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Two essays on user experience with chatbots

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CERTIFICAT D'APPROBATION ÉTHIQUE

La présente atteste que le projet de recherche décrit ci-dessous a fait l'objet d'une évaluation en matière d'éthique de la recherche avec des êtres humains et qu'il satisfait aux exigences de notre politique en cette matière.

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Chercheur principal :
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Comité d'éthique de la recherche - HEC Montréal

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CERTIFICAT D'APPROBATION ÉTHIQUE

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Résumé

Ce mémoire vise à explorer l'expérience utilisateur créée par les agents conversationnels (chatbots) du point de vue de l'utilisateur à travers une étude exploratoire sur l'expérience de l'utilisateur en réponse à différents formats de contenu média utilisés par les chatbots et une étude en laboratoire sur les comportements de divulgation d'information des utilisateurs avec les chatbots et l'effet des *nudges* de divulgation d'information dans la réduction de la quantité d'information divulguées par les utilisateurs aux chatbots.

Mots clés : chatbot, expérience utilisateur, format de contenu média, type de tâche, divulgation d'information, *nudge*, réaction émotionnelle

Méthodes de recherche : Les articles présents dans ce mémoire ont utilisé deux méthodologies différentes. Le premier article est le produit d'un test utilisateur intra-sujet mené à distance avec treize participants, incluant des tâches à compléter, des questionnaires, ainsi qu'une entrevue. Le deuxième article est basé sur une étude en laboratoire intra-sujet qui a été menée auprès de dix-neuf participants durant laquelle les participants furent amenés à compléter des tâches à l'ordinateur et répondre à une entrevue. Un pré-test a également été réalisé pour cette recherche à travers un questionnaire sur Amazon Mechanical Turk. Trois cent seize personnes ont participé à ce pré-test.

Ce mémoire est divisé en quatre parties. Il commence par une introduction suivie des deux articles sur l'expérience utilisateur avec les chatbots. Le premier article a été publié et présenté à la conférence NeuroIS Retreat en juin 2021. Le second article a été préparé pour être soumis à une revue d'interaction homme-machine (Human-Computer Interaction). Ce mémoire se termine par une conclusion résumant les résultats et les contributions des deux articles.

Abstract

This thesis aims to explore the experience of chatbots from a user's perspective through a pilot study on the user experience with chatbots' different media content formats and an empirical study on users' information disclosure behaviors with chatbots and the effect of information disclosure nudges in reducing the amount of information disclosed by users to chatbots.

Keywords: chatbots, user experience, media content format, task type, information disclosure, information disclosure nudges, emotional response

Research methods: The articles in this thesis used two different methodologies. The first paper is the product of a within-subject user test conducted remotely with thirteen participants, including tasks to complete, questionnaires, and an interview. The second paper is based on a within-subject laboratory experiment. The nineteen participants were asked to complete tasks on the computer and answer interview questions. A pre-test was also conducted for this research through a questionnaire administrated on Amazon Mechanical Turk. Three hundred and sixteen people participated in this pre-test.

This thesis is divided into four parts. It begins with an introduction followed by the two articles on user experience with chatbots. The first article was published and presented at the NeuroIS Retreat Conference in June 2021. The second article was prepared to be submitted to a Human-Computer Interaction (HCI) journal. This thesis ends with a conclusion summarizing the results and contributions of both articles.

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List of Abbreviations

AFEA: Automated Facial Expression Analysis

AI: Artificial Intelligence

AIM: Affect Infusion Model

CASA: Computer As Social Actors

EDA: Electro Dermal Activity

ELM: Elaboration Likelihood Model

HCI: Human-Computer Interaction

MRT: Media Richness Theory

Mturk: Amazon Mechanical Turk

Q&A: Question & Answer

RA: Research Assistant

RQ: Research Question

Foreword

The request to submit this thesis in the form of articles was approved by the administrative management of the M.Sc. program at HEC Montréal. Authorization was also provided by the Academic Affairs office. This thesis consists of two articles. The first article was published and presented at the NeuroIS Retreat Conference in June 2021. The approval from the ethics committee at HEC Montréal was provided for this research in October 2021 under the project number 2021-4259. In addition, the agreement of all co-authors was obtained for this article to be presented in this thesis. The second article was prepared to be submitted to a Human-Computer Interaction (HCI) journal. The university's ethics committee granted approval for this research in October 2022 under the project number 2022-4721.

Acknowledgments

First and foremost, I would like to express my deepest gratitude to my directors – Constantinos Coursaris and Sylvain Sénécal – and everyone at Tech3Lab for the opportunities and valuable comments you provided. Without your passionate participation and input, none of this would have been possible.

I would also like to acknowledge the substantial contribution of the Social Science and Humanities Research Council of Canada in the completion of my masters' studies and this thesis with their generous scholarship.

I am also thankful for Armel, Rosetta, and Sara-Maude, who shared the wins but also the challenges of the past two years with me.

The journey here has been no less than an emotional rollercoaster, but I am forever grateful for the people have always been here for me – maman, papa, Zak. Thank you.

Chapter 1: Introduction

1.1 Context of this thesis

Although the first machines to interact with humans through language date back to the period between the mid-20th Century and the turn of the millenium (Turing's imitation game (Turing, 1950), conversational softwares such as ELIZA (Weizenbaum, 1966), PARRY (Colby et al., 1971), ALICE (Wallace, 2009)), it is at the beginning of the 2010s that the chatbot market saw its biggest wave of investments. It is around that time that companies started to invest in chatbots as a technology that "could provide more depth on specific topics" than simply being able to communicate (Rapp, 2021, p. 2). Nowadays, chatbots are mostly powered by artificial intelligence (AI) and can perform a plethora of tasks, including web searching, notifying users, and making appointments (Rapp et al., 2021). Specifically in the e-commerce market, chatbots are used by businesses to assist consumers in their online purchases by giving product-related information, recommending personalized products or services and even completing transactions with users.

At the time of writing this thesis in 2022, chatbots are still seeing increasing usage by companies and users for e-commerce purposes. On one hand, the e-commerce chatbot market is expected to continue its growth trajectory as chatbots continue to lower operating expenses for businesses. Insider Intelligence (Yuen, 2022) predicts that by 2024, consumer retail spending via chatbots will reach $142 billion globally, up from a mere $2.8 billion in 2019. On the other hand, although users were originally perceived as hesitant to adopt this "new" technology, there was a recent increase in usage and acceptance by users in the market: "in the U.S., 27% of adults have used chatbots for shopping at least once, and nearly 40% of them favor this kind of shopping experience" (Jovic, 2020, p. 2).

Taking the increasing importance of chatbots for e-commerce purposes, it is crucial to study how consumers react, evaluate, and behave in response to the user experience created by these systems. With this idea in mind, this thesis presents two articles on chatbots' user experience and design. The first article is a short pilot study looking at different media content formats used by chatbots and their effect on users lived and perceived experience. The second article investigates, from an ethical perspective, the effect of information disclosure influence tactics - called nudges - on users' information disclosure behaviors to chatbots.

1.2 Presentation of the two articles and their respective research questions

1.2.1 Article 1

Chatbots are communication media that use a variety of technologies and designs to exchange information and provide responses to user queries (Sheth et al., 2019; Kantarci, 2021). However, from a user's perspective, little research investigating the contributors and irritants related to the media content format used by chatbots has been performed. Except for the more traditional question and answer (Q&A) communication, other media formats used by the chatbot have been overlooked. Therefore, there is a need for research that extends our understanding of how the media content format used by chatbots may affect the experience of users when performing different tasks in an e-commerce setting.

The first article presented in this thesis explores both the lived and perceived experience of users in response to performing informational and transactional tasks with a chatbot when the latter uses different media content formats. The media content formats explored include presenting the information as a link to a webpage, a video, and a Q&A format. The goal is to investigate what the optimal way is for chatbots to present information in, from a user perspective, so as to maximize the user's information disclosure in their interactions with the chatbot. This article is exploratory in nature and answers the following research questions:

Does the media content format, one that varies in richness – such as interactive conversation, video, and link to a webpage – used by a chatbot impact the users' lived and/or perceived experience?

Does the task type, whether users ask for information or transactional assistance, moderate the relation between the type of media content format and the users' lived and/or perceived experience?

This article was presented and published at the NeuroIS Retreat Conference in 2021. This process allowed to gain feedback from fellow researchers and get inspiration for a subsequent article to complement the results of this study. This first article highlighted that users' concerns over the security of chatbots could be an important, impeding factor in the success of human-chatbot interactions. From there, the idea of privacy and responsible artificial intelligence was discussed at the conference and became the topic of the second article of this thesis.

1.2.2 Article 2

To provide better and more personalized recommendations to consumers, e-commerce platforms collect an immense amount of data on their users (Hong & Thong, 2013). Consequently, privacy concerns due to the sensitivity of the information collected by online platforms has become a top issue for users (Hong & Thong, 2013). Given that chatbots are increasingly being utilized by businesses to provide these personalized product or service recommendations, it is plausible that users' privacy worries when engaging with digital technology has been alleviated by chatbots (Ischen et al., 2019). Indeed, chatbots have to collect information on users to tailor recommendations to the latter's needs and preferences (Ischen et al., 2019).

The literature on chatbots has shown that users' perceptions of and experiences with dangers associated with online information disclosure have a detrimental influence on their experience (Cheng & Jiang, 2020; Rese et al., 2016). This is because customers are not always aware of when and how data is collected throughout their interactions with a company, or how that data will be utilized by this company in the future (Ischen et al., 2019). Research on users' disclosures to chatbots has been conducted in the past (Lee et al., 2020; van der Lee et al., 2019; van Wezel et al., 2021). However, most of them focus on how to increase users' disclosure (Ischen et al., 2019; Ng et al., 2020) rather than making them aware of – and potentially decrease – the information they put out on the internet.

Thus, the second article of this thesis explores the effect of two tactics - called information disclosure nudges - on influencing users to limit their information disclosure in their interaction with chatbots. Nudges are defined as "any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives" (Thaler & Sunstein, 2008, p. 2253). In the context of information disclosure, nudges are used here to promote informed decision-making by users when they choose to disclose or not disclose information of varying sensitivity to a chatbot. The information disclosure nudges used in this research include a *sensitivity signal*, which, by informing about the level of sensitivity of the question asked by the chatbot could impact the users' disclosure behaviors. The second information disclosure nudge is centered around the idea of *social proof.*

Social proof was first presented in Cialdini's (2009) *Persuasion Theory*, which explains how people's behaviors are heavily influenced and can be predicted by the actions of others in a similar context. This is based on the fact that humans tend to mirror their peers' behaviors. In this study, social proof is deployed by informing users about how their peers behaved in the situation (i.e., whether they disclosed or not the information being asked by the chatbot).

The role of emotional response in the relationship between question sensitivity, information disclosure nudges, and information disclosure behaviors is also investigated in order to understand how influence functions in user-chatbot interactions. The *Affect Infusion Model* (AIM) explains ways in which people's judgments are influenced by their emotional response as they process information and their resulting actions (Forgas, 1995). According to the AIM, users base their judgments on their emotional state as a result of the available cues in an interaction's context. This suggests that users may feel emotional responses in reaction to the chatbot interaction environment, which in turn would impact their disclosure behaviors.

The objective of this research is to make users aware of the information they share online to promote the ethical development of AI systems, such as chatbots. This empirical article permits to answer the following research questions:

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?

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

1.3 Structure of the thesis

The present thesis is divided as follows: this first chapter covers an overview of the papers as well as the context of the two studies. The second chapter is the exploratory article on the user experience with chatbots using different media content formats, which was presented and published at the NeuroIS Retreat Conference in June 2021. The third chapter presents the empirical article that is in preparation to be submitted to a Human-Computer Interaction (HCI) journal. The study covers the effect of information disclosure nudges on user disclosure behaviors with chatbots. Each article presents the key concepts that were investigated, allowing gaps in the research to be identified. They also provide the experimental approach employed and discuss the findings inferred from the results. The concluding chapter of this thesis presents a summary of the two studies and their implications for what we know about user experience with chatbots.

Given that this thesis was conducted in the Tech3Lab, which involved several collaborators at varying levels of contributions across varying stages of the thesis, Figure 1 below is meant to convey my personal intellectual contribution in each aspect of the thesis. According to the standards of the lab, an *overall* level of 50% in contribution is expected by the student, with levels well below 50% being acceptable and often the case. For dimensions where my personal contribution exceeds 50%, it suggests leadership and ownership of the corresponding phase.

Figure 1 Student's contribution and responsibilities in the realization of this thesis

Step of the process	Contribution
Research questions	**Identifying gaps in literature and problems to be addressed in the thesis - 70%** ● I identified the initial research questions for both articles. ● I identified the initial variables and constructs for both articles. ● My supervisors and co-authors helped refine the scope.
Experimental design	**Developing the experimental design - 60%** ● For Article 1, the study was developed in collaboration with the partner, Tech3Lab's operations team, and me. ● For Article 2, I developed the entire study. **Preparing the experimental stimuli - 50%** ● For Article 1, the partner developed the chatbot prototype to match their brand's style and website, while I developed the stimuli to integrate the different tasks of the experiment, the prototype, and questionnaires. ● For Article 2, I developed the chatbot prototype, tasks, and stimuli to integrate the study altogether. My supervisors provided feedback to iterate each version of the stimuli. **Creating the questionnaires - 80%** ● My supervisors guided me as I researched the scales to be used and created the questionnaires for both articles. **Applying to the research ethics committee - 80%** ● For Article 1, the application to the research ethics committee was done in collaboration with Tech3lab's operations team. ● For Article 2, I drafted the document and Tech3Lab's operation team helped finalize the application before sending it to the research ethics committee.

Pre-tests	**Conducting pre-tests before the start of data collection - 70%** ● For Article 1, I was part of a team of three responsible for conducting pre-tests. ● For Article 2, I was responsible for the operations for all pre-tests.
Recruitment	**Recruiting and compensating participants - 30%** ● For Article 1, the recruitment was done with an external firm hired by the partner of this research to get participants to fit their typical consumers. The partner was also responsible for distributing the compensation. ● For Article 2, the recruitment was done differently for the two phases. I provided the criteria for participation for the online questionnaire and Tech3Lab's operations team oversaw applying them on Amazon Mechanical Turk. For the lab experiment, I handled the entire recruitment process. For both phases, Tech3Lab's team distributed the compensation to participants.
Data collection	**Collecting data and supervising operations - 70%** ● For Article 1, I was the moderator and responsible for operations for most of the participants. The other participants were handled by Tech3Lab's operations team. ● For Article 2, I oversaw the entire data collection and operations.
Analysis	**Formatting data - 80%** ● For Article 1, a statistician from Tech3Lab's team helped format the quantitative data collected, while I oversaw the qualitative data. ● For Article 2, I formatted all the data collected. **Analyzing data - 50%** ● For Article 1, the statistical analyses for the quantitative data were determined by Tech3Lab's team and a statistician performed them, while I took charge of the qualitative data. ● For Article 2, I determined the statistical analyses to be conducted. I performed the analyses of the data from the questionnaire from phase 1. I collaborated with Tech3Lab's statistician to perform the analyses of the data from the lab experiment in phase 2.
Writing	**Writing the articles and thesis - 75%** ● For both articles, I wrote the first draft, while my supervisors provided feedback and edits in the text. The remaining co-authors made minor edits to the articles. ● I also wrote the initial draft of the thesis and my supervisors provided feedback.

Chapter 2: Article 1

Does media richness influence the user experience of chatbots: A pilot study[1]

Laurie Carmichael, Sara-Maude Poirier, Constantinos K. Coursaris, Pierre-Majorique Léger, and Sylvain Sénécal

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Abstract: From a user's perspective, this pilot study investigates the contributors and irritants related to the media content format used by chatbots to assist users in an online setting. In this study, we use automated facial expression analysis (AFEA), which analyses users' facial expressions and captures the valence of their lived experience. A questionnaire and a single-question interview were also used to measure the users' perceived experience. All measures taken together allowed us to explore the effects of three media content formats (i.e., an interactive question and answer (Q&A), a video, and a link referring to a webpage) used in chatbots on both the lived and perceived experiences of users. In line with Media Richness Theory (MRT), our results show that an interactive Q&A might be an optimal chatbot design approach in providing users with sought-after information or assistance with transactions. Moreover, important avenues for future research emerge from this study and will be discussed.

Keywords: chatbot, media content format, media richness theory, task type, automated facial expression analysis

[1] This article was presented at the NeuroIS Retreat Conference 2021 and published in the conference's proceedings book: Information Systems and Neuroscience, NeuroIS Retreat 2021; This research was approved by the Research Ethics Board (REB) from HEC Montréal (Certificate 2021-4259).

2.1 Introduction

AI-based software such as chatbots are used by retailers and service providers to offer 24/7 user assistance. It is expected that by 2022, 75-90% of user's queries will be answered by chatbots [1]. Moreover, human-computer-interaction (HCI) literature has shown that chatbots have proven to be relevant and effective in assisting consumers in online settings [2]. To date, most of the research that studied chatbots has tried to understand the technical aspects of algorithms behind these systems [3]. However, from a user's perspective, little research has been performed investigating contributors and irritants related to the media content *format* used by chatbots to provide information to users. Therefore, there is a need for research that extends our understanding of how the media content format used by chatbots may affect user experience in e-commerce. This raises two important research questions: Does the media content format, one that varies in richness – such as interactive conversation, video, and link to a webpage – used by a chatbot impact the users' lived and/or perceived experience? Does the task type, whether users ask for information or transactional assistance, moderate the relation between the type of media content format and the users' lived and/or perceived experience?

In this pilot study, we utilize automated facial expression analysis (AFEA), a questionnaire with self-reported measures, and an open-ended question about the users' preference to assess the user's lived and perceived experiences when using chatbots to perform both an informational and a transactional task. Based on Media Richness Theory (MRT) [4], the more a media is synchronized and adapted to the user, the more positive the perceived and lived experience with the technology (here, chatbot) will be at the intersection of HCI and neuroscience. This study contributes to enriching the body of knowledge regarding chatbots and their design. Study results will also shed light on several avenues of future research surrounding the type of task performed with a chatbot and the appropriate type of media content format practitioners would be recommended to use so as to improve their online services and customer support.

2.2 Theoretical background and hypotheses

Chatbots are robots that can maintain a textual or vocal conversation with human users [5]. Due to the growing number of instant messaging services on social media or directly on the retailer or service provider website, in this study we focus on text-based chatbots designed to converse and interact with users [6]. Thus, we defined the chatbot as a “computer program, which simulates human language with the aid of a text-based dialogue system” [7]. The main interest in using chatbots from the user’s point of view is that they can increase users’ productivity by providing efficient and fast assistance [2].

A positive or negative experience with a chatbot depends on whether the users’ expectations are met [8]. Therefore, chatbots must have the ability to correctly interpret user queries and provide accurate answers that are also perceived to be trustworthy and useful [9, 10]. To date, researchers have mainly explored the effect of appearance, personality, and the written style of the chatbot on the overall users’ experience, perceived information quality, and satisfaction with it [11]. However, except for question and answer (Q&A) communication [12], the media format used by the chatbot to assist users in accomplishing their task has been overlooked. Next, we present the main media content formats employed by chatbots to redirect users to the right information and explain how these different media can affect users' both lived and perceived experiences.

2.2.1 Media content formats used by chatbots

According to MRT, communication media formats are positioned on a continuum from richer to leaner in order to predict their effectiveness during conversation exchanges [4]. To be considered rich, a medium must provide (1) immediate feedback from the receiver to the sender, (2) multiple cues that reduce equivocality of the message, (3) a variety of language (e.g., gesture) and (4) a personal focus [5]. Consequently, face-to-face is ranked as the richness medium while unaddressed documents (e.g., wall posts, flyer, SMS) are classified relatively leaner.

The literature shows that chatbots are communication media for which the richness varies greatly [13]. Therefore, chatbots are built on different technologies and architectures and their answers to user requests vary [1]. In all cases, the chatbot acts as a digital self-service tool that orients users to the right information or that can directly communicate it through textual or verbal exchanges [14]. During this interactive and timely conversation, questions and answers (Q&A) can be provided in an automated format (e.g., frequently ask questions), or in a more natural format (i.e., personalized dialogue) similar to an exchange with a human [14].

In this pilot study, we focus on three ways users may receive information from a chatbot such as a Q&A representing a more natural conversation format and two unaddressed media content formats (i.e., thumbnail or static webpage text). Due to the more personal and adapted exchanges between users and chatbots during Q&A interactions, as well as the elevated level of synchronicity that allows immediate feedback, we posit that this type of communication will result in a more positive lived and perceived experiences than a thumbnail preview of a video or a link leading to a webpage with static text, both previously created for general user consumption. Furthermore, because the video provides visual and auditory cues, we also expect that this media content format will result in a more positive lived and perceived experiences by the user compared to the static text on a webpage. According to the richness of the media content format, less effort during the exchanges with the chatbot should be required from the user to accomplish their query. Moreover, the exchanges with the chatbot should be pleasurable and the information should be perceived as being of quality. Since the complexity of the communication exchanges also depends on the nature of the task users intend to perform when interacting with a chatbot – ranging from obtaining information to completing a transaction [14] – the next section presents the moderating role of task type.

2.2.2 Moderating role of task type (information versus transactional)

Chatbots can be divided into two main categories, i.e., whether they are used for conversational or transactional purposes [11]. In the former case, chatbots can provide information to users or act as virtual companions to mainly socialize with them [11]. In the latter, transactional chatbots complete a transaction within the context of the conversation [15]. These chatbots are mainly used in the service sector such as financial, insurance, or telecommunication services to perform tasks usually done by an employee [15]. For instance, chatbots can confirm an outgoing transfer of money or make users sign documents regarding their cell phone contract. Based on the above, we decide to focus on both informational and transactional chatbots so as to explore differences between them in regard to user experience [5].

Through these exchanges, users expect to be provided with the right information in response to a query or to be able to complete a transaction. In the context of informational tasks, the answer provided by the chatbot represents the end of the exchange, whereas for transactional tasks, the user can choose to partially or totally delegate the task to the chatbot. Then, the chatbot may be able to complete the transaction with input from the users or provide users with the right information to let them execute the task. According to [16], engaging users in a collaborative experience with the chatbot improves their experience with chatbots. Therefore, users enter into a dyadic relationship with the chatbot arguably in a more involved way than in the case of an informational task. According to the trust-commitment theory, a transactional chatbot needs to be trusted to accomplish the task correctly so users believe in the benevolence of chatbots to fulfill their needs [17]. Then, expectations are higher toward the chatbot and the final result, because the notion of investment in this exchange is omnipresent. Since it is even more important in a transactional task to directly cooperate with the chatbot to accomplish a task, it is expected that user's lived and perceived experiences will benefit more from media and message richness compared to informational tasks. Thus, we propose the following hypotheses:

H1: Comparing transactional to information tasks, there will be a statistically significant difference in the user's lived experience with the chatbot, such that the valence will be more positive (a) for Q&A than for either video or webpage, and (b) for video than for webpage.

H2: Comparing transactional to informational tasks, there will be a statistically significant difference in the user's perceived experience with the chatbot, such that the (a) pleasure during exchanges (b) info quality, and (c) format preference will be higher for Q&A than for either webpage or video. Conversely, (d) the perceived effort exerted by the user during the chatbot-user exchange will be lower for the Q&A than for either the webpage or video.

H3: Comparing transactional to informational tasks, there will be a statistically significant difference in the user's perceived experience with the chatbot such that the (H3a) pleasure, (H3b) info quality, and (H3c) preference will be higher for the video than for the webpage. Conversely, (H3d) the perceived level of effort deployed by the user during the chatbot-user exchange will be lower for the video than for the webpage.

2.3 Methodology

2.3.1 Design and participants

To test our hypotheses, we have used a 3 (media content formats: Q&A vs. video vs. static webpage text) X 2 (task types: informational and transactional) within-subjects design. For this experiment, 14 participants, aged between 27 to 64 years old, were recruited through a research panel. One participant did not have AFEA data due to a technical problem; we thus excluded their data from the results. Out of the remaining 13 participants, 6 were women and 7 were men. In exchange for their time, the participants were each compensated with $125 CAD.

2.3.2 Experimental Protocol

Data collection was performed using the procedure proposed by Giroux et al. [18] and Alvavez et al. [19]. The experiment was conducted remotely using Lookback (Lookback Inc, Palo Alto, CA), an online platform that records participants' facial expressions while they are performing tasks. Participants were randomly presented six scenario-based conversations regarding the services of a telecommunications company. These scenarios were provided by the company to test their most often customer-asked informational question and transactional request from customer service. These conversations were between a chatbot and a fictional user, and participants were asked to put themselves in the user's situation.

Moreover, the conversations were presented free of any visual context (e.g., branding, digital environment) to avoid related biases. In the informational task, the fictional user contacted the chatbot for assistance with a technical issue concerning an online service whereas in the transactional task, the fictional user asked the chatbot to subscribe to a new online service. In the Q&A format of the transactional task, the chatbot completed the transaction for the user, whereas in the other two formats, the chatbot only gave the steps on how to proceed to an online video showing its thumbnail as a preview (which was not viewed) or providing a hyperlink to a static webpage containing only textual information (which was viewed), leaving the user to complete the transaction on their own. In the informational task, the fictional user received the same information but in the three different formats. The Q&A format was natural, typing exchanges directly made in the chatbot, the video format was a thumbnail of the video that appeared in the chat with the chatbot and finally, for the webpage, the user received a link in the chat that redirected them toward a webpage that the user visited.

After reading each conversation, participants were presented a questionnaire to assess their perceived experience with the chatbot. Specifically, participants reported their perceived pleasure and effort during exchanges, and also evaluated the information quality of what was provided by the chatbot. Each task type was followed by a question by a moderator to ask the participant's preference between the three media content formats. In total, the experiment lasted about one hour.

2.3.3 Data collection, measurements, and postprocessing

For the physiological measurement of the lived experience, we exported and analyzed the videos in FaceReader 5 (Noldus Technology Inc, Wageningen), an automated facial expression analysis software [20]. FaceReader is the most widely used AFEA software in NeuroIS research (e.g., [21, 22, 23, 24]). Valence was calculated using a scale from –1 to 1 that contrasts states of pleasure (e.g., happiness) with states of displeasure (e.g., anger) felt during the reading of each chatbot conversations; specifically, it was measured as the intensity of happiness minus the intensity of the negative emotion with the highest intensity [25].

The perceived experience of participants was measured by using a questionnaire, in which participants self-reported after each of the six conditions their perceptions of our dependent variables. All scales used were adapted from prior research for context, maintaining their original scale answer formats. A 1-item scale was chosen for pleasure and effort [26]. Thus, participants reported their Pleasure during the exchanges with the chatbot on an affective slider from 0 to 100 (0 = low pleasure; 100 = high pleasure) [27]. The perceived level of Effort during the task was measured with a single item: "What is the level of effort that you would have deployed if you had this exchange with the chatbot in real life?" on a five-point Likert scale (1= very low; 5= very high) [28]. Participants also evaluated the quality of the information (Info Quality) provided by the chatbot on a seven-item, seven-point Likert scale (1= totally disagree; 7= totally agree) [29]. Finally, after the experiment, a open-ended interview question about users' preference question was asked to participants by a moderator to better understand which condition was their favorite and why (Preferred).

Data post-processing and synchronization followed the procedure proposed by Léger et al. [30] and Cube HX (Cube Human Experience Inc, Montréal, Qc) was used prior to analysis [31, 32, 33].

2.4 Results

A linear regression with random intercept model was performed to compare the media formats in terms of valence. The 2-tailed p-values are adjusted for multiple comparisons using Holm's method. Wilcoxon Signed Rank tests with significance level of 0.05 were performed to compare the media formats in terms of perceived pleasure, effort, info quality, and preference. Info quality was measured as an index (Cronbach alpha=0.9), taking the average of the responses to the seven items on a scale from 1 to 7 (low to high perceived info quality). The open-ended question's answers were transcribed and its content analyzed to report the preference for each media format per task. The reasons for these preferences were reported by coding and clustering similar answers together.

Results (see Figures 1 and 2) for the lived experience show that, in the informational task, Q&A format has the highest valence (-0.14), followed by the video (-0.17), and the webpage format (-0.18). Conversely, for the transactional task, the webpage has a higher valence (-0.13), followed by the video (-0.15) and the Q&A (-0.18). Thus, H1a and H1b are supported for the informational task, but not for the transactional task.

For the perceived experience, the pleasure for the informational task is significantly higher for the Q&A (60.53) than for the webpage (50.54), but no statistical difference is observed between the Q&A and the video format (59.92). On the other hand, for the transactional task, the pleasure is statistically significantly higher for the Q&A format (75.92) than both the video (64.54) and the webpage (64.15). Moreover, the perceived info quality in the informational task is higher for the Q&A format (6.08) than both the video (5.60) and the webpage (5.58). The transactional task shows similar results, where the Q&A format (6.48) has a statistically higher info quality (6.48) than the video (5.92) and a marginally significant difference with the webpage format (6.07). Finally, the perceived effort in the informational task is significantly lower for the Q&A (2.23) than the webpage format (3.15), but no statistical difference is found between the Q&A and the video format (2.54). For the transactional task, on its part, the perceived effort is significantly lower for the Q&A (1.69) than both the video (2.77) and the webpage (2.69). Thus, H2a, H2b and H2d are supported.

The Q&A format in the informational task was preferred by more participants (n=7) participants than the video (n=5) and the webpage (n=1), although the difference between the Q&A and video was not statistically significant. Participants preferred the Q&A because the conversation was perceived to be equivalent to a human-to-human interaction (n=2), the answer was directly in the chat (n=2), and that it let user be in control in the problem solving (n=1). Participants (n=2) also preferred the Q&A because it was a clear and fast interaction. For the transactional task, the Q&A format was also preferred by more participants (n=12) than the webpage (n=1) and the video (n=0). Participants preferred the Q&A because it was simple and easy (n=11) and that it avoided a conversation with a human agent (n=1). Thus, H2c is supported.

Moreover, the preference question revealed that 2 participants seemed positively surprised by the chatbot being able to complete the transaction for them:

"Honestly, I was amazed that it was able to add the new service, I found that really pleasant."

Nonetheless, 3 participants also reported discomfort when it came time to disclose personal information to the chatbot, such as their account password, during the transactional task for the Q&A format.

Finally, there is a marginally significant difference in the perceived pleasure between the video (29.92) and the webpage (50.54) in the informational task. Comparatively, no difference is reported between the two formats in the transactional task. There is also no difference in the perceived info quality, effort, and preference between the webpage and the video formats for both task types. Thus, H3 is not supported.

		Valence	Pleasure	Effort	Info quality	Preferred
Info. task	Q&A	**-0.14**	**60.53**	**2.23**	**6.08**	**7/13**
	Link to webpage	-0.18 *** ***	50.54 *	3.15 *	5.58 * *	1/13 *
	Video	-0.17 *	59.92 ^	2.54	5.60	5/13

Figure 2 Results of lived and perceived experiences for informational task per media format[2]

[2] Valence calculated excluding the first part of the conversation, which was the same for all conversations
^ Marginal statistically significant difference of 0.10
* Statistically significant difference of 0.05
** Statistically significant difference of 0.01
*** Statistically significant difference of <0.0001

		Valence	Pleasure	Effort	Info quality	Preferred
Transac. task	Q&A	-0.18	**75.92**	**1.69**	**6.48**	**12/13**
	Link to webpage	**-0.13** ***	64.15 * *	2.69 ** *	6.07 ^ *	1/13 * *
	Video	-0.15	64.54	2.77	5.92	0/13

Figure 3 Results of lived and perceived experiences for transactional task per media format[3]

2.5 Discussion and conclusion

In the context of informational tasks, findings were in line with what was expected from the MRT in terms of the lived experience, where the Q&A performed the best followed by the video and the webpage text formats. In the context of transactional tasks, however, unexpected results were obtained. To explain this gap, it is plausible that concerns over the (perceived) security of chatbots were at play. Indeed, a few participants indicated they were not comfortable disclosing personal information, such as a username and password, with the chatbot in the Q&A transactional task. This suggests that there may be an interaction effect between task type and perceived security on the lived experience, which would be interesting to investigate further in future research.

For the perceived experience, results were also in line with MRT, such that the Q&A format was associated with a more favorable perceived experience than that of the two other media formats, except for the perceived pleasure and effort between the Q&A and the webpage in the informational task. However, our results did not offer support for the difference in perceived experience between the video and the webpage formats. One factor that could have contributed to this is the fact that the video format was not fully developed. In fact, only a thumbnail of a video was shown to participants. A future experiment could thus study the user experience resulting from different media content formats more in depth by using fully developed chatbot prototypes and the

[3] Valence calculated excluding the first part of the conversation, which was the same for all conversations
^ Marginal statistically significant difference of 0.10
* Statistically significant difference of 0.05
** Statistically significant difference of 0.01
*** Statistically significant difference of <0.0001

user is actually directed to an online video, which they view, rather having them participate in a review of a scenario-based user-chatbot exchange.

Furthermore, our results indicate there was a difference in the lived experience between the video and webpage formats in the two task types, but participants did not report so in their perceived experience. This suggests the limits of self-reported measurements that rely on recalling an experience. Thus, our results give rise to an important consideration for chatbots developers: evaluating a chatbot solely based on perceived measures is done at the risk of missing key insights that physiological data could help generate.

Moreover, given the differences between the results of the informational vs. the transactional task, our results indicate a plausible moderation of the task type on the relation between media content format and users' lived and perceived experiences. One avenue for future research could be to explore further the difference in user experience resulting from various tasks carried out by chatbots and compare which type produces the best experience overall.

To conclude, we explored the effects of three media content formats used in chatbots on both the lived and perceived experiences of users. Despite the small sample size of this experiment – which limits our ability to generalize our results to the population – it seems that indeed an interactive Q&A format might be an optimal chatbot design approach in providing users with sought-after information or assistance with transactions.

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Chapter 3: Article 2

Users' information disclosure behaviors during interactions with chatbots: The effect of information disclosure nudges[6]

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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 in low and high sensitivity questions asked by chatbots. Nineteen people participated in this within-subject laboratory study where they were asked to interact with chatbots asking pre-tested questions of varying sensitivity and presenting different information disclosure nudges. The results suggest that question sensitivity negatively impacts users' 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' behaviors. Finally, considering the growing importance attributed to chatbots and data collection risks online, the theoretical and managerial contributions of this paper are discussed.

Keywords: chatbots, information disclosure, information disclosure nudges, emotional response, privacy, human-chatbot interactions

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3.1 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" (Hussain et al., 2019, p. 946). They are powered by AI and commonly used as recommendation agents. Chatbots work by gathering information from users to deliver better-curated product or service recommendations (Jannach et al., 2021). With the recommendation angle in mind, research on how to make the most powerful chatbots to obtain information from users has been conducted in recent years (Dev & Camp, 2020; Liao & Sundar, 2021; Schanke et al., 2021; Shi et al., 2020). In the same time period, increased chatbots usage by companies raised concerns from users, scholars, and policymakers as data protection became a top issue (Ali, 2014; Gondaliya et al., 2020; Roland, 2020; Saleilles & Aïmeur, 2021). This dichotomy is embodied in the personalization-privacy paradox, which refers to the tension between a company's desire for customer information to tailor experiences and a consumer's need for privacy (Fan et al., 2022).

User risk linked to information disclosure online through chatbots has been proven to negatively impact their experience (Cheng & Jiang, 2020; Rese et al., 2020). On the surface, sharing personal information online can appear totally acceptable to users. Giving up some privacy in exchange for personalized services can be interpreted as a well-considered, even logical, decision by consumers (Rodríguez-Priego et al., 2016; Wu et al., 2012). However, even if they are aware of this trade-off, users may still end up making judgments about disclosure that they subsequently come to regret (Lusoli et al., 2012; Rodríguez-Priego et al., 2016; Wang et al., 2016). This is due to the fact that they are not always aware of when and how data collection happens in their interactions with a company and how this data will be used (Ischen et al., 2020). This reality has also caught governments' attention. Policies regulating how AI is used and chatbot-specific regulations have emerged in many places (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).

However, the current ethical guidelines given by governments fail to provide practical tactics that are proven to make users aware of - and potentially influence - their information disclosure behaviors (Jobin et al., 2019). Arguably, some privacy notices exist, providing users with information on “how and for which purpose their data will be collected, used and managed” (Rodríguez-Priego et al., 2016, p. 434). However, in reality, users tend to rarely read those notices (Groom & Calo, 2011). Moreover, it has been proven that when there is a link to a privacy policy on a website, consumers may end up giving more personal information (Groom & Calo, 2011; Hoofnagle et al., 2010). 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 (Martin, 2015). Another difficulty with the measures in place is the large number of policies present online, each specific to the website they represent, and the often-difficult legal language used (Mao & Ouyang, 2020). Thus, there is a need for simple and standardized tools that make users aware of the information they are about to share, especially with chatbots. By promoting informed decision-making, these tools could represent tactics to influence users’ behaviors in an ethical way and potentially reduce the breadth and depth of information people put on the internet.

The objective of this study is to test measures that could help design more ethical chatbots. Information is commonly disclosed while surfing online and is characterized by being routine and directed by fast thinking (Kahneman, 2011). 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 (Petty & Cacioppo, 1986; Rodríguez-Priego et al., 2016). Information disclosure is also known to be malleable. This means that certain aspects of the online environment can be manipulated to influence privacy behavior (Acquisti et al., 2015; Rodríguez-Priego et al., 2016). Therefore, there is room for interventions that raise awareness of the risks and allow for more cautious disclosure of information. This study evaluates the impact of different nudges in advising users about the information they share with chatbots. This is with the aim of promoting users’ informed behaviors online. 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?**

Based on the literature on chatbots’ design and experience, this research uses Persuasion Theories (Cialdini, 2009; Thaler & Sunstein, 2008) to create two information disclosure nudges: a *sensitivity* *signal* and a *social proof* nudge. These nudges represent tactics that have the potential power to influence human behavior. On one hand, the sensitivity signal which, by simply labeling different questions asked by a chatbot as low or high sensitivity in nature, could influence a user by making them conscious of the sensitivity of the information they are about to share (Thaler & Sunstein, 2008). On another hand, the social proof nudge which, by referring to how many other users disclosed their information in a similar situation, could influence users by making them mimic the same behavior as their fellows (Cialdini, 2009). To the best of the researchers' knowledge, nudges pertaining to information disclosure have been overlooked by research in the context of privacy and user-chatbot interactions so far.

To understand how influence works in users-chatbot interactions, the role of emotional response in the relation between question sensitivity, information disclosure nudges, and information disclosure behaviors is also explored. The *Affect Infusion Model* (AIM) explains ways in which people's judgments are influenced by their emotional response as they process information and their resulting actions (Forgas, 1995). According to the AIM, users may process the information disclosure nudges investigated in this study heuristically, which means they may base their choice to reveal specific information on their emotional state as a result of the available cues in the interaction context. This suggests that users may feel emotional responses in reaction to the chatbot interaction environment, which in turn would impact their behaviors. User emotional response in the context of chatbots have been investigated in the literature, such as how generating positive versus negative emotional response from users lead to more or less conversational breakdowns or the role of empathy in providing supportive medical information through chatbots (Liu & Sundar, 2018; Tärning & Silvervarg, 2019; Wang & Nakatsu, 2013). Nonetheless, emotional response in the context of privacy notices and 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 the user experience and legal aspects but also for the larger ethical discussions surrounding AI (e.g., the lack of regulatory framework, the rapid development of technology, the significant risks, and the high return potential of AI) (Gupta et al., 2021).

Chatbots, powered by AI, are also being pointed at and their usage, as well as power, are being questioned, especially surrounding the data they capture and use (Bang et al., 2021).

Data ethics is a branch of ethics that seeks to evaluate ethical issues brought about by data practices (Cote, 2021). 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 (Martineau, 2022). 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 (Følstad et al., 2021).

In a 2x3x2 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 chatbots' user experience and design with 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 potency of two tangible information disclosure nudges (i.e., sensitivity signal and social proof) in skewing users' disclosures online by confirming the moderate impact of sensitivity signal and refuting the effect of social proof on users' behaviors. 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, the approach used to investigate the manipulation of these information disclosure nudges and their impact on user information disclosure behaviors is explained in depth. The results are then presented. Finally, a discussion around the contributions of this study for researchers and implications for managers is presented.

3.2 Literature review & Theoretical foundation

3.2.1 Chatbots as recommendation agents and users' privacy concerns

Recommender systems have been used by companies in a plethora of industries for a long time (Qomariyah, 2020). Recently, the same ability to recommend products and services has been given to chatbots, known as "recommendation agents", and employed by e-commerce organizations (Chew, 2022). 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 (Adamopoulou & Moussiades, 2020). Data is collected from multiple sources, including the direct messages exchanged between the chatbot and the user (Adamopoulou & Moussiades, 2020).

Most of the earlier research on recommender systems and chatbots focused exclusively on delivering the right recommendation to the user (Ikemoto et al., 2018; Mahmood & Ricci, 2009; Nica et al., 2018). However, it was later found that these agents, because of the way they operate, increase privacy concerns, which in turn negatively impacts the user experience. Cheng and Jiang (2020) found that perceived privacy risk reduces the level of users' satisfaction with chatbots. Rese et al. (2020, 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" (Cheng & Jiang, 2020, p. 6) - such as phone numbers, names, or addresses - which can be exploited by companies and/or shared with unauthorized third parties (Eeuwen, 2017).

Therefore, there exists a clash between the firm's requirement for consumer data in order to customize experiences and the users' desire for privacy (Awad & Krishnan, 2006). This phenomenon is known in the marketing literature as the *personalization-privacy trade-off* (Awad & Krishnan, 2006). 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 (Eeuwen, 2017).

Research confirmed that privacy concerns negatively impacted the information disclosure of users to chatbots (Ischen et al., 2020). 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 (Ischen et al., 2020) or giving the chatbot a human name and qualities to increase the sense of social presence (Ng et al., 2020). However, these strategies all have companies' agenda in mind, where the goal is to gain more data from customers. 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 (Murtarelli et al., 2021). 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" (Murtarelli et al., 2021, p. 928). However, the study of information disclosure from a user's perspective - as to make users aware of and potentially decrease their disclosures to chatbots - has been overlooked in the literature.

3.2.2 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 (Lee et al., 2015; Metzger, 2007) and the relevance of the information asked to the given context (Li et al., 2010, 2011). These variables "have been most frequently shown to have a significant impact" (Kolotylo-Kulkarni et al., 2021, p. 225).

Question sensitivity

Question sensitivity depends on the sensitivity of the information being requested. There exist numerous definitions that aim to describe information sensitivity (Ohm, 2015). In this research, 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" (Harrison, 2006, p. 67). Question sensitivity is known to change through time and cultures (Harrison, 2006). It has also been proven that people are more averse to disclosing more sensitive information (Lee et al., 2015; Metzger, 2007; Mothersbaugh et al., 2012).

Question sensitivity is relevant to user-chatbot interactions, as chatbots usually ask multiple questions to gain information from users, naturally ranging from general to more sensitive in nature (Lee et al., 2020).

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" (Stone, 1981, p. 92). Question relevance has been proven to impact the way users disclose information. People are more likely to disclose information that is perceived as relevant to the context (Li et al., 2010, 2011).

When it comes to chatbots, they are known to be used in specific contexts. Thus, queries made by the chatbot need to be related to the context of use. This is to exclude bias that could arise by asking questions that users would simply refuse to answer because they were related to the context presented.

Information disclosure

Customers' information disclosure originates from the idea of *self-disclosure* in the psychology literature defined as "any information about [oneself] which Person A communicates verbally to a Person B" (Cozby, 1973, p. 73). Information disclosure online can happen implicitly or explicitly (Xiao & Benbasat, 2007). On one hand, data can be collected indirectly through the use of cookies, location data, etc. On the other hand, data can also be gathered directly by asking users for their information (Hasal et al., 2021). This research focuses on the latter, by looking into information disclosure that is explicit from users to chatbots.

People's disclosures are known to be multidimensional (Knijnenburg et al., 2013) meaning disclosures can be broken down into distinct factors 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 (Joinson, 2001; Wang et al., 2016). Despite these, one of the simplest ways to assess disclosure is through the use of two simple axes: the *breadth* and the *depth* of disclosure (Joinson et al., 2008). Breadth means the number of disclosures, while depth refers to the sensitivity of each disclosure. Joinson et al.'s research (2008) found two proxy measures to evaluate these axes. Allowing users to leave a question unanswered permits to measure the breadth of disclosure and the "inclusion of items of varying sensitivity" measures the depth of disclosure (Joinson et al., 2008, p. 2168).

Disclosure in the context of chatbots has mostly been studied for social bots and mental health conversational agents (Lee et al., 2020; van der Lee et al., 2020; van Wezel et al., 2021). User disclosure to chatbots used as recommendation agents in an e-commerce context is not as covered in the literature. To better understand how information disclosure happens in online transactions, two phenomena are presented below.

Privacy calculus

The *privacy calculus* originates from the Theory of Reasoned Action (Ajzen & Fishbein, 1980) and Theory of Planned Behavior (Ajzen, 1991) and is defined as the risk-benefit dilemma users face when engaging in online transactions (Dinev & Hart, 2006; Hui et al., 2007). In general, in a transaction, incentives are offered by the company in exchange for a certain degree of privacy of the user (Dinev & Hart, 2006; Hui et al., 2007). 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 experiences. 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 services recommendations that are deemed tailored to their profile (Kobsa et al., 2016). 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 lower in sensitivity.

Taking the above into consideration, we predict that the relationship between question sensitivity and information disclosure will be as followed:

H1: Question sensitivity negatively influences user's information disclosure to chatbots.

Online privacy paradox

Looking further into information disclosure online, there also exists a phenomenon called the *online privacy paradox* (Brown, 2001). This phenomenon states that privacy concerns do not necessarily correlate with actual disclosure (Kokolakis, 2017). In fact, there is a paradox between users' *willingness to disclose* information versus what they *actually* disclose (Dienlin & Trepte, 2015). In other words, 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 studies information disclosure in human-chatbot interactions focuses on users' willingness to disclose (Carlton, 2019; Zierau et al., 2021). However, the online privacy paradox implies that these results might be skewed, and users would in practice disclose more than they say in theory. Moreover, this paradox challenges the assumption that people's information disclosure behaviors to be always come from a rational decision-making process (Wilson & Valacich, 2012). This phenomenon shows the importance of creating tactics that make users aware of their disclosures online.

3.2.3 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" (Simons, 1976, p. 7). In recent years, it has been proven that persuasion is not only specific to human-human conversations but can be applied by other entities, such as chatbots (Rönnberg, 2020). This is in line with the *Computer Are Social Actor* (CASA) paradigm which states that humans mindlessly apply the same social heuristics used for human interactions to computers, because they call to mind similar social attributes as humans (Nass & Moon, 2000). Thus, the persuasion literature could be leveraged to create tactics to influence users in their behaviors when it comes to disclosing information to chatbots.

Elaboration likelihood model

The *Elaboration Likelihood Model* (ELM) comes from the psychology literature and helps understand how humans process information cognitively and are persuaded when presented with different stimuli (Petty & Cacioppo, 1986). The main idea of this model is that people process information with two paths (or routes): 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" (Petty & Cacioppo, 1986, 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 (Petty & Cacioppo, 1984). When elaboration likelihood is low, factors other than logic 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 (Petty & Cacioppo, 1984).

A common example to explain how the ELM works 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 small informational cues about the car.

In sum, this model helps understand how people are persuaded. Persuasion happens when a persuader is successful in influencing a person in a certain way. Persuasion in the peripheral route happens when the former processes information through cues that trigger the peripheral instead of the central path. Based on this theory, we leverage existing cues and apply them to user-chatbot interactions to inform users in an efficient manner that they are about to disclose certain information. These cues could consequently influence their behaviors when sharing - or not - information with the chatbot. The *Nudge Theory* (Thaler & Sunstein, 2008) and Cialdini's (2009) *Persuasion Theory* presented below are examples of these cues put into practice and will serve as a base to create what we will call *information disclosure nudges* for this research.

Nudge Theory

The *Nudge Theory* was first introduced by Thaler and Sunstein (2008) 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 it is affected by the display of possibilities in a choice context (Schneider et al., 2018; Sunstein, 2014; Weinmann et al., 2016).

Nudging aims to design the environment within which a choice is made to make people lean a certain way versus another. Nudging also pledges to respect freedom of choice (Kahneman et al., 1991; Thaler & Sunstein, 2008). Nudges have been used in the digital world, by changing certain user-interface design elements to guide users' behaviors (Adam & Klumpe, 2019; Benlian, 2015; Fleischmann et al., 2016; Wessel et al., 2019).

Sensitivity signal

Based on the *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 (Kerr et al., 2015). Being informed of the calories, for instance, in each menu item has been proven to improve transparency to customers about what they put in their body and, in some cases, change order behavior (Borgi, 2018). 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 (FTC, 2013).

When it comes to information disclosure to chatbots, the same kind of reasoning could be applied. Based on the literature since information sensitivity is known to be a determining factor in disclosure. 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 user's information disclosure is moderated by the question *sensitivity signal*, whereas:

> **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.

Cialdini's persuasion tactics

Another common nudge is the *social proof* originating from Cialdini's (2009) 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 nudge theory and can be deployed for the scope of this research (Acquisti et al., 2015; Ioannou et al., 2021; Klumpe, 2020; Zhang & Xu, 2016).

Social proof is a subset of the nudge theory defined as "social influence refers to the way individuals change behavior in direct response to unwritten social laws" (Klumpe, 2020). According to Mirsch et al. (2017), 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 (Cialdini & Goldstein, 2004). 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 user's information disclosure such as greater social proof leads to more disclosure and less social proof leads to less disclosure.

3.3.5 Mediating effect of Arousal

Affect Infusion Model

Emotions are an important component of both human-human communication and human-machine interaction (Brave & Nass, 2002; Rapp et al., 2021). 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” (Rapp et al., 2021, 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 (Forgas, 1995). In other words, it explores how emotions are infused into thoughts as people process information and their resulting response behaviors in interactions with others. An emotion is defined as a brief but powerful feeling resulting from a clear cause and cognitive content (Forgas, 1995). 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)” (Cosby, 2020, p. 19). 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 (Russell, 1980). Arousal assesses the intensity of an emotional state, whereas emotional valence specifies whether an emotion is positive or negative (Russell, 1980).

The 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 the *Heuristic processing* or *Affect-as-information* (Clore & Parrott, 1991; Schwarz & Clore, 1988). Referring to the ELM proposed by Petty and Cacioppo (1986) and discussed above, the heuristic processing is comparable to the peripheral route to processing information (Forgas, 1995). 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 (Paulhus & Lim, 1994). 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 (Schwarz & Clore, 1988). 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 (2013) 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. (2020) 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 (2018) studied the role of empathy in chatbots' ability to provide comforting medical information. Finally, in the context of customer service, Xu et al. (2017) analyzed 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 (Gaffey & Wirth, 2014). As the *privacy calculus* presented above explains, being asked sensitive questions represents a risk for users (Dinev & Hart, 2006). Thus, emotional response could be a natural response in chatbot interactions when sensitive questions are asked, compared to general questions. Moreover, emotional response may act as a predictor of users' information disclosure. Emotional response is an automatic physiological reaction to events (Gaffey & Wirth, 2014). 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 (Cannon, 1915; Gaffey & Wirth, 2014). 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 mediate the relationship between question sensitivity and information disclosure such as:

H4a Question sensitivity positively influences emotional response.

H4b Emotional response 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 (Miniard et al., 1992). 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 among users, we posit that the relationship between question sensitivity signal and emotional response is moderated by sensitivity signal such as:

H5a: When a low sensitivity signal is present (vs. absent) for less sensitive questions, emotional response decreases.

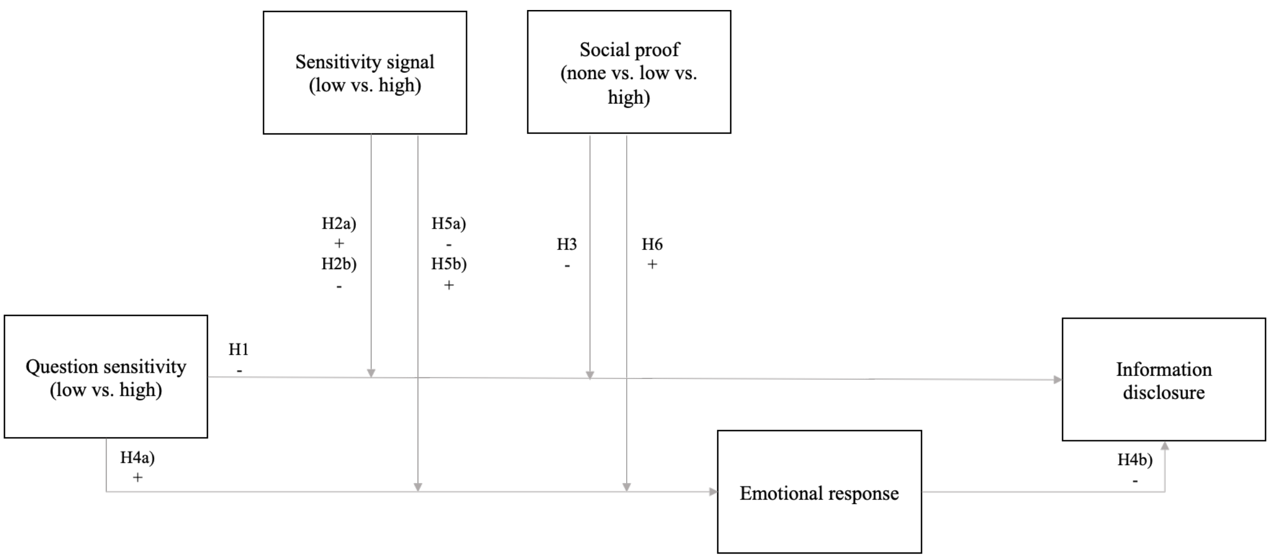
H5b: When a high sensitivity signal is present (vs. absent) for more sensitive questions, emotional response increases.

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 and less social proof leads to higher emotional response.

To conclude the literature review, the following figure depicts the research model as a summary of the relationships presented above.

Figure 1 Research Model



3.3 Method

To test the user behaviors when interacting with chatbots and the potential effect of information disclosure nudges, an experimental design was developed. The study measured the impact of question sensitivity, information disclosure nudges, and emotion on user behaviors in a lab experiment conducted at Tech3Lab. This study was approved by the Research Ethics Board (REB) from HEC Montréal (Certificate 2022-4721).

3.3.1 Experimental design

To test the hypotheses, a 2 (question sensitivity: low vs. high) x 2 (sensitivity signal: absence vs. presence) x 3 (social proof: none vs. low vs. high) within-subject 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 get 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.

The following figure depicts the experimental design, including the tasks, the nudges combination each task represents, their randomly assigned context, and the questions’ sensitivity levels.

Figure 2 Experimental design

		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*

3.3.2 Stimuli development

Chatbot interface

The 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; 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.

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 bank of 210 questions centered around 6 contexts (35 questions per context) was prepared in advance based on inspiration from research in the literature that also studied sensitive topics (Knapp & Kirk, 2003; Ng et al., 2020) (e.g. in the travel context: Are you fully vaccinated against Covid19?; Refer to Appendix 1 for the full list of questions).

To be eligible to complete the questionnaire, participants had to be located in North America and have a HIT approval rate of at least 90% to ensure the quality of responses. Participants were given a $1 USD compensation for their participation. 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 or answered questions randomly, 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. 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.

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 (Harrison, 2006). 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.

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

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 with 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 on SPSS (Armonk, NY, USA) to confirm that the difference between the low and high sensitivity questions 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.

Table 2 Comparison of low and high sensitivity questions per context

		Low sensitivity questions			***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	4.20	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 on SPSS to verify that all the low sensitivity questions groups from the six different contexts were not statistically different - in other words, equivalent - and the same was done for all the high sensitivity questions groups. The summary of these tests is presented in the following tables.

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			

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

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 0.042. 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 the low sensitivity manipulation, and the questions classified as sensitive, the high sensitivity manipulation. Meanwhile, *relevance* was a control variable in this study.

Sensitivity signal

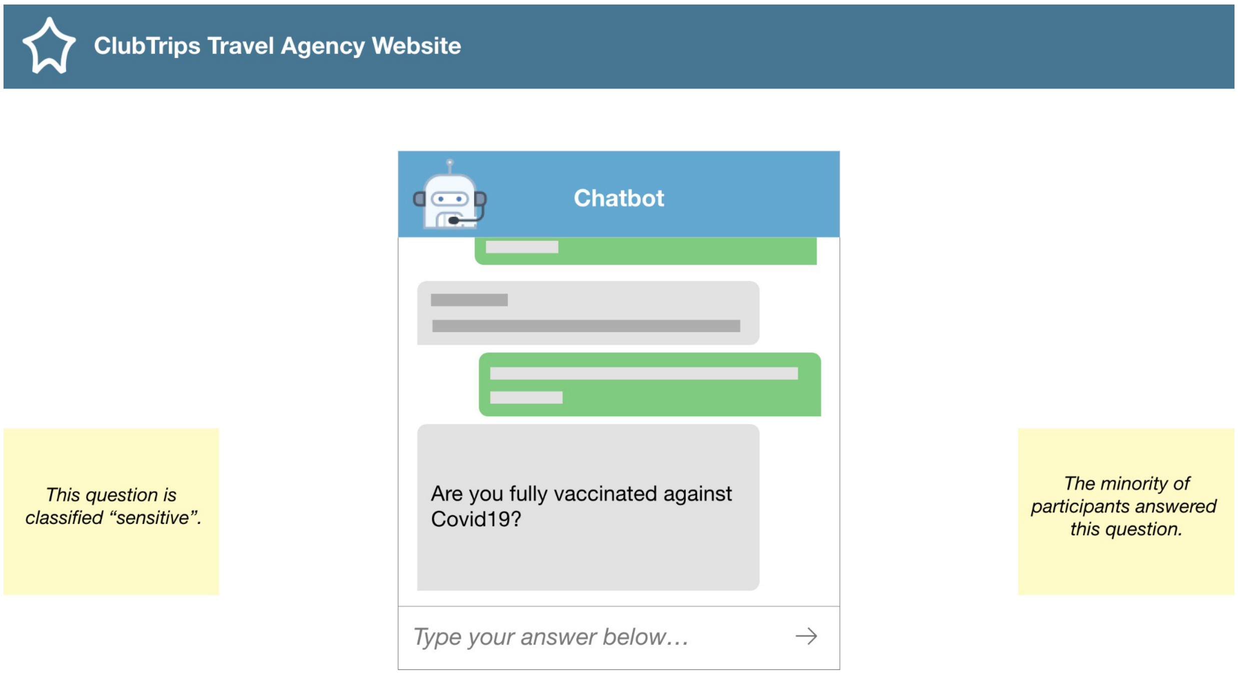
In this research, the sensitivity signal took the form of labels. The *sensitivity signal* was represented as a sticker on the left side of the chatbot, if present, and signaled to the user the question's level of sensitivity: *general* (low sensitivity) or *sensitive* (high sensitivity).

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.

The figure below shows an example of the chatbot stimuli where a high sensitivity question in the travel context including a present sensitivity signal and low-level social proof nudge are present.

Figure 3 Example of a high sensitivity question in the travel context with sensitivity signal (present; high) and social proof nudge (low)



3.3.3 Lab experiment

<u>Participants</u>

In total, 26 people 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 were compensated for their time with a $25 interact transfer. The table below presents the participants' demographics.

Table 5 Demographic variables

Gender		N=19	
	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]
	Morrocco	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

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 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 get 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 participants unplugged the electrodermal activity device and fill out the compensation form. They were then thanked for their time and escorted out. Overall, the experiment lasted about an hour.

Measures

We captured the participants' eye movements on the computer screen, as well as sweat in the palm 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). Regarding *valence*, the contexts used in this research imply chatbots that are used to get recommendations, which represents a utilitarian process, meaning not much variation in valence is expected to be derived (Tessier, 2018). Thus, valence was not included in this study.

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*

(Carlton, 2019; Zierau et al., 2021) and to minimize 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. The following table presents the variables' operationalization.

Table 6 Variables operationalization

Construct	Item(s)	Scale	Source
Question sensitivity	Pre-tested questions	Low and high sensitivity questions	Developed by researchers
Sensitivity signal	Low sensitivity signal: This question is classified "general". High sensitivity signal: This question is classified "sensitive".	Present vs. Absent	Developed by researchers
Social proof	Low social proof: The minority of participants answered this question. High social proof: The majority of participants answered this question.	None vs. Low social proof vs. High social proof	Developed by researchers
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	Arousal (EDA)	Phasic EDA	Biopac inc. (Goleta, CA, USA)
Information disclosure	Response rate	Answer vs. no answer to the question	Developed by researchers

3.4 Results

3.4.1 Results

Manipulation check

Before looking at the results predicted by our hypotheses, we conducted a manipulation check to confirm that users look at the information disclosure nudges when presented with 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 seconds (std dev=7.41) when present compared to 0.02 seconds (std dev=0.04) when absent. For the social proof nudge, people looked on average 2.03 seconds (std. dev=6.87) when present compared to 0.00 seconds (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.

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 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%). The following figure summarizes these results in a table.

Table 7 Response rate per nudge combination and question sensitivity

		Social proof		
		None	Low	High
Sensitivity signal	Absence	*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
	Presence	*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 and maximum 12.60µS. 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 (9.9µS) than high sensitivity questions (10.4µS). When only the sensitivity signal was present, arousal was higher in low sensitivity questions (10.6µS) compared to high sensitivity questions (10.3µS). When low social proof was present, arousal was higher for low sensitivity questions (9.3µS) than for high sensitivity questions (9.1µS). When high social proof was present, arousal was higher in low sensitivity questions (10.5µS) than in high sensitivity questions (10.1µS). When both the sensitivity signal and low social proof were present, arousal was the same for the low sensitivity questions (9.0µS) and high sensitivity questions (9.0µS). When both the sensitivity signal and high social proof were present, arousal was lower for low sensitivity questions (8.9µS) compared to high sensitivity questions (10.2µS). The following figure summarizes these results in the form of a table.

Table 8 Arousal per nudge combination and question sensitivity

		Social proof		
		None	Low	High
Sensitivity signal	Absence	*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
	Presence	*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

3.4.3 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 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).

Effect of question sensitivity on information disclosure (H1)

To test whether question sensitivity negatively influences user's 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.

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 user's information disclosure such as greater social proof leads to more disclosure and less social proof leads to less disclosure (H3). The following table 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	tValue	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 question 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 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.

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 influences emotional response (H4a) and emotional response negatively influences 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, emotional response decreases (H5a) and that when a high sensitivity signal is present (vs. absent) for more sensitive questions, emotional response increases (H5b). Moreover, we hypothesized that social proof moderates the relationship between question sensitivity and emotional response such as greater social proof leads to lower emotional response and less social proof leads to higher emotional response (H6). The table below summarizes these results.

Table 10 Linear regressions: effect of information disclosure nudges on emotional response

Nudge comparison	Question sensitivity	Estimate	StdErr	DF	tValue	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.

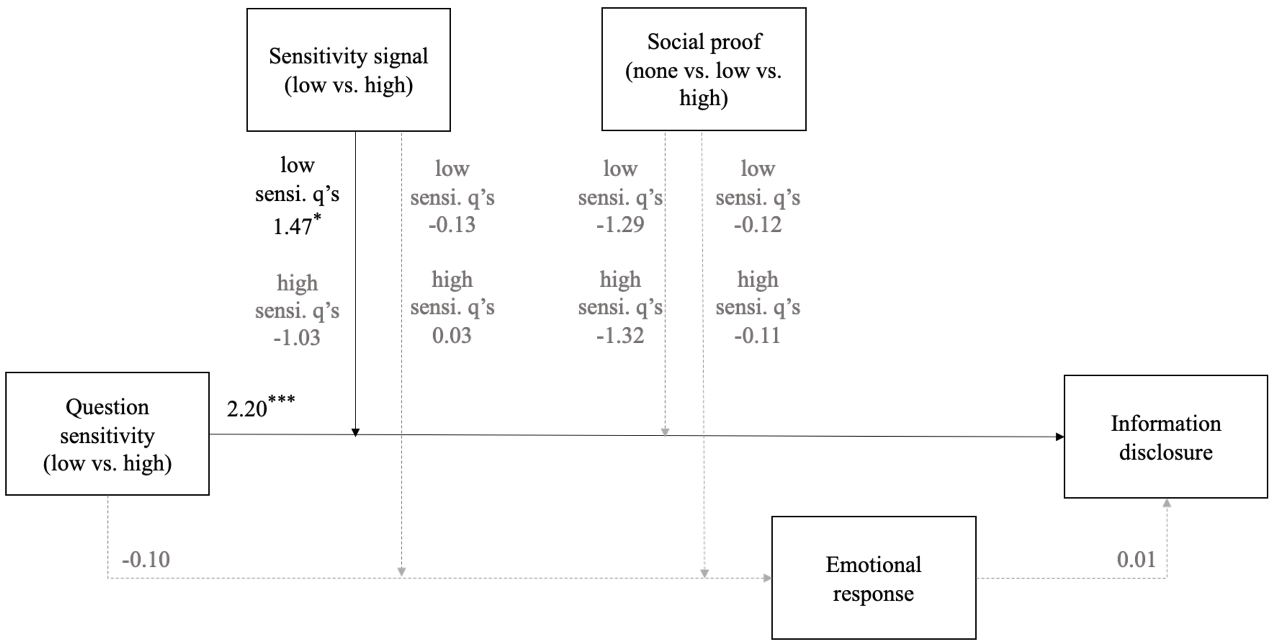
The results show that, for high sensitivity questions, emotional response decreases (estimate=-0.03) when high sensitivity signal is present compared to when absent. This result is marginally significant with a p-value of 0.0511. Since the results are contrary to the hypothesis, H5b is not supported.

For the social proof nudge, the results show that emotional response decreases when social proof is low compared to when 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 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.

To conclude the results section, the following figure depicts validated research model.

Figure 4 Validated research model



3.6 Discussion and conclusion

3.6.1 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 seem to decrease emotional response. On the other hand, the social proof nudge does not seem to affect users' disclosure behaviors not their emotional response. Finally, it was suggested that emotional response does not seem to be a mechanism explaining how user disclosure operates in interactions with chatbots.

3.6.2 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. Indeed, research on antecedents to disclosure had previously proven that sensitivity played a role in disclosure, however, it had not been explored in a chatbot context (Lee et al., 2015; Metzger, 2007; Mothersbaugh et al., 2012). The present study suggested that this link 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 don't make judgments about their privacy based on what others do. These results come to complement previous research on nudging and privacy for disclosure of personal information online (not 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 (Ioannou et al., 2021). 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 (Becker et al., 2020; Rudnicka et al., 2019). In our case, the low sensitivity signal goes in accord with these previous results, by increasing 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 social proof, used to affect users' privacy decision-making online (Ioannou et al., 2021). According to research, social cues, such as knowledge that a majority of users' peers have taken similar actions, like disclosing personal information, can lead to an increase in information disclosure on websites (Acquisti et al., 2015; Zhang & Xu, 2016). In the present case, by refuting the effect of such a nudge in user-chatbot interaction, this study complements previous results in the literature by marking a distinction between online and chatbot-specific interactions.

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, 7 participants answered all questions and 12 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 5 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 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 (Lee et al., 2020; Liu & Sundar, 2018; Pérez-Marín & Pascual-Nieto, 2013; Xu et al., 2017). 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 (Forgas, 1995). 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.

3.6.3 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 (Schmidt & Engelen, 2020). The information disclosure nudges tested in this research did not always predict user behavior. Nonetheless, from an ethical perspective, users deserve to make informed decision-making in their online interactions. At the end of the day, the goal of interfaces should be to give users control, not to choose for them what they put out on the internet, especially through chatbot interactions

(Murtarelli et al., 2021). Thus, policymakers can scrutinize this research for inspiration when drafting policies that provide more information to users in online interactions with chatbots.

3.6.4 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 ethics 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 gives potential avenues for other nudges that could promote informed decision-making when it comes to information disclosure to chatbots and should 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. In terms of the placement of the information disclosure nudges, we put them in strategic places for the eye tracking technology used in this research. The nudges were thus placed on either side of the chatbot. Along the same line, although the nudges were uniform in size and color, it is possible that larger or the design of the nudges would have made them more impactful. Future research could investigate the most optimal location and design for the information disclosure nudges to be more influential on users' behaviors.

Finally, the results of this study showed that almost more than a third of participants (7 out of 19) 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. Some avenues to explain this phenomenon could involve the users' level of comfort with online privacy and sensitive issues or the cultural background of these individuals. These factors should be explored in the future as finding this determining factor could be valuable for both business organizations to better understand their customers and policymakers to draft distinct policies for different types of users.

3.6.5 Conclusion

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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Chapter 4: Discussion and Conclusion

This thesis aimed to explore the experience of chatbots from a user's perspective in two different ways. First, through a pilot study on the user experience with chatbots' different media content formats. Second, with an empirical study on users' information disclosure behaviors with chatbots.

This chapter presents a summary of each article by reminding the method used in each study, their respective research questions, as well as their results. Finally, the theoretical and managerial contributions of this thesis as well as future research avenues are discussed.

4.1 Reminder of research questions and main findings

4.1.1 Article 1

The effect of three media content formats used in chatbot design on both the lived and perceived experiences of users was explored in a 3 (media content format: link to a webpage vs. video vs. Q&A) x 2 (task type: informational vs. transactional) within-subject experimental design. Thirteen people participated in this study consisting of reading and rating pre-determined user-chatbot interactions. The results of this study made it possible to confirm or reject the proposed hypotheses.

First, this study's results suggested that in an informational task, users' valence is more positive when a chatbot uses a Q&A format rather than a video or webpage format. Second, the results suggested that users' perceived pleasure is significantly higher when chatbots use a Q&A format rather than a webpage in an informational task. In transactional tasks, a Q&A format yields high perceived pleasure than both a video and webpage format. Similarly, information quality is perceived as significantly higher when a chatbot uses a Q&A format than a video or a webpage format when performing informational and transactional tasks. Moreover, effort is perceived as significantly lower when users are chatting with a chatbot using a Q&A format over a webpage when a task is informational, while it was perceived as lower than both a video and webpage when a task is transactional. Results also suggested that users prefer a Q&A format over a webpage format when performing an informational task with a chatbot and both a video and webpage in a transactional task.

Finally, when comparing chatbots using a video format versus a webpage format, the results showed that valence is more positive for a video format in an informational task. However, for a transactional task, no significant difference in valence is observed between the two media formats. Concerning the perceived pleasure, a marginal difference is observed between the two formats putting the video higher than the webpage in the informational task, but no difference is observed in a transactional task. There is also no difference in the perceived info quality nor the perceived effort between these two media formats for both informational and transactional tasks. Finally, no significant difference is found in the users' preference between the webpage and the video formats for both informational and transactional tasks

These hypotheses were developed to answer the research question: **Does the media content format, one that varies in richness – such as interactive conversation, video, and link to a webpage – used by a chatbot impact the users' lived and/or perceived experience?** These results showed that an interactive Q&A might be an optimal chatbot design approach (compared to a link to a webpage or a video) in providing users with sought-after information or assistance with transactions. These results confirm that the Media Richness Theory is applicable to user-chatbot interaction. This is consistent with other research, such as Lei et al.'s (2021) findings which revealed that a higher media richness positively influenced trust and reuse intention of chatbots. Androutsopoulou at al. (2019) also confirmed the use of MRT in chatbot research by proving that chatbots are better suited than traditional online forms to help users perform information and transaction tasks on governmental websites because chatbots represent a richer channel for interaction.

These hypotheses also helped answer the research question: **Does the task type, whether users ask for information or transactional assistance, moderate the relation between the type of media content format and the users' lived and/or perceived experience?** Based on the differing results between the informational and the transactional task, this study highlighted a plausible moderation of the task type on the relation between media content format and users lived and perceived experiences. Other research in the chatbot literature have also detected this distinction. Kvale et al. (2021) reported a variation in the customer satisfaction in response to different customer service tasks performed by chatbots. Følstad & Brandtzaeg (2020) studied the spectrum of user experience generated by chatbots based on Hassenzhal's pragamatic-hedonic framework. The researchers noted two differing application and resulting experience when chatbots are used for pragmatic purposes. On one hand, the user experience generated by pragamtic chatbots used for help and assistance was heightened when the chatbot was perceived as useful and of practical value. On the other hand, pragamtic chatbots used for information and updates performed better when they were perceived as supporting.

4.1.2 Article 2

The second research explored the impact of question sensitivity, information disclosure nudges, and emotional response on users' information disclosure behaviors in chatbot interactions. A 2 (question sensitivity: low vs. high) x 2 (sensitivity signal: absence vs. presence) x 3 (social proof: none vs. low vs. high) experimental design was used in this study. An online questionnaire was administrated to 316 participants to test the sensitivity and relevance of the questions to be asked by the chatbots in the lab experiment. Subsequently, 19 people participated in a lab experiment consisting of chatting with six different chatbots to get better product and service recommendations. Based on the results, the research hypotheses in this study were either supported or rejected.

First, the findings suggested that a question is less likely to be answered if it is highly sensitive compared to when it is low in sensitivity. Second, when looking at the effect of a sensitivity signal on users' disclosure behaviors, the results showed that the response rate to low sensitivity questions increases when a low sensitivity signal is present. However, for high sensitivity questions, the difference in the response rate when a high sensitivity signal is present compared to when absent is not significant. Third, the results of the social proof nudge suggested no effect on users' disclosure behaviors.

These hypotheses were developed to answer the research question: **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?** This research suggested that question sensitivity has an impact on disclosure in user-chatbot interactions. This result is consistent with previous research on question sensitivity and disclosure (not specific to chatbot interactions) (Lee et al., 2015; Metzger, 2007; Mothersbaugh et al., 2012). In fact, Motherbaugh's (2012) research suggested that the sensitivity of information is an antecendent to disclosure in an online service context, while Lee et al. (2015) reported the same results in an e-commerce setting.

Moreover, the results of this research proposed that a sensitivity signal seems to influence disclosure by increasing disclosure to low sensitivity questions when a low sensitivity signal is present. However, a high sensitivity signal and a social proof nudge does not seem to affect users' disclosure behaviors to chatbots. Overall, the results showed that people seem to rely more on their own judgment than information disclosure nudges when it comes to disclosing general and sensitive information online to chatbots. These ambiguous results of the effect on nudges is consistent with previous research on nudges and information disclosure: "while some studies found nudging to be highly effective, other studes found no such effect" (Ioannou et al., 2021, p.1). For example, Becker et al. (2020) found that using persuasive messages with a more positively framed attributed and messages with high argument strength based on the reasons for data collection led to more information disclosure by individuals. On the other hand, Rudnicka et al., (2019) found that while persuasive messages framed around learning increased disclosure to sensitive items, people did not change their disclosure behavior for messages framed around social proof, contribution, and altruism.

Concerning the results around the role of emotional response, this study suggested that for high sensitivity questions, a high sensitivity nudge seems to marginally decrease emotional response. However, the other results of the effect of emotional response were not significant.

These hypotheses were related to the research question: **Does user emotional response mediate the effects of question sensitivity and information disclosure nudge type on their disclosure behavior?** The results show that arousal does not appear to be a mechanism that explains how disclosure works in user-chatbot interactions. However, previous research on affect and online information dislcosure tells another story. Wakefield (2013) suggested that positive affect has a signifcant effect on users' online information disclosure. Additionally, Coker & McGill (2020) stated that arousal increases self-disclosure. Their contradictory results to the ones reported in this research could highlight a plausible difference in users' behaviors when interacting with websites versus chatbots.

4.2 Theoretical and managerial contributions

4.2.1 Theoretical contributions

From a theoretical perspective, the results of this thesis permit to add to the existing knowledge in the literature on human-computer interaction in three ways. First, given the increasingly common integration of chatbots in e-commerce contexts, understanding the impact of the media content format of chatbots on perceived and lived user experience is crucial (Sheth et al., 2019; Kantarci, 2021). The main results of this thesis highlight that the optimal design approach for the user experience with chatbots when providing users with sought-after information or assistance with transactions is an interactive questions and answers format. These results are consistent with the *Media Richness Theory* (Daft & Lengel, 1986), in a chatbot context. Moreover, given the differences between the results of the different tasks in this study, the results indicate a plausible moderation of the task type on the relation between media content format and users' experiences.

Second, this thesis explored how information disclosure happens in user-chatbot interactions. Scholars need to investigate this question and promote informed disclosure behaviors to users, given the importance and risk that information disclosure online via chatbots represents (Ali, 2014; Gondaliya et al., 2020; Roland, 2020; Saleilles & Aïmeur, 2021). The results of this thesis back up previous research on people's disclosure behaviors suggesting that sensitivity has an impact on disclosure (Lee et al., 2015; Metzger, 2007; Mothersbaugh et al., 2012). This research adds to the body of knowledge by confirming this relationship in the context of chatbot interactions.

Third, the results of this research suggested that information disclosure nudges did not always predict user behavior, although the sensitivity signal seemed more promising than social proof. The stronger results for the sensitivity signal might be due to the fact that user disclosure is an intrinsic behavior and people don't make judgments about their privacy based on what others do. These results complement previous research on nudging and privacy for disclosure of personal information online (not specific to chatbots) (Acquisti et al., 2015; Becker et al., 2020; Ioannou et al., 2021; Rudnicka et al., 2019; Zhang & Xu, 2016).

4.2.3 Managerial contributions

The results of this thesis also have an impact on managers and policymakers. First, the main results of this thesis highlight that an interactive questions and answers is the optimal format for chatbot design when providing users with sought-after information or assistance with transactions. Companies should consider these results when investing in new customer service technologies such as chatbots. Second, this research suggested that when it comes to information disclosure to chatbots, users base their decision to answer queries from chatbots on their own judgments rather than external cues such as information disclosure nudges. Nonetheless, the results also suggested that the nudges may serve to confirm users' decisions to answer a question. Specifically, 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. This is important for policymakers when drafting policies to promote the ethical use of AI systems in an e-commerce context.

4.3 Limitations and future research avenues

To contextualize the results of this paper, some limitations must be addressed. Most importantly, the samples of the studies presented in this thesis consisted of 13 and 19 participants, which could be characterized as small. Although these are typical sample sizes for NeuroIS research (Riedl in Leger, 2016), future research could still replicate these studies by increasing the sample size to confirm the results presented above. Additionally, using larger sample sizes would allow future research to consider cultural differences that may impact the way users interact with chatbots.

Both studies presented in this thesis evaluated the user experience between users and chatbots in a question-and-answer format. Additional research building on the results of the presented two articles should be conducted to optimize this particular interaction format further.

To conclude, more research on user experience with chatbots need to be conducted to get a better understanding of the limitations and opportunities of using these AI-powered systems. Looking at the chatbot experience from a users' perspective is crucial for business organizations in the age of personalization and user-centered design. This will allow to further contribute to the creation of design as well as ethical guidelines on chatbot development and usage.

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Appendix 1: Article 2 - Full list of 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
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 your life?	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
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 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

Which places in the world do you think are too dangerous to visit and why?	Travel	High
Is there a legal reason why you could not travel to a specific country?	Travel	High