

## **When Live Chats Make Us Disclose More**

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# When Live Chats Make Us Disclose More

Short Paper

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## Abstract

*To facilitate a synchronous communication with website users, numerous organizations have started implementing live chats on their websites. The current study asks whether and when the mere presence of live chats affects website users' disclosure of personal information on a website. The findings of two empirical studies reveal that the mere presence of a live chat on a website decreases the extent of website users' subsequent self-disclosure. A human- compared to an artificial intelligence (AI)-based live chat reduces the breadth of self-disclosure. These findings offer the various implications for website providers.*

**Keywords:** Live chat, self-disclosure, chatbots, artificial intelligence

## Introduction

Organizations across industries (e.g., retailers, service providers, and public authorities) have started using live chats on their customer-facing websites. In this way, website users can enter a real time communication with a service agent. This agent can be either a human or an artificial intelligence (AI) (i.e., bot) (McLean & Osei-Frimpong, 2019; McLean, Osei-Frimpong, Wilson, & Pitardi, 2020). Live chats — especially those operated by AI — contribute to an automation of services while trying to warrant high service quality standards. For instance, AI-based live chats can serve a large volume of customers simultaneously while conducting natural and personalized dialogues with complex requests (Luo, Tong, Fang, & Qu, 2019; Magelan Solutions, 2020).

Despite the increasing use of live chats on websites, systematic research on their effects is still incomplete. Existing research has looked at the factors determining peoples' initial and continued use of live chats (McLean et al., 2020; McLean & Osei-Frimpong, 2017, 2019). Previous research has also gained an understanding on how AI-based live chats affect the relationship to the service provider in terms of trust and loyalty (Hildebrand & Bergner, 2020; Mozafari, Weiger, & Hammerschmidt, 2021a). While evidence exists for that the interaction with live chats strengthens the relationship to the firm (Hildebrand & Bergner, 2020), available findings also suggest that this loyalty-enhancing effect of chatbots depends on the type of chatbot (Mozafari, Weiger, & Hammerschmidt, 2021b). These works imply that an interaction with live chats is required to unfold an effect on individuals' subsequent responses. However, individuals' responses might also be triggered by the mere or non-interactive presence of website cues, such as live chats. The mere presence of *social* website cues, such as social media icons or like buttons, was found to influence

individuals' behavior (Townsend, Neal, & Morgan, 2019). Live chats might also be categorized as a type of social cue as they offer the opportunity to communicate with someone else. This might be particularly true when the live chat is operated by a human instead of an AI service agent.

Hence, the aim of this research is to investigate how and when the mere presence of live chats affects individuals' website usage behavior. More specifically, we look at the effects of the mere presence of live chats on individuals' self-disclosure (i.e., the voluntary disclosure of personal information). Peoples' self-disclosure is an important indicator for ones' willingness to enter a relationship with the service/website provider because humans typically disclose personal information in social situations when they seek to make a connection to another person (Jacobs, Hyman, & McQuitty, 2001; Moon, 2000). Technically, website users' voluntary disclosure of personal information is fundamental for executing or personalizing services. Hence, self-disclosure is a non-monetary payment method for a service (Yuchao, Ying, & Liao, 2020). Besides this, understanding the underlying mechanisms of self-disclosure is important because peoples' voluntary self-disclosure on the Internet can represent a severe threat to privacy (e.g., risk of data breaches).

Our research underlies the assumption that the mere presence of social cues on websites, such as live chats, makes websites to a social environment where people apply rules that they typically apply in physical social interactions (Moon, 2000; Wang, Baker, Wagner, & Wakefield, 2007). As people were found to perceive the mere presence of other social actors in physical surroundings as an invasion to privacy (Esmark, Noble, & Breazeale, 2017), this research assumes that the mere presence of live chats reduces the extent of self-disclosure. Moreover, this research suggests that the type of live chat (human *versus* AI) affects the extent of self-disclosure. In other words, this research provides answers to these questions: (1) To what extent does the mere presence of a live chat affect ones' self-disclosure on a website? (2) To what extent does the mere presence of a human- *versus* an AI-based live chat affect ones' self-disclosure on a website?

## Conceptual Development

### *Live Chats on Websites*

Numerous organizations have started implementing live chats on their websites (Magelan Solutions, 2020). With instant messaging applications, these tools facilitate a one-to-one synchronous communication in an environment which is naturally characterized by a lack of real-time interaction. Chatting with representatives of an organization can help website users to overcome problems during website use, get answers to questions, or obtain immediate assistance (Turel & Connelly, 2013). In short, live chats complement — besides social network channels and online help desks — the portfolio of web-based services (McLean & Osei-Frimpong, 2019). One of the major points that differentiates available live chats is whether the communication through the live chat is text- and/or voice-based (McLean et al., 2020). An additional and most recently discussed difference is whether the organization operates its live chat with the help of a human representative or with the help of an AI.

Knowledge has accumulated regarding the factors determining peoples' usage (McLean & Osei-Frimpong, 2019; Turel, Connelly, & Fisk, 2013) and re-usage (McLean & Osei-Frimpong, 2017; Turel & Connelly, 2013) of live chats. The key conclusion of this work is that the characteristics or the design of the potential chat partner direct people in their decision to use/re-use live chats. Nonetheless, these works have the following key limitations: They (1) focus on human-based live chats and thus overlook the role of AI-based live chats, (2) make conclusions based on individuals' interaction with live chats and thus overlook the behavioral consequences resulting from the mere or non-interactive presence of live chats. Overall, much fewer insights are available on the downstream consequences of the integration of live chats on websites. Although research illustrates that the interaction with an AI-based live chat can promote (1) product purchasing on the website (Lv, Jin, & Huang, 2018) and (2) strengthen the loyalty to the service provider (Hildebrand & Bergner, 2020; Mozafari et al., 2021a), information is missing on the effects of the mere or non-interactive presence of live chats on website users' immediate behavioral responses, such as ones' self-disclosure.

## **Live Chats and Self-Disclosure on Websites**

Self-disclosure means the communication of personal information to another person or entity during face-to-face or mediated interactions. The extent of self-disclosure can be described from a quantitative (i.e., amount of information disclosed) and/or qualitative (i.e., type of information disclosed) perspective (Moon, 2000). On a website, users can be asked to disclose personal information at different points. For instance, during the interaction with live chats, people might be asked to indicate information about themselves. However, in this study, we do not mean individuals' provision of information during interaction with a live chat (Ho, Hancock, & Miner, 2018), but self-disclosure on a website *after* having contact with a live chat.

The "online disinhibition effect" suggests that people are more likely to reveal personal information in online than in offline settings because they experience an increased degree of social invisibility in online settings (Suler, 2004). Nonetheless, besides individual factors (e.g., privacy concerns, perceived information control) (Masur, 2019; Mothersbaugh, Foxx, Beatty, & Wang, 2012), current research reveals that the context (e.g., device to access online content) determines individuals' extent of online self-disclosure (Melumad & Meyer, 2020). Moreover, features embedded in websites such as the display of other peoples' disclosure have been found to affect ones' online self-disclosure (Trepte, Scharkow, & Dienlin, 2020). However, the effects of the mere presence of live chats on websites have not been investigated yet.

To overcome a lack of physical presence or human warmth in online settings (Wang et al., 2007), organizations have implemented live chats. In this way, they want to convey the feeling to be available for people visiting their website and create as such a social environment. Hence, website users might interpret live chats as a sort of social cue triggering the feeling of being part of a social environment. Previous research shows that the mere presence of social cues in both online and offline environments affects peoples' responses (Das, Spence, & Agarwal, 2021; Herhausen, Emrich, Grewal, Kipfelsberger, & Schoegel, 2020; Naylor, Lamberton, & West, 2012; Söderlund, 2016; Wang et al., 2007). Most of this research argues that the mere presence of social cues promotes peoples' trust. However, in offline environments, the mere presence of others was also found to elicit feelings of privacy invasion which, in turn, decrease the willingness to connect to the service provider (Esmark et al., 2017; Esmark Jones, Stevens, Noble, & Breazeale, 2020). This finding could also extend to the online environment. The mere presence of live chats might reduce the perceived anonymity during website interaction. Feelings of reduced anonymity, in turn, raise privacy concerns which then elicit protective behaviors, such as a reduced disclosure of personal information (Jiang, Heng, & Choi, 2013; Joinson, 2001). Hence:

*H1: The mere presence of a live chat on a website will lead to a lower extent of peoples' disclosure of personal information than the absence of a live chat.*

The extent of peoples' disclosure of personal information might also depend on the type of live chat that is present on a website. Even when website users do not interact with the live chat, they are expected to behave differently after having contact with a human- compared to an AI-based live chat. Current research concludes that the mere presence of a human face during personal interviews can inhibit self-disclosure (Pickard & Roster, 2020). Moreover, evidence exists that the mere presence of anthropomorphic cues leads to fewer responses to a website because of an increases in public self-awareness (Sah & Peng, 2015). The disclosure processing framework further suggests that non-human partners, such as AI-based partners in live chats, can encourage peoples' self-disclosure. People sometimes avoid disclosing information to other humans because they fear to be judged or rejected for the disclosed information. From non-human actors, individuals do not expect to be judged (Lucas, Gratch, King, & Morency, 2014). Hence:

*H2: The mere presence of a human-based live chat on a website will lead to a lower extent of peoples' disclosure of personal information than the mere presence of an AI-based live chat.*

## **Study 1**

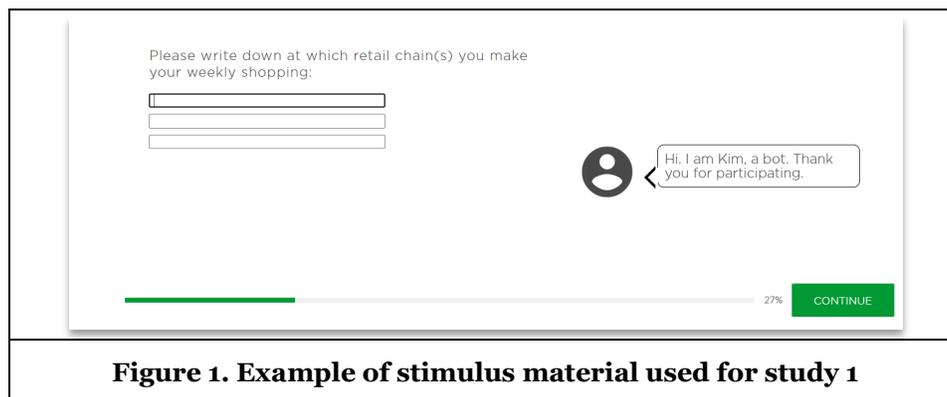
### **Methods**

To test the hypothesis H1, we designed a one-factorial between-subjects online experiment. This experiment was realized using an online survey platform (Questback Unipark) with an implemented functionality ensuring the random assignment of subjects either to the treatment or to the control group. The chosen setting facilitated the integration of a chat window. From a user perspective, access to an online

survey is comparable with an access to other online platforms. Moreover, surveys are a typical context for disclosing personal information (e.g., in the form of open-ended questions which are expected to provide more material to analyze).

For the treatment group, a chat window appeared during survey interaction (Figure 1). This window appeared on the right-hand side and did not overlap any content of the survey. It was activated when subjects entered a response in the given text field. For the control group, no chat window was integrated in the online survey. However, we also thanked subjects in the control group for participation in the survey, but as a part of the question.

In the introduction to the survey, we told participants that the major aim of this survey was to capture their experiences with previous product purchasing. It is likely that most people can report on a previous product purchasing (Melumad & Meyer, 2020). Then, we collected several socio-demographic information. Afterwards, we asked them to name retail chains where they typically make their weekly shopping. After the manipulation of the independent variable, we asked subjects to think about a product that they purchased at one of the retail chains. Specifically, we asked participants to indicate the type of product and to tell us about their experiences with the product. Questions like “what led you to buy this product?” or “how have you felt about using it?” guided them to indicate these experiences in a large field for text entry. We used this material to measure subjects’ self-disclosure. Then, we used further filler questions (e.g., likelihood of repurchasing the product, perceived product qualities) before we collected information about individuals’ privacy experience (Malhotra, Kim, & Agarwal, 2004) and their tendency to provide inaccurate information (Mothersbaugh et al., 2012). The latter variables were used as covariates during data analysis. Towards the end of the survey, we asked subjects for their experience with the survey using bipolar scales (e.g., not at all interactive – very interactive) and included these variables as controls in our data analysis. The survey was closed with both a suspicion probe and a manipulation check. On the last page of the survey, attendees were thanked and debriefed.



**Figure 1. Example of stimulus material used for study 1**

Seventy participants were recruited from Amazon Mechanical Turk (MTurk) because MTurk offers an integrated compensation system, access to a large pool of demographically diverse participants (Buhrmester, Kwang, & Gosling, 2016). Participants were recruited based on several criteria: (1) previous approval rate is higher than 98%, and (2) participants location is in the US. Prior to data analysis, the answers of four participants who failed the attention check were excluded, leaving a total sample of 66 participants (28 females; mean age = 40.26 years (SD = 13.69)). The data was analyzed in two steps: (1) the collected text material was prepared for the second step of data analysis using Linguistic Inquiry and Word Count (LIWC, Pennebaker, Boyd, Jordan, & Blackburn, 2015), and (2) analysis of covariance (ANCOVA) was used to finally test the hypothesis. Based on integrated and validated dictionaries, LIWC helps to systematically extract linguistic markers from text material. Linguistic markers, in turn, have been found to be valid indicators of self-disclosure (Melumad & Meyer, 2020).

In accordance with previous research (Doyle & Campbell, 2020), we used both the total word count and the level of authenticity as linguistic markers in this study to measure individuals’ self-disclosure from a quantitative and qualitative perspective. The more people write and the higher the authenticity score of their writing is, the more they are supposed to disclose themselves (Melumad & Meyer, 2020). A higher score of authenticity indicates usage of “more honest, personal, and disclosing text” whereas a lower score

reflects the use of a “more guarded, distanced form of discourse” (Pennebaker et al., 2015, p. 22). To validate whether the used scores reflect the respective level of self-disclosure, we conducted a follow-up study in which a different sample was recruited on MTurk ( $n = 50$ ). Participants were asked to assess six to ten randomly assigned text entries collected in study 1 in terms of how self-disclosing they perceive this quote to be (1 – not at all self-disclosing, 7 – very self-disclosing).

## Results and Discussion

The results of study 1 show that when a chat window is present, people are writing less ( $M = 64.28$ ,  $SD = 26.64$ ) compared to when a chat service is absent ( $M = 91.93$ ,  $SD = 44.78$ ;  $F(1, 59) = 10.663$ ,  $p = .002$ ,  $\eta^2 = .153$ ). Moreover, when a chat window is embedded at some point before the information request, the provided information is less authentic ( $M = 50.17$ ,  $SD = 26.01$ ) than when a chat service is absent ( $M = 64.78$ ,  $SD = 29.33$ ;  $F(1, 59) = 3.962$ ,  $p = .051$ ,  $\eta^2 = .063$ ). Examples for the different levels of authenticity in the responses identified by LIWC are:

- Low levels of authentic style: *“Recently I purchased a smart speaker. These speakers are fairly new. Their main attraction is their smart capabilities, not their sound quality. The Google Dot might be the best buy because it is on sale right now.”*
- High level of authentic style: *“I have been using Benadryl for many years. I began using it when I discovered that I had reactions to being bitten by certain insects. My allergies used to be much worse than they currently are. I also use Benadryl when I am bitten by a hornet or wasp to prevent severe reactions. Occasionally I will use it if I cannot sleep at night as well. I am quite happy using it. I don't have any reservations or hesitations about using it at all. I don't use it often, but it definitely is a product that I like to keep around in case of an emergency.”*

The results of the follow-up study reveal that others perceive the texts in the treatment group ( $M = 3.12$ ,  $SD = .82$ ) disclose less personal information than the texts in the control group ( $M = 3.58$ ,  $SD = .90$ ;  $F(1, 64) = 4.686$ ,  $p = .034$ ,  $\eta^2 = .068$ ). Moreover, both the total word count ( $t = 4.847$ ,  $p < .001$ ) and the level of authenticity ( $t = 2.294$ ,  $p = .025$ ) are significant predictors of the perceived self-disclosure in the texts, supporting the findings of Melumad and Meyer (2020).

## Study 2

### Methods

We tested the hypothesis H2 using a self-created website of a fictitious health insurance company “SDS Insurance” which contained a live chat (Figure 2). The insurance industry was used for two reasons: (1) Services of insurance companies require the collection of the diverse personal information of different degrees of sensitivity. Therefore, this context has been used to study individuals’ self-disclosure (Jacobs et al., 2001). (2) Live chats have become most prominent in the insurance industry (Magelan Solutions, 2020).

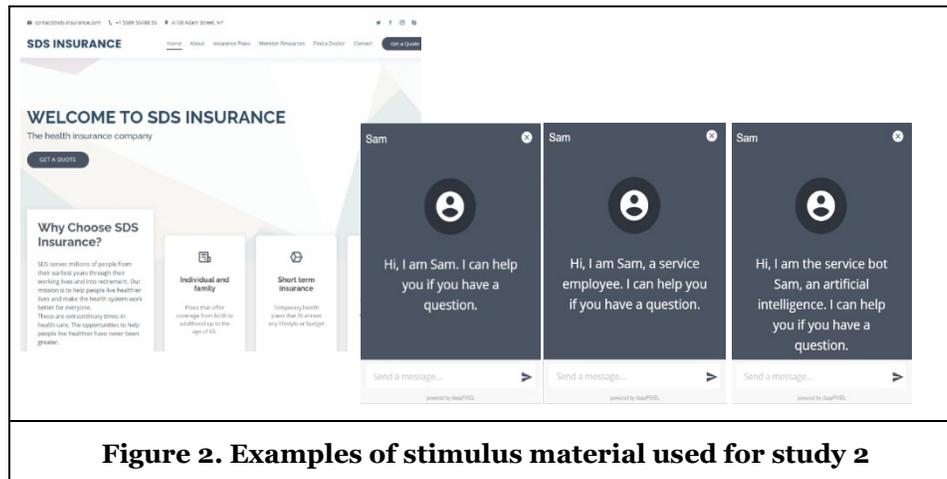
We created two versions of the live chat to measure the effects of the type of live chat defined and an additional control group: (1) control: live chat without disclosure of the chat partners’ identity, (2) live chat with disclosure of the partners’ AI-identity, (3) live chat with disclosure of the partners’ human identity. In this way, we designed a one-factorial between-subjects experiment. As part of an online survey, subjects were randomly assigned to one of the three versions of the website (website access was embedded in the online survey where, in turn, a randomized assignment was programmed). Except for the verbal content of the live chat, all elements of the websites were kept consistent across the treatment groups. For instance, the live chat always appeared on the landing page of the website.

Before subjects were asked to browse the website and to request a quote by clicking through to the next page of the website, we briefed participants and told them that this survey was to test the usability of the new online website of “SDS Insurance”. Then, we collected several socio-demographic information. Afterwards, we informed subjects on how to use the website. They were given the task to request a quote on the website for a private health insurance. To keep the interactivity of the website constant and low, the live chat appeared directly with opening the website on its home page. A highlighted button on the landing page guided subjects to the page where they could request a quote. After submitting the quote, they were

automatically redirected to the online survey. As part of the quote request, open-ended questions regarding subjects' health status provided the basis for measuring subjects' self-disclosure in this study.

After manipulating the type of live chat on the landing page and measuring the dependent variable on the next pages of the website, subjects replied to further questions in the online survey that served as controls or manipulation checks. For instance, to rule out that the live chat does not affect task performance, we asked subjects to select the best price for a series of product bundles (Selin Atalay, Onur Bodur, & Bressoud, 2017). The analysis reveals non-significant differences regarding the task performance scores between treatment groups. Then, we captured information on the perceived usability of the website.

Further, we collected information on how difficult and effortful subjects perceived the task of requesting a quote were. We also asked them to indicate their perceived self-efficacy about the task completion. Then, we collected information on subjects' familiarity with live chats. Finally, we asked them to indicate the perceived chat partners' identity disclosure and the perceived humanness of the chat partner (Ho et al., 2018; Mozafari et al., 2021a).



**Figure 2. Examples of stimulus material used for study 2**

For data analysis, using a randomly created identifier, information collected on the website related to the information collected in the online survey. On the website, we collected information about the duration of both entire use of website and quote request. Moreover, we captured the cursor movements around the live chat and the interaction with the live chat and used all these behavioral variables as controls. The data analysis in this study followed a similar procedure as in study 1. Thus, we used LIWC in a first step and an ANCOVA in a second step.

One hundred thirty-five participants were recruited from MTurk. Using the MTurk worker ID, we excluded the participants of study 1 and then used the same selection criteria as for study 1. Prior to data analysis, the answers of eleven participants who failed the attention check were excluded, leaving a total sample of 124 participants (69 females; mean age = 44.09 years (SD = 13.25)). The manipulation of the chat partners' identity worked as expected: Subjects perceived the human-based live chat as more human ( $M = 2.95$ ,  $SD = 1.82$ ) than the AI-based live chat ( $M = 1.43$ ,  $SD = .94$ ;  $F(1, 70) = 20.844$ ,  $p = .000$ ) and the live chat without identity disclosure ( $M = 1.91$ ,  $SD = 1.04$ ;  $F(1, 71) = 10.165$ ,  $p = .002$ ). The live chat in the control scenario induced marginally higher perceived humanness ( $M = 1.91$ ,  $SD = 1.04$ ) than the AI-based live chat ( $M = 1.43$ ,  $SD = .94$ ;  $F(1, 75) = 3.226$ ,  $p = .077$ ).

## Results and Discussion

The results show that the AI-based live chat ( $M = 28.86$ ,  $SD = 26.11$ ) leads to a higher breadth of self-disclosure than the human-based live chat ( $M = 18.37$ ,  $SD = 16.33$ ;  $F(1, 70) = 4.256$ ,  $p = .043$ ,  $\eta^2 = .057$ ). However, no significant differences can be observed regarding the depth of self-disclosure. Hence, hypothesis H2 can be accepted partially.

Additional analyses reveal that subjects' breadth of self-disclosure (i.e., word count) was higher for the AI-based live chat ( $M = 28.86$ ,  $SD = 26.12$ ) than for the live chat without identity disclosure ( $M = 18.51$ ,  $SD =$

15.10;  $F(1, 75) = 4.045$ ,  $p = .048$ ,  $\eta^2 = .051$ ). Similarly, the depth of self-disclosure is higher for the AI-based live chat ( $M = 74.85$ ,  $SD = 36.62$ ) than for the control group ( $M = 54.04$ ,  $SD = 41.60$ ;  $F(1, 75) = 5.053$ ,  $p = .028$ ,  $\eta^2 = .063$ ). However, a human-based live chat elicits a similar breadth and depth of self-disclosure like a live chat without identity disclosure.

In sum, the results of the second study show that the type of live chat can direct website users' subsequent self-disclosure. People tend to reveal more information (i.e., quantitatively) when the live chat is operated by an AI than by a human service agent. When the live chat is operated by an AI, the self-disclosure is more extended than when no identity is revealed.

## **Conclusion and Next Steps**

This research provides first evidence for the effects of live chats embedded in websites on website users' self-disclosure. In harmony with our initial assumption, the findings of the first study show that the mere presence of a live chat on a website decreases website users' self-disclosure both from a quantitative and a qualitative perspective. With the presence of a live chat, the extent of self-disclosure depends on the type of live chat (human versus AI-based). The findings of this work suggest that compared to human-based, AI-based live chats promote self-disclosure. The findings of our work contribute to existing knowledge in two ways. On the one hand, they advance the understanding of the effects of live chats embedded on websites. Considering live chats from a non-interactive or mere presence perspective advances existing knowledge as it broadens the view on the downstream consequences that live chats can have. In other words, whereas previous work looked at the interaction with, for instance, chatbots and concluded that the type of chatbot shapes users' self-disclosure during interaction (Ho et al., 2018), this work goes a step further as it finds that (1) the mere presence of live chats on websites affects website usage behavior, and (2) the type of the live chat (human versus AI-based) decides about the extent of peoples' self-disclosure. On the other hand, this work contributes to the understanding of people's online self-disclosure as it looks at the relevance of website features for online self-disclosure (Melumad & Meyer, 2020). Moreover, our finding, that the mere presence of AI-based compared to human-based live chats affects peoples' behavior differently, offers a novel perspective to the Computers as Social Actors framework (Moon, 2000).

To sum up, organizations are well-advised to consciously decide whether they want to implement a live chat on their website. As this study suggests, the mere presence of a live chat on a website can affect website usage behavior and the disclosure of personal information, respectively. Hence, if organizations want users to disclose personal information (e.g., to offer a service) on their websites, it is not recommended to implement a live chat. However, if they still wish to implement one, they should refer to an AI-based live chat because compared to a human-based live chat, this was found to encourage self-disclosure. Most importantly, these findings inform organizations about the powerful and privacy-invading effects of the mere presence of specific types of live chats on their websites. Hence, when using AI- instead of human-based live chats, organizations are well-advised to inform users about potential privacy threats and notice them about a conscious disclosure of personal information.

Even though this work has implications for theory and practice, further work should be conducted to broaden the acquired knowledge in the current study. First, we suggest broadening the understanding on the conditions under which the mere presence of live chats on websites does or does not inhibit website users' self-disclosure. Whereas this study looks at the type of the live chat, in a next step we recommend considering individual (e.g., regulatory focus, lay beliefs about live chats), situational (e.g., task orientation) and/or other supply-side (e.g., strategy of website provider regarding digital corporate responsibility, design of the website) factors that could serve as moderators of the observed effects. Moreover, it could be of interest to investigate the effects of different types of AI-based live chats (e.g., presence versus absence of anthropomorphic features) (Feine, Gnewuch, Morana, & Maedche, 2019). Most importantly, the observed effects should be validated in other research settings (e.g., goods- versus service-based websites, insurance websites of different levels of intrusiveness). Tests for H1 should be redone in the same research setting as for testing H2. Second, we want to deepen our understanding on why the mere presence of live chats affects peoples' self-disclosure. Of particular interest might be to examine the mediating role of the perceptions of trust, privacy invasion, and anonymity. Third, this study uses a quantitative approach to analyze people's self-disclosure following a contact with a live chat on a website. In future research, we plan to consider a more in-depth and qualitative analysis of the text entries. This might provide us with further insights on how the mere contact to an AI- compared to a human-based live chat affects peoples' depth of

self-disclosure. This, in turn, could broaden previous findings outlining that the style of disclosure is different in human-human as compared to human-AI interactions (Hill, Randolph Ford, & Farreras, 2015). Moreover, considering additional linguistic markers (e.g., emotional tone of disclosed information) might also broaden the insights of this study on self-disclosure (Melumad & Meyer, 2020).

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## References

- Buhrmester, M., Kwang, T., & Gosling, S. D. (2016). Amazon's Mechanical Turk: A new source of inexpensive, yet high-quality data? In A. E. Kazdin (Ed.), *Methodological issues and strategies in clinical research (4th ed.)* (pp. 133–139). Washington: American Psychological Association.
- Das, G., Spence, M. T., & Agarwal, J. (2021). Social selling cues: The dynamics of posting numbers viewed and bought on customers' purchase intentions. *International Journal of Research in Marketing*, *38*(1), 1–15.
- Doyle, P. C., & Campbell, W. K. (2020). *Linguistic Markers of Self-Disclosure: Using YouTube Coming Out Videos to Study Disclosure Language*.
- Esmark, C. L., Noble, S. M., & Breazeale, M. J. (2017). I'll Be Watching You: Shoppers' Reactions to Perceptions of Being Watched by Employees. *Journal of Retailing*, *93*(3), 336–349. Retrieved July 14, 2020, from <https://linkinghub.elsevier.com/retrieve/pii/S0022435917300349>
- Esmark Jones, C. L., Stevens, J. L., Noble, S. M., & Breazeale, M. J. (2020). Panic Attack: How Illegitimate Invasions of Privacy Cause Consumer Anxiety and Dissatisfaction. *Journal of Public Policy & Marketing*, *39*(3), 334–352. Retrieved July 14, 2020, from <http://journals.sagepub.com/doi/10.1177/0743915619870480>
- Feine, J., Gnewuch, U., Morana, S., & Maedche, A. (2019). A Taxonomy of Social Cues for Conversational Agents. *International Journal of Human-Computer Studies*, *132*, 138–161.
- Herhausen, D., Emrich, O., Grewal, D., Kipfelsberger, P., & Schoegel, M. (2020). Face Forward: How Employees' Digital Presence on Service Websites Affects Customer Perceptions of Website and Employee Service Quality. *Journal of Marketing Research*, *57*(5), 917–936.
- Hildebrand, C., & Bergner, A. (2020). Conversational robo advisors as surrogates of trust: onboarding experience, firm perception, and consumer financial decision making. *Journal of the Academy of Marketing Science*.
- Hill, J., Randolph Ford, W., & Farreras, I. G. (2015). Real conversations with artificial intelligence: A comparison between human-human online conversations and human-chatbot conversations. *Computers in Human Behavior*, *49*, 245–250.
- Ho, A., Hancock, J., & Miner, A. S. (2018). Psychological, Relational, and Emotional Effects of Self-Disclosure After Conversations With a Chatbot. *The Journal of communication*, *68*(4), 712–733.
- Jacobs, R. S., Hyman, M. R., & McQuitty, S. (2001). Exchange-Specific Self-Disclosure, Social Self-Disclosure, and Personal Selling. *Journal of Marketing Theory and Practice*, *9*(1), 48–62.
- Jiang, Z., Heng, C. S., & Choi, B. C. F. (2013). Research Note —Privacy Concerns and Privacy-Protective Behavior in Synchronous Online Social Interactions. *Information Systems Research*, *24*(3), 579–595.
- Joinson, A. N. (2001). Self-disclosure in computer-mediated communication: The role of self-awareness and visual anonymity. *European Journal of Social Psychology*, *31*(2), 177–192.
- Lucas, G. M., Gratch, J., King, A., & Morency, L.-P. (2014). It's only a computer: Virtual humans increase willingness to disclose. *Computers in Human Behavior*, *37*, 94–100.
- Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science*, *38*(6), 937–947.
- Lv, Z., Jin, Y., & Huang, J. (2018). How do sellers use live chat to influence consumer purchase decision in China? *Electronic Commerce Research and Applications*, *28*, 102–113.
- Magellan Solutions. (2020). *Live Chat Statistics 2020: Trends and Insights Businesses Should Know*. Retrieved from <https://www.magellan-solutions.com/blog/live-chat-statistics-2020/>
- Malhotra, N. K., Kim, S. S., & Agarwal, J. (2004). Internet Users' Information Privacy Concerns (IUIPC): The Construct, the Scale, and a Causal Model. *Information Systems Research*, *15*(4), 336–355. Retrieved July 13, 2020.

- Masur, P. K. (2019). *Situational Privacy and Self-Disclosure*. Cham: Springer International Publishing. Retrieved July 13, 2020, from <http://link.springer.com/10.1007/978-3-319-78884-5>
- McLean, G., & Osei-Frimpong, K. (2017). Examining satisfaction with the experience during a live chat service encounter-implications for website providers. *Computers in Human Behavior*, *76*, 494–508.
- McLean, G., & Osei-Frimpong, K. (2019). Chat now... Examining the variables influencing the use of online live chat. *Technological Forecasting and Social Change*, *146*, 55–67.
- McLean, G., Osei-Frimpong, K., Wilson, A., & Pitardi, V. (2020). How live chat assistants drive travel consumers' attitudes, trust and purchase intentions. *International Journal of Contemporary Hospitality Management*, *32*(5), 1795–1812.
- Melumad, S., & Meyer, R. (2020). Full Disclosure: How Smartphones Enhance Consumer Self-Disclosure. *Journal of Marketing*, *84*(3), 28–45. Retrieved July 14, 2020, from <http://journals.sagepub.com/doi/10.1177/0022242920912732>
- Moon, Y. (2000). Intimate Exchanges: Using Computers to Elicit Self-Disclosure From Consumers. *Journal of Consumer Research*, *26*(4), 323–339.
- Mothersbaugh, D. L., Fogg, W. K., Beatty, S. E., & Wang, S. (2012). Disclosure Antecedents in an Online Service Context: The Role of Sensitivity of Information. *Journal of Service Research*, *15*(1), 76–98. Retrieved July 14, 2020, from <http://journals.sagepub.com/doi/10.1177/1094670511424924>
- Mozafari, N., Weiger, W. H., & Hammerschmidt, M. (2021a). Resolving the Chatbot Disclosure Dilemma: Leveraging Selective Self-Presentation to Mitigate the Negative Effect of Chatbot Disclosure. In T. Bui (Ed.): *Proceedings of the Annual Hawaii International Conference on System Sciences, Proceedings of the 54th Hawaii International Conference on System Sciences*. Hawaii International Conference on System Sciences.
- Mozafari, N., Weiger, W. H., & Hammerschmidt, M. (2021b). Trust me, I'm a bot – repercussions of chatbot disclosure in different service frontline settings. *Journal of Service Management, ahead-of-print*(ahead-of-print).
- Naylor, R. W., Lamberton, C. P., & West, P. M. (2012). Beyond the “Like” Button: The Impact of Mere Virtual Presence on Brand Evaluations and Purchase Intentions in Social Media Settings. *Journal of Marketing*, *76*(6), 105–120.
- Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. (2015). *The Development and Psychometric Properties of LIWC2015*.
- Pickard, M. D., & Roster, C. A. (2020). Using computer automated systems to conduct personal interviews: Does the mere presence of a human face inhibit disclosure? *Computers in Human Behavior*, *105*, 106197.
- Sah, Y. J., & Peng, W. (2015). Effects of visual and linguistic anthropomorphic cues on social perception, self-awareness, and information disclosure in a health website. *Computers in Human Behavior*, *45*, 392–401.
- Selin Atalay, A., Onur Bodur, H., & Bressoud, E. (2017). When and How Multitasking Impacts Consumer Shopping Decisions. *Journal of Retailing*, *93*(2), 187–200.
- Söderlund, M. (2016). Employee Mere Presence and Its Impact on Customer Satisfaction. *Psychology & Marketing*, *33*(6), 449–464.
- Suler, J. (2004). The online disinhibition effect. *Cyberpsychology & behavior : the impact of the Internet, multimedia and virtual reality on behavior and society*, *7*(3), 321–326.
- Townsend, C., Neal, D. T., & Morgan, C. (2019). The impact of the mere presence of social media share icons on product interest and valuation. *Journal of Business Research*, *100*, 245–254.
- Trepte, S., Scharnow, M., & Dienlin, T. (2020). The privacy calculus contextualized: The influence of affordances. *Computers in Human Behavior*, *104*, 106115.
- Turel, O., & Connelly, C. E. (2013). Too busy to help: Antecedents and outcomes of interactional justice in web-based service encounters. *International Journal of Information Management*, *33*(4), 674–683.
- Turel, O., Connelly, C. E., & Fisk, G. M. (2013). Service with an e-smile: Employee authenticity and customer use of web-based support services. *Information & Management*, *50*(2-3), 98–104.
- Wang, L. C., Baker, J., Wagner, J. A., & Wakefield, K. (2007). Can A Retail Web Site be Social? *Journal of Marketing*, *71*(3), 143–157.
- Yuchao, W., Ying, Z., & Liao, Z. (2020). Health Privacy Information Self-Disclosure in Online Health Community. *Frontiers in public health*, *8*, 602792.