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Users' Information Disclosure Behaviors during Interactions with Chatbots: The Effect of Information Disclosure Nudges

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Abstract: Drawing from the tension between a company's desire for customer information to tailor experiences and a consumer's need for privacy, this study aims to test the effect of two information disclosure nudges on users' information disclosure behaviors. Whereas previous literature on user-chatbot interaction focused on encouraging and increasing users' disclosures, this study introduces measures that make users conscious of their disclosure behaviors to low and high-sensitivity questions asked by chatbots. A within-subjects laboratory experiment entailed 19 participants interacting with chatbots, responding to pre-tested questions of varying sensitivity while being presented with different information disclosure nudges. The results suggest that *question sensitivity* negatively impacts users' *information disclosures* to chatbots. Moreover, this study suggests that adding a *sensitivity signal*—presenting the level of sensitivity of the question asked by the chatbot—influences users' information disclosure behaviors. Finally, the theoretical contributions and managerial implications of the results are discussed.

Keywords: chatbot; information disclosure; information disclosure nudge; emotional response; privacy; human-chatbot interaction

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1. Introduction

The use of artificial intelligence (AI) and chatbots have attracted the attention of researchers in the human-computer interaction (HCI) and marketing literature for the past decade. Chatbots are defined as "computer programs that can maintain a textual or vocal conversation with human users" [1] (p. 946). They are powered by AI and are commonly used as recommendation agents. Chatbots work by gathering information from users to deliver better-curated product and service recommendations [2]. With this recommendation function in mind, recent research has started to explore how to design chatbots for greater levels of information disclosure by users [3–6]. At the same time, privacy and data protection have become important issues in society, and the increasing use of chatbots by companies has raised concerns among users, scholars, and policymakers [7–10]. This dichotomy is embodied in the personalization-privacy paradox, which refers to the tension between a company's desire for obtaining customer information to tailor experiences and a consumer's need for privacy [11].

The risks to users stemming from their information sharing with chatbots have been shown to negatively impact user experience [12,13]. On the surface, sharing personal information online may seem acceptable to users. Giving up some privacy in exchange for service personalization can be interpreted as a well-considered, even logical, consumer decision [14,15]. However, even if users are aware of this trade-off, they may still end up making decisions to disclose information that they subsequently come to regret [14,16,17]. Users are not always aware of when and how data collection happens during their interactions with a company and how this data will subsequently be used [18]. This reality has also caught the attention of governments and regulators. Policies regulating chatbots and AI more broadly have emerged in many jurisdictions (e.g., Ethics guidelines for trustworthy AI proposed by the European Union in 2019; Montreal AI Institute introduced in 2018; California's bot law put in place in 2019).

Yet, the current ethical guidelines provided by governments fail to provide practical tactics that are proven to make users aware of—and potentially influence—their information disclosure behaviors [19]. Arguably, some privacy notices exist, providing users with information on "how and for which purpose their data will be collected, used and managed" [14] (p. 434). However, in reality, users tend to rarely read those notices [20]. Moreover, it has been shown that when a privacy policy is provided on a website, consumers may end up disclosing more personal information [20,21]. This is because consumers tend to place an excessive amount of trust in websites that display a privacy notice since they believe they will be better protected [22]. Additional challenges faced by the contemporary measures in place in effectively informing consumers include a large number of policies present online, each specific to the website they represent, and the often-difficult legal language being used [23].

Thus, there is a need for simple tools to make users aware of the information they are about to share, especially with chatbots. Such tools could, thus, enhance the ethical practices of companies while concurrently promoting informed decision-making among users, who may choose to reduce the breadth and depth of information they share online. Marketers have investigated the impact of tools such as nudges (i.e., displaying strings of information to consumers) to encourage certain behaviors (e.g., how to present information to users so they tend to accept more of chatbots' recommendations [24]). Past research has demonstrated that these nudging methods do have an impact on consumers' behaviors [24–26].

Information is commonly disclosed by users while surfing online and is characterized by being routine and directed by fast thinking [27]. As a result, attempts to direct or influence this behavior in chatbot interactions should focus on cues triggering automatic thinking (i.e., peripheral) rather than intentional (i.e., central) thinking [14,28]. Information disclosure is also known to be malleable. This means that certain aspects of the online environment can be manipulated to influence privacy behavior [14,29]. Therefore, there is room for interventions that raise awareness of the risks and allow for more cautious disclosure of information.

Persuasion Theories [30,31] may be considered when designing information disclosure nudges of various types, such as sensitivity signals and social proof nudges. Sensitivity signals are simple labels that describe the level of sensitivity (e.g., low or high) of the various questions being asked by a chatbot. Making users conscious of the sensitivity of the information they are about to share may influence their subsequent disclosure behaviors [31]. Social proof nudges are indications of how popular something is; in the context of information disclosure, a social proof nudge would suggest to what extent a chatbot question had been answered by other users. This validation of sorts may influence users into mimicking the same behavior as their fellows [30].

To the best of the authors' knowledge, nudges pertaining to information disclosure have been largely overlooked by extant privacy and chatbot research. Given the above-mentioned need for promoting users' informed decision-making about online information disclosures and the potential for nudges to achieve that outcome, this research intends to answer the following research question (RQ):

RQ 1. *How do different types of information disclosure nudges (here, sensitivity signal and social proof) and question sensitivity affect the level of users' behavioral information disclosure during chatbot interactions?*

To understand how nudging influence manifests in users-chatbot interactions, the role of a user's emotional response to information disclosure nudges and the consequent information disclosure behaviors is also explored. The Affect Infusion Model (AIM) explains ways in which people's judgments are influenced by their emotional responses as they process information and their resulting actions [32]. According to the AIM, users may process information disclosure nudges heuristically, i.e., they may base their choice to reveal specific information on their emotional state evoked by the available cues in the interaction context. Limited research on user emotional responses during chatbot exchanges exists, including studies on how generating positive versus negative emotional responses from users, leads to more or less conversational breakdowns, and exploring the role of empathy in providing supportive medical information through chatbots [33–35]. Nonetheless, emotional responses in the context of privacy notices and/or information disclosure behaviors have not been explored yet. Therefore, this research also aims to answer the following RQ:

RQ 2. *Does user emotional response mediate the effects of question sensitivity and information disclosure nudge type on their disclosure behavior?*

This research is important not only for advancing knowledge in user experience and informing regulatory policies, but also for the larger ethical discussions surrounding AI (e.g., the lack of regulatory frameworks, the rapid development of technology, the significant risks associated with online information disclosure, and the high return potential of AI) [36]. Chatbots powered by AI are also being studied, and their usage, as well as power, is being questioned, especially surrounding the data they capture and use [37]. Data ethics is a branch of ethics that seeks to evaluate ethical issues brought about by data practices [38]. Ethical questions happen throughout the data life cycle (i.e., collection, storage, processing, use, sharing, and archive) and every step represents a risk for the user [39]. In the case of chatbots, data collection is a particularly important issue as they are the frontline for many companies: they take part in the collection of large amounts of data when interacting with users [40].

In a $2 \times 3 \times 2$ experimental design, this study observes users' interactions with different chatbots. Two types of information disclosure nudges will be manipulated to answer the above research questions. This study adds to the existing body of knowledge on user experience with chatbots via two contributions. First, by showing that question sensitivity negatively impacts user disclosure, this study confirms this previously known link in the context of user-chatbot interactions. Second, this study evaluates the potential of two information disclosure nudges (i.e., sensitivity signal and social proof) in shaping users' online disclosures. Considering the growing importance attributed to chatbots and data collection risks online, the findings from this study are relevant for management and policymakers by offering a new perspective on information disclosure prevention. By introducing measures that make users conscious of their behaviors when it comes to sharing information online in day-to-day life, organizations can differentiate themselves by promoting the ethical use of AI systems and data collection online.

This article is structured as follows: a literature review presents the important themes of this work as well as the gaps in current research. Following those, the approach used to investigate the effects of these information disclosure nudges on user information disclosure behaviors is described in detail. The data analyses and results are presented next. Finally, a discussion of this study's findings along with the contributions of this study to theory and practice is presented.

2. Literature Review and Theoretical Foundation

2.1. Chatbots as Recommendation Agents and Users' Privacy Concerns

Recommender systems have been used by companies in a plethora of industries for a long time [41]. Recently, the same ability to recommend products and services has been given to chatbots, known as "recommendation agents", and employed by e-commerce organizations [42]. These systems powered by AI perform by using algorithms combining data collected from users and the company's databases with pattern matching, machine learning, and natural language to provide personalized recommendations to users [43].

Data is collected from multiple sources, including the direct messages exchanged between the chatbot and the user [43].

Most of the earlier research on recommender systems and chatbots focused exclusively on delivering the right recommendation to the user [44–46]. However, it was later found that these agents, because of the way they operate, increase privacy concerns, which in turn negatively impacts user experience. Cheng and Jiang [12] found that perceived privacy risk reduces the level of users' satisfaction with chatbots. Rese et al. [13] (p. 11) established that "the respondents generally had privacy concerns, which negatively affected the intended usage frequency of chatbots."

Privacy concerns refer to the "users' uncertainty about using chatbot services because of potential negative outcomes associated with the revealing of customers' information" [12] (p. 6)—such as phone numbers, names, or addresses—which can be exploited by companies and/or shared with unauthorized third parties [47].

Therefore, tension exists between the firm's business need for collecting and analysing consumer data in order to customize experiences on the one hand, and the users' desire for privacy on the other [48]. This phenomenon is known in the marketing literature as the *personalization-privacy trade-off* [48]. Chatbots used to personalize the experience embody this dichotomy: when customers use chatbots as recommender systems, they are placed in a trade-off situation between personalized product recommendations and privacy invasion [47].

Research shows that privacy concerns negatively impact users' information disclosure to chatbots [18]. Knowing this, research has studied strategies to decrease users' privacy concerns and in turn, increase users' disclosure to chatbots. Strategies studied include giving the chatbot anthropomorphic cues such as adapting the chatbot's messages to evoke emotion to build rapport with users [18] or giving the chatbot a human name and qualities to increase the sense of social presence [49]. However, these strategies are centered on the business need, where the goal is to gain more data from customers (e.g., [50]). The *status quo* is that information disclosure is unilateral from the user to the chatbot. Each time a user engages with a chatbot, the information asymmetry as well as the chatbot's power increases [51]. This represents a problem as "the party with less information, [the user], may not make fully informed choices or may have made different choices if they had the same information as the other party in the exchange" [51] (p. 928). However, the study of information disclosure from a user's perspective—so as to make users aware of and potentially decrease their disclosures to chatbots—has been overlooked in the literature.

2.2. Antecedents to Information Disclosure

The literature on information disclosure, not specific to chatbot use, has identified two antecedents to users' information disclosure: the level of sensitivity of the information asked [52,53] and the relevance of the information asked to the given context [54,55]. These variables "have been most frequently shown to have a significant impact" [56] (p. 225).

2.2.1. Question Sensitivity

Question sensitivity refers to the sensitivity of the information being requested. Multiple definitions exist to describe information sensitivity [57]. For this study, question sensitivity is defined as "material that is delicate and could be personal, political, economic, social, or cultural in nature. It can range from matters connected to national security, to personal emotions and feeling, to taboo topics which would not be shared with an outsider" [58] (p. 67). Question sensitivity is known to change through time and vary across cultures [58]. In general, it has been shown that people are more averse to disclosing more sensitive information [52,53,59].

Question sensitivity is relevant in user-chatbot interactions, as chatbots usually ask multiple questions to gain information from users, naturally ranging from more general to more sensitive in nature [60].

2.2.2. Question Relevance

Question relevance to the given context is defined as "the degree to which the data requested appear relevant or appear to have a bearing upon the purpose of the inquiry" [61] (p. 92). Question relevance has been shown to impact the way users disclose information. People are more likely to disclose information that is perceived as relevant in the context [54,55]. Chatbots are used in specific contexts (e.g., education [62], mental health services [60], e-commerce [50]). Thus, queries made by a chatbot need to be perceived as being related to the context of use, if the aim is to increase the likelihood of disclosure.

2.2.3. Information Disclosure

Customer information disclosure originates from the idea of *self-disclosure* in the psychology literature, which is defined as "any information about [oneself] which Person A communicates verbally to a Person B" [63] (p. 73). Information disclosure online can happen implicitly or explicitly [64]. On the one hand, data can be collected indirectly through the use of cookies, location data, and many other means. On the other hand, data can also be gathered directly by asking users for their information [65].

People's disclosures are known to be multidimensional [66] meaning disclosures can be broken down into distinct elements and analyzed in different ways. Some of these factors include the number of words used to answer or the use of emotional vocabulary in the response [17,67]. One of the simplest ways to assess disclosure is through the use of two simple axes: the *breadth* and the *depth* of the disclosure [68]. Breadth refers to the number of disclosure instances, while depth refers to the sensitivity of each disclosure. Joinson et al.'s [68] research found two proxy measures to evaluate these axes. Allowing users to leave a question unanswered permits measuring the breadth of disclosure and the "inclusion of items of varying sensitivity" measures the depth of disclosure [68] (p. 2168).

Disclosure in the context of chatbots has mostly been studied for social bots and mental health conversational agents [60,69,70]. On the contrary, user disclosure to chatbots used as recommendation agents in an e-commerce context has been under-investigated. To better understand how information disclosure happens in online communication exchanges, two phenomena are presented below.

2.2.4. Privacy Calculus

The privacy calculus originates from the Theory of Reasoned Action [71] and the Theory of Planned Behavior [72] and is defined as the risk-benefit dilemma users face when engaging in online transactions [73,74]. In general, in a transaction, incentives are offered by the company in exchange for a certain degree of privacy of the user [73,74]. Because humans are rational beings, this theory explains that users will always try to limit the risk required to maximize their benefit.

This phenomenon also applies to information disclosure in chatbot exchanges. Specifically, the sensitivity of the query increases the risk for the user to disclose, while the benefit is often the promise of a better experience. In other words, users trade information of varying sensitivity (e.g., habits, preferences, personal identification) in exchange for better products and service recommendations that are deemed tailored to their profile [75]. Thus, according to the privacy calculus, users will perceive the value of sensitive information as higher than more general information. When it comes to chatbot interactions, it could be argued that users will be inclined to gatekeep more information classified as high in terms of sensitivity compared to those classified as lower in sensitivity.

Taking the above into consideration, we propose a relationship between question sensitivity and information disclosure as follows:

H1. *Question sensitivity negatively influences users' information disclosure to chatbots.*

2.2.5. Online Privacy Paradox

Looking further into online information disclosure, there also exists a phenomenon called the online privacy paradox [76]. This phenomenon suggests that privacy concerns do not necessarily correlate with actual disclosure [77]. In fact, there is a paradox between users' willingness to disclose information versus what they actually disclose [78]; specifically, people tend to disclose more information than they say they do.

This creates a dilemma in research: whether to measure users' willingness to disclose information or their actual disclosures. To date, most research that has studied information disclosure in human-chatbot interactions focuses on users' willingness to disclose [79,80]. However, the online privacy paradox implies that these studies' results may be skewed, and users would in practice disclose more than they report. Moreover, this paradox challenges the assumption that people's information disclosure behaviors always come from a rational decision-making process [81]. This phenomenon shows the importance of creating tactics that make users aware of their disclosures online.

2.3. Information Disclosure Nudges (Sensitivity Signal and Social Proof) Effect on Information Disclosure

Persuasion can be defined, in its simplest form, as "human communication that is designed to influence others by modifying their beliefs, values, or attitudes" [82] (p. 7). In recent years, it has been shown that persuasion is not only specific to human-human conversations but can be applied in human exchanges with other entities, such as chatbots [83]. The Computer Are Social Actor (CASA) paradigm posits that humans mindlessly apply the same social heuristics used for human interactions to computers, because they call to mind similar social attributes as humans [84]. Thus, the persuasion literature could be leveraged to create tactics to influence users in their behaviors when it comes to disclosing information to chatbots.

2.3.1. Elaboration Likelihood Model

The Elaboration Likelihood Model (ELM) comes from the psychology literature and helps explain how humans process information cognitively and are persuaded when presented with different stimuli [28]. The main idea of this model is that people process information with two routes (or paths), the central and peripheral paths. The central route represents "the processes involved when elaboration likelihood is high", whereas the peripheral route is the "processes operative when elaboration likelihood is low" [28] (p. 674). When elaboration likelihood is high, issue-relevant thinking, such as careful consideration of the true benefits of the information presented, will predict the recipient's response to the stimuli [85]. When elaboration likelihood is low, factors other than reasoning come into play, and cues (e.g., credibility and attractiveness of the stimuli, quality of the message) tend to be the more important determinant of persuasion [85].

A common example to explain the ELM is the purchase of a car. Some consumers might base their choice based on the fuel efficiency of the car, its reliability, and price information given by their car dealership, while others might be convinced to opt for the sporty car that comes in a flashy red color and will impress their friends. In this case, the former is known to use the central, more rational, route to information processing, while the former uses the peripheral route by basing their choice on fewer informational and more emotional cues about the car.

In sum, ELM helps explain how people are persuaded. Persuasion occurs when a persuader is successful in influencing a person in a certain way. Based on ELM theory, we leverage cues in user-chatbot interactions to inform users that they are about to disclose certain types of information. These cues could consequently influence users' information sharing behaviors with the chatbot. The *Nudge Theory* [31] and Cialdini's [30] *Persuasion Theory* presented below provide the theoretical foundation to inform the design of chatbot design elements that we call *information disclosure nudges* for this research.

2.3.2. Nudge Theory and Sensitivity Signal

The Nudge Theory was first introduced by Thaler and Sunstein [31] which stated that people's behaviors can be influenced by small suggestions and positive reinforcements. Nudging is founded on the assumption that people's behaviors are not always rational due to cognitive limitations, and that said behavior is affected by the display of possibilities in a choice context [86–88]. Hence, nudging is used in the design of an environment within which a choice is made to make people lean a certain way versus another. However, nudging also respects freedom of choice [31,89]. Nudges have been used in the digital world, by changing certain user-interface design elements to guide users' behaviors [90–93].

Based on Nudge Theory, there are different ways that users could be notified about the information they share online, specifically when they interact with chatbots. An example of a nudge can be as simple as increasing the salience of the desired option. For example, labeling menu items with their respective calorie count or nutritional facts have been used in the food industry for decades as a strategy to help people make informed and healthy choices [94]. Being informed of the calories, for instance, in each menu item has been shown to improve transparency to customers about what they put in their bodies and, in some cases, change order behavior [95]. Another example is the disclosure of ads on social media and websites. The United States Federal Trade Commission promoted back in 2013 the use of labels and visual cues to help consumers recognize and distinguish ads from the regular content on different interfaces [96].

The above reasoning could also be applied to information disclosure to chatbots. Based on the literature, it is known that information sensitivity is a determining factor in disclosure behaviors. Thus, explicitly signaling the sensitivity level of the question being asked by the chatbot could have an effect on user disclosure. Hence, we posit that the relationship between question sensitivity and users' information disclosure is moderated by the question sensitivity signal, such that:

H2a. *When a low sensitivity signal is present (vs. absent) for less sensitive questions, disclosure increases.*

H2b. *When a high sensitivity signal is present (vs. absent) for more sensitive questions, disclosure decreases.*

2.3.3. Cialdini's Persuasion Tactics

Another common nudge is the social proof originating from Cialdini's [30] seven persuasion tactics. According to Cialdini, seven tactics signal the use of a peripheral message (i.e., authority, commitment, contrast, liking, reciprocity, scarcity, and social proof). These have found wide use in the application of nudge theory [29,97–99]. Social proof is one of the seven tactics and is defined as "signals of popularity and demand" [98]. Social proof is a type of social nudge, i.e., a nudge based on social influences. "Social influence refers to the way individuals change behavior in direct response to unwritten social laws" [98]. According to Mirsch et al. [96] social influences are one of the most powerful psychological mechanisms that can be utilized. Why and how it works comes from the desire to accurately interpret reality, behave correctly in society, and gain social recognition from others [100]. A common use of social proof is by stating how others behaved in the same position. In this case, social proof would predict that people, when presented with what their peers did in a similar situation, will match their behavior. Based on the literature, social proof would influence users in the following way: when social proof is low, the rational choice in the user's mind will be not to share the information being asked to match their peers' behaviors, independently from the question's sensitivity. On the other hand, when social proof is high, no matter the sensitivity level, users will be influenced to match their peers' behaviors. Thus, we posit that:

H3. *Social proof moderates the relationship between question sensitivity and users' information disclosure such that greater social proof leads to more disclosure and less social proof leads to less disclosure.*

2.4. Mediating Effect of Emotional Response

Emotions are an important component of both human-human communication and human-machine interaction [101,102]. Any interface that disregards a user's emotional state or fails to display the proper emotion risks being viewed as "cold, socially inept, untrustworthy, and incompetent" [102] (p. 14). Taken from the psychology literature, the Affect Infusion Model (AIM) explains that people use their emotional state as data when making a judgment [32]. In other words, it explores how emotions are infused into thoughts as people process information, which results in response behaviors during interactions with others. An emotion is defined as a brief but powerful feeling resulting from a clear cause and cognitive content [32]. For example, "if a situation makes you feel scared (an intense feeling that has clear cause and cognitive content), then you interpret the situation as being dangerous (short lived until out of danger)" [103] (p. 19). The emotional response is described in a two-dimensional space that is spanned by the two dimensions, "valence" and "arousal", which are known to be distinct from one another [104]. Arousal assesses the intensity of an emotional state, whereas emotional valence specifies whether an emotion is positive or negative.

AIM argues that the extent to which emotional response dictates judgment depends on the individual's motivation level going into the judgment. When motivation is low or judgments are made fast, this model predicts that mood will greatly affect judgment. This type of processing is known as Heuristic processing or Affect-as-information [105,106]. Referring to the ELM proposed by Petty and Cacioppo [28] and discussed above, the heuristic processing is comparable to the peripheral route to processing information [32]. This processing happens because people often want to achieve judgment with the minimum possible effort, which could include considering only a small portion of the available data and relying on whatever shortcuts or simplifications they can find in a given situation [107]. For example, when asked to form an opinion about a suggested product, individuals can base their judgment on the simple question "How do I feel about it?" rather than recalling the features of the target [106]. Thus, in this case, affect—the emotions felt in the moment—becomes information and impacts judgment.

This research uses peripheral cues to influence users' information disclosure behaviors. Based on the AIM, these cues would be processed heuristically by users. Specifically, in the face of these cues, users will be less inclined to judge extensively whether to answer the questions being asked by the chatbots. In other words, users would simply rely on their emotional state in response to the available cues in the interaction environment—such as the information disclosure nudges presented in this research—to base their decision on whether to disclose information or not.

Although research on users' emotional response in chatbot interactions has been conducted, few employ the AIM to ground their work. Moreover, the contexts that have been studied do not include question sensitivity and information disclosure behaviors in an e-commerce setting. For example, Pérez-Marín and Pascual-Nieto [108] underlined that the mood of the chatbot itself may have an impact on the users' inclination to continue the interaction in a context where chatbots are used as pedagogical agents to children in primary school. On the other hand, Lee et al. [60] discovered that when a chatbot providing support in a mental health context uses language that conveys emotional states, it draws users' cognitive attention to the social component of their interaction partner, increasing the feeling of co-presence. Similarly, Liu and Sundar [33] studied the role of empathy in chatbots' ability to provide comforting medical information. Finally, in the context of customer service, Xu et al. [109] suggest that more than 40% of user queries to chatbots on social media are emotional rather than informational, meaning users communicate their emotional state rather than a request or inquiry. Similarly, we can expect that in the case of interactions with chatbots asking for user information in an e-commerce context, emotional response also plays an important role. Indeed, even if users are not rationally able to appraise the risk involved in a situation, they can still experience subconscious activation of their nervous system—in other words, emotional response. The AIM predicts that this activation would in turn influence their behaviors. First, a high level of emotional response could occur as a physiological response to questions of varying levels of sensitivity. It is known that when facing a threat, humans' nervous system automatically activates [110]. As the privacy calculus presented above explains, being asked sensitive questions represents a risk for users [73]. Thus, an emotional response could be evoked in chatbot interactions when sensitive questions are asked. Emotional response is an automatic physiological reaction to events [110] and may act as a predictor to users' information disclosure. This is crucial in motivating certain natural behaviors, such as the fight-or-flight response, which occurs as a result of an event deemed threatening [110,111]. Therefore, higher activation of the nervous system could result in users feeling averse (flight) to what they perceive as a threat, in this case, disclosing their information to a chatbot. To assess the role of emotional response in the relation between question sensitivity and information disclosure, we posit that emotional response (measured here via arousal) mediates the relationship between question sensitivity and information disclosure such as:

H4a. *Question sensitivity positively influences emotional response (arousal).*

H4b. *Emotional response (arousal) negatively influences disclosure.*

Second, emotional response could also explain how the information disclosure nudges evoke a reaction in users. Peripheral cues are said to serve an important role in consumer behaviors [112]. The sensitivity signal and social proof nudges used in this study are presented to give users cues on the level of sensitivity of each question and whether other users answer them. They could predict the activation of the nervous system of users as they represent a clear cause, with cognitive content, that could trigger an emotional response from users. For the sensitivity signal nudge, since it informs users on the categorization of the question asked, the resulting activation would be proportional to the level of sensitivity of the question. For the social proof nudge, the reaction would depend on the behavior of others, independently of the question sensitivity. Specifically, knowing that a minority of people answered a question would be perceived as a higher risk and the opposite would be observed for when a majority of people answered a question, regardless of the question's sensitivity. To assess the extent to which the presence of information disclosure nudges evokes emotional response (measured with arousal) among users, we posit that the relationship between question sensitivity signal and emotional response is moderated by sensitivity signal such that:

H5a. *When a low sensitivity signal is present (vs. absent) for less sensitive questions, emotional response (arousal) decreases.H5b: When a high sensitivity signal is present (vs. absent) for more sensitive questions, emotional response (arousal) increases.*

We also posit that:

H6. *Social proof moderates the relationship between question sensitivity and emotional response such as greater social proof leads to lower emotional response (arousal) and less social proof leads to higher emotional response (arousal).*

To conclude, Figure 1 depicts the research model as a summary of the relationships proposed above.

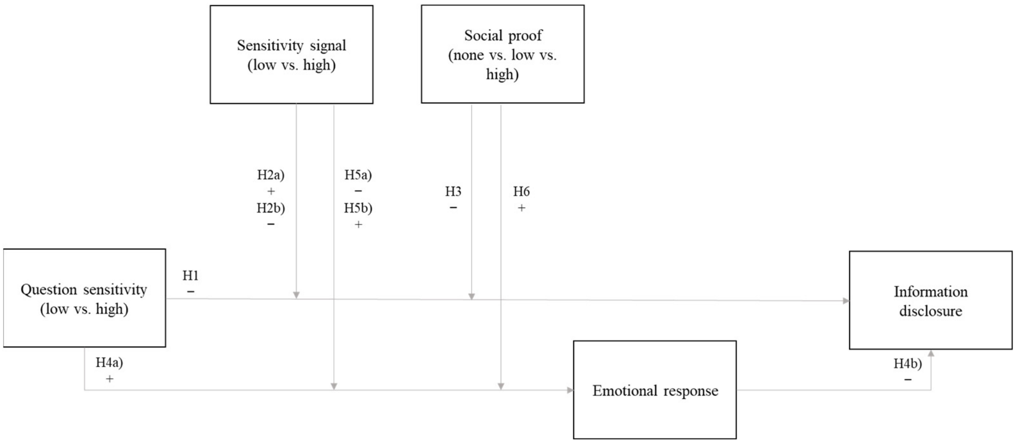

Figure 1. Research Model.

3. Methods

To test the user behaviors when interacting with chatbots and the potential effect of information disclosure nudges, an experiment was conducted at the laboratory of the authors. The study measured the impact of question sensitivity, information disclosure nudges, and emotion on user behaviors. This study was approved by the Research Ethics Board (REB) from HEC Montréal (Certificate 2022-4721).

3.1. Experimental Design

To test the hypotheses, a 2 (question sensitivity: low vs. high) × 2 (sensitivity signal: absence vs. presence) × 3 (social proof: none vs. low vs. high) within-subjects design was developed. Here, the social proof level "none" was used, although not explicitly stated in the hypotheses to be able to measure the effect of the sensitivity signal on its own. To test all the possible combinations of the nudges, six tasks were developed, each consisting of asking the participants to chat with a chatbot to create a user profile on a fictional website in order to obtain better product and service recommendations in the future. To create the user profiles, the participants had to answer questions varying in level of sensitivity: low and high sensitivity questions. Each website represented a different context in which a user could be brought to create a user profile to make sure the questions would vary throughout the experiment. The contexts were randomly assigned to a specific nudges combination and included: a career website, an insurance company website, a dating website, a travel agency website, a gym's website, and an online grocery website.

Figure 2 depicts the experimental design, including the tasks, the nudges combination each task represents, their randomly assigned context, and the questions' sensitivity levels.

		Social proof		
		None	Low	High
Sensitivity signal	Absence	Task 1 (Career) *Low sensitivity q's* *High sensitivity q's*	Task 2 (Insurance) *Low sensitivity q's* *High sensitivity q's*	Task 3 (Groceries) *Low sensitivity q's* *High sensitivity q's*
	Presence	Task 4 (Gym) *Low sensitivity q's* *High sensitivity q's*	Task 5 (Travel) *Low sensitivity q's* *High sensitivity q's*	Task 6 (Dating) *Low sensitivity q's* *High sensitivity q's*

Figure 2. Experimental Design.

3.2. Stimuli Development

3.2.1. Chatbot Interface

To create the experimental stimuli, a chatbot prototype was developed using Axure RP software (San Diego, CA, USA). Through this software, individual web pages for each question in each context were created. The webpages were then randomized in the eye-tracking software (Tobii Pro Lab v. 181; Danderyd, Stockholm, Sweden) used in the lab experiment to generate eye-tracking and electrodermal activity (EDA) data per question automatically. The prototype presented the website's banner on the top left corner of the screen to remind the participants of the context of the given task throughout the task. The chatbot was positioned in the middle of the screen. The chatbot environment included a conversation section, where the chatbot asked questions, and an answer section, where participants could write in a textbox. The nudges messages were placed on either side of the chatbot prototype. This specific placement was chosen to ensure readability for the eye tracker by distinguishing between the different areas of interest (i.e., the chatbot prototype vs. the nudges) through a physical space between these elements.

3.2.2. Question Sensitivity (Pre-Test)

To generate a pool of low and high-sensitivity questions to be used in the lab experiment and control for the relevance of each question to their assigned context, a within-subject online questionnaire was administered on Qualtrics (Provo, UT, USA) and distributed through Amazon Mechanical Turk (Mturk). To build the questionnaire, a pool of 210 questions centered around six contexts (35 questions per context) was generated based on prior research investigating sensitive topics [49,113] (e.g., in the travel context: "Are you fully vaccinated against Covid19? Refer to Appendix A for the full list of questions").

To be eligible to complete the questionnaire, participants had to be located in North America and have a Mturk HIT approval rate of at least 90% (i.e., the proportion of prior completed tasks performed by the user that were approved by Mturk requesters) to ensure the quality of responses. Participants were given 1 USD compensation for the time they took to participate in the study. In total, 400 participants answered the questionnaire. After a meticulous review of the questionnaire data and exclusion of participants that failed one of the attention checks, the final sample for the first phase of this research was 316. The sample included 66% (207 participants) men and 34% (109) women ranging from 18 to over 66 years of age; 22% of participants (70) were from Canada and 78% were from the United States (246).

The questionnaire consisted of presenting participants with one of the contexts developed for the lab experiment. Then, participants were asked to rate a group of questions within the given context on two dimensions: the question's sensitivity and relevance to the given context (see Table 1). Each participant was randomly assigned to one context and rated the sensitivity and relevance of all questions (35) for that given context. Each context got between 49 and 57 participants' responses. At the end of the rating of the 35 questions, participants had to answer a few demographic questions.

Table 1. Pre-test Variables Operationalization.

Variable	Item	Scale	Source
Question sensitivity	Rank the sensitivity of each question the chatbot asks you	7-point Likert scale from "Extremely general" to "extremely sensitive"	Developed by researchers
Question relevance	Rank the relevance of each question to the context	7-point Likert scale from "Extremely irrelevant" to "extremely relevant"	Developed by researchers

Given that sensitivity can vary, as previously mentioned, in time and through cultures, the sensitivity item was chosen as a pre-test for the lab experiment to ensure that the questions to be asked were perceived by users as low vs. high in sensitivity specifically in the North American context where this study took place. The relevance item was also added to control for relevance. The items were created using 7-point Likert scales. For the question sensitivity item, participants had to rate from 1 (extremely general) to 7 (extremely sensitive) the sensitivity of each question given the context presented. Participants were provided with the definition of information sensitivity used in this research [58]. For the question's relevance item, participants had to rate from 1 (extremely irrelevant) to 7 (extremely relevant) the relevance of each question to the context they were presented with.

To narrow down the question pool based on the survey's results, the mean relevance and sensitivity of each question were calculated. Then, all the questions averaging less than four out of seven (4/7) on the relevance axis were eliminated. After, the remaining questions were separated into groups based on their sensitivity: one group consisted of the questions with the lowest average sensitivity and the other of the questions with the highest average sensitivity. To make sure that each context had the same number of questions in each group, the number of questions per group was reduced to 8. T-tests were performed with SPSS (Armonk, NY, USA) to confirm that the difference between low and high-sensitivity question groups was statistically different. The results of these tests revealed that the low and high-sensitivity questions were statistically different for each context. The statistics relating to the question sensitivity comparisons per context are summarized in the following Table 2.

Table 2. Comparison of Low and High Sensitivity Questions Per Context.

		Low Sensitivity Question			High Sensitivity Questions			
Context	**Question Sensitivity Comparison**	**N**	**Mean**	**Std.**	**N**	**Mean**	**Std.**	***p*-Value**
Career	Low vs. High	8	2.82	0.44	8	4.76	0.46	<0.0001
Dating	Low vs. High	8	2.84	0.62	8	4.94	0.67	<0.0001
Grocery	Low vs. High	8	2.78	0.21	8	4.2	0.31	<0.0001
Gym	Low vs. High	8	2.88	0.25	8	4.51	0.33	<0.0001
Insurance	Low vs. High	8	3.36	0.41	8	4.74	0.26	<0.0001
Travel	Low vs. High	8	2.91	0.13	8	4.58	0.57	<0.0001

These tests confirmed that the low-sensitivity questions were statistically different from the high-sensitivity questions in each context. Moreover, two one-way ANOVA were also performed with SPSS to verify that all the low-sensitivity question groups from the six different contexts were not statistically different—in other words, they were equivalent—and the same was done for all the high sensitivity questions groups. The summary of these tests is presented in the following Tables 3 and 4.

Table 3. Comparison of Contexts for Low Sensitivity Questions.

	Degrees of Freedom	Sum of Squares	Mean Square		
Source	**DF**	**SS**	**MS**	**F-Stat**	***p*-Value**
Between Groups	5	1.8546	0.3709	2.5645	0.041
Within Groups	42	6.0746	0.1446		
Total	47	7.9291			

Table 4. Comparison of Contexts for High Sensitivity Questions.

	Degrees of Freedom	Sum of Squares	Mean Square		
Source	**DF**	**SS**	**MS**	**F-Stat**	***p*-Value**
Between Groups	5	2.6537	0.5307	2.5544	0.042
Within Groups	42	8.7265	0.2078		
Total	47	11.3802			

These results show that the p-value equals 0.041. Thus, the difference between the low-sensitivity groups is not statistically significant.

These results show that the p-value equals 0.042. Thus, the difference between the high-sensitivity groups is not statistically significant. In sum, these tests confirmed that the low and high-sensitivity questions in each context were statistically equivalent.

In the end, the pre-tested questions were used to manipulate the question sensitivity in the experiment. The questions classified as general represented low sensitivity manipulation, and the questions classified as sensitive, the high sensitivity manipulation. Meanwhile, relevance was a control variable in this study.

3.2.3. Sensitivity Signal

In this research, the sensitivity signal took the form of labels. The sensitivity signal was represented as a sticker on the left side of the chatbot, if present, and signaled to the user the question's level of sensitivity: general (low sensitivity) or sensitive (high sensitivity).

3.2.4. Social Proof

This research also used social proof in an attempt to influence users' disclosure behaviors. The social proof nudge was represented as a sticker on the right side of the chatbot, if present, and presented to the users whether the minority (low social proof) or majority (high social proof) of other participants answered the question being asked by the chatbot.

Figure 3 shows an example of the chatbot stimuli, where a high-sensitivity question in the travel context is asked with both a sensitivity signal and a low-level social proof nudge being present.

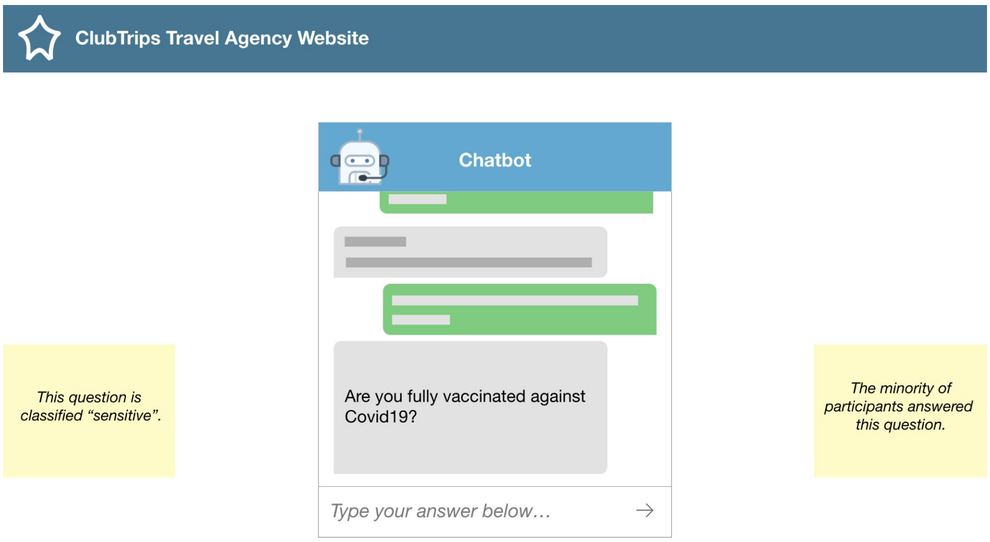

Figure 3. Example of a High Sensitivity Question in the Travel Context with Sensitivity Signal (Present; High) and Social Proof Nudge (Low).

3.3. Lab Experiment

3.3.1. Participants

Since the questions were pre-tested on a North American sample, a North American audience was also selected for the lab experiment. In total, 26 people located in Canada participated in the study. After cleaning the data and removing participation with issues in the post-experiment data processing, the final sample for the second phase of this research was 19. The experiment lasted an hour and participants received 25 USD compensation for their time, a thank you for their participation in the study, and to reimburse any transport cost they might have incurred in traveling to and from the lab where the experiment took place. Table 5 presents the participants' demographics.

Table 5. Participant Demographics (N = 19).

Variable/ Response			Response Frequency	Response Count
Gender	Man		47%	[9]
	Woman		53%	[10]
	Non-binary/agender/other		0%	[0]
Birth Country	Canada		53%	[10]
	France		5%	[1]
	Japan		5%	[1]
	Iran		5%	[1]
	Mexico		5%	[1]
	Morocco		11%	[2]
	Turkey		5%	[1]
	South Korea		5%	[1]
	United-States		5%	[1]
Occupation	Full-time worker		11%	[2]
	Student		84%	[16]
	Both		5%	[1]
Age	Mean	26.16		
	Median	26		
	Mode	23 and 30		
	Std. Deviation	3.06		
	Minimum	22		
	Maximum	31		

3.3.2. Procedure

The experiment went as follows: Once participants arrived at the lab, they were welcomed by a research assistant (RA) and directed towards the experiment room where a computer was set up. They were then asked to read and sign consent forms. The RA then assisted them in the placement of the physiological equipment including placing the sensors of the electrodermal device on the palm of their non-dominant hand and calibrating an eye tracker device to track their eye movements on the computer screen. Then, they performed the six randomized tasks described in the experimental design section above by chatting with six chatbots and asking questions of varying levels of sensitivity presented in a randomized order. In each task, participants were put in a context where they had to create a user profile with the help of a chatbot for a fictional website (i.e., a career website, an insurance company website, a dating website, a travel agency website, a gym's website, and an online grocery website). To create a trade-off between risk and benefit, they were informed that the chatbot would ask them questions to come to know them to provide better product and service recommendations in the future. Participants were also advised that they could decide not to answer questions. If they did not wish to answer a question, they had to put a "-" in the text box of the chatbot prototype.

While the participant chatted with chatbots, the RA noted the unanswered questions. At the end of the experiment, the RA went over all the unanswered questions with the participant and asked the reason why they did not answer them. If the participant answered all questions, they would be asked why they chose to answer them all. These questions were added to complement the behavioral and physiological data captured during the experiment with the participants' impressions and thoughts regarding the questions.

After the short interview, the RA unplugged the electrodermal activity device and the participant filled out the compensation form. They were then thanked for their time and escorted out. Overall, the experiment lasted about an hour.

3.3.3. Measures

We captured the participants' eye movements on the computer screen, as well as the electrodermal activity of their hands to understand what happens on a physiological level when users engage with chatbots. These technologies were chosen to help establish the plausible causal link between users' physical reactions and information disclosure behaviors to chatbots.

First, we measured the participants' visual attention to the information disclosure nudges. This variable was chosen as a manipulation check to confirm whether participants looked at the nudges and how long they did so. To do so, we used an eye tracker system to capture the eye movements of the participants on the computer screen. The technology used was Tobii Pro Lab (Danderyd, Stockholm, Sweden), an eye-tracking software, and the measure used was the duration of fixations on each area of interest (i.e., the chatbot prototype and the two nudges).

Second, we measured user emotional response through an electrodermal activity device to calculate the fluctuations in the dermal activity, or arousal, of participants while chatting with the chatbots and answering—or not—low and high sensitivity questions (Biopac inc., Goleta, CA, USA).

To measure the information disclosure, we looked at the response rate to the questions asked by the chatbot using the notes from the RA. Since most research focuses on willingness to disclose [79,80] and on minimizing the risk of results falling into the online privacy paradox, the present research differentiates itself by looking at the actual disclosure of users when information disclosure nudges are present versus absent. During the experiment, the RA noted the questions that were not answered by each participant. The data was then computed into an excel spreadsheet including the list of all participants, the question, the sensitivity level of each question, and the response rate. The response rate was presented as a binary variable: 0 did not answer the question; 1 answered the question. Table 6 presents the variables' operationalization.

Table 6. Variables Operationalization.

Construct	Definition	Measure	Source
Visual attention	Duration (in seconds) of fixations on each area of interest (i.e., sensitivity signal and social proof)	Seconds	Eye tracker Tobii Pro Lab (Danderyd, Stockholm, Sweden)
Emotional response	Level of arousal	Phasic EDA	Biopac inc. (Goleta, CA, USA)
Information disclosure	Response rate	Answer vs. no answer to the question	Developed by researchers

4. Results

4.1. Results

4.1.1. Manipulation Check

We conducted a manipulation check to confirm that users looked at the information disclosure nudges when presented to them. We extracted the data from the eye tracker used in the experiment and calculated the average duration of fixations on the two different nudges per question. The results show that, on average, people look at the sensitivity signal nudge 3.12 s (std. dev = 7.41) when present compared to 0.02 s (std. dev = 0.04) when absent. For the social proof nudge, people looked on average 2.03 s (std. dev = 6.87) when present compared to 0.00 s (std. dev = 0.00) when absent. The results for both nudges are statistically significant (p-values < 0.0001), thus, confirming that the nudges were successful in capturing the attention of participants when present.

4.1.2. Descriptive Statistics

Before testing our hypotheses, we extracted the response rates compiled during the study. Overall, we can observe different information disclosure rates depending on the combination of nudges present in the scenario and the question's sensitivity level. When no nudge was present, participants answered more (96.7%) low-sensitivity questions than high-sensitivity questions (94.0%). When only the sensitivity signal was present, the response rate to low-sensitivity questions was higher (100%) than to high-sensitivity questions (95.9%). When low social proof was present, participants answered more low-sensitivity questions (95.6%) than high-sensitivity questions (84.4%). When high social proof was present, participants answered more low-sensitivity questions (100%) compared to high-sensitivity questions (93.6%). When both the sensitivity signal and low social proof were present, the response rate was higher for low-sensitivity questions (98.8%) than for high-sensitivity questions (93.5%). When both the sensitivity signal and high social proof were present, participants answered more low-sensitivity questions (99.2%) than high-sensitivity questions (84.2%). Table 7 summarizes these results.

Table 7. Response Rate Per Nudge Combination and Question Sensitivity.

Social Proof/ Sensitivity Signal	No Social Proof	Low Social Proof	High Social Proof
No Sensitivity Signal	Low sensitivity q's 96.7 ± 17.9	Low sensitivity q's 95.6 ± 20.6	Low sensitivity q's 100.0 ± 00.0
	High sensitivity q's 94.0 ± 22.6	High sensitivity q's 84.4 ± 36.3	High sensitivity q's 93.6 ± 24.7
With Sensitivity Signal	Low sensitivity q's 100.0 ± 00.0	Low sensitivity q's 98.8 ± 11.0	Low sensitivity q's 99.2 ± 8.7
	High sensitivity q's 95.9 ± 20.0	High sensitivity q's 93.5 ± 24.7	High sensitivity q's 84.2 ± 36.4

Finally, we extracted the level of phasic arousal per question, measured in microsiemens (µS), compiled during the study. The minimum phasic arousal for one question was −0.27 µS and the maximum 12.60 µS. Overall, we can observe different arousal rates depending on the combination of nudges present in the context and question sensitivity. When no nudge was present, arousal was lower for low-sensitivity questions (9.9 µS) than for high-sensitivity questions (10.4 µS). When only the sensitivity signal was present, arousal was higher in low-sensitivity questions (10.6 µS) compared to high-sensitivity questions (10.3 µS). When low social proof was present, arousal was higher for low-sensitivity questions (9.3 µS) than for high-sensitivity questions (9.1 µS). When high social proof was present, arousal was higher in low-sensitivity questions (10.5 µS) than in high sensitivity questions (10.1 µS). When both the sensitivity signal and low social proof were present, arousal was the same for the low-sensitivity questions (9.0 µS) and high-sensitivity questions (9.0 µS). When both the sensitivity signal and high social proof were present, arousal was lower for low-sensitivity questions (8.9 µS) compared to high-sensitivity questions (10.2 µS). Table 8 summarizes these results.

Table 8. Arousal Per Nudge Combination and Question Sensitivity.

Social Proof/ Sensitivity Signal	No Social Proof	Low Social Proof	High Social Proof
No Sensitivity Signal	Low sensitivity q's 9.932 ± 4.936	Low sensitivity q's 9.352 ± 4.642	Low sensitivity q's 10.499 ± 5.288
	High sensitivity q's 10.372 ± 5.334	High sensitivity q's 9.118 ± 4.849	High sensitivity q's 10.101 ± 4.403
With Sensitivity Signal	Low sensitivity q's 10.633 ± 6.003	Low sensitivity q's 8.970 ± 4.935	Low sensitivity q's 8.871 ± 5.096
	High sensitivity q's 10.269 ± 5.177	High sensitivity q's 8.972 ± 5.043	High sensitivity q's 10.232 ± 5.147

4.2. Hypotheses Testing

For the testing of hypotheses H1 to H7, we conducted two types of analyses because some relationships tested included a dependent variable that is discrete in nature (information disclosure (response rate): count of questions answered) and others tested for a continuous dependent variable (emotional response (arousal): continuous phasic EDA). We used logistic regressions with a random intercept for models with information disclosure (response rate) as the dependent variable (H1 to H3, and H4b). We used linear regressions with random intercept for models with emotional response (arousal) as the dependent variable (H4a, H5, H6).

4.2.1. Effect of Question Sensitivity on Information Disclosure (H1)

To test whether question sensitivity negatively influences users' information disclosure to chatbots (H1), we first extracted the response rate per question sensitivity. The average response rate for low-sensitivity questions was 98.4% (±13.5), while the response rate for high-sensitivity questions was 91.0% (±28.6). The results of the logistic regression showed that a question is less likely to be answered if it is highly sensitive compared to when it is low in sensitivity (estimate = −2.20, *p*-value < 0.0001). Thus, H1 is supported.

4.2.2. Effect of Information Disclosure Nudges on Information Disclosure (H2 and H3)

To test whether the information disclosure differed in the presence of nudges (H2a, H2b, and H3), we looked at the effect of the nudges on the response rate per question sensitivity. When hypothesized that when a low sensitivity signal is present (vs. absent) for less sensitive questions, disclosure increases (H2a) and that when a high sensitivity signal is present (vs. absent) for more sensitive questions, disclosure decreases (H2b). We also hypothesized that social proof moderates the relationship between question sensitivity and users' information disclosure, such as greater social proof, leads to more disclosure and less social proof leads to less disclosure (H3). Table 9 presents a summary of the results.

Table 9. Logistic Regressions: Effect of Nudges on Response Rate Per Question Sensitivity.

Nudge Comparison	Question Sensitivity	Estimate	StdErr	DF	t-Value	One-Tail Probt	Hypothesis
Sensitivity signal: Present vs. Absent	Low	1.47	0.80	1774	1.84	0.0334	H2a
	High	−1.03	0.85	1774	−1.21	0.1142	H2b
Social proof: Low vs. High	Low	−1.29	1.15	1772	−1.13	0.1301	H3
	High	−1.32	1.5	1770	−1.14	0.1269	H3
Social proof: Low vs. None	Low	−0.75	0.73	1772	−1.03	0.1519	-
	High	−0.38	0.82	1772	−0.47	0.6418	-
Social proof: High vs. None	Low	1.14	1.17	1772	0.98	0.1637	-
	High	−1.67	1.23	1772	−1.36	0.3248	-

The above results show that the response rate to low-sensitivity questions increases (estimate = 1.47, *p*-value = 0.0334) when the low-sensitivity signal is present. Thus, H2a is supported.

The results show that, for high-sensitivity questions, the response rate decreases (estimate = −1.03) when the high-sensitivity signal is present compared to when absent, however, this result is not statistically significant (*p*-value = 0.1142). H2b is not supported.

For the social proof nudge, the results go in the same direction as the hypothesis, where disclosure decreases with social proof is low compared to when social proof is high for both question sensitivity levels (estimates = −1.29 and −1.32) but these results are not statistically significant (*p*-values = 0.1301 and 0.1269). Thus, H3 is not supported.

The comparison between the two social proof levels when present vs. when absent (no social proof) was also tested, but found not to be significant. Moreover, the interaction between the effect of the two nudges on disclosure was also tested, but also found to be not significant.

4.2.3. Effect of Emotional Response (H4 to H6)

We hypothesized that emotional response would mediate the relationship between question type and information disclosure such as question sensitivity positively influencing emotional response (H4a) and emotional response negatively influencing disclosure (H4b).

The results of the linear regression show that emotional response tends to decrease when high-sensitivity questions are asked compared to low-sensitivity questions (estimate = −0.10), but this result is not statistically significant (p-value = 0.3226). Thus, H4a is not supported.

The result of the logistic regression on the effect of emotional response on information disclosure (estimate = 0.01) is not statistically significant (p-value = 0.1948). Therefore, H4b is not supported.

We then tested the effect of the information disclosure nudges on emotional response. We hypothesized that when a low sensitivity signal is present (vs. absent) for less sensitive questions, the emotional response decreases (H5a) and that when a high sensitivity signal is present (vs. absent) for more sensitive questions, the emotional response increases (H5b). Moreover, we hypothesized that social proof moderates the relationship between question sensitivity and emotional response, such that greater social proof leads to lower emotional response and less social proof leads to higher emotional response (H6). Table 10 summarizes these results.

Table 10. Linear Regressions: Effect of Information Disclosure Nudges on Emotional Response.

Nudge Comparison	Question Sensitivity	Estimate	StdErr	DF	t-Value	One-Tail Probt	Hypothesis
Sensitivity signal: Present vs. Absent	Low	−0.13	0.15	1728	−0.86	0.1948	H5a
	High	−0.03	0.21	1728	−0.13	0.0511	H5b
Social proof: Low vs. High	Low	−0.12	0.26	1726	0.44	0.1717	H6
	High	−0.11	0.26	1724	0.43	0.1651	H6
Social proof: Low vs. None	Low	−0.59	0.18	1726	−3.28	0.0006	-
	High	−0.20	0.25	1726	−0.77	0.2196	-
Social proof: High vs. None	Low	0.03	0.18	1726	0.18	0.4281	-
	High	−0.08	0.25	1726	−0.31	0.1231	-

The above results show that emotional response to low-sensitivity questions decreases (estimate = −0.13) when the low-sensitivity signal is present compared to when absent, however, this result is not statistically significant (p-value = 0.1948). Thus, H5a is not supported.

The results show that, for high-sensitivity questions, the emotional response decreases (estimate = −0.03) when high sensitivity signal is present compared to when absent. This result is marginally significant with a p-value of 0.0511. Since the results are contrary to the hypothesis, H5b is not supported.

For the social proof nudge, the results show that emotional response decreases when the social proof is low compared to when the social proof is high for both question sensitivity levels (estimates = −0.12 and −0.11). These results are not statistically significant (p-values = 0.1717 and 0.1651). Thus, H6 is not supported.

The comparison between the two social proof levels when present vs. when absent (no social proof) was also tested. The only significant result is the decrease in the emotional response (estimate = −0.59) to low-sensitivity questions when the low social proof is present compared to when it is absent (p-value = 0.0006). The other comparisons' results were not significant. The interaction between the effect of the two nudges on emotional response was also tested, but also found to be not significant.

The validated research model is shown Figure 4.

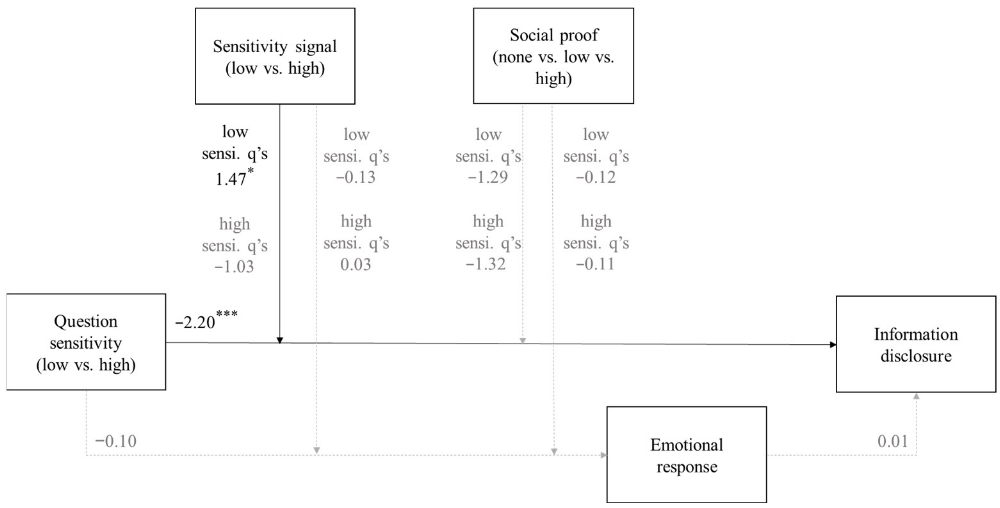

Figure 4. Validated Research Model. * significant at 0.05 level; *** = significant at 0.001 level.

5. Discussion

5.1. Main Findings

To summarize the findings of this study, the results suggest that question sensitivity has an impact on disclosure in the context of interactions with chatbots. Concerning the effect of the sensitivity signal, the results show that for less sensitive questions, a low-sensitivity nudge increases disclosure. Results also suggest that for high-sensitivity questions, a high-sensitivity nudge seems to decrease emotional response. On the other hand, the social proof nudge does not seem to affect users' disclosure behaviors, nor their emotional responses. Finally, it was suggested that emotional response does not seem to be a mechanism explaining how user disclosure operates in interactions with chatbots.

5.2. Theoretical Contributions

From a theoretical standpoint, this research makes three main contributions. First, this research complements the literature on user disclosure by confirming that question sensitivity has an impact on disclosure in the context of interactions with chatbots. This result is consistent with previous research on question sensitivity and disclosure (not specific to chatbot interactions) [52,53,59]. Indeed, research on antecedents to disclosure had previously shown that sensitivity played a role in disclosure. In fact, Mothersbaugh [59] suggested that the sensitivity of information is an antecedent to disclosure in an online service context, while Lee et al. [52] reported the same results in an e-commerce setting. However, sensitivity of information had not been explored in a chatbot context [52,53,59]. The present study suggests that this relationship does apply to interactions with chatbots. This result strengthens our understanding of the differences between human-human and human-AI interactions.

Second, comparing the two types of nudges tested, this research suggests that a sensitivity signal seems more promising than social proof in influencing users' disclosure behaviors to chatbots. The difference between the two nudges might be due to the fact that user disclosure is an intrinsic behavior and people do not make judgments about their privacy based on what others do. These results come to complement previous research [97,114,115] on nudging and privacy for the disclosure of personal information online (not just specific to chatbots). Overall, empirical research on digital nudging to alter users' disclosure behaviors has produced conflicting findings in the past, with some studies finding it to be quite effective while others have found no such results [97]. On one hand, studies have demonstrated that motivating communications and persuasive messages with stronger arguments or more positive framings can enhance the disclosure of private information [114,116]. In our case, the low-sensitivity signal goes in accord with these previous results, by increasing the disclosure of low-sensitivity information. However, there is still a question mark as to how to decrease—rather than increase—disclosure of high-sensitivity information. On the other hand, a growing interest has been shown in examining the impact of social nudges, centered around the social proof, used to affect users' privacy decision-making online [97]. According to research, social cues, such as the knowledge that a majority of users' peers have taken similar actions, such as disclosing personal information, can lead to an increase in information disclosure on websites [29,99]. In the present case, by refuting the effect of such a nudge in user-chatbot interaction, this study complements previous results in the literature [29,99] by marking a distinction between online and chatbot-specific interactions. These results also go hand in hand with other recent findings such as Rudnicka et al. [114] who found that while persuasive messages framed around learning increased the disclosure of sensitive items, people did not change their disclosure behavior for messages framed around social proof, contribution, and altruism.

Nonetheless, the nudges used in this research may still have value by perhaps confirming users' judgments regarding questions they are prompted with. In our results, seven participants answered all questions, and twelve skipped some questions. The reasons for disclosure and non-disclosure given by participants show that, in the case where users have the same judgment as the nudge, the nudge may serve to confirm their decision to answer the question or not (confirmed by five participants).

Third, evidence from this study showed that emotional response does not appear to be a mechanism describing how disclosure functions in user-chatbot interactions. Previous research on affect and online information disclosure tells another story. Wakefield [117] suggested that positive affect has a significant effect on users' online information disclosure. Additionally, Coker and McGill [118] stated that arousal increases self-disclosure. The contradictory results of these studies to the ones reported in this research could highlight a plausible difference in users' behaviors when interacting with websites versus chatbots, that is, only in certain settings. Indeed, previous studies in user-chatbot interactions had underlined the role of emotional response, but mostly in contexts that pertain to mental health or education rather than privacy in e-commerce [33,60,108,109]. Referring to the Affect Infusion Model, the results of the present study could be because information disclosure to chatbots is not a high infusion situation for users. Rather than performing a heuristic processing of the available information, it is possible that in chatbot interactions, users could use more direct access or motivation-based processing [32]. Under these strategies, people base their judgment either by reproducing a past behavior in a similar situation or by searching for specific information with a clear purpose in mind to base their decision. In these two types of processing, the AIM states that affect does not serve as information in the judgment, which could explain the insignificant results of this study. Thus, interactions with chatbots might not be a situation where emotional response is inferred into information.

5.3. Managerial Implications

From a managerial standpoint, the fact that this research marginally supports the influence of information disclosure nudges on users' behaviors has one main implication. In practice, the use of nudges has been debated since their inception. It is believed that to be ethical, nudges should aim to enhance people's decisions by altering how alternatives are given rather than altering the options themselves or motivating or coercing people a certain way [115]. The information disclosure nudges tested in this research did not always predict user behavior. Nonetheless, from an ethical perspective, users should maintain their right to make informed decision-making in their online interactions. Ultimately, the goal of interfaces should be to give users control and freedom rather than to choose for them what they put out on the internet, especially through chatbot interactions [51]. Thus, policymakers can scrutinize this research for inspiration when drafting policies that provide more information to users in online interactions with chatbots.

5.4. Limitations and Research Avenues

The results of this study on the impact of nudges on disclosure could be due to some limiting factors. First, the inconclusive results could be due to the fact that not enough questions were asked per nudge combination and per question sensitivity level to find significant differences in information disclosure. Second, the nature of the interactions between the users and chatbots in the experiment consisted of a series of questions and answers. Considering these points, future research could explore consumers' information disclosure behaviors when they communicate with chatbots in the form of extended conversations, rather than in a question-and-answer format. Another explanation for these partially supported results could be due to limitations in choosing to conduct this experiment in a lab setting. In fact, this research was conducted under high ethical standards. Participants were informed that their responses would be anonymized and were asked to sign consent forms before the start of the experiment. Additionally, the websites used to host the chatbot prototypes were all fictional. This environment might have made participants overly trusting towards the chatbots by reminding them they are in a lab setting that is controlled by high ethical standards and in turn increasing their disclosure. Future research on information disclosure should try to mitigate this by conducting their experiment in association with real websites.

Considering the choice of nudges (i.e., sensitivity signal and social proof) in this experiment, this research also provides potential avenues for other nudges that could promote informed decision- making when it comes to information disclosure to chatbots and could be explored in the future. For example, in our experimental design, participants were told that they could choose to not answer a question if they did not want to. Future research could explore the difference in information disclosure when users are given the cue that they can choose not to respond versus no cue.

The peculiarities of our stimulus materials and study design may have restricted the study's findings. We placed the information disclosure nudges in locations that were conducive for the use of the eye-tracking technology used in this research. The nudges were thus placed on either side of the chatbot. In addition, although the nudges were uniform in size and color, it is possible that varying the design of the nudges would have made them more impactful. Future research could investigate the optimal location and design for information disclosure nudges to be maximally influential on users' behaviors.

Finally, the results of this study showed that more than a third of the participants (seven out of nineteen) answered all questions prompted by the chatbots, regardless of their sensitivity level. This heterogeneous data suggests that some users are comfortable sharing information online with chatbots, being general or sensitive. Given the small sample size of this study, our results did not make it possible to find a distinguishing factor better for the group that answered all questions versus the group that skipped some questions. Although the sample size used is typical for NeuroIS research [119] future research could still replicate and extend this study by increasing the sample size in order to investigate if some personal characteristics impact disclosure decisions. For example, measuring the users' level of comfort with online privacy and sensitive issues [50] or taking into account the cultural background of individuals [120] could bring out behavioral differences between groups. Considering that the participants in this study were located in North America, it is plausible that the results would differ greatly in other regions of the world where the very definition of sensitive matters may vary. Looking forward, finding determining factors between individuals could be valuable for both business organizations to better understand their customers and policymakers to draft distinct policies for different types of users.

6. Conclusions

To conclude, this research explored the impact of question sensitivity, information disclosure nudges, and arousal on users' information disclosure behaviors in chatbot interactions. The results show that people rely more on their own judgment than information disclosure nudges when it comes to disclosing information online to chatbots.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy and compliance with the protocol approved by the Ethics Committee.

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Appendix A

Table A1. Full List Questions.

Question	Context	Sensitivity Level
How many years of work experience do you have?	Career	Low
What country do you currently live in?	Career	Low
What is your biggest strength?	Career	Low
What is your highest completed education level?	Career	Low
What languages do you speak fluently?	Career	Low
What high school did you go to?	Career	Low
What country were you born in?	Career	Low
Are you a hard worker or the less the better?	Career	Low
Do you feel like you earn enough money?	Career	High
Have you ever been in trouble with the law?	Career	High
Have you ever lied to your superior to get a day off work?	Career	High
Do you prioritize your professional or your personal life?	Career	High
Have you ever lied in a job interview or on your CV?	Career	High
Have you ever lied on your CV?	Career	High
What's the biggest mistake you've made at work?	Career	High
Have you ever drank at work?	Career	High
Do you tend to be an optimist or pessimist and why?	Dating	Low
Do you want to have children/do you have children?	Dating	Low
Is intelligence or looks more important for you?	Dating	Low
What is your eye colour?	Dating	Low
What is your favorite movie?	Dating	Low
What is your favorite music genre?	Dating	Low
What is your gender?	Dating	Low
What is your relationship status?	Dating	Low
Are you religious? If so, what religion do you practice?	Dating	High
Do you fall in love easily?	Dating	High

Table A1. *Cont.*

Question	Context	Sensitivity Level
During sex, do you take precautions against unwanted pregnancies?	Dating	High
During sex, do you take precautions against STDs?	Dating	High
Have you ever been on a date with the sole purpose of having sex with the person?	Dating	High
Have you ever cheated on your significant other?	Dating	High
How many serious relationships have you been in throughout	Dating	High
What is your sexual orientation?	Dating	High
Do you prefer sweet or savoury food?	Groceries	Low
Do you enjoy trying new foods?	Groceries	Low
Do you enjoy eating different cuisines of the world?	Groceries	Low
Do you always buy brand-name products?	Groceries	Low
Do you usually use coupons and discount while groceries shopping?	Groceries	Low
Do you always shop at the same grocery store?	Groceries	Low
How often do you shop for your groceries online?	Groceries	Low
Do you prefer vegetables or fruits?	Groceries	Low
Overall, how healthy is your diet?	Groceries	High
Do you track your calories?	Groceries	High
Do you take any supplements?	Groceries	High
Counting yourself, how many people live in your household?	Groceries	High
Do you have any allergies?	Groceries	High
Would you say your diet is healthier than most people's diet?	Groceries	High
What is your address?	Groceries	High
How much do you spend on groceries per week?	Groceries	High
Do you play sports?	Gym	Low
How many cups of coffee/tea do you drink per day?	Gym	Low
How many glasses of water do you drink per day?	Gym	Low
How many hours do you practice physical activity per week?	Gym	Low
How many meals do you eat per day?	Gym	Low
What is your height (cm/feet and inches)?	Gym	Low
How much time per week are you willing to dedicate to personal training?	Gym	Low
What sports do you play?	Gym	Low
How many cigarettes do you smoke per week?	Gym	High
How many glasses of alcohol do you drink per week?	Gym	High
How much do you weight (kg/lbs)?	Gym	High
What is one thing you would like to change about yourself (physically or mentally)?	Gym	High
Do you experience binge eating episodes (uncontrollable eating of large amounts of food)	Gym	High
How often do you think you feel too much stress?	Gym	High
Do you have a stressful lifestyle?	Gym	High
Have you ever been told by a physician that you have a metabolic disease (e.g., heart disease, high blood pressure)?	Gym	High
Do you always read the terms and conditions before checking the box?	Insurance	Low
Do you have a car?	Insurance	Low

Table A1. *Cont.*

Question	Context	Sensitivity Level
Do you have any pets?	Insurance	Low
Do you have renters/homeowners insurance?	Insurance	Low
How old are you?	Insurance	Low
What is your current occupation?	Insurance	Low
What is your phone model?	Insurance	Low
Do you smoke?	Insurance	Low
Do you have more than 5000 USD in savings at this time?	Insurance	High
Do you pay off your credit card in full every month?	Insurance	High
How many credit cards do you have?	Insurance	High
How much do you pay on rent/mortgage per month?	Insurance	High
What is your current income per year?	Insurance	High
What is your email address?	Insurance	High
What is your phone number?	Insurance	High
Do you have an investment portfolio?	Insurance	High
Would you also try typical dishes—that you would normally never eat—while traveling?	Travel	Low
Is room service important to you?	Travel	Low
What type of accommodation do you prefer when travelling?	Travel	Low
Do you like to talk to the local people when you travel?	Travel	Low
What modes of transportation do you prefer to use when you travel?	Travel	Low
Have you ever traveled abroad?	Travel	Low
Which country would you most like to visit?	Travel	Low
What is your dream destination for a vacation?	Travel	Low
Are you fully vaccinated against Covid19?	Travel	High
Which countries, regions, or cities irritate you the most and why?	Travel	High
What would you never do on your travels and why?	Travel	High
How much money do you typically spend per day while travelling?	Travel	High
Would you feel insecure if you were to travel alone?	Travel	High
Are there regions that you would never want to visit and why?	Travel	High
Is there a legal reason why you could not travel to a specific country?	Travel	High

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