation of AI-enabled information systems in healthcare and other sensitive domains.

Keywords: AI chatbots, algorithm aversion, stigma, information-seeking, misinformation, judgment, health and wellness

1 INTRODUCTION

Access to accurate information plays a crucial role in mitigating the adverse effects of challenging circumstances. However, stigma presents a significant psychological barrier to seeking information (Ahmedani, 2011; Vogel et al., 2007). Stigma refers to "stereotypes or negative views attributed to a person or groups of people when their characteristics or behaviors are viewed as different from or inferior to societal norms." (Dudley, 2000). For instance, individuals experiencing mental health challenges, such as depression, may be stereotyped as unmotivated, and those struggling with weight management may encounter negative stereotypes implying a lack of self-discipline (Stangl et al., 2019). Stigma can lead people to hide their struggles because they fear being labeled, which deters them from seeking professional help (Aggarwal et al., 2023; Ahmedani, 2011; Link & Phelan, 2001). Because information-seeking is often the first step toward pursuing diagnosis, treatment, or other forms of professional support (Lambert & Loiselle, 2007; Rickwood et al., 2005), addressing stigma-related barriers to this stage is an important societal goal.

Recently, chatbots powered by generative artificial intelligence (e.g., ChatGPT, Copilot, and Gemini) have become increasingly prevalent and powerful, making them a popular source of information (Deldjoo et al., 2021; Hou et al., 2024). These AI chatbots are conversational agents powered by large language models (LLMs), which integrate deep neural architectures, self-supervised pretraining on massive corpora, and reinforcement learning from human feedback (Chau & Xu, 2025). AI chatbots facilitate conversational information-seeking through interactive dialogue, enabling clarification, personalization, and follow-up questions that yield more customized responses (Trippas et al., 2017; Zamani et al., 2022). These capabilities have driven the growing use of generative AI chatbots for information-seeking across health and wellness apps, from stress reduction and mood improvement (e.g., Wysa, WoebotGPT) to health and lifestyle guidance (e.g., K Health) and mindfulness and personal development (e.g., Headspace). National and global health institutions (e.g., NHS, WHO, UNICEF, Cleveland Clinic, Mayo Clinic) are also adopting generative AI chatbots to support information-seeking.

Many digital wellness platforms now simultaneously offer human and generative AI support through text-based chat to make care more accessible and scalable. For instance, Wysa allows users to choose between an AI coach and a human therapist. Text-based interactions are especially appealing because they are cost-effective, widely accessible, and already embedded in mobile apps and telehealth platforms. This growing side-by-side presence of human and AI options could have significant, unanticipated effects on information-seeking behavior, and therefore, raises a critical question of how individuals form preferences between the two, especially when stigma shapes the context.

Two counteracting factors shape user choices between human experts and AI chatbots in stigmatic contexts. On the one hand, individuals may fear being negatively evaluated, labeled, or morally judged, increasing hesitance to seek information from humans. In contrast, AI chatbots are perceived as non-judgmental (De Gennaro et al., 2020; Lucas et al., 2014), potentially making them a more appealing choice for those affected by stigma. On the other hand, individuals may be concerned that AI chatbots provide inaccurate, unreliable, or unverified information, leading to concerns about misinformation (Cornelison et al., 2024). Thus, it remains unclear whether the fear of judgment will outweigh concerns about misinformation, or whether individuals will still prefer human experts in stigmatized situations, perceiving them as more trustworthy and informed sources (Tolmeijer et al., 2022).

While lower judgment and higher misinformation concerns can also arise with other technologies, such as search engines, these concerns tend to operate independently on such platforms. Users typically experience low fear of judgment because interactions are impersonal and anonymous, and they recognize misinformation as external content that can be verified or dismissed. In contrast, users perceive AI chatbots as non-judgmental because they simulate social interaction through conversation (Gennaro et al., 2020; Lucas et al., 2014). This conversational style can make individuals less cautious and more susceptible to misinformation. This is because people tend to perceive information conveyed through conversation as more credible compared to information presented in the non-interactive and static format of search engines (Stokel-Walker, 2023). Concerns about misinformation are also amplified with generative AI, given their reliance on large language models that are prone to hallucination (Shao, 2025).

Moreover, chatbots are often overly agreeable, offering comforting but uncritical responses that affirm users' incorrect beliefs, reinforcing misinformation.[1,2] Thus, it is essential to examine this unique tradeoff between users' desire for non-judgmental support and their desire for informational accuracy, and how this tension informs their preferences. We therefore propose the following research questions:

1. *What is the effect of stigma on individuals' preference for seeking information from an AI chatbot (versus a human expert)?*
2. *How do individuals' judgment and misinformation concerns influence their preferences for seeking information from an AI chatbot (versus a human expert) in stigmatized situations?*

We address these research questions using three online randomized controlled experiments and one field experiment. In the online experiments, employing a scenario-based study design (Werner & Muradova, 2022), we curated seven diverse scenarios focused on health and well-being. Given that stigma is essentially a perceived construct (Becker & Arnold, 1986), we first measured perceived stigma levels and commonly held stigmatic stereotypes for each scenario. We then created a baseline (control) condition and a high-stigma (treatment) condition to manipulate stigma exposure and measure the willingness to seek information from AI chatbots or human experts.

In the baseline condition, participants read seven scenarios. In the high-stigma condition, participants read the *same* scenarios and additionally encountered a stigmatizing radio prompt reinforcing the predominant stereotype for each scenario. This design enabled us to manipulate perceived stigma while keeping scenarios the same in control and treatment groups, isolating the causal effect of stigma on the willingness to seek information. Using the same design, through a mediation analysis, we examined judgment and misinformation concerns as potential underlying mechanisms. Finally, in a field experiment aimed at strengthening ecological validity, we created a social media page for a fictional diet solution company. We ran four advertisements, where users saw two messages, one neutral and the other

[1]https://www.article19.org/resources/algorithmic-people-pleasers-are-ai-chatbots-telling-you-what-you-want-to-hear

[2] https://news.stanford.edu/stories/2025/06/ai-mental-health-care-tools-dangers-risks

stigmatizing, and were prompted to chat with a human expert or an AI chatbot. In all four studies, stigma consistently led to an increased preference for AI chatbots, effectively reducing algorithm aversion, and in one case reversing it. This shift in preference was due to changes in judgment and misinformation concerns. Individuals in the high-stigma condition reported higher judgment concern and lower misinformation concern, both of which, in turn, resulted in a greater preference for information-seeking from AI chatbots.

Our study makes several significant contributions to IS research by advancing the understanding of information-seeking from IT artifacts under stigma. Substantively, we extend the literature on algorithm aversion (Dietvorst et al., 2015; Jussupow et al., 2024) by conceptualizing it as the willingness to seek information, a less-examined outcome. We demonstrate that stigma, an unexamined task-specific factor, increases preferences for chatbots relative to human experts through a series of cross-contextual studies. Theoretically, we show not only that stigma affects information-seeking but also identify judgment and misinformation concerns as key mechanisms. We employ online and field randomized controlled experiments that manipulate stigma precisely, allowing us to identify its causal effect on willingness to seek information. Capturing both stated and revealed preferences for ecological validity, our approach demonstrates an ethical and effective framework for studying sensitive topics without reinforcing stigma.

This research also has important practical implications. Our findings highlight that AI chatbots can serve as a useful preliminary source for individuals seeking information about stigmatized situations, as they offer a low-judgment alternative. While this shift toward AI can facilitate information-seeking, our results show that users in stigmatized contexts are likely to be less alert to misinformation risks, increasing the need for thorough accuracy checks and safeguards in chatbot design. By judiciously integrating AI chatbots within broader support systems, organizations can utilize their benefits to improve access to information while mitigating risks, enabling responsible adoption of AI in sensitive domains.

2 LITERATURE REVIEW

Our research draws upon and contributes to three streams of literature: (1) Algorithm aversion and AI chatbot adoption, (2) help-seeking under stigma, and (3) AI and misinformation.

2.1 Algorithm Aversion and AI Chatbot Adoption

AI chatbots are designed to simulate human conversation using techniques including natural language processing and machine learning (Bansal & Khan, 2018). Central to their functionality is the underlying algorithm, which processes user input and generates responses. Two contrasting attitudes toward algorithms have been documented: *algorithm aversion*, the preference for humans over algorithms in decision-making (e.g., Dietvorst et al., 2015; Jussupow et al., 2024), and *algorithm appreciation*, reliance on AI agents under certain conditions (e.g., Logg et al., 2019).

Algorithm aversion arises from various factors, including the ethical implications of relying on algorithms for consequential decisions (Bigman & Gray, 2018), the perceived inadequacy of algorithms to consider human individuality (Longoni et al., 2019), skepticism about their suitability to perform subjective tasks (Castelo et al., 2019), the opaque nature of AI algorithms (Lebovitz et al., 2022; Turel et al., 2023), and negative reactions to observed errors (Dietvorst et al., 2015; Ozdemir et al., 2024). The contingent factors that increase or decrease algorithm aversion can be categorized into *algorithm* characteristics (e.g., Dietvorst et al., 2018), *user* characteristics (e.g., Han et al., 2023; Logg et al., 2019), and *task* characteristics (e.g., Bigman & Gray, 2018; Castelo et al., 2019). Likewise, attitudes specifically toward AI chatbots are also shaped by *algorithm characteristics* such as human likeness (Jia et al., 2025; Song & Kim, 2022) and fast service time (Kagan et al., 2022), *user characteristics* such as age (Nadarzynski et al. 2019; Ng et al. 2020) and technological experience (Mogaji et al., 2021), and *task characteristics* such as risk perceptions (Følstad et al., 2018).

The present study addresses three gaps in this stream of research. First, we examine stigma, an unexplored task-specific factor influencing algorithm aversion. Second, studies have operationalized algorithm aversion using different dependent variables, such as trust (Bauer & Gill, 2024; You & Robert Jr., 2024), confidence in algorithms (Dietvorst et al., 2018), and fairness (Starke et al., 2022). We examine the willingness to seek information from AI, a crucial but less-examined manifestation of algorithm aversion. Finally, prior studies have mainly measured algorithm aversion through stated rather than revealed preferences, a gap we bridge by examining revealed preferences in our field experiment.

2.2 Help-Seeking Under Stigma

Research consistently shows a negative association between stigma and help-seeking from human agents (Ahmedani, 2011). According to the modified labeling theory (Link et al., 1989), individuals often conceal their struggles and avoid seeking help, fearing social judgment. This concern is particularly evident in mental health treatment, where the fear of being judged and labeled discourages individuals from seeking professional help (Aggarwal et al., 2023; Clement et al., 2015). Our study focuses on information-seeking, which is often the first stage of help-seeking (Lambert & Loiselle, 2007; Rickwood et al., 2005). Information-seeking refers to a conscious effort to acquire information in response to a need or gap in one's knowledge (Case et al., 2016).

Information-seeking under stigma from IT artifacts, despite its high practical relevance, has received scant attention in the literature. Examining search engines, Berger et al. (2005) and Comulada et al. (2020) found that those with stigmatized illnesses were more likely to use internet search for health information. Findings from these studies are unlikely to apply to AI chatbots because their conversational nature amplifies misinformation concern. Information conveyed in a conversational style tends to be perceived as more credible compared to the non-interactive results from search engines (Stokel-Walker, 2023). Moreover, the accuracy of information generated by AI chatbots is harder to verify (Shao, 2025).

Focusing on help-seeking in stigmatic contexts from AI chatbots, Mills et al. (2023) and Brennan (2025) synthesized literature and developed propositions regarding the appropriateness of AI chatbots for use in sexual and reproductive health. In the context of sexually transmitted diseases, Yıldız & Söğütdelen (2025) analyzed the readability and reliability of information provided by AI chatbots and found that Perplexity and Copilot provided more reliable health information than ChatGPT and Gemini, but all of their outputs were too complex for the general public, particularly those with low health literacy. In the context of mental health, Raimi et al. (2025) exposed participants to identical chat screenshots and found that participants perceived a chatbot to be more judgmental than a human mental healthcare professional.

While these studies provide important insights, significant gaps remain in this literature. First, nearly all these studies focus on information-seeking in a single context (Brennan, 2025; Mills et al., 2023;

Raimi et al., 2025), which makes it unclear whether the preference for the AI chatbot stems from general perceptions of AI chatbots or is specific to a particular context (Jussupow et al., 2024, pp. 2). Second, much of the literature has employed methods such as theoretical syntheses of literature (Brennan, 2025; Yıldız & Söğütdelen, 2025) and surveys (Kosyluk et al., 2024), yielding descriptive results. While Branley-Bell et al. (2023) and Miles et al. (2021) use experimental methods to examine the effect of stigma on information-seeking from AI chatbots, they use entirely different contexts in control and treatment conditions, which introduces potential confounds. Finally, some studies have focused on information-seeking from AI chatbots alone without a comparison to human agents (Kosyluk et al., 2024; Mills et al., 2023; Yıldız & Söğütdelen, 2025), which is a significant departure from the real world, where information-seekers often choose between the two information sources (for a visual comparison of the literature, see Appendix A).

2.3 AI and Misinformation

Misinformation is false, inaccurate, or incorrect information (Ayers & Reder, 1998) without the necessary intent to deceive (Lewandowsky et al., 2012). Internet users increasingly struggle to distinguish truth from fiction (Kim & Dennis, 2018; Moravec et al., 2019). Prior research has examined the prevalence of misinformation, its effects, and ways to mitigate it (Hwang & Lee, 2024; Moravec et al., 2019).

As the applications of AI chatbots increase, their potential to disseminate misinformation or inaccurate information has raised significant concerns (Park, 2024). Modern AI chatbots, such as OpenAI's GPT series, rely on LLMs trained on online books, articles, and content. The quality and accuracy of chatbot outputs are directly tied to the training data (Chau & Xu, 2025). Biases, inaccuracies, or outdated information in these datasets can result in factually incorrect responses (Brown et al., 2018). AI chatbots are also susceptible to "hallucination," the generation of plausible but fabricated or erroneous information, undermining their reliability (Huang et al., 2024). Users often struggle to differentiate between accurate and fabricated information presented by chatbots, which can erode trust (Amaro et al., 2024), which in turn leads to the avoidance of chatbots for tasks that require accurate and reliable

information (Meyrowitsch et al., 2023). This algorithm aversion is further fueled by the lack of transparency in how AI outputs are generated (Jones-Jang & Park, 2022).

While research in information systems has extensively examined misinformation in the context of social media and online fake news (e.g., George et al., 2021; Hwang & Lee, 2024; Moravec et al., 2019), limited work has explored user attitudes toward misinformation with AI chatbots as the focal artifact. Our study is among the first to investigate how misinformation concerns influence users' preference for AI chatbots, particularly in stigmatized contexts. We identify misinformation concern as a key mechanism driving stigma's effect on AI Aversion. By doing so, we also contribute to research on the misinformation paradox, the phenomenon where individuals, despite being distrustful of the content they encounter, continue to read, share, and engage with it (e.g., Munyaka et al., 2022; Shin, 2024). Our study illustrates how stigma, as a contextual factor, shapes users' perceptions of misinformation risk.

3 THEORY AND HYPOTHESES

3.1 The Effect of Stigma on Information-Seeking from AI Chatbots

Stigma is a perceived construct that is socially shaped rather than being grounded in objective, universal standards (Major & O'Brien, 2005). It refers to the social process of devaluation, stereotyping, and marginalization directed at individuals or groups based on attributes, behaviors, or identities deemed undesirable by societal norms (Dudley, 2000). When exposed to stigma, individuals may experience negative emotions such as shame, guilt, and fear (Steele, 1997). Shame arises from a sense of failure or personal inadequacy tied to the stigmatic condition (Dolezal, 2015), while guilt stems from a sense of self-blame for not meeting societal expectations. Even when individuals do not internalize stigma, they may still fear potential rejection, disapproval, or discrimination, reflecting the emotional burden of living under social devaluation (Link & Phelan, 2001). In addition to the condition-related emotions, individuals can also experience *conversation-related* emotions when seeking information from others. Discussing stigmatized topics is inherently difficult due to social taboos and limited public discourse (Chrisler, 2013). This difficulty can evoke feelings of frustration, helplessness, and anxiety as individuals attempt to articulate their concerns without saying something incorrect or inappropriate.

In the context of information-seeking, appraisal theory posits that negative emotions reduce action readiness, which refers to the motivational state that determines whether individuals seek or avoid information (Savolainen, 2014). In stigmatized contexts, such as mental health or obesity, condition-related negative emotions like shame and guilt can diminish the motivation to seek information and increase avoidance behaviors. Conversation-related negative emotions can not only influence whether individuals seek information but can also affect their selection of information sources.

AI chatbots can be an attractive information source for individuals experiencing negative emotions for several reasons. First, AI chatbots are perceived as emotionally neutral, creating a more comfortable environment for discussing sensitive topics (Nadarzynski et al., 2019). Second, modern generative AI chatbots are increasingly designed to respond with supportive and reassuring language, which can further alleviate emotional discomfort and foster openness (Bickmore & Picard, 2005; Zhou et al., 2020). Third, several studies have found that people are willing to self-disclose personal information to a chatbot (e.g., Ho et al., 2023) and that users tend to feel safer self-disclosing to chatbots than to humans (Brandtzaeg & Følstad, 2018; Lee et al., 2020). The emotional safety with AI chatbots may arise from the impression that one's disclosures "simply disappear into the computer" (Weisband & Kiesler, 1996). The willingness to disclose can, in turn, contribute to a more positive assessment of chatbot efficacy in meeting individuals' information needs (Van Wezel et al., 2021). Finally, AI chatbots, powered by the generative capabilities of large language models, enable users to rephrase or refine their questions throughout the conversation. This conversational flexibility helps individuals articulate stigmatic topics without fearing social consequences, reducing frustration, anxiety, and embarrassment.

Therefore, by alleviating emotional discomfort, AI chatbots become an appealing source of information in stigmatized contexts. While individuals exhibit algorithm aversion in general (Jussupow et al., 2024), the emotions triggered by perceived stigma can shift these preferences.

Hypothesis 1: Perceived stigma increases individuals' preference for seeking information from an AI chatbot compared to a human expert (reducing algorithm aversion).

3.2 The Mediating Role of Judgment Concern

Appraisal theory also posits that emotions stem from how individuals cognitively evaluate events and their relevance to personal goals or social standing (Scherer, 1999). For instance, when people appraise an event as unjust, they feel anger; when they perceive a situation as beyond their control, they feel helplessness or frustration; and when they interpret a circumstance as a loss or missed opportunity, they experience sadness (Lazarus, 2023). These cognitive appraisals and interpretations of events precede and shape emotional responses, which in turn influence motivation and behavior (Scherer, 1999).

In stigmatized contexts, one particularly relevant cognitive appraisal is judgment concern, which is the belief or anticipation of being negatively evaluated by others (Crocker & Garcia, 2006; Major & O'Brien, 2005). Judgment concern is a cognitive appraisal that can give rise to multiple negative emotions, such as shame, embarrassment, or anxiety (Savolainen, 2014). For instance, when individuals believe that others will view their condition as a personal failure or moral shortcoming, they experience shame; when they believe that others may see them as socially inappropriate or awkward, they feel embarrassment; and when they anticipate that others might reject them or respond unfavorably, they experience anxiety. These negative emotions, triggered by the cognitive appraisal of judgment concern, can, in turn, reduce individuals' action readiness to seek information.

Studies consistently show that people fear judgment from other humans but perceive chatbots as non-judgmental (Nadarzynski et al., 2021). Mind perception theory explains how people attribute "mind" to other entities, such as humans, animals, and robots, based on perceived mental capacities along two key dimensions: *agency* (i.e., the capacity to plan and act) and *experience* (i.e., the capacity to feel and evaluate) (Gray et al., 2007). AI chatbots are generally perceived as high in agency but low in experience, meaning that while users view them as capable of performing tasks and providing information, they do not perceive them as capable of forming social judgments or moral evaluations. This asymmetry in mind perception is especially consequential in stigmatized contexts: users can rely on chatbots for their instrumental competence stemming from chatbots' high agency, while feeling psychologically safe from interpersonal judgment due to chatbots' low experience. This perceived absence of experience reduces the

anticipation of negative evaluation, thereby attenuating judgment concern and facilitating greater willingness to seek information from AI chatbots. This low experience, combined with a lack of physical presence (Cook & Doyle, 2002), absence of non-verbal cues (King et al., 2006), and perceived anonymity (Jiang et al., 2022), contributes to the perception of AI chatbots as non-judgmental. To summarize, perceived stigma heightens judgment concern, which in turn increases individuals' preference for AI chatbots for information-seeking due to the perception of AI chatbots as non-judgmental. We hypothesize as follows.

Hypothesis 2: The effect of perceived stigma on individuals' preference for seeking information from an AI chatbot is mediated by their judgment concern.

3.3 The Mediating Role of Misinformation Concern

Misinformation concerns about AI chatbots are typically higher than those about human experts, whose judgments are perceived to be informed by personal expertise, ethical considerations, and lived experience, for several reasons. First, there is growing awareness that AI chatbots rely on datasets that may contain biased (Ho et al., 2023), inaccurate, or outdated information (Binns et al., 2017). Second, the lack of transparency regarding how responses are generated exacerbates this concern (Pasquale, 2015). Third, people attribute a lack of contextual understanding to chatbots, believing they are less adept at considering nuanced, situational factors that human experts inherently grasp (Holohan & Fiske, 2021).

Discerning misinformation is a *cognitively demanding* process. It requires active critical thinking, comparing information against prior knowledge, external sources, and logical consistency (Pennycook & Rand, 2019). This process draws heavily on limited cognitive resources (De Jong, 2010), particularly when content is complex or nuanced (Gruszka & Nęcka, 2017). Today's information landscape overwhelms users with conflicting data, making it burdensome to find credible information. Even before actively engaging in evaluating information accuracy, committing to the task of detecting misinformation is a cognitively costly process because it demands significant anticipatory effort (Botvinick & Rosen, 2009).

At the same time, navigating stigma can be an *emotionally demanding* experience, as it involves exposure to social disapproval (Goffman, 1963), which can trigger multiple negative emotions (Toni Schmader & Brian Lickel, 2006). Dealing with these negative emotions requires active emotion regulation, which is the process of managing one's emotional reactions to maintain social and personal functioning (Hatzenbuehler et al., 2009). Therefore, exposure to stigma can lead to emotional exhaustion (Gaines & Jermier, 1983), imposing a heavy psychological cost on the individual being stigmatized.

Ego depletion theory proposes that the self's capacity for volition is limited, and that *both emotional and cognitive efforts* draw on the same limited effort budget (Baumeister et al., 1998). When dealing with stigma, individuals are likely to be in a state of mental resource depletion (Hatzenbuehler et al., 2009). They may be unable to dedicate the cognitive resources they normally would toward dealing with misinformation. This would imply that stigma can significantly reduce the extent to which individuals prioritize the discerning of misinformation. Therefore, stigma lowers individuals' sensitivity to misinformation risks. This, in turn, lowers the resistance individuals may otherwise feel toward AI chatbots due to their perceived potential to generate misinformation. Thus, stigma diminishes concern about misinformation, reducing resistance toward seeking information from AI chatbots.

Hypothesis 3: The effect of perceived stigma on individuals' preference for seeking information from an AI chatbot is mediated by their misinformation concern.

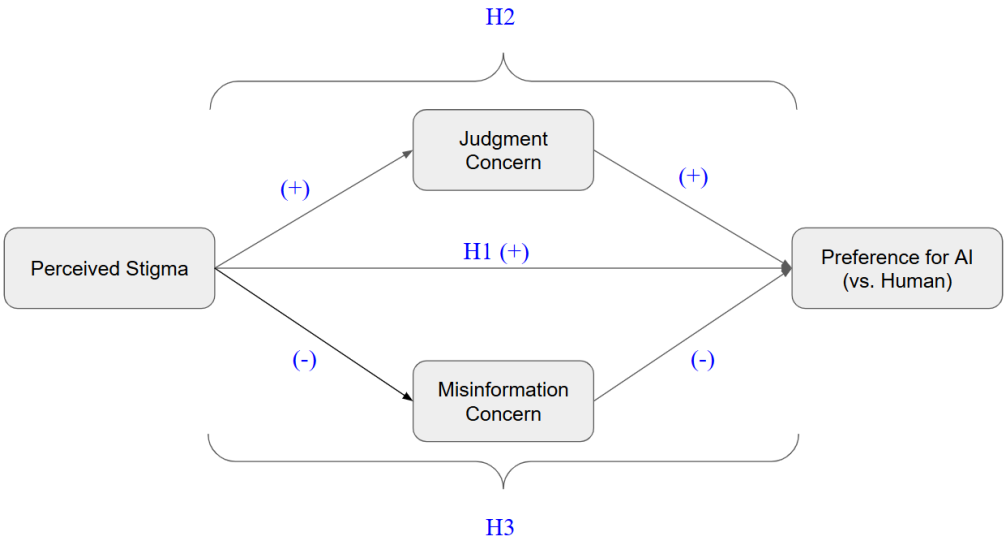


Figure 1. Theoretical Model

4 EXPERIMENTAL STIMULI AND PRETESTS

4.1 Curating Scenarios and Identifying Predominant Stigmatic Associations

To measure the effect of stigma on preference to seek information from an AI chatbot versus a human expert, we curated seven scenarios, each depicting a challenging situation with the need for information-seeking.[3] These scenarios, centered on individuals' overall well-being, describe challenging situations that address physical and mental health issues as well as personal and professional development challenges. For example, a weight-management scenario states: "*You suddenly gained a noticeable amount of weight in a short period, and you are concerned. You want to know about the reasons and potential solutions.*"

Scenario-based experiments offer ethical advantages for studying sensitive issues such as stigma. By presenting participants with carefully designed vignettes instead of exposing them to real discrimination, we minimize the risk of distress or harm. This design safeguards participant well-being and broadens our inquiry by enabling systematic examination of stigma across diverse and realistic contexts. This approach effectively elicits nuanced decision-making in a controlled manner (Werner & Muradova, 2022; Weyrich et al., 2020). Table 1 summarizes the seven scenarios (See Appendix B for more details).

Number	Context	Scenario Seeking Information About…	Predominant Stigmatic Associations
1	Weight Management	Managing sudden weight gain	Lazy and overeating
2	Addiction	Quitting smoking	Weak and lacking self-control
3	Fatigue	Feeling tired every day	Slacking and lazy
4	Work motivation	Struggling with low mood and work motivation	Irresponsible
5	Stage fear	Boosting confidence for a work presentation	Unprepared and incompetent
6	Work-life balance	Balancing a part-time job with maintaining a high GPA	Slacking
7	Social etiquette	Choosing appropriate attire for a company event	Uncultured and incompetent

Table 1. Context and Stigmatic Associations for Scenarios

To curate a diverse set of scenarios, three independent raters evaluated them on key stigma dimensions: *visibility* (how apparent the condition is to others) (Jones, 1984), *origin* (whether the

[3] We initially considered thirteen scenarios. Based on pre-tests and a manipulation check (Section 4.4), we retained seven scenarios that had reliably different levels of stigma in the baseline and high-stigma conditions (details in Section 4.4). All analyses reported are based on these seven validated scenarios.

condition is perceived as the person's fault) (Jones, 1984), and *controllability* (the extent to which the condition can be controlled or changed) (Corrigan et al., 2000). The ratings are provided in Appendix B.

In addition, we conducted a survey in which 30 participants from Prolific Academic identified the stereotypes or negative views they believed people might associate with each scenario. To identify the predominant stereotypes, we analyzed participants' responses and visualized the key themes with word clouds. Figure 2 shows the word cloud for an example scenario (weight management), highlighting the stereotypes associated with the situation. Table 1 lists the main stigmatic associations for each scenario.

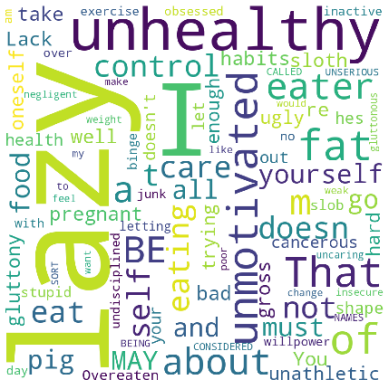


Figure 2. Stigmatic Associations for Weight Management Scenario

4.2 Designing Control and Treatment Conditions for Manipulating Stigma

It is important to note that simply comparing the outcomes across different scenarios (e.g., weight gain scenario vs. addiction) would not allow causal inferences about the effect of stigma on the likelihood of information seeking. This is because different scenarios may potentially differ along dimensions other than stigma, such as the perceived severity of the situation, subjectivity of the task, or whether the task is health-related. These factors can independently affect information-seeking behavior, making it essential to control for them in our experimental design.

To address this challenge, we created two experimental conditions to manipulate the level of stigma: a *baseline* (control) condition and a *high-stigma* (treatment) condition. In the baseline condition, participants read the seven scenarios without additional inputs, allowing us to measure their preferences under typical circumstances. In the high-stigma condition, participants are presented with the same seven scenarios, each followed by a stigmatizing radio prompt that reminds them of a predominant negative

stereotype. For example, a weight-management scenario in both conditions states: "*You suddenly gained a noticeable amount of weight in a short period of time, and you are concerned. You want to know about the reasons and potential solutions*." Additionally, only in the treatment group, this statement is followed by a stigmatizing radio prompt, "*Yesterday, you heard someone say this on the radio: Overweight people must be lazy and eating too much.*" Detailed descriptions of the radio prompt for each scenario can be found in Appendix C. This design allows us to manipulate the perceived stigma while keeping the scenario consistent across control and treatment conditions. By holding the scenario constant and only varying the presence of a stigmatizing radio prompt, we ensure that other dimensions, such as task subjectivity, remain unchanged. As a result, any observed differences in information-seeking behavior can be attributed causally to differences in perceived stigma.

To ensure the validity of our manipulation, we designed two pre-tests. Pre-test 1 measures the baseline level of perceived stigma for each scenario. Pre-test 2 is a manipulation check testing whether participants perceive a significant difference in stigma between the baseline and high-stigma conditions. These pre-tests ensure the rigor and precision necessary for causal inference in subsequent studies.

4.3 Pre-test 1: Measuring Perceived Stigma in Baseline (Control) Condition

Stigma is a perceived construct that is socially shaped rather than being grounded in objective, universal standards (Major & O'Brien, 2005). To measure the baseline level of perceived stigma for each of the seven scenarios used in the baseline condition, we conducted a survey. We recruited 100 participants from Prolific Academic and asked them to rate their likelihood of experiencing stigma when seeking information in each scenario, using a 5-point Likert scale from "Extremely Unlikely" to "Extremely Likely". To ensure well-informed responses, we provided a definition of stigma: "Stigma refers to stereotypes or negative views attributed to a person or groups of people when their characteristics or behaviors are viewed as different from or inferior to societal norms. For example, there is a stigma around overweight people that assumes they are lazy." Detailed descriptions of stigma measurement items can be found in Appendix C. We excluded data from 25 participants who failed attention checks. The bottom line

in Figure 3 displays the average level of perceived stigma for each scenario, as denoted by *baseline* stigma. The results reveal variation in the inherent level of perceived stigma across scenarios.

4.4 Pre-test 2: Measuring Perceived Stigma in High-Stigma (Treatment) Condition

Pre-test 2 is a *manipulation check* to ensure that our radio prompt resulted in scenarios with sufficiently higher perceived stigma levels in the high-stigma condition compared to the baseline. We recruited 120 participants from Prolific Academic and randomly assigned them to one of two groups. The first group of participants saw the seven scenarios, and the second group saw the stigmatizing radio prompts in addition to the same scenarios. We then asked them to rate the likelihood of experiencing stigma as they sought information in each scenario, on a 5-point Likert scale from "Extremely Unlikely" to "Extremely Likely." Figure 3 shows the average perceived level of stigma for each scenario in the baseline and high-stigma conditions, demonstrating that our manipulation successfully created variants with significantly higher perceived stigma levels in the high-stigma condition compared to the baseline condition.

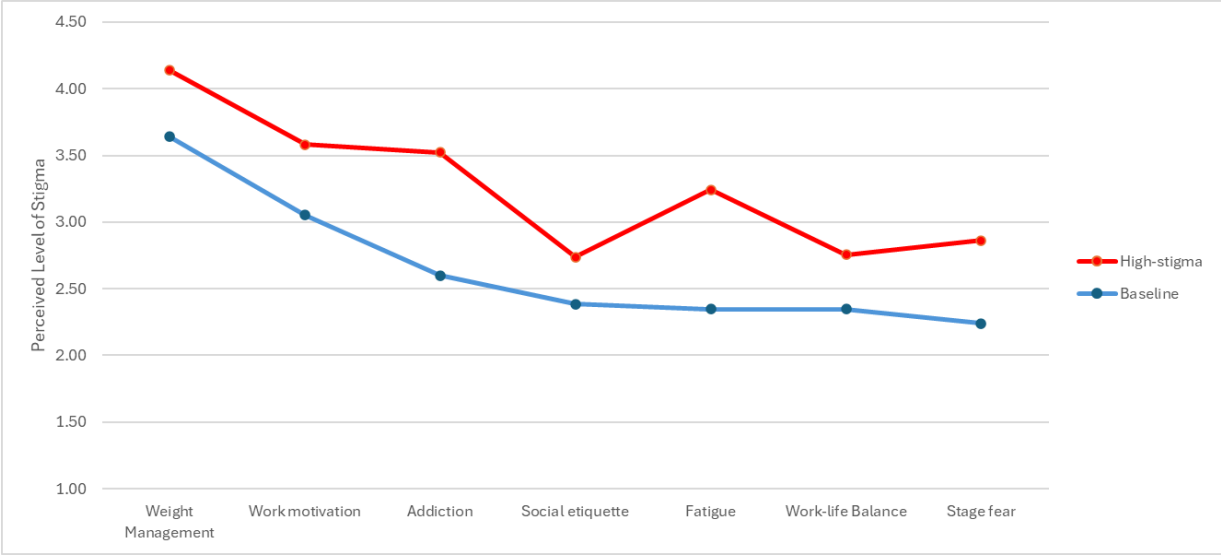


Figure 3. Perceived Level of Stigma in Baseline and High-Stigma Conditions

Table 2 presents the statistical comparison of the manipulation check for each scenario between the baseline and high-stigma conditions. We found that the scenarios in the high-stigma condition (same as the baseline condition but with radio prompts) were perceived as significantly more stigmatic ($M = 3.29$, $SD = 1.26$, $N = 115$) than the baseline condition ($M = 2.813$, $SD = 1.260$, $N = 75$, $p > |t| = 0.011$).

Scenario	Baseline (n=75)		High-Stigma (n=115)		
	Mean	Standard Deviation	Mean	Standard Deviation	$p > \|t\|$
Weight Management	3.64	1.16	4.14	0.99	0.003
Work Motivation	3.05	1.17	3.58	1.08	0.002
Addiction	2.60	1.32	3.52	1.18	0.000
Social Etiquette	2.39	1.13	2.74	1.25	0.045
Daily Fatigue	2.35	1.14	3.24	1.20	0.000
Work-life Balance	2.35	1.17	2.76	1.22	0.021
Stage Fear	2.24	1.08	2.86	1.26	0.000

Table 2. Perceived Level of Stigma in Baseline and High-Stigma Conditions

5 STUDIES

In this section, we describe three online and one field randomized controlled experiments. The key objectives, methodologies, and findings of all the studies are summarized in Appendix D.

5.1 Study 1 – Online Experiment (Within-Subjects)

The goal of Study 1 is to test Hypothesis 1 on the effect of perceived stigma on individuals' preference for information-seeking from an AI chatbot versus a human expert. The study includes two stigma conditions (high-stigma vs. baseline) in a within-subjects design, where each participant views both information sources (AI chatbot and human expert), enabling a direct measure of individual-level treatment effects.

***Procedure*:** In study 1, we randomly assigned 500 participants recruited from Prolific Academic to one of two conditions: 1) baseline and 2) high-stigma. In both conditions, participants were first presented with definitions of the AI chatbot and the human expert to establish a common understanding of the information sources (see Appendix E). Participants in the baseline group viewed seven scenarios, and those in the high-stigma group viewed the *same* seven scenarios but with an additional radio prompt introducing a stigmatizing association along with each scenario. After each condition, participants rated their willingness to seek information about the situation from both an AI chatbot and a human expert, using a 7-point Likert scale from "Extremely Unlikely" to "Extremely Likely". At the end of the study, we collected subjects' demographic data and other control variables.

Participants: After exclusion for failed attention checks, the final sample included 406 U.S. participants (209 males, 196 females, 1 undisclosed), aged 18–75 (Mean = 33). The sample was ethnically

diverse (275 White, 32 Black, 45 Asian, 32 Mixed, 17 Other, 5 missing). A within-subject power analysis based on N = 406 participants confirmed sufficient power to detect meaningful effects (See Appendix F).

Main Results: The results of Study 1, a within-subjects experiment, are summarized in Table 3. All models employed a fixed-effects regression, where we control for scenario-fixed effects to account for non-stigma factors related to each scenario (e.g., severity) that might influence participants' information-seeking behavior. In model W1, the negative and significant effect of *I(Stigma=High)* (-0.215, $p < 0.01$) shows that individuals are less likely to seek information under the high-stigma condition compared to the baseline condition. This finding aligns with prior literature on stigma and help-seeking. The negative and significant effect of *I(Source=AI)* (-0.931, $p < 0.01$) shows that individuals are less likely to seek information from an AI chatbot compared to a Human expert when both options are presented. This result is consistent with prior literature on AI aversion.

	(W1)	**(W2)**	**(W3)**
I(Stigma=High)	-0.215***	-0.371***	-0.357***
	(0.068)	(0.077)	(0.078)
I(Source=AI)	-0.931***	-1.093***	-1.099***
	(0.059)	(0.082)	(0.082)
I(Source=AI) ×		0.313***	0.319***
I(Stigma=High)		(0.117)	(0.117)
Constant	3.860***	3.941***	3.899***
	(0.054)	(0.054)	(0.397)
Scenario FE	Yes	Yes	Yes
Controls	No	No	Yes
Individuals	406	406	405
Observations	5,684	5,684	5,670
R-Squared	0.129	0.132	0.151
Standard errors in parentheses. * *p < 0.1,* ** *p < 0.05,* *** *p < 0.01*.			

Table 3. The Effect of Perceived Stigma on the Likelihood of Seeking Information

In model W2, we introduced the interaction effect between the information source and the stigma condition. The positive and significant interaction effect (0.313, $p < 0.01$) shows an increased relative preference for seeking information from AI chatbots in the high-stigma condition. In model W3, we controlled for the demographic variables (age, gender, ethnicity, and location) as well as AI experience, measured by asking participants, *"Have you ever used any of these AI chatbots (e.g., ChatGPT, Bing AI, Google Bard, etc.?*" Controlling for this factor accounts for baseline differences in familiarity or comfort

with modern, generative AI-powered chatbots. The interaction effect remains positive and significant (0.319, $p < 0.01$), corroborating hypothesis H1.

To further validate this interpretation, we conducted an additional analysis in which we computed the *relative preference* for AI over humans by subtracting the likelihood of seeking information from a human from the likelihood of seeking information from AI (AI minus Human). This transformation allows us to directly model the net preference for AI relative to humans rather than modeling each likelihood separately. The results are provided in Appendix G and are consistent with our earlier finding that stigma increases individuals' relative preference for AI chatbots compared to human experts.

***Heterogeneous Effects*:** As shown in Figure 3, the first three scenarios have higher *inherent* baseline stigma levels than the latter four, allowing us to group them as high-baseline vs. low-baseline stigma. In Table 4, model W4 (high-baseline scenarios, e.g., weight management) shows a stronger interaction effect of *I(Source=AI) × I(Stigma=High)* (0.433, $p < 0.01$), while model W5 (low-baseline scenarios, e.g., stage fear) shows a smaller and weaker interaction effect (0.233, $p < 0.10$). Thus, preference for AI chatbots is significantly stronger in contexts that are inherently more stigmatic.

	(W4) High-Baseline	**(W5) Low-Baseline**	**(W6) With AI Experience**	**(W7) No AI Experience**
I(Stigma=High)	-0.443***	-0.292***	-0.339***	-0.495**
	(0.092)	(0.083)	(0.081)	(0.226)
I(Source=AI)	-1.303***	-0.946***	-1.019***	-1.640***
	(0.098)	(0.087)	(0.086)	(0.246)
I(Source=AI) × I(Stigma=High)	0.433***	0.233*	0.355***	0.258
	(0.138)	(0.124)	(0.123)	(0.332)
Constant	3.569***	4.076***	4.037***	4.251***
	(0.446)	(0.419)	(0.383)	(0.854)
Scenario FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Individuals	405	405	346	59
Observations	2,430	3,240	4,844	826
R-Squared	0.189	0.127	0.125	0.328
Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.				

Table 4. Heterogeneous Effects of Perceived Stigma on Likelihood of Seeking Information

Next, we examined whether prior AI chatbot experience moderates the effect of stigma on source preference. As shown in Table 4, model W6 for participants with AI experience shows a positive and significant interaction effect for *I(Source=AI) × I(Stigma=High)* (0.355, $p < 0.01$). In contrast, model W7

for participants without AI experience shows a positive but insignificant interaction effect. Thus, prior AI chatbot experience strengthens preference for AI in stigmatized contexts.

5.2 Study 2 – Online Experiment (Between-Subjects)

The goal of Study 2 is to replicate the findings from Study 1 using a 2 (stigma: high vs. baseline) × 2 (information source: an AI chatbot vs. a human expert) between-subjects design. Without the side-by-side contrast present in the within-subjects design, participants' responses are less likely to be influenced by experimental cues about the purpose of the study, resulting in more natural evaluations of each information source in the between-subjects design (List, 2025).

***Procedure*:** In study 2, we randomly assigned 465 participants from Prolific to one of four conditions: (1) high-stigma with AI chatbots, (2) baseline with AI chatbots, (3) high-stigma with human experts, and (4) baseline with human experts. In each condition, participants were presented with seven scenarios across various contexts. Those in high-stigma groups received an additional radio prompt with a stigmatizing association following each scenario. Participants rated their likelihood of seeking information about each scenario from either an AI chatbot (in conditions 1 and 2) or a human expert (in conditions 3 and 4), using a 7-point Likert scale from "Extremely Unlikely" to "Extremely Likely." In all conditions, we included a definition of the AI chatbot or human expert, depending on the assigned source; these definitions are provided in Appendix E. Demographic and control variables (e.g., education, location, age) were collected at the end.

***Participants*:** After exclusion criteria for failed attention checks, the final sample included 395 U.S. participants (141 males, 251 females, and 3 undisclosed), aged 18–78 (Mean = 36). The sample was ethnically diverse (233 White, 59 Black, 51 Asian, 29 Mixed, and 19 Other, 4 missing). Formal power analyses confirmed adequate power to detect meaningful effects (See Appendix F).

***Main Results*:** The results of Study 2, a between-subjects experiment, are summarized in Table 5. All models employed fixed-effects regression with scenario-fixed effects, controlling for scenario-specific factors (e.g., severity) that could affect participants' likelihood of information seeking. In model B1, the negative and significant effect of *I(Stigma=High)* (-0.237, $p < 0.01$) shows that individuals are less likely

to seek information under the high-stigma condition compared to the baseline condition. The negative and significant effect of *I(Source=AI)* (-0.542, $p < 0.01$) indicates that individuals are less likely to seek information under the AI condition compared to the human condition.

In model B2, we introduced the interaction effect between the information source and the stigma condition. The positive and significant interaction effect of *I(Source=AI) × I(Stigma=High)* (0.371, $p < 0.01$) shows an increased preference for seeking information from AI chatbots in the high-stigma condition. In model B3, we controlled for the demographic variables, age, gender, ethnicity, and location. Additionally, we controlled for *scenario relevance* to account for individual differences in personal connection to the scenarios presented. We measured scenario relevance by asking the participants at the end of the survey, "*Which of these scenarios are relevant to you personally, now or in the past?*". When participants perceive a situation as personally relevant, whether currently or in the past, they may experience stronger engagement or motivation to seek information, which could influence their preference for information sources, either AI chatbots or human experts. By including situation relevance as a control variable, we aim to isolate the effect of stigma on source preference, ensuring that observed differences are not simply a result of varying levels of personal resonance with the scenarios. This control variable also mitigates potential concerns regarding the hypothetical nature of the scenarios presented to the participants. The direction and significance of the interaction effects remain the same (0.454, $p < 0.01$), corroborating hypothesis H1.

	(B1)	**(B2)**	**(B3)**
I(Stigma=High)	-0.237***	-0.424***	-0.427***
	(0.075)	(0.106)	(0.106)
I(Source=AI)	-0.542***	-0.730***	-0.773***
	(0.075)	(0.106)	(0.106)
I(Source=AI) × I(Stigma=High)		0.371**	0.454***
		(0.149)	(0.149)
Constant	4.109***	4.205***	4.325***
	(0.112)	(0.119)	(0.427)
Scenario FE	Yes	Yes	Yes
Controls	No	No	Yes
Individuals	395	395	395
Observations	2,765	2,765	2,765
R-Squared	0.039	0.041	0.069
Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.			

Table 5. The Effect of Stigma on Likelihood of Seeking Information (Between-Subjects Design)

5.3 Study 3 – Online Experiment (Mechanism Examination)

The goal of Study 3 is to test the potential mediating roles of judgment concern and misinformation concern. As stated in Hypotheses 2 and 3, we investigate whether perceived stigma increases judgment concern and decreases misinformation concern, and whether judgment and misinformation concerns, in turn, influence the relationship between AI and information-seeking.

***Procedure*:** Study 3 used the same 2 (stigma: high vs. baseline) × 2 (source: AI chatbot vs. a human expert) between-subjects design as Study 2, with 500 Prolific participants randomly assigned to one of four conditions: (1) baseline with AI chatbots, (2) high-stigma with AI chatbots, (3) baseline with human experts, and (4) high-stigma with human experts. Participants rated their likelihood of seeking information about each scenario via text-chat on a 7-point scale ("Extremely Unlikely" to "Extremely Likely"). They then rated their judgment and misinformation concerns on a 5-point scale ("Not at all concerned" to "Extremely concerned"). Demographic and control variables were collected last.

***Participants*:** After exclusions for failed attention checks, the final sample included 361 U.S. participants (140 males, 218 females, and 3 undisclosed) aged 18–71 (Mean = 34). The sample was ethnically diverse (218 White, 38 Black, 48 Asian, 36 Mixed, and 17 Other, 4 missing). Power analyses confirmed sufficient power to detect meaningful effects (See Appendix F).

***Mediation Results*:** To examine the mediating effects of judgment and misinformation concerns, we follow Grant and Berry (2011). This method suits studies that begin with a primary moderating effect, in this case, the effect of perceived stigma on the relationship between AI and information-seeking, and then uncover the mechanisms underlying this moderated effect, namely judgment concern and misinformation concern, as illustrated in Figure 1. This approach involves two steps to estimate the mediation effects.

In the first step, we examine the direct effect of perceived stigma on judgment and misinformation concerns. As shown in Table 6, model M1, high stigma increases judgment concern (0.149, $p < 0.01$), while the AI source reduces it. Model M2 shows that high stigma lowers misinformation concern (-0.085, $p < 0.05$), whereas the AI source raises it.

	(M1) *Judgment*	(M2) *Misinformation*
I(Stigma=High)	0.149***	-0.085**
	(0.042)	(0.036)
I(Source=AI)	-0.282***	0.494***
	(0.043)	(0.040)
Constant	5.559***	2.756***
	(0.606)	(0.520)
Scenario FE	No	No
Controls	Yes	Yes
Individuals	361	361
Observations	2,527	2,527
R-Squared	0.263	0.164
Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.		

Table 6. Effect of Stigma on Judgment and Misinformation Concerns

In the second step, we examine whether judgment and misinformation concerns mediate the effect of perceived stigma on information-seeking. To do this, we first establish the moderating role of perceived stigma on information-seeking in model M3, showing that high stigma (-0.571, $p < 0.01$) and AI source (-0.577, $p < 0.01$) both reduce information seeking, while their interaction increases preference for AI chatbots under high stigma. Next, in model M4, adding Judgment and its interaction with AI reveals that the interaction effect of *I(Source=AI)* × *Judgment* is positive and significant (0.227, $p < 0.01$), while the interaction effect of *I(Source=AI)* × *I(Stigma=High)* is weakened (0.322, $p < 0.05$) compared to model M3 (0.378, $p < 0.05$), showing that judgment concern partially mediates the effect of perceived stigma, corroborating Hypothesis 2.

Similarly, to examine the mediating effect of misinformation concern, model M5 includes *Misinformation* and its interaction with AI. The interaction effect of *I(Source=AI)* × *Misinformation* is negative and significant (-0.170, $p < 0.05$), while the interaction effect of *I(Source=AI)* × *I(Stigma=High)* weakens (0.338, $p < 0.05$) compared to model M3 (0.378, $p < 0.05$), indicating partial mediation through reduced misinformation concern, providing support for Hypothesis 3.

	(M3)	(M4)	(M5)	(M6)	(M7) Baseline Stigma	(M8) High Stigma
I(Stigma=High)	-0.571***	-0.591***	-0.568***	-0.591***		
	(0.101)	(0.101)	(0.101)	(0.101)		
I(Source=AI)	-0.577***	-1.129***	0.052	-0.415	0.435	-1.180***
	(0.105)	(0.181)	(0.252)	(0.274)	(0.359)	(0.391)
I(Source=AI) ×	0.378**	0.322**	0.338**	0.265*		
I(Stigma=High)	(0.147)	(0.149)	(0.147)	(0.148)		
Judgment		-0.066		-0.080*	0.018	-0.172***
		(0.041)		(0.041)	(0.059)	(0.059)
I(Source=AI) ×		0.227***		0.268***	0.216**	0.378***
Judgment		(0.058)		(0.058)	(0.085)	(0.082)
Misinformation			-0.056	-0.037	-0.014	-0.099
			(0.052)	(0.052)	(0.076)	(0.072)
I(Source=AI) ×			-0.170**	-0.226***	-0.422***	-0.000
Misinformation			(0.071)	(0.072)	(0.106)	(0.101)
Constant	4.363***	4.505***	4.400***	4.488***	3.494***	4.782***
	(0.990)	(1.009)	(1.002)	(1.018)	(0.738)	(1.155)
Scenario FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Individuals	361	361	361	361	361	361
Observations	2,527	2,527	2,527	2,527	1,281	1,246
R-Squared	0.065	0.071	0.072	0.080	0.092	0.089

Standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 7. Mediation Effects of Judgment & Misinformation Concerns on Likelihood of Seeking Information

Finally, in model M6, adding both Judgment and Misinformation and their interaction with AI, further reduces the interaction effect of *I(Source=AI) × I(Stigma=High)* (0.265, $p < 0.1$) compared to model M3 (0.378, $p < 0.05$), suggesting that both judgment and misinformation concerns fully mediate the effect of perceived stigma on information seeking. In Table 7, we controlled for demographic variables (age, gender, ethnicity, location), *scenario relevance,* and *privacy concern*, as privacy sensitivity may influence preferences for AI chatbots vs. human experts, especially in high-stigma situations (Cichy et al., 2021; Jiang et al., 2013). Participants with higher privacy concerns may prefer human experts who assure confidentiality. Controlling for privacy concern isolates its effect from judgment concern and misinformation concerns. We confirmed that stigma did not affect privacy concern in our experiment.

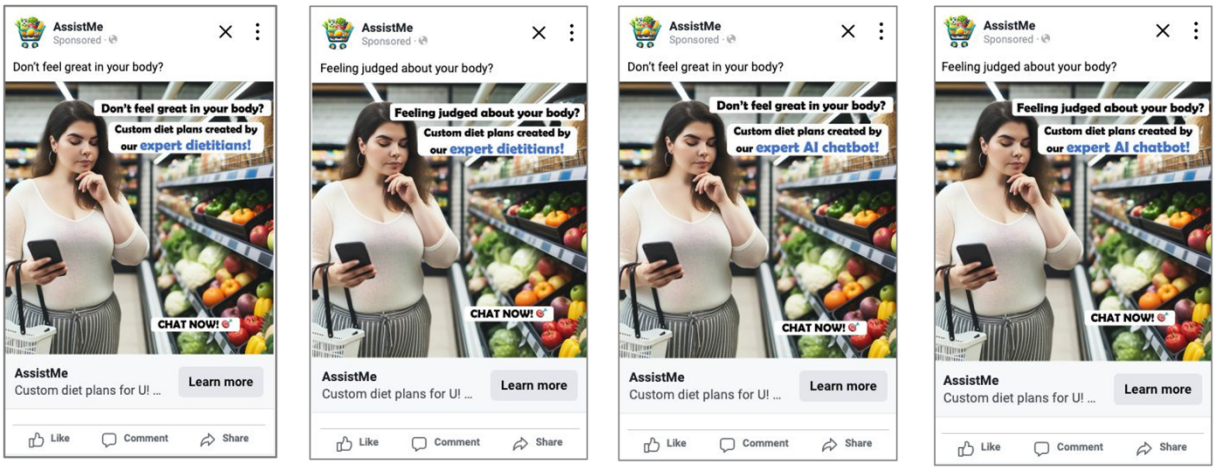
***Tradeoff between Judgment and Misinformation Concerns*:** Next, we examine the tradeoff between judgment and misinformation concerns across control and treatment conditions. As shown in Table 7, model M7, under the baseline (non-stigmatized) condition, the interaction of *I(Source=AI) × Judgment* is positive and significant (0.216, $p < 0.01$), suggesting that concerns about judgment increase the relative appeal of AI chatbots. At the same time, the interaction of *I(Source=AI) × Misinformation* is negative and significant (–0.422, $p < 0.01$), indicating that misinformation concerns reduce willingness to rely on AI. Together, these effects reveal a tension: in non-stigmatized contexts, AI chatbots are valued for alleviating judgment concerns but penalized more strongly for raising misinformation concerns. Since the negative effect of misinformation outweighs the positive effect of judgment, the net impact is aversion to AI in the baseline condition. In contrast, under the high-stigma condition (model M8), the interaction of *I(Source=AI) × Judgment* is positive and even stronger (0.378, $p < 0.01$), while the interaction of *I(Source=AI) × Misinformation* is small, near zero, and insignificant. This shift suggests that when stigma is salient, heightened judgment concern drives a stronger preference for AI, while reduced misinformation concern weakens its negative impact on participants' willingness to seek information from AI.

5.4 Study 4 – Field Experiment

This study replicates and complements our main findings through a field experiment. While the online experiments examine the effect of stigma in controlled settings, Study 4 serves two key objectives. First, it validates these findings in a real-world context, bolstering ecological validity (Lu et al., 2024). Second, while the lab experiments capture *stated* preferences (participants' intention to adopt or avoid AI chatbots), the field experiment captures *revealed* preferences (real users' engagement with advertisements). Since intentions do not always translate into real-world behavior, the field experiment in Study 4 is crucial for understanding how stigma influences actual behavior beyond controlled environments.

***Experimental Design*:** We created a Facebook page for a fictional custom diet solution company called *AssistMe*. Using a 2 (stigma: high vs. baseline) × 2 (information source: an AI chatbot vs. a human expert) between-subjects design, we ran four advertisements for this fictional company: (1) baseline with

an AI chatbot, (2) high-stigma with an AI chatbot, (3) baseline with a human expert, and (4) high-stigma with a human expert. We then compared click-through rates (CTRs) across the four groups to analyze revealed preferences for information-seeking. By presenting a fictional company on Facebook, we were able to observe user reactions to businesses adopting AI or human agents. As shown in Figure 4, all four ads used the same design and the same image of a woman shopping in a grocery store. The advertisements varied only in two aspects: the information source (an AI chatbot vs. a human expert) and the stigma level (high vs. baseline). By modifying only these two elements while keeping all other aspects constant, this design allows us to isolate and measure the effect of stigma on information-seeking behavior from AI chatbots in a real-world setting.



Baseline, Human Expert | High Stigma, Human Expert | Baseline, AI Chatbot | High Stigma, AI Chatbot

Figure 4. Facebook Ads for Four Conditions

To vary the information source, the ads offered users to "Chat Now" with either a human expert or an AI chatbot to receive a custom diet plan. Clicking the ad served as a revealed preference measure, indicating willingness to converse with the presented source. To vary the stigma level, the baseline ads used a neutral message, "Don't feel great in your body?", while the high-stigma ads used a stigmatizing message, "Feeling judged about your body?"[4]. Unlike the online experiments, here, we did not include explicit stigmatizing associations or use excessively stigmatizing language. These choices were driven by

[4] Body image is widely recognized as an area associated with high stigma (Meadows & Calogero, 2018).

ethical considerations and the inability to conduct debriefing afterward. By referencing social judgment in the high-stigma message, we highlight a key facet of stigma, the fear of negative evaluation by others (Goffman, 1963; Link & Phelan, 2001; Major & O'Brien, 2005), whereas the baseline message focuses on personal discomfort without invoking societal judgment. By using succinct yet distinct prompts and maintaining consistency in other dimensions (e.g., length, valence) between the baseline and high-stigma prompts, any observed differences in user engagement can be more confidently attributed to variation in stigma rather than other factors. We allocated equal budgets to each ad and ran all four ads over two days (12:00 AM November 29 to 12:00 AM December 1, 2023), targeting adults in North America. Following Orazi & Johnston (2020) and Braun & Schwartz (2025), our campaign settings ensured optimal random ad assignment, with each user exposed to only one condition (See Appendix H for details).

Results: Figure 5 presents the click-through rates for all four conditions. In the baseline condition, users showed a stronger preference for human experts (0.15% CTRs) over AI chatbots (0.05% CTRs). Interestingly, this trend is flipped in high-stigma condition, where users exhibited a higher preference for AI chatbots (0.12% CTRs) compared to human experts (0.08% CTRs). The results of the field experiment are summarized in Appendix I. We conduct tests to determine whether these differences are statistically significant, following Orazi & Johnston (2020), using a non-parametric chi-square test on click counts and a logistic regression on a simulated dataset. As explained in Appendix I, AI aversion persists in the baseline conditions but disappears under high-stigma conditions.

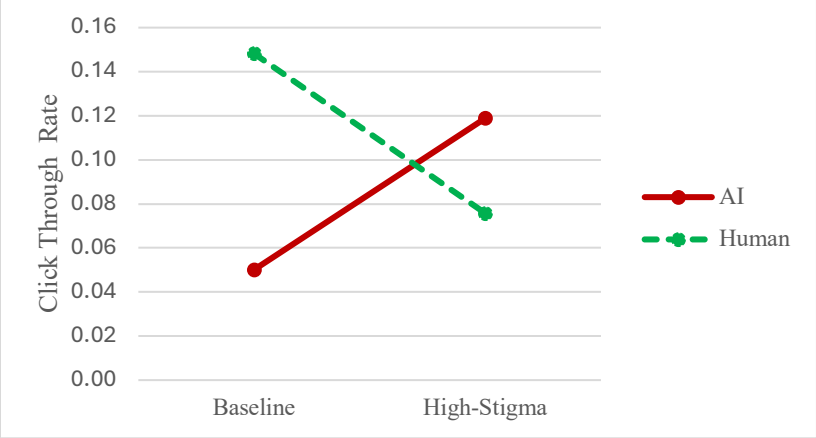


Figure 5. Results from Study 4 (Field Experiment)

6 DISCUSSION

In this research, using three online scenario-based randomized controlled experiments and a field experiment, we found that while perceived stigma typically deters people from seeking information, users show an increased preference for AI chatbots relative to human experts under high-stigma conditions, effectively *reducing* algorithm aversion. Moreover, we identify two mechanisms driving this effect. First, judgment concern is heightened under stigma, and because people see AI chatbots as less judgmental, it nudges them toward AI chatbots for information-seeking. Second, misinformation concern, typically higher for AI chatbots than human experts, becomes less salient under stigma. As a result, people weigh judgment concerns more and misinformation concerns less, increasing their preference for AI chatbots over human experts. We address alternative explanations in Appendix J.

Our research makes important contributions to IS research. Information seeking under stigma from IT artifacts, despite its high practical relevance, has received scant attention in the literature. Substantively, we contribute to the research stream on algorithm aversion by studying the effect of stigma, an underexamined task-specific factor, and find that the perceived stigma associated with a situation decreases AI aversion. An understanding of how task-specific factors influence attitudes toward AI agents is crucial for building effective human-AI hybrid systems (Rai et al., 2019). We also extend the literature on algorithm aversion by conceptualizing it as the willingness to seek information from AI, a less-examined outcome. Moreover, we extend prior work by moving beyond single-context studies (e.g., Raimi et al., 2025) and those without comparisons to human agents (Brennan, 2025; Kosyluk et al., 2024; Mills et al., 2023; Yıldız & Söğütdelen, 2025). Our research provides one of the first cross-contextual examinations of how stigma shapes individuals' reliance on AI chatbots versus human experts.

Theoretically, we advance IS research by explaining not only *what* the effect of stigma is but also *how* it manifests. By identifying judgment and misinformation concerns as underlying mechanisms, we show how stigma shapes evaluations of AI artifacts and the adoption of AI chatbots. Extending prior IS research that examines misinformation primarily in social media and online news (e.g., George et al., 2021; Hwang & Lee, 2024; Moravec et al., 2019), we demonstrate that misinformation concerns also shape the adoption

of AI chatbots. We find that users may overlook typical skepticism about chatbot accuracy when stigmatized, showing how perceptions of accuracy can be contextually and psychologically shaped.

Methodologically, our study is among the first to examine the effect of stigma on information-seeking utilizing both online and field randomized controlled experiments. Unlike prior research relying on theoretical syntheses or descriptive surveys (Brennan, 2025; Kosyluk et al., 2024; Mills et al., 2023; Yıldız & Söğütdelen, 2025), we experimentally manipulate stigma in control and treatment groups, enabling us to isolate the causal effect of stigma on the willingness to seek information. Moreover, we capture both stated and revealed preferences for AI chatbots, enhancing the ecological validity of our findings and offering IS research a framework to study sensitive topics without exacerbating stigma.

Our research also has critical implications for practice. An encouraging implication is the potential of AI chatbots to serve as an information source for information-seeking in stigmatized contexts. This could help people overcome the initial barriers of stigma and seek the information they need in a convenient, efficient, and cost-effective manner. Platforms can strategically utilize AI chatbots as an access point for engaging individuals in stigmatic contexts and channel them to human experts once this initial barrier is lowered. Second, perceived stigma reduces users' concern about misinformation; that is, they may underweight accuracy risks when seeking a non-judgmental source. For organizations deploying AI chatbots for information-seeking, this emphasizes the importance of ensuring the validity of the information dispensed by the chatbots and promptly incorporating human oversight into the information-seeking process. Practitioners must design AI systems with robust guardrails, including continuous content updates, curated knowledge bases, or disclaimers that clarify the chatbot's training data.

Our study has some limitations, which point to opportunities for future research. First, participants' overall familiarity with generative AI tools (e.g., ChatGPT and Llama) could evolve rapidly, which might alter users' preferences and behaviors over time. Second, we focused on information-seeking and intentionally isolated it from seeking emotional support. However, in real interactions, AI or humans often blend practical advice with empathetic responses. Exploring how empathy perceptions further shape stigma-driven chatbot preference would be valuable. Third, while our design used scenario-based

manipulations and a field study, future research might examine longitudinal user engagement with chatbots in real-life clinical or professional environments. Finally, the focus of this study is limited to modern generative AI chatbots that are text-based and powered by large language models. It is also limited to the effects of public stigma and is influenced by the cultural context in which the study was conducted. We clarify the detailed inclusion and exclusion criteria of our scope in Appendix K.

As stigma leads more users to sidestep human experts, they may miss out on essential real-world medical or professional advice. If chatbots become the preferred source in stigmatized contexts, there is a risk that over-reliance on AI deprives individuals of the expert knowledge that human professionals develop through years of education and professional training. This is especially critical for diagnostic or high-stakes advice, where partial or incorrect information can have serious consequences. Organizations should maintain the co-presence of experts, ensuring the chatbot is not perceived as a permanent substitute but rather as a triage or preliminary channel. While chatbots excel at anonymity and immediate response, human attention remains pivotal for complex needs, ensuring that stigma does not isolate individuals from vital, professional human expertise.

To conclude, our findings demonstrate that perceived stigma can significantly influence individuals' preference for information seeking from AI chatbots compared to human experts. By identifying judgment concern and misinformation concern as two parallel mechanisms, we show that, on average, under stigma, individuals worry more about social judgment, placing less emphasis on AI's factual reliability. Designing chatbots that balance low judgment with safeguards against misinformation will be essential to ensuring more inclusive access to crucial information.

REFERENCES

Aggarwal, M., Chakrabarti, A. S., & Chatterjee, C. (2023). Movies, stigma and choice: Evidence from the pharmaceutical industry. *Health Economics*, *32*(5), 1019–1039. https://doi.org/10.1002/hec.4653

Ahmedani, B. K. (2011). Mental Health Stigma: Society, Individuals, and the Profession. *Journal of Social Work Values and Ethics*, *8*(2), 41–416.

Amaro, I., Barra, P., Greca, A. D., Francese, R., & Tucci, C. (2024). Believe in Artificial Intelligence? A User Study on the ChatGPT's Fake Information Impact. *IEEE Transactions on Computational Social Systems*, *11*(4), 5168–5177. https://doi.org/10.1109/TCSS.2023.3291539

Ayers, M. S., & Reder, L. M. (1998). A theoretical review of the misinformation effect: Predictions from an activation-based memory model. *Psychonomic Bulletin & Review*, *5*(1), 1–21. https://doi.org/10.3758/BF03209454

Bansal, H., & Khan, R. (2018). A Review Paper on Human Computer Interaction. *International Journals of Advanced Research in Computer Science and Software Engineering*, *8*(4).

Bauer, K., & Gill, A. (2024). Mirror, Mirror on the Wall: Algorithmic Assessments, Transparency, and Self-Fulfilling Prophecies. *Information Systems Research*, *35*(1), 226–248. https://doi.org/10.1287/isre.2023.1217

Baumeister, R. F., Bratslavsky, E., Muraven, M., & Tice, D. M. (1998). Ego depletion: Is the active self a limited resource? *Journal of Personality and Social Psychology*, *74*(5), 1252–1265. https://doi.org/10.1037/0022-3514.74.5.1252

Becker, G., & Arnold, R. (1986). Stigma as a Social and Cultural Construct. In S. C. Ainlay, G. Becker, & L. M. Coleman (Eds.), *The Dilemma of Difference* (pp. 39–57). Springer US. https://doi.org/10.1007/978-1-4684-7568-5_3

Berger, M., Wagner, T. H., & Baker, L. C. (2005). Internet use and stigmatized illness. *Social Science & Medicine*, *61*(8), 1821–1827. https://doi.org/10.1016/j.socscimed.2005.03.025

Bickmore, T. W., & Picard, R. W. (2005). Establishing and maintaining long-term human-computer relationships. *ACM Transactions on Computer-Human Interaction*, *12*(2), 293–327. https://doi.org/10.1145/1067860.1067867

Bigman, Y. E., & Gray, K. (2018). People are averse to machines making moral decisions. *Cognition*, *181*, 21–34. https://doi.org/10.1016/j.cognition.2018.08.003

Binns, R., Veale, M., Van Kleek, M., & Shadbolt, N. (2017). Like Trainer, Like Bot? Inheritance of Bias in Algorithmic Content Moderation. In G. L. Ciampaglia, A. Mashhadi, & T. Yasseri (Eds.), *Social Informatics* (Vol. 10540, pp. 405–415). Springer International Publishing. https://doi.org/10.1007/978-3-319-67256-4_32

Botvinick, M. M., & Rosen, Z. B. (2009). Anticipation of cognitive demand during decision-making. *Psychological Research Psychologische Forschung*, *73*(6), 835–842. https://doi.org/10.1007/s00426-008-0197-8

Brandtzaeg, P. B., & Følstad, A. (2018). Chatbots: Changing user needs and motivations. *Interactions*, *25*(5), 38–43. https://doi.org/10.1145/3236669

Branley-Bell, D., Brown, R., Coventry, L., & Sillence, E. (2023). Chatbots for embarrassing and stigmatizing conditions: Could chatbots encourage users to seek medical advice? *Frontiers in Communication*, *8*, 1275127. https://doi.org/10.3389/fcomm.2023.1275127

Braun, M., & Schwartz, E. M. (2025). Where A/B Testing Goes Wrong: How Divergent Delivery Affects What Online Experiments Cannot (and Can) Tell You About How Customers Respond to Advertising. *Journal of Marketing*, *89*(2), 71–95. https://doi.org/10.1177/00222429241275886

Brennan, K. (2025). Chatbots in sexual and reproductive health: Bridging the divide in accessibility and equity. *Contraception*, 111199. https://doi.org/10.1016/j.contraception.2025.111199

Brown, A. W., Kaiser, K. A., & Allison, D. B. (2018). Issues with data and analyses: Errors, underlying themes, and potential solutions. *Proceedings of the National Academy of Sciences*, *115*(11), 2563–2570. https://doi.org/10.1073/pnas.1708279115

Case, D. O., Given, L. M., & Mai, J.-E. (2016). *Looking for Information: A Survey of Research on Information Seeking, Needs, and Behavior* (4th ed). Emerald Group Publishing Limited.
Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-Dependent Algorithm Aversion. *Journal of Marketing Research*, *56*(5), 809–825. https://doi.org/10.1177/0022243719851788
Chau, M., & Xu, J. (2025). An IS Research Agenda on Large Language Models: Development, Applications, and Impacts on Business and Management. *ACM Transactions on Management Information Systems*, *16*(1), 1–11. https://doi.org/10.1145/3713032
Chrisler, J. C. (2013). Teaching Taboo Topics: Menstruation, Menopause, and the Psychology of Women. *Psychology of Women Quarterly*, *37*(1), 128–132. https://doi.org/10.1177/0361684312471326
Cichy, P., Salge, T. O., & Kohli, R. (2021). Privacy Concerns and Data Sharing in the Internet of Things: Mixed Methods Evidence from Connected Cars. *MIS Quarterly*, *45*(4), 1863–1891. https://doi.org/10.25300/MISQ/2021/14165
Clement, S., Schauman, O., Graham, T., Maggioni, F., Evans-Lacko, S., Bezborodovs, N., Morgan, C., Rüsch, N., Brown, J. S. L., & Thornicroft, G. (2015). What is the impact of mental health-related stigma on help-seeking? A systematic review of quantitative and qualitative studies. *Psychological Medicine*, *45*(1), 11–27. https://doi.org/10.1017/S0033291714000129
Comulada, W. S., Step, M., Fletcher, J. B., Tanner, A. E., Dowshen, N. L., Arayasirikul, S., Keglovitz Baker, K., Zuniga, J., Swendeman, D., Medich, M., Kao, U. H., Northrup, A., Nieto, O., Brooks, R. A., & Special Projects Of National Significance Social Media Initiative Study Group. (2020). Predictors of Internet Health Information–Seeking Behaviors Among Young Adults Living With HIV Across the United States: Longitudinal Observational Study. *Journal of Medical Internet Research*, *22*(11), e18309. https://doi.org/10.2196/18309
Cook, J. E., & Doyle, C. (2002). Working Alliance in Online Therapy as Compared to Face-to-Face Therapy: Preliminary Results. *CyberPsychology & Behavior*, *5*(2), 95–105. https://doi.org/10.1089/109493102753770480
Cornelison, B. R., Erstad, B. L., & Edwards, C. (2024). Accuracy of a chatbot in answering questions that patients should ask before taking a new medication. *Journal of the American Pharmacists Association*, *64*(4), 102110. https://doi.org/10.1016/j.japh.2024.102110
Corrigan, P. W., River, L. P., Lundin, R. K., Wasowski, K. U., Campion, J., Mathisen, J., Goldstein, H., Bergman, M., Gagnon, C., & Kubiak, M. A. (2000). Stigmatizing attributions about mental illness. *Journal of Community Psychology*, *28*(1), 91–102. https://doi.org/10.1002/(SICI)1520-6629(200001)28:1%253C91::AID-JCOP9%253E3.0.CO;2-M
Crocker, J., & Garcia, J. A. (2006). Social stigma. In *The handbook of social psychology* (pp. 504–553). McGraw-Hill.
De Gennaro, M., Krumhuber, E. G., & Lucas, G. (2020). Effectiveness of an Empathic Chatbot in Combating Adverse Effects of Social Exclusion on Mood. *Frontiers in Psychology*, *10*, 3061. https://doi.org/10.3389/fpsyg.2019.03061
De Jong, T. (2010). Cognitive load theory, educational research, and instructional design: Some food for thought. *Instructional Science*, *38*(2), 105–134. https://doi.org/10.1007/s11251-009-9110-0
Deldjoo, Y., Trippas, J. R., & Zamani, H. (2021). Towards Multi-Modal Conversational Information Seeking. *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*, 1577–1587. https://doi.org/10.1145/3404835.3462806
Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General*, *144*(1), 114–126. https://doi.org/10.1037/xge0000033
Dietvorst, B. J., Simmons, J. P., & Massey, C. (2018). Overcoming Algorithm Aversion: People Will Use Imperfect Algorithms If They Can (Even Slightly) Modify Them. *Management Science*, *64*(3), 1155–1170. https://doi.org/10.1287/mnsc.2016.2643
Dolezal, L. (2015). *The body and shame: Phenomenology, feminism, and the socially shaped body*. Lexington books.

Dudley, J. R. (2000). Confronting Stigma within the Services System. *Social Work*, *45*(5), 449–455. https://doi.org/10.1093/sw/45.5.449

Følstad, A., Nordheim, C. B., & Bjørkli, C. A. (2018). What Makes Users Trust a Chatbot for Customer Service? An Exploratory Interview Study. In S. S. Bodrunova (Ed.), *Internet Science* (Vol. 11193, pp. 194–208). Springer International Publishing. https://doi.org/10.1007/978-3-030-01437-7_16

Gaines, J., & Jermier, J. M. (1983). Emotional Exhaustion in a High Stress Organization. *Academy of Management Journal*, *26*(4), 567–586. https://doi.org/10.2307/255907

George, J., Gerhart, N., & Torres, R. (2021). Uncovering the Truth about Fake News: A Research Model Grounded in Multi-Disciplinary Literature. *Journal of Management Information Systems*, *38*(4), 1067–1094. https://doi.org/10.1080/07421222.2021.1990608

Goffman, E. (1963). Embarrassment and Social Organization. In N. J. Smelser & W. T. Smelser (Eds.), *Personality and social systems.* (pp. 541–548). John Wiley & Sons, Inc. https://doi.org/10.1037/11302-050

Grant, A. M., & Berry, J. W. (2011). The Necessity of Others is The Mother of Invention: Intrinsic and Prosocial Motivations, Perspective Taking, and Creativity. *Academy of Management Journal*, *54*(1), 73–96. https://doi.org/10.5465/amj.2011.59215085

Gray, H. M., Gray, K., & Wegner, D. M. (2007). Dimensions of Mind Perception. *Science*, *315*(5812), 619–619. https://doi.org/10.1126/science.1134475

Gruszka, A., & Nęcka, E. (2017). Limitations of working memory capacity: The cognitive and social consequences. *European Management Journal*, *35*(6), 776–784. https://doi.org/10.1016/j.emj.2017.07.001

Han, E., Yin, D., & Zhang, H. (2023). Bots with Feelings: Should AI Agents Express Positive Emotion in Customer Service? *Information Systems Research*, *34*(3), 1296–1311. https://doi.org/10.1287/isre.2022.1179

Hatzenbuehler, M. L., Nolen-Hoeksema, S., & Dovidio, J. (2009). How Does Stigma "Get Under the Skin"?: The Mediating Role of Emotion Regulation. *Psychological Science*, *20*(10), 1282–1289. https://doi.org/10.1111/j.1467-9280.2009.02441.x

Ho, Y.-J. (Ian), Jabr, W., & Zhang, Y. (2023). Ai Enforcement: Examining the Impact of Ai on Judicial Fairness and Public Safety. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4533047

Holohan, M., & Fiske, A. (2021). "Like I'm Talking to a Real Person": Exploring the Meaning of Transference for the Use and Design of AI-Based Applications in Psychotherapy. *Frontiers in Psychology*, *12*, 720476. https://doi.org/10.3389/fpsyg.2021.720476

Hou, T., Li, M., Tan, Y. (Ricky), & Zhao, H. (2024). Physician Adoption of AI Assistant. *Manufacturing & Service Operations Management*, *26*(5), 1639–1655. https://doi.org/10.1287/msom.2023.0093

Huang, L., Yu, W., Ma, W., Zhong, W., Feng, Z., Wang, H., Chen, Q., Peng, W., Feng, X., Qin, B., & Liu, T. (2024). A Survey on Hallucination in Large Language Models: Principles, Taxonomy, Challenges, and Open Questions. *ACM Transactions on Information Systems*, 3703155. https://doi.org/10.1145/3703155

Hwang, E. H., & Lee, S. (2024). A Nudge to Credible Information as a Countermeasure to Misinformation: Evidence from Twitter. *Information Systems Research*, isre.2021.0491. https://doi.org/10.1287/isre.2021.0491

Jia, L., Hu, X., Yu, Y., & Liang, H. (2025). AI Voice Matters: AI's Pragmatics and Sociophonetics in Persuasion. *Available at SSRN*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5202834

Jiang, Y., Ho, Y.-C. (Chad), Yan, X., & Tan, Y. (2022). What's in a "Username"? The Effect of Perceived Anonymity on Herding in Crowdfunding. *Information Systems Research*, *33*(1), 1–17. https://doi.org/10.1287/isre.2021.1049

Jiang, Z. (Jack), Heng, C. S., & Choi, B. C. F. (2013). Privacy Concerns and Privacy-Protective Behavior in Synchronous Online Social Interactions. *Information Systems Research*, *24*(3), 579–595. https://doi.org/10.1287/isre.1120.0441

Jones, E. E. (Ed.). (1984). *Social stigma: The psychology of marked relationships*. Freeman.

Jones-Jang, S. M., & Park, Y. J. (2022). How do people react to AI failure? Automation bias, algorithmic aversion, and perceived controllability. *Journal of Computer-Mediated Communication*, *28*(1), zmac029. https://doi.org/10.1093/jcmc/zmac029

Jussupow, E., Benbasat, I., & Heinzl, A. (2024). An Integrative Perspective on Algorithm Aversion and Appreciation in Decision-Making. *MIS Quarterly*, *48*(4), 1575–1590. https://doi.org/10.25300/MISQ/2024/18512

Kagan, E., Dada, M., & Hathaway, B. (2022). AI Chatbots in Customer Service: Adoption Hurdles and Simple Remedies. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4283285

Kim, A., & Dennis, A. (2018). *Says Who?: How News Presentation Format Influences Perceived Believability and the Engagement Level of Social Media Users*. Hawaii International Conference on System Sciences. https://doi.org/10.24251/HICSS.2018.497

King, R., Bambling, M., Lloyd, C., Gomurra, R., Smith, S., Reid, W., & Wegner, K. (2006). Online counselling: The motives and experiences of young people who choose the Internet instead of face to face or telephone counselling. *Counselling and Psychotherapy Research*, *6*(3), 169–174. https://doi.org/10.1080/14733140600848179

Kosyluk, K., Baeder, T., Greene, K. Y., Tran, J. T., Bolton, C., Loecher, N., DiEva, D., & Galea, J. T. (2024). Mental Distress, Label Avoidance, and Use of a Mental Health Chatbot: Results From a US Survey. *JMIR Formative Research*, *8*, e45959. https://doi.org/10.2196/45959

Lambert, S. D., & Loiselle, C. G. (2007). Health Information—Seeking Behavior. *Qualitative Health Research*, *17*(8), 1006–1019. https://doi.org/10.1177/1049732307305199

Laviola, F., Palese, B., Kim, S. T., & Cucari, N. (2024). Not all AI Chatbots are Created Equal: The Case of a Soft Skills Coaching Bot in Education. *Academy of Management Proceedings*, *2024*(1). https://doi.org/10.5465/amproc.2024.55bp

Lazarus, R. S. (2023). *Emotion and adaptation*. Oxford University Press.

Lebovitz, S., Lifshitz-Assaf, H., & Levina, N. (2022). To Engage or Not to Engage with AI for Critical Judgments: How Professionals Deal with Opacity When Using AI for Medical Diagnosis. *Organization Science*, *33*(1), 126–148. https://doi.org/10.1287/orsc.2021.1549

Lee, Y.-C., Yamashita, N., & Huang, Y. (2020). Designing a Chatbot as a Mediator for Promoting Deep Self-Disclosure to a Real Mental Health Professional. *Proceedings of the ACM on Human-Computer Interaction*, *4*(CSCW1), 1–27. https://doi.org/10.1145/3392836

Lewandowsky, S., Ecker, U. K. H., Seifert, C. M., Schwarz, N., & Cook, J. (2012). Misinformation and Its Correction: Continued Influence and Successful Debiasing. *Psychological Science in the Public Interest*, *13*(3), 106–131. https://doi.org/10.1177/1529100612451018

Link, B. G., Cullen, F. T., Struening, E., Shrout, P. E., & Dohrenwend, B. P. (1989). A Modified Labeling Theory Approach to Mental Disorders: An Empirical Assessment. *American Sociological Review*, *54*(3), 400. https://doi.org/10.2307/2095613

Link, B. G., & Phelan, J. C. (2001). Conceptualizing Stigma. *Annual Review of Sociology*, *27*(1), 363–385. https://doi.org/10.1146/annurev.soc.27.1.363

List, J. A. (2025). *The Experimentalist Looks Within: Toward an Understanding of Within-Subject Experimental Designs*. NATIONAL BUREAU OF ECONOMIC RESEARCH. http://www.nber.org/papers/w33456

Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes*, *151*, 90–103. https://doi.org/10.1016/j.obhdp.2018.12.005

Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to Medical Artificial Intelligence. *Journal of Consumer Research*, *46*(4), 629–650. https://doi.org/10.1093/jcr/ucz013

Lu, Y., Li, X., & Jiang, Z. (2024). *Human vs. Virtual Endorser? Interaction Effect of Endorser Type and Product Type on Consumers' Product Attitudes*. ICIS 2024 Proceedings. 3.

Lucas, G. M., Gratch, J., King, A., & Morency, L.-P. (2014). It's only a computer: Virtual humans increase willingness to disclose. *Computers in Human Behavior*, *37*, 94–100. https://doi.org/10.1016/j.chb.2014.04.043

Major, B., & O'Brien, L. T. (2005). The Social Psychology of Stigma. *Annual Review of Psychology*, *56*(1), 393–421. https://doi.org/10.1146/annurev.psych.56.091103.070137
Meadows, A., & Calogero, R. M. (2018). Studies on Weight Stigma and Body Image in Higher-Weight Individuals. In M. Cuzzolaro & S. Fassino (Eds.), *Body Image, Eating, and Weight* (pp. 381–400). Springer International Publishing. https://doi.org/10.1007/978-3-319-90817-5_28
Meyrowitsch, D. W., Jensen, A. K., Sørensen, J. B., & Varga, T. V. (2023). AI chatbots and (mis)information in public health: Impact on vulnerable communities. *Frontiers in Public Health*, *11*, 1226776. https://doi.org/10.3389/fpubh.2023.1226776
Miles, O., West, R., & Nadarzynski, T. (2021). Health chatbots acceptability moderated by perceived stigma and severity: A cross-sectional survey. *DIGITAL HEALTH*, *7*, 20552076211063012. https://doi.org/10.1177/20552076211063012
Mills, R., Mangone, E. R., Lesh, N., Mohan, D., & Baraitser, P. (2023). Chatbots to Improve Sexual and Reproductive Health: Realist Synthesis. *Journal of Medical Internet Research*, *25*, e46761. https://doi.org/10.2196/46761
Mogaji, E., Balakrishnan, J., Nwoba, A. C., & Nguyen, N. P. (2021). Emerging-market consumers' interactions with banking chatbots. *Telematics and Informatics*, *65*, 101711. https://doi.org/10.1016/j.tele.2021.101711
Moravec, P., Minas, R., & Dennis, A. (2019). Fake News on Social Media: People Believe What They Want to Believe When it Makes No Sense At All. *MIS Quarterly*, *43*(4), 1343–1360. https://doi.org/10.25300/MISQ/2019/15505
Moro-Visconti, R. (2024). Chatbots and Generative Artificial Intelligence. In R. Moro-Visconti, *Artificial Intelligence Valuation* (pp. 507–568). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-53622-9_8
Munyaka, I., Hargittai, E., & Redmiles, E. (2022). Misinformation Paradox: Older Adults are Cynical about News Media, but Engage with It Anyway. *Journal of Online Trust and Safety*, *1*(4). https://doi.org/10.54501/jots.v1i4.62
Nadarzynski, T., Miles, O., Cowie, A., & Ridge, D. (2019). Acceptability of artificial intelligence (AI)-led chatbot services in healthcare: A mixed-methods study. *DIGITAL HEALTH*, *5*, 205520761987180. https://doi.org/10.1177/2055207619871808
Nadarzynski, T., Puentes, V., Pawlak, I., Mendes, T., Montgomery, I., Bayley, J., & Ridge, D. (2021). Barriers and facilitators to engagement with artificial intelligence (AI)-based chatbots for sexual and reproductive health advice: A qualitative analysis. *Sexual Health*, *18*(5), 385–393. https://doi.org/10.1071/SH21123
Ng, M., Coopamootoo, K. P. L., Toreini, E., Aitken, M., Elliot, K., & Van Moorsel, A. (2020). Simulating the Effects of Social Presence on Trust, Privacy Concerns & Usage Intentions in Automated Bots for Finance. *2020 IEEE European Symposium on Security and Privacy Workshops (EuroS&PW)*, 190–199. https://doi.org/10.1109/EuroSPW51379.2020.00034
Orazi, D. C., & Johnston, A. C. (2020). Running field experiments using Facebook split test. *Journal of Business Research*, *118*, 189–198. https://doi.org/10.1016/j.jbusres.2020.06.053
Ozdemir, D. Y., Ayvaci, M., & Zentner, A. (2024). What People Think of Machines as Doctors: Unveiling the Value of Gen-AI for e-Health. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4765222
Park, H. J. (2024). The rise of generative artificial intelligence and the threat of fake news and disinformation online: Perspectives from sexual medicine. *Investigative and Clinical Urology*, *65*(3), 199. https://doi.org/10.4111/icu.20240015
Pasquale, F. (2015). *The Black Box Society: The Secret Algorithms That Control Money and Information*. Harvard University Press. https://doi.org/10.4159/harvard.9780674736061
Patricia L. Moravec, Randall K. Minas, & Alan R. Dennis. (2019). Fake News on Social Media: People Believe What They Want to Believe When it Makes No Sense At All. *MIS Quarterly*, *43*(4).
Pattyn, E., Verhaeghe, M., Sercu, C., & Bracke, P. (2014). Public Stigma and Self-Stigma: Differential Association With Attitudes Toward Formal and Informal Help Seeking. *Psychiatric Services*, *65*(2), 232–238. https://doi.org/10.1176/appi.ps.201200561

Pennycook, G., & Rand, D. G. (2019). Lazy, not biased: Susceptibility to partisan fake news is better explained by lack of reasoning than by motivated reasoning. *Cognition*, *188*, 39–50. https://doi.org/10.1016/j.cognition.2018.06.011

Rai, A., Constantinides, P., & Sarker, S. (2019). Next generation digital platforms: Toward human-AI hybrids. *MIS Quarterly*, *43*(1), iii–ix.

Raimi, R., Kim, A., Ayabakan, S., & Dennis, A. R. (2025). Judgmental Bot: Conversational Agents in Online Mental Health Screening. *MIS Quarterly*. https://doi.org/10.25300/MISQ/2025/18555

Rickwood, D., Deane, F. P., Wilson, C. J., & Ciarrochi, J. (2005). Young people's help-seeking for mental health problems. *Australian E-Journal for the Advancement of Mental Health*, *4*(3), 218–251. https://doi.org/10.5172/jamh.4.3.218

Savolainen, R. (2014). Emotions as motivators for information seeking: A conceptual analysis. *Library & Information Science Research*, *36*(1), 59–65. https://doi.org/10.1016/j.lisr.2013.10.004

Scherer, K. R. (1999). Appraisal Theory. In T. Dalgleish & M. J. Power (Eds.), *Handbook of Cognition and Emotion* (1st ed., pp. 637–663). Wiley. https://doi.org/10.1002/0470013494.ch30

Shao, A. (2025). New sources of inaccuracy? A conceptual framework for studying AI hallucinations. *Harvard Kennedy School Misinformation Review*. https://doi.org/10.37016/mr-2020-182

Shin, D. (2024). Misinformation, Paradox, and Nudge: Combating Misinformation Through Nudging. In D. Shin, *Artificial Misinformation* (pp. 171–194). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-52569-8_7

Song, S. Y., & Kim, Y.-K. (2022). Factors Influencing Consumers' Intention to Adopt Fashion Robot Advisors: Psychological Network Analysis. *Clothing and Textiles Research Journal*, *40*(1), 3–18. https://doi.org/10.1177/0887302X20941261

Stangl, A. L., Earnshaw, V. A., Logie, C. H., Van Brakel, W., C. Simbayi, L., Barré, I., & Dovidio, J. F. (2019). The Health Stigma and Discrimination Framework: A global, crosscutting framework to inform research, intervention development, and policy on health-related stigmas. *BMC Medicine*, *17*(1), 31. https://doi.org/10.1186/s12916-019-1271-3

Starke, C., Baleis, J., Keller, B., & Marcinkowski, F. (2022). Fairness perceptions of algorithmic decision-making: A systematic review of the empirical literature. *Big Data & Society*, *9*(2), 20539517221115189. https://doi.org/10.1177/20539517221115189

Steele, C. M. (1997). A threat in the air: How stereotypes shape intellectual identity and performance. *American Psychologist*, *52*(6), 613–629. https://doi.org/10.1037/0003-066X.52.6.613

Stokel-Walker, C. (2023). AI chatbots are coming to search engines—Can you trust the results? *Nature*, d41586-023-00423–00424. https://doi.org/10.1038/d41586-023-00423-4

Tolmeijer, S., Christen, M., Kandul, S., Kneer, M., & Bernstein, A. (2022). Capable but Amoral? Comparing AI and Human Expert Collaboration in Ethical Decision Making. *CHI Conference on Human Factors in Computing Systems*, 1–17. https://doi.org/10.1145/3491102.3517732

Toni Schmader & Brian Lickel. (2006). Stigma and shame: Emotional responses to the stereotypic actions of one's ethnic ingroup. In *Stigma and group inequality* (pp. 275–300). Psychology Press.

Trippas, J. R., Spina, D., Cavedon, L., & Sanderson, M. (2017). How Do People Interact in Conversational Speech-Only Search Tasks: A Preliminary Analysis. *Proceedings of the 2017 Conference on Conference Human Information Interaction and Retrieval*, 325–328. https://doi.org/10.1145/3020165.3022144

Turel, O., Kalhan, S., & skalhan@student.unimelb.edu.au. (2023). Prejudiced against the Machine? Implicit Associations and the Transience of Algorithm Aversion. *MIS Quarterly*, *47*(4), 1369–1394. https://doi.org/10.25300/MISQ/2022/17961

Van Wezel, M. M. C., Croes, E. A. J., & Antheunis, M. L. (2021). "I'm Here for You": Can Social Chatbots Truly Support Their Users? A Literature Review. In A. Følstad, T. Araujo, S. Papadopoulos, E. L.-C. Law, E. Luger, M. Goodwin, & P. B. Brandtzaeg (Eds.), *Chatbot Research and Design* (Vol. 12604, pp. 96–113). Springer International Publishing. https://doi.org/10.1007/978-3-030-68288-0_7

Vogel, D. L., Wade, N. G., & Hackler, A. H. (2007). Perceived public stigma and the willingness to seek counseling: The mediating roles of self-stigma and attitudes toward counseling. *Journal of Counseling Psychology*, *54*(1), 40–50. https://doi.org/10.1037/0022-0167.54.1.40

Weisband, S., & Kiesler, S. (1996). Self disclosure on computer forms: Meta-analysis and implications. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems Common Ground - CHI '96*, 3–10. https://doi.org/10.1145/238386.238387

Werner, H., & Muradova, L. (2022). *Scenario Experiments*. https://doi.org/10.5167/UZH-259844

Weyrich, P., Scolobig, A., Walther, F., & Patt, A. (2020). Responses to severe weather warnings and affective decision-making. *Natural Hazards and Earth System Sciences*, *20*(10), 2811–2821. https://doi.org/10.5194/nhess-20-2811-2020

Willison, D. J., Steeves, V., Charles, C., Schwartz, L., Ranford, J., Agarwal, G., Cheng, J., & Thabane, L. (2009). Consent for use of personal information for health research: Do people with potentially stigmatizing health conditions and the general public differ in their opinions? *BMC Medical Ethics*, *10*(1), 10. https://doi.org/10.1186/1472-6939-10-10

Wolczynski, N., Saar-Tsechansky, M., & Wang, T. (2024). *The Value of AI Advice: Personalized and Value-Maximizing AI Advisors Are Necessary to Reliably Benefit Experts and Organizations* (Version 1). arXiv. https://doi.org/10.48550/ARXIV.2412.19530

Yang, L. H., Kleinman, A., Link, B. G., Phelan, J. C., Lee, S., & Good, B. (2007). Culture and stigma: Adding moral experience to stigma theory. *Social Science & Medicine*, *64*(7), 1524–1535. https://doi.org/10.1016/j.socscimed.2006.11.013

Yıldız, H. A., & Söğütdelen, E. (2025). AI Chatbots as Sources of STD Information: A Study on Reliability and Readability. *Journal of Medical Systems*, *49*(1), 43. https://doi.org/10.1007/s10916-025-02178-z

You, S., & Robert Jr., L. P. (2024). Trusting and Working with Robots: A Relational Demography Theory of Preference for Robotic over Human Co-Workers. *MIS Quarterly*, *48*(4), 1297–1330. https://doi.org/10.25300/MISQ/2023/17403

Yu, X., Zhang, Z., Niu, F., Hu, X., Xia, X., & Grundy, J. (2024). What Makes a High-Quality Training Dataset for Large Language Models: A Practitioners' Perspective. *Proceedings of the 39th IEEE/ACM International Conference on Automated Software Engineering*, 656–668. https://doi.org/10.1145/3691620.3695061

Zamani, H., Trippas, J. R., Dalton, J., & Radlinski, F. (2022). *Conversational Information Seeking*. https://doi.org/10.48550/ARXIV.2201.08808

Zhou, L., Gao, J., Li, D., & Shum, H.-Y. (2020). The Design and Implementation of XiaoIce, an Empathetic Social Chatbot. *Computational Linguistics*, *46*(1), 53–93. https://doi.org/10.1162/coli_a_00368

APPENDIX

Appendix A. Literature Summary

Paper	AI chatbot Focus	Context-Spanning	Human Agent Comparison	Stigma Manipulated	Mechanisms Examined	Methods	Outcome
Berger et al., 2005		✓				Survey	Intention to use search engine
Comulada et al., 2020						Survey	Intention to use search engine
Branley-Bell et al., 2023	✓	✓	✓			Online Experiment	Preference for consultation
Raimi et al., 2025	✓		✓		✓	Online Experiments Qualitative Analysis	Willingness to use, disclose info, follow recommendation
Mills et al., 2023	✓					Theoretical	Literature reviewed to identify assumptions about chatbots
Kosyluk et al., 2024	✓					Survey	Acceptance for screening and advice
Miles et al., 2021	✓	✓	✓			Online Experiment	Willingness to use
Yıldız & Söğütdelen, 2025	✓					Theoretical	Reliability of AI information
Brennan, 2025	✓					Theoretical	Literature reviewed to explore utilization of chatbots
Our Paper	✓	✓	✓	✓	✓	Online & Field Experiments	Preference for information-seeking (stated and revealed)

Table A. Help-Seeking Under Stigma from IT Artifacts

Appendix B. Baseline Scenarios and Corresponding Stigma Ratings (Control Condition)

Context	Baseline Scenario	Visiblity	Origin	Control-ability	Dominant Streotype	Baseline Stigma (1-5)
Weight Management	You gained a noticeable amount of weight in a short period of time, and you are concerned. You don't know the reasons and potential solutions.	High	High	High	Lazy and overeating	Mean = 3.64, SD = 1.16
Addiction	You have been a smoker for years and have failed to quit. You are not sure how to quit.	High	High	High	Weak and lacking self-control	Mean = 2.60, SD = 1.32
Fatigue	Recently, you have been feeling tired every day. You don't know the potential reasons and solutions for your fatigue.	Medium	Medium	High	Slacking and lazy	Mean = 2.35, SD = 1.14
Work Motivation	You have been struggling to wake up and make it to work on time recently. You don't know the potential reasons and solutions for your low mood and lack of motivation.	Medium	High	High	Irresponsible	Mean = 3.05, SD = 1.17
Stage Fear	You have an important work presentation coming up. You feel nervous and you don't know how to boost your confidence.	High	Medium	Medium	Unprepared and incompetent	Mean = 2.24, SD = 1.08
Work-life Balance	You are a junior in college with a part-time job. You want to challenge yourself but also maintain your high GPA. You are wondering if your current enrolled courses are too demanding.	Low	Medium	Medium	Slacking	Mean = 2.35, SD = 1.17
Social Etiquette	You are attending your company's new year party. You don’t know what kind of outfits are both festive and appropriate.	High	High	High	Uncultured and incompetent	Mean = 2.39, SD = 1.13

Table B. Stigma Ratings of Baseline Scenarios

Appendix C. High-Stigma Prompts (Treatment Condition)

Table A3 summarizes the scenarios and high-stigma radio prompts used in the treatment condition of Studies 1–3, along with the items used to measure stigma and information-seeking across both conditions. The stigma measure used a 5-point Likert scale (from “Extremely Unlikely” to “Extremely Likely”), and the information-seeking measure used a 7-point Likert scale (from “Extremely Unlikely” to “Extremely Likely”).

Context	Baseline Scenario	High-Stigma Radio Prompt	Stigma Measurement (1-5)	Information-Seeking Measurement (1-7)
Weight Manage-ment	You gained a noticeable amount of weight in a short period of time, and you are concerned. You don't know the reasons and potential solutions.	"Overweight people must be lazy and eating too much."	How likely are you to experience stigma as you seek information about your sudden gain weight?	How likely are you to have a text-chat conversation to seek information with an AI chatbot (a human expert) about your weight gain?
Work Motivation	You have been struggling to wake up and make it to work on time recently. You don't know the potential reasons and solutions for your low mood and lack of motivation.	"People who go to work late are lazy and irresponsible."	How likely are you to experience stigma as you seek information about your low mood and lack of motivation?	How likely are you to have a text-chat conversation to seek information with an AI chatbot (a human expert) about your low mood and lack of motivation?
Addiction	You have been a smoker for years and have failed to quit. You are not sure how to quit.	"People who can't quit smoking are weak and have no self-control."	How likely are you to experience stigma as you seek information about how to quit smoking?	How likely are you to have a text-chat conversation to seek information with an AI chatbot (a human expert) about how to quit smoking?
Social Etiquette	You are attending your company's new year party. You don’t know what kind of outfits are both festive and appropriate.	"People who don't know the dress code for work events are uncultured and incompetent."	How likely are you to experience stigma as you seek information about choosing the right outfit?	How likely are you to have a text-chat conversation to seek information with an AI chatbot (a human expert) about choosing an outfit?
Fatigue	Recently, you have been feeling tired every day. You don't know the potential reasons and solutions for your fatigue.	"People who are constantly complaining about being tired are just making	How likely are you to experience stigma as you seek information about your fatigue?	How likely are you to have a text-chat conversation to seek information with an AI chatbot (a human

Context	Baseline Scenario	High-Stigma Radio Prompt	Stigma Measurement (1-5)	Information-Seeking Measurement (1-7)
		excuses to slack."		expert) about your fatigue?
Work-life Balance	You are a junior in college with a part-time job. You want to challenge yourself but also maintain your high GPA. You are wondering if your current enrolled courses are too demanding.	"Students who take easy courses are lazy and slacking."	How likely are you to experience stigma as you seek information about managing your course load?	How likely are you to have a text-chat conversation to seek information with an AI chatbot (a human expert) about managing your course load?
Stage Fear	You have an important work presentation coming up. You feel nervous and you don't know how to boost your confidence.	"People who are a nervous wreck at work presentations must be unprepared and incompetent."	How likely are you to experience stigma as you seek information about improving your confidence for the upcoming presentation?	How likely are you to have a text-chat conversation to seek information with an AI chatbot (a human expert) about improving your confidence for the upcoming presentation?

Table C. Online Experiment Details

Appendix D. Summary of Studies

Table A4 outlines the key objectives, methodologies, and findings of all the studies.

Study	Description	Purpose	Result
Pre-test 1	Survey	To measure the level of perceived stigma for each scenario.	Recorded average perceived stigma level for each scenario (Figure 3).
Pre-test 2	Survey with two conditions	Stigma manipulation check.	The manipulation via the radio prompts was successful; Participants in the high-stigma condition perceived scenarios as significantly more stigmatizing than those in the baseline condition (Figure 3 and Table 2).
Study 1	Between-subject Experiment	To test H1: examining the effect of perceived stigma on willingness to seek information from AI chatbots vs. humans.	People have an increased preference for AI chatbots in the high-stigma condition (Table 3), corroborating H1.
Study 2	Within-subject Experiment	To replicate the results of Study 1 using a within-subjects design.	People have an increased preference for AI chatbots in the high-stigma condition (Table 4), corroborating H1.
Study 3	Between-subject Experiment	To test H2 & H3: examine judgment and misinformation concerns as potential mediators of the effect of perceived stigma on willingness to seek information from AI chatbots vs. humans.	Both judgment and misinformation concerns partially mediate the effect of stigma on information seeking (Table 5), corroborating H2 and H3.
Study 4	Field Experiment	To replicate the results with higher external validity and to capture revealed preferences.	In a real-world setting, people have an increased preference for AI chatbots in the high-stigma condition, captured as higher Click-Through Rates for AI chatbots compared to human experts (Figure 5), corroborating H1.

Table D. Summary of Studies

Appendix E. Definition of AI Chatbot and Human Expert Used in Studies 1–3

Information Source	Definition
AI Chatbot	When we mention an AI chatbot, we mean a chatbot that uses techniques such as natural language processing on large amounts of data to generate responses to your inquiries. You can assume that the capability of the AI chatbot is comparable to ChatGPT, Bing AI chatbot, Google Bard AI chatbot and other modern AI chatbots.
Human Expert	When we mention a human expert, we mean someone who acquired their knowledge through education, training, and practical experience. Their knowledge allows them to provide answers to your inquiries (e.g., a therapist or a dietitian offering an online service).

Table E. Definition of AI Chatbot and Human Expert Shown in Online Experiments

Appendix F. Power Analysis

Study 1: To assess whether our sample size was sufficient, we conducted a within-subject power analysis based on N = 406 participants. Human ratings (*M = 3.77, SD = 0.80*) were significantly higher than AI ratings (*M = 2.84, SD = 1.01*), mean difference = -0.93, t(405) = -15.76, $p < .001$, Cohen's dz = 0.78. An a priori calculation indicated that only 64 participants would be required to detect a medium effect (*dz = 0.35*) with 80% power, $\alpha = 0.05$. Given the achieved N, the minimum detectable effect size was dz ≈ 0.14, showing the study was highly powered and the observed effect size was well above this threshold.

Study 2: To evaluate the adequacy of our sample, we conducted formal power analyses. The analytic sample comprised 395 unique participants, distributed nearly evenly across the four experimental cells (Human & Low-Stigma = 96, Human & High-Stigma = 100, AI & Low-Stigma = 99, AI & High-Stigma = 100). A priori, detecting a medium effect size (*Cohen's d = 0.35*) at $\alpha = .05$ with 80% power would require only 130 participants per group (*N = 260 total*), well below our actual group sizes (*N = 395*). Sensitivity analysis further indicated that with our achieved sample, the study had adequate power to detect effects as small as $d \approx 0.28$ for two-group contrasts. For the full factorial regression model including three main predictors (AI, High-Stigma, and their interaction), the achieved power was approximately 0.80 for small effects ($f^2 = 0.02$). These results confirm that the study was well-powered to detect theoretically meaningful effects.

Study 3: The final analytic sample used in study 3 included N = 361 unique participants, distributed nearly evenly across the four conditions (Human & Low-Stigma = 95, Human & High-Stigma = 96, AI & Low-Stigma = 88, AI & High-Stigma = 82). Power analysis indicated that, for detecting a medium effect of *d = 0.35* with $\alpha = .05$ and 80% power, a total of 260 participants (130 per group) would be required. Given our achieved sample, the minimum detectable effect size was $d \approx 0.30$, suggesting adequate sensitivity to detect small-to-moderate effects. For regression models including the main predictors, an

approximation using $f^2 = 0.02$ (a small effect) yielded a power estimate of ≈ 0.76. Taken together, these results confirm that the study had sufficient statistical power to detect theoretically meaningful effects.

Appendix G. Effect of Stigma on Relative Preference for AI Chatbot

The results in Table G reinforce our earlier conclusions in Study 1. In Model P1, the coefficient for the *I(Stigma=High)* is positive and significant (0.313, $p < 0.01$), indicating that under high-stigma condition, individuals exhibit a greater relative preference for seeking information from AI chatbots compared to Human experts. In Model P2, where we include demographic controls and prior AI experience, the effect of *I(Stigma=High)* remains positive and significant (0.351, $p < 0.01$). These results are consistent with the interaction effects reported in Table 3, providing evidence for Hypothesis H1: perceived stigma increases the relative preference for AI chatbots compared to human experts as sources of information.

	(P1) Preference (AI minus Human)	(P2) Preference (AI minus Human)
I(Stigma=High)	0.313***	0.351***
	(0.117)	(0.113)
Constant	-1.226***	-2.615***
	(0.101)	(0.643)
Observations	2,842	2,835
R-squared	0.048	0.085
Situation FE	Yes	Yes
Controls	No	Yes
Individuals	406	406

Table G. The Effect of Perceived Stigma on Relative Preference for AI Compared to Human

Appendix H. Ad Campaign and Randomization

We allocated an equal budget to each advertisement and ran all four ad sets over two days (from 12:00 AM on November 29 to 12:00 AM on December 1, 2023), targeting all adults in North America. This campaign generated approximately 16,000 impressions per advertisement. In order to randomize the distribution of the ads, we set randomization at the campaign level by selecting "Reach" as the campaign objective and enabling the "Create A/B Test" function in Facebook Ads Manager. This setting ensures that the platform randomly assigns each ad variant to an even split of the target audience while holding other conditions constant (Orazi & Johnston, 2020). To prevent algorithmic optimization from biasing delivery, we did not select "Campaign Budget Optimization" and set "Optimization for Ad Delivery" to Reach with a frequency cap of one impression per user over the duration of the study. These settings restrict Facebook's delivery algorithm from adjusting exposure based on predicted engagement and ensure that each user is exposed to only one treatment condition (Braun & Schwartz, 2025). Finally, we exported reach and demographic breakdowns (age, gender) from Facebook's Ad Manager after the campaign to check for balance. This allowed us to verify that reach, impressions, and spending were evenly distributed across conditions, with only trivial percentage differences in demographic composition. The final sample consisted of 64,000 participants, including 30,235 males, 25,023 females, and 8,742 who preferred not to disclose their gender. Participants' ages ranged from 18 to 65+, with an average age range of [45,54].

Appendix I. CTR Analysis in Facebook Experiment

While click-through rates (CTR) offer managerial insights into the relative effectiveness of each condition, we rely on statistical tests to determine whether these differences are statistically significant, following Orazi & Johnston (2020). First, we used a non-parametric test, specifically a chi-square comparison using click counts. We compared the proportion of users in the baseline condition who clicked on an ad versus those who did not for Human experts (*Adjusted Clicks* = 18 vs. *Non-Clicks* = 12,149) and AI chatbots (*Adjusted Clicks* = 6 vs. *Non-Clicks* = 11,449). The results indicate a significant difference ($\chi 2(1) = 5.30$, $p = 0.021$). Next, we conducted the same comparison in the high-stigma condition for Human experts (*Clicks* = 9 vs. *Non-Clicks* = 11,841) and AI chatbots (*Clicks* = 14 vs. *Non-Clicks* = 11,776) and found no significant difference ($\chi 2(1) = 1.11$, $p = 0.291$). As hypothesized, AI aversion persists in the baseline conditions, whereas in the high-stigma conditions, it disappears.

	Low Stigma Human	**High Stigma Human**	**Low Stigma AI Chatbot**	**High Stigma AI Chatbot**
Impressions (# times ad is seen)	16,192	15,845	15,968	15,985
Reach (# unique users who saw ad)	12,167	11,850	11,455	11,790
Frequency (Impressions/Reach)	1.33	1.34	1.39	1.36
Clicks	24	12	8	19
Adjusted Clicks (Clicks/Frequency)	18	9	6	14
Adjusted non-Clicks (Reach - Adjusted Clicks)	12,149	11,841	11,449	11,776
CTR (Adjusted Clicks/Impressions)	0.15	0.08	0.05	0.12

Table I1. Facebook Field Experiment Results

A second approach to CTR analysis involves logistic regression on a simulated dataset based on click and non-click counts across conditions (Orazi & Johnston, 2020). The dataset includes a column for stigma manipulation, where high-stigma conditions are coded as 1 and baseline conditions as 0, a column for service provider manipulation, where AI is coded as 1 and human as 0, and a column for user engagement, where clicks are coded as 1 and non-clicks as 0. This simulated data allows us to conduct a logistic regression analysis, providing a statistical significance test to assess the impact of stigma and AI usage on user engagement.

As shown in Table I2, the negative and significant effect of *I(Source = AI)* (-1.039, $p < 0.05$) supports the presence of AI aversion. However, the positive and significant interaction effect of *I(Source = AI) × I(Stigma = High)* (1.487, $p < 0.05$) indicates a greater preference for AI chatbots in the high-stigma condition.

	(I1)
I(Stigma=High)	-0.667
	(0.408)
I(Source=AI)	-1.039**
	(0.471)
I(Source=AI) × *I(Stigma=High)*	1.487**
	(0.636)
Constant	-6.515***
	(0.236)
Observations	47,262
Pseudo R-Squared	0.009
Standard errors in parentheses: ** p < 0.1, ** p < 0.05, *** p < 0.01*.	

Table I2. Results from Study 4 (Field Experiment)

Appendix J. Addressing Alternative Explanations

Our design helps to rule out several alternative explanations, such as perceived competence, availability, cost, novelty, and privacy, in the following ways.

Competence: Participants in both the control (baseline) and treatment (high-stigma) groups in studies 1–3 saw standardized definitions of the two information sources (AI chatbot vs. human expert) to establish a common benchmark of quality and reliability (see Appendix C). This procedure minimizes the risk that differences in perceived competence could explain our results.

Availability, Cost, and Novelty: While AI chatbots may generally be viewed as more available than humans, lower cost, or novel, our focal treatment was the manipulation of stigma. There is no theoretical or empirical reason to expect stigma to systematically shift perceptions of these factors for a given source (AI or human).

Privacy Concerns: Stigma could, in principle, heighten sensitivity to privacy (Willison et al., 2009). To address this, we measured privacy concerns directly. The analyses showed no significant effect of stigma on privacy, indicating that privacy concerns do not mediate or explain our observed interaction effects. Together, these checks strengthen confidence that the results are attributable to the theorized mechanism rather than alternative explanations.

Appendix K. Scope and Generalizability

This appendix discusses the scope of our study and the extent to which its findings may generalize across different technological, contextual, and cultural dimensions. Chatbots differ in the underlying algorithms that power them. Chatbots can be powered by simple, rule-based algorithms or by generative artificial intelligence and large-language models (Moro-Visconti, 2024). Rule-based chatbots follow a decision tree or script to determine the appropriate response to user inputs. Generative AI- powered chatbots use large-language models (LLMs) and reinforcement learning to provide more human-like responses. In our studies, participants were explicitly informed that the AI chatbots mentioned in the survey were of the latter type. As a result, our findings may not generalize to rule-based or other non-generative chatbot systems (Laviola et al., 2024), where user expectations and interaction patterns may differ significantly.

Conversational AI agents also differ in their modality, ranging from speech-based voice assistants to text-based chatbots. In our study, to make the human and AI information sources as comparable as possible, we repeatedly reminded the participants that we were asking them about their preferences regarding text-based conversations. Voice-based conversation preferences entail more nuanced considerations about paralinguistic traits, such as the tone and the perceived age of the voice, the pitch variance, and fluency (Belin et. al., 2017). Our findings would, therefore, need to be validated explicitly for modalities other than text.

Stigma can manifest in different forms, including public stigma and self-stigma (Ahmedani, 2011). Public stigma can emerge through interactions with one's social network, such as family and friends (Pattyn et al., 2014). Self-stigma arises when individuals internalize societal judgments and experience feelings of shame (Pattyn et al., 2014). Each of these stigma types can influence an individual’s willingness to seek information from different sources in distinct ways. In this study, we focused on public stigma. Self-stigma, while important, can be difficult to manipulate and measure reliably in an experimental setting, and it also raises potential ethical issues related to the impact on participants’ self-perception and well-

being. In other words, we are not measuring individual-level stigma but are focused on societal-level average perceptions.

Finally, stigma is inherently shaped by cultural context (Yang et al., 2007), meaning that attitudes and stereotypes can vary widely depending on societal norms and values. What is considered stigmatic in one culture may not have the same impact in another, as localized beliefs and customs ultimately determine which behaviors and characteristics are marginalized or sanctioned. In this research, we secured approval from the institutional review board to run our studies in the United States. Consequently, our findings may not fully capture cultural nuances or transfer seamlessly to populations beyond the U.S., and future investigations should test these assumptions across diverse cultural settings.