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Speaking the news

How conversational agents influence trust and issue salience

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Chapter III

The influence of conversational agents on trust in news recommenders

A comparison between a conversational agents and a website

This chapter has been submitted for publication: Resendez, V., Araujo, T., Helberger, N., & de Vreese, C. (2024). The influence of conversational agents on trust in the news recommender. A comparison between a conversation and a website [Manuscript submitted for publication]

Abstract

Conversational Agents (CAs) are transforming how news is distributed, offering a more dialogic and personalized approach for users. This transformation may help news organizations reach new audiences and hold the potential not only for them to engage with a new public, but also to enhance trust in their news recommenders. Despite the growing use of CAs for news recommendations, there is a limited understanding of how news recommendations through CAs in comparison to websites affect trust in the news recommender. To fill this gap, we assess the influence of various potential antecedents of trust (i.e., perceived ease of use, enjoyment, personalization, and privacy concerns) in this specific context, through an online experiment. The experiment (N=595) compared a news recommender in either a traditional news website or a CA. The results showed that participants had lower levels of trust in CAs compared to websites, with this finding being explained by lower levels of perceived enjoyment for CAs than for websites. This finding suggests that the dialogic nature of CAs does not inherently enhance enjoyment in a news context. Additionally, perceived personalization was found to be an important antecedent influencing trust in the news recommender. Overall, these findings suggest that news organizations offering conversational news should prioritize enjoyable interactions with relevant content for the users to enhance trust.

In an overloaded information ecosystem, increasingly fueled by misinformation and disinformation, trust in news recommenders becomes increasingly important. Trust in the news recommender is crucial as it can impact users' trust in the news selection presented (Thurman et al., 2019). Additionally, trust in the news recommender can positively influence the users' intention to use and adopt a recommender system (Choi et al., 2011). Among the various antecedents of trust in different technologies, previous studies have highlighted perceived ease of use (Gefen et al., 2003), perceived enjoyment (Hwang & Kim, 2007), perceived personalization (Komiak & Benbasat, 2006), and privacy concerns (Kim et al., 2023). However, the interface where the news recommenders are embedded can also impact how these antecedents are affected (Beldad et al., 2010; Diakopoulos, 2015). Thus, it is important to consider the interface when evaluating trust in news recommender systems.

Previous studies have highlighted the impact of the different interfaces, such as CAs and websites, on these different antecedents of trust (Alimamy & Kuhail, 2023; Ischen, Araujo, van Noort, et al., 2020; Ischen, Araujo, Voorveld, et al., 2020; Xiu et al., 2023; Zhao et al., 2023). For instance, Zhao et al. (2023) noticed that users perceived CAs as easier to use than websites when conveying fact-checked information. Specifically, Zhao et al. (2023) suggest that the exchange of information with CAs provides all the information to the user in the same place without the need to navigate to another place. Similarly, Ischen, Araujo, van Noort, et al. (2020) and Xiu et al. (2023) revealed that CAs in comparison to websites may increase perceived enjoyment in the context of advertisement and news due to the dialogue of CAs. Alimamy & Kuhail, (2023), while not directly comparing CAs with websites, explored the extent to which perceived personalization in CAs influence trust, finding a positive effect on it. Additionally, Ischen, Araujo, Voorveld, et al., (2020) argue that a certain type of CA might enhance privacy concerns as interactions might be perceived as more personal.

This existing body of research shows that CAs may influence some of the antecedents that affect trust in a technology differently than other interfaces. However, only a few studies have drawn a comparison between websites and CAs (Ischen, Araujo, van Noort, et al., 2020; Ischen, Araujo, Voorveld, et al., 2020; Xiu et al., 2023; Zhao et al., 2023).From earlier studies comparing websites and CAs, none have tested whether these differences also take place in the context of news recommendations. In addition, none of the studies have evaluated these four antecedents in the same design. Therefore, there remains a gap in understanding the way CAs impact trust in comparison to news websites in the context of news recommendations. Thus, the overall research question in this study is: *What antecedents affect trust in a news recommender when interacting with a recommender system in a conversational agent or a news website?*

From a theoretical point of view, this research examines four different antecedents that could influence trust in the news recommender.

Building upon existing studies primarily focused on e-commerce contexts, we extend these studies to the context of news recommenders. Additionally, as news organizations are increasingly experimenting with CAs (Jones & Jones, 2021), it is important to understand how these agents impact user trust in recommender systems. Our findings can guide news organizations in optimizing their conversational agents to engage with their audiences.

From a News Recommender System to an Interface: Conversational Agents and Websites

News recommenders' systems, powered by algorithms, act as information filters to deliver relevant content to users (Karimi et al., 2018). These systems gather data about particular characteristics (e.g., interests, preferences, or curiosities) of an individual and, based on that information, offer recommendations specifically tailored for the user (Karakayali et al., 2018). These recommenders usually create a user profile using historical datasets, collecting information through the user interface (Bozdag, 2013). The information is derived from explicit feedback (e.g., profile customization) or implicit feedback (e.g., usage behavior) in the interface (Zanker et al., 2019).

The news recommender can have multiple interfaces. Two of the possible news recommender interfaces are conversational agents and websites, which is what this study specifically focuses on. We refer to conversational agents as "a software that accepts natural language as input and generates natural language as output, engaging in a conversation with the user" (Griol et al., 2013, p. 760). In contrast, websites are a collection of pages with structured information navigated by the user through menus (Nguyen et al., 2022).

A critical distinction between CAs and websites is that CAs typically interact through an implicit and explicit exchange of information through natural language to collect user data (Jannach, 2023). In a way, CAs allow the users to explicitly customize the information from the recommender (Sundar & Liao, 2023). In contrast, websites interact with users typically in a unidirectional way. Websites do not afford users the opportunity for explicit input (Jannach, 2023). Instead, websites infer preferences from implicit feedback derived from user clicks in menus (Nguyen et al., 2022). The difference in interaction styles—dialogue versus non-dialogue—affects the user's perceptions of the recommended content. As Diakopoulos (2015) highlights, for the end user, the interface in which the recommender is embedded is an important element in experiencing the output of the recommender. Thus, the interface may affect the extent to which users trust a news recommender. The following section further clarifies the concept of trust in news recommenders.

Trust in the News Recommender

III

Trust in the recommender systems is a multidimensional concept involving several factors, including a combination of cognitive and emotional aspects. This combination is based on the assumption that trust involves both reasoning and feeling (Komiak & Benbasat, 2006; Komiak et al., 2004). Komiak and Benbasat (2006) refer to trust as a combination of competence, benevolence, and integrity of the recommender to provide relevant, truthful, and reliable recommendations. Integrity is a cognitive perception that the technology adheres to accepted rules of conduct, such as honesty and keeping promises (Mayer & Davis, 1999). Benevolence is an affective perception that the technology, apart from wanting to make a lawful profit, wants to do good to the customer. Competence is also a cognitive perception about the skills and competence of trusted technology (Hwang & Kim, 2007). We adapted the definition of trust in recommender systems to fit the context of news recommenders.

Since trust is a multidimensional concept, with cognitive and emotional components, multiple antecedents may influence trust in the news recommender (i.e., perceived ease of use, perceived enjoyment, perceived personalization, privacy concerns) (Gefen et al., 2003; Hwang & Kim, 2007; Komiak & Benbasat, 2006). Our research takes an initial step and evaluates four key antecedents from the context of e-commerce and assesses their applicability in the context of news recommenders.

By selecting these antecedents, we combine elements from the Technology Acceptance Model (TAM) with privacy calculus. TAM focuses on two main characteristics, perceived ease of use and perceived usefulness (Davis, 1989). However, Gefen et al. (2003) showed that perceived ease of use acted as an antecedent for trust. Additionally, in extended versions of the TAM model (Davis et al., 1992), perceived enjoyment has been found as an important variable for trust (Hwang & Kim, 2007; Rouibah et al., 2016).

Furthermore, it is necessary to consider that in the context of recommender systems, there are multiple data points gathered that could affect users' trust in the recommender (Schomakers et al., 2022). Consequently, it becomes important to consider perceptions such as personalization and privacy concerns. The privacy calculus framework is useful in this regard, as it allows us to explore how users weigh the benefits of the news recommender against their privacy concerns (Schomakers et al., 2022).

These antecedents are also chosen as the interface where the recommender is embedded (i.e., CAs vs. websites) has a direct impact on it (Blut et al., 2021; Ischen, Araujo, van Noort, et al., 2020; Ischen, Araujo, Voorveld, et al., 2020; Nguyen et al., 2022; Rapp et al., 2021; Xiu et al., 2023; Zarouali et al., 2018). In the following section, we explain in greater detail each of these antecedents, exploring their relationship with trust in news

recommenders and the interface.

Perceived Ease of Use

Davis (1989) describes perceived ease of use as the extent to which technology will be free of effort. This mechanism (i.e., perceived ease of use), as suggested by previous studies, influences trust in different technologies (e.g., e-vendor, mobile apps, technologies) (Gefen et al., 2003; Nel & Boshoff, 2017; Sarkar et al., 2020; Vance et al., 2008). Audiences often perceive technologies that are easy to use as reflecting quality and having good intentions toward serving the user (Nel & Boshoff, 2017; Sarkar et al., 2020). Thus, perceived ease of use serves as a cue to assess trust (Vance et al., 2008). For these reasons, we argue that perceived ease of use is a mechanism that influences trust in the news recommender.

There are different ways interfaces may influence perceived ease of use. For instance, CAs affect perceived ease of use by streamlining the information retrieval process. Unlike websites, interacting with CAs occurs through natural language, setting an expectation of understandability and accessibility (L. Li et al., 2021). This approach is often familiar to users, as interacting in natural language does not require additional developed skills. In addition, other studies (Blut et al., 2021; Valtolina et al., 2020) highlighted that users find exchanging information with CAs more convenient than searching for information themselves. This is partly because CAs can actively provide information in an efficient way (Brandtzaeg & Følstad, 2017). As a result, users do not need to navigate through various links or web pages. Thus, CAs' affordances may contribute to an increased perceived ease of use. In contrast, website interactions often require users to evaluate and determine the most effective way to access the information they seek (Nguyen et al., 2022). The process tends to be less intuitive, as it involves navigating through multiple links and sorting through extensive information. This process can be more time-consuming and require additional steps (Zhao et al., 2023). Consequently, the structure of websites may diminish users' perceived ease of use compared to CAs.

Hence, when users interact with CAs in comparison to websites, we assume that they will experience a higher perceived ease of use. This is attributed to a more intuitive interaction through natural language and a serial interface that centralizes information in one place. Increased perceived ease of use leads to higher trust in the news recommender, mainly because it is a signal of quality, serving the users as a cue to trust in the news recommender. Thus, we hypothesize:

H1: *A news recommender in a conversational agent (versus a website) leads to (a) higher perceived ease of use, (b) subsequently leading to higher trust in the news recommender.*

Perceived Enjoyment

Venkatesh (2000, p. 351) refers to perceived enjoyment as the "*extent to* which the activity of using a specific system is perceived to be enjoyable in its own right, aside from any performance consequences resulting from system use." Perceived enjoyment is an important factor for trust (Hwang & Kim, 2007; Rouibah et al., 2016).

Hwang and Kim (2007) propose that enjoyment can enhance individuals' distortion of time and perceived control during the interaction, increasing trust in the technology. Additionally, they suggest that enjoyment can operate through affect infusion, a process through which interactions that involve positive emotions influence other cognitive processes such as the evaluation of trust. Aligning with this finding, Rouibah et al. (2016) further demonstrated that enjoyment is key to building trust in online technologies.

Earlier studies (Hwang & Kim, 2007; Rouibah et al., 2016) suggest that perceived enjoyment generates value for the users, thus increasing their trust in the technology. For these reasons, perceived enjoyment may influence trust in the news recommender. In technologies such as CAs, the exchange of feedback through dialogue has been linked to an enhancement in perceived enjoyment. Prior studies across various sectors—including health, customer service, and business—have shown CAs lead to higher perceived enjoyment compared to websites (Ischen, Araujo, van Noort, et al., 2020; Nicolescu & Tudorache, 2022; Selamat & Windasari, 2021). Selamat and Windasari (2021) suggest that the dynamism and responsiveness of CAs reduce boredom, creating a more pleasant experience during the interaction. Additionally, Xiu et al. (2023) argue that conversational interactions alleviate the boredom of reading plain text on a webpage, thus improving users' interest in the news.

Therefore, when interacting with a CA compared to a website, users experience higher perceived enjoyment due to the dynamism of the interaction through dialogue in natural language. An increase in perceived enjoyment leads to higher trust in the news recommender due to an effect infusion process that influences users' perceptions. Therefore, we hypothesize:

H2: *A news recommender in a conversational agent (versus a website) leads to (a) higher perceived enjoyment, subsequently leading to (b) higher trust in the news recommender.*

Perceived Personalization

Perceived personalization as a mechanism has been associated with increased trust in various technologies such as virtual reality, recommender

systems, social media, and voice assistants (Alimamy & Gnoth, 2022; Alimamy & Kuhail, 2023; Komiak & Benbasat, 2006). We refer to perceived personalization as the users' perception of messages tailored to their preferences (C. Li, 2016). Perceived personalization increases trust in technology since it indicates a provider's competence to provide information relevant to the user (Guo et al., 2016). In addition, perceived personalization can enhance the impression that the system acts in the best interest to provide them with relevant information (Komiak & Benbasat, 2006).In this sense, perceived personalization influences trust by increasing users' perception that the system acts to serve users' interests (Alimamy & Kuhail, 2023; Komiak & Benbasat, 2006).

The influence of perceived personalization on trust can also be extended to CAs (Alimamy & Kuhail, 2023). For instance, in CAs, exchanging information can play an important role in increasing perceived personalization. When interacting with CAs, users may unconsciously reveal aspects of their personal communication styles, such as the level of formality, tone, or urgency in their requests. The contextual content provided to the system, apart from the explicit request, might later serve to anticipate users' needs (e.g., routines) (Natale & Cooke, 2021). This interaction facilitates an indirect form of customization for the user (Sundar & Liao, 2023). However, it also creates an illusion for the user since the process of exchanging explicit and implicit information can contribute to a sense of mutual understanding (Natale & Cooke, 2021; Skjuve et al., 2021). This process influences the relevance of the information provided, amplifying the user's perception of a personalized experience (Jia & Sundar, 2023; Skjuve et al., 2021). Moreover, the adaptability of conversational agents to understand the user despite the different expressions can further enhance the perception of perceived personalization (Sidlauskiene, 2022).

Thus, when users interact with a CA in comparison to a website, they experience higher levels of perceived personalization since there is an exchange of information between the parties and indirect customization. An increase in perceived personalization leads to higher trust in the news recommender since it acts as a cue indicating an intention of the technology to serve the user, thus we hypothesize:

H3: *A news recommender in a conversational agent (versus a website) leads to (a) higher perceived personalization, and (b) subsequently leading to higher trust in the news recommender.*

Privacy Concerns

Privacy concerns are an important mechanism to evaluate since they have been linked with diminished trust in the technology (Kim et al., 2023). Privacy concerns refer to the concern of institutions capitalizing on users' personal

information (Dinev et al., 2017). Privacy concerns have different causes, but they are mainly due to a lack of control over personal data and a concern of privacy leakage from the institution behind the technology (Boerman et al., 2017; Kim et al., 2023). Discomfort with online interactions can be further intensified when platforms do not manage users' privacy expectations, for example, by forcing them to provide information when interacting with a system (Kim et al., 2023). These factors can lead to reduced trust in CAs as an exchange of information is necessary to receive feedback from the CA (Brandtzaeg & Følstad, 2017; Zamora, 2017).

Navigating the web involves interacting with different interfaces, each with distinct privacy implications (Boerman et al., 2021). Privacy concerns can prevent users from freely disclosing personal information (Bol et al., 2018). When interacting with CAs, two main reasons might enhance privacy concerns, thus posing a challenge for trusting CAs. First, CAs require users to explicitly disclose certain details to deliver the requested information (Foehr & Germelmann, 2020; Ischen, Araujo, Voorveld, et al., 2020). In other words, when conversing with a CA, users need to share specific details so CAs can provide the answers users are looking for. In this process, users might not be able to control the information given to the CA. In combination, the interaction and lack of agency can raise privacy concerns (Belen Saglam et al., 2021). Second, CAs use multiple algorithms to interact with the user and provide the information required. Given that CAs are able to provide natural language responses, the usage of algorithms in CAs might be more easily noticed than in websites (Belen Saglam et al., 2021). The awareness of algorithms could heighten concerns regarding the processing of personal data and the risk of privacy violations. For these two reasons, interaction with the CA may enhance privacy concerns.

Hence, when users interact with a CA in comparison to a website, they experience higher levels of privacy concern since there is a need for explicit information disclosure. An increase in privacy concerns can lead to lower trust in the news recommender since users experience a lack of control over their personal information, thus we hypothesize:

H4: *A news recommender in a conversational agent (versus a website) leads to (a) higher privacy concerns, (b) subsequently leading to lower trust in the news recommender.*

News Recommenders in Conversational Agents vs Websites

In summary, the use of conversational agents, which primarily interact with users through dialogue, can significantly enhance various factors that contribute to trust in news recommenders. CAs can enhance users' familiarity with the technology (Blut et al., 2021), reduce boredom (Selamat &

Windasari, 2021), and lead users to be personally invested in the interaction (Natale & Cooke, 2021), while raising privacy concerns due to force dialogue interactions (Belen Saglam et al., 2021; Ha et al., 2021; Ischen, Araujo, Voorveld, et al., 2020). Overall, we hypothesized conversational agents have a greater impact on trust in the news recommender compared to interactions through a website-based news recommender (Figure 3.1). Therefore, we hypothesize:

H5: *A news recommender in a conversational agent leads to higher trust in the news recommender than a news recommender in a website.*

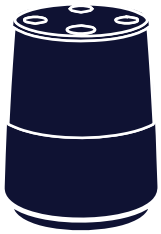
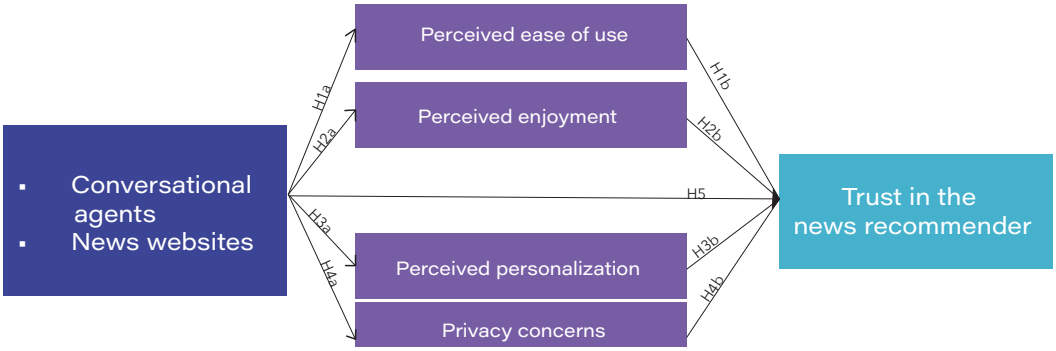


Figure 3.1.
Summary of the model



Methodology

To test the hypotheses regarding the mediating factors for trust in the news recommender, we conducted a between-subjects experiment in December 2023. In the experiment, we manipulated the interface of the news recommender. Participants interacted with a news recommender embedded in a news website or with a CA. When interacting with the CA or the website, users were requested to indicate their areas of interest by selecting topics for the system to generate news recommendations. This step served to (1) align on common affordances found in current news websites and CAs, (2) obtain explicit user feedback in the topic selection algorithm, and (3) facilitate a more similar comparison between the two interfaces (i.e., CAs vs website) (Loecherbach & Trilling, 2020). After indicating their areas of interest, participants were then exposed to a set of recommendations. The recommender system employed a dynamic news article selection, updating the articles daily to emulate real-world conditions (Loecherbach & Trilling, 2020). The experiment was pre-registered in OSF: t.ly/2y2wL

Data Collection and Procedure

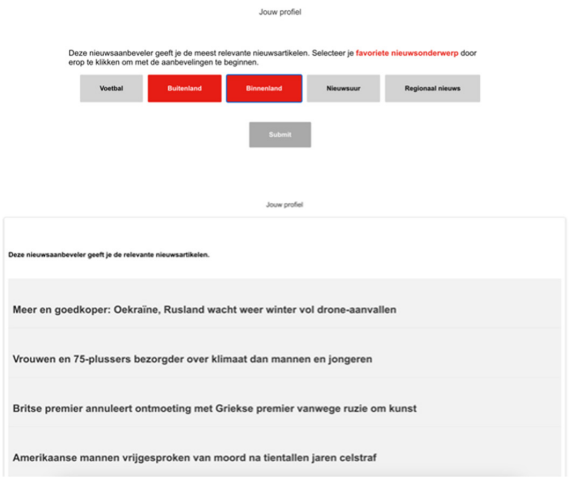
In our initial plan, as pre-registered: t.ly/2y2wL, our goal was to recruit a minimum of 500 participants based on a Montecarlo power analysis ($\alpha = .05$, power = 0.8).To gain further insights into the interactions with the conversational agent (CA) or the website, we adopted a two-phase approach. Initially, we conducted a soft launch with 100 participants to evaluate the effectiveness of the CA and the website in providing recommendations. Following the success of the soft launch, we extended our recruitment to 516 participants. In total, we recruited 616 participants. The research procedure was structured in three stages. Firstly, participants provided demographic information, including age, gender, and education level, before their interaction with either the CA or the website. Secondly, they interacted with the news recommender system on either the website or the CA. Finally, after this interaction, participants completed attention checks and evaluated several aspects such as the perceived ease of use, enjoyment, personalization, privacy concerns, and trust in the news recommender.

Participants

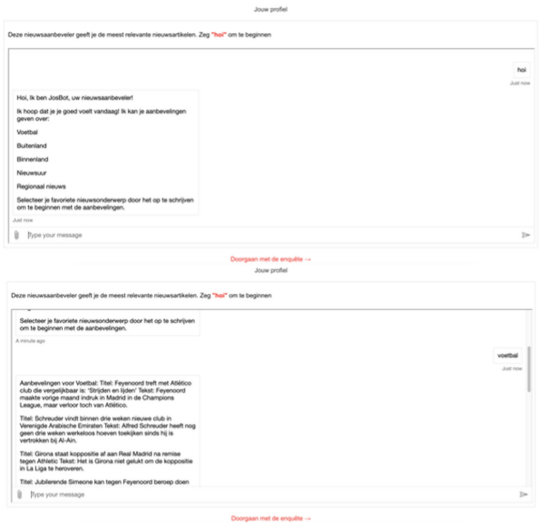
In December 2023, we recruited a total of 616 participants through the panel company Panel Inzicht. Our final sample included 595 participants, excluding all those outliers based on cutoff points previously preregistered: t.ly/2y2wL.T The sample was limited to individuals older than 18 years and

living in the Netherlands, as the news recommender was designed to operate in Dutch. We selected the Netherlands as a case study due to the high levels of connectivity and proclivity toward embracing novel technologies (van Deursen et al., 2022). The sample involved 273 male participants and 221 female participants aged 19 to 88 years (M = 55.7, SD = 17.5). During the experiment, participants were randomly assigned to either the website or CA condition to ensure the equal distribution of participants. To assess the effectiveness of the randomization, we conducted a randomization check focusing on demographic variables, including age, gender, and education. We conducted t-tests to compare age and education between the conditions. The results revealed significant differences. Specifically, we observed a significant age difference between the conditions (t(592.24) = 4.25, p < .001). Participants in the CA condition had a younger age than those in the website condition. Similarly, a significant difference in education levels was found between the groups (t(593) = −3.15, p = .001). Participants in the CA condition had a higher level of education compared to those interacting with the website condition. In contrast, to evaluate any potential gender differences between the groups, we conducted a chi-square test. The results indicated no significant differences in gender distribution ($\chi 2$ (1) = 0.00, p = 1.00). However, considering the significant age and education differences, we decided to include these variables as covariates in our subsequent analyses to control for any potential effects.

Figure 3.2.
Examples news recommenders



(a) Example of the news recommender in the website



(b) Example of the news recommender in the CA

Validity and Reliability

In this study, we conducted a confirmatory factor analysis (CFA) to evaluate the factor validity of all variables (Table 3.1). We assessed the factor loading estimates of the latent variables and only used the items with a loading higher than 0.70 (Hair et al., 2019). Subsequently, we examined the construct reliability of all measures, which showed scores above 0.80 for all variables (Cronbach, 1951). Details of the constructs can be found in the OSF link: t.ly/2y2wL

Table 3.1.
Model fit indices

Fit statistics	Model
x2 (df)	602.167 (199)
p-value	0.000
RMSEA	0.067
CFI	0.967
TLI	0.961
Akaike Information Crierion (AIC)	31778.172

Independent Variable

Conversational Agents and Websites. The website was designed with two main interactive elements for the users (Ischen, Araujo, van Noort, et al., 2020; Xiu et al., 2023) (Figure 3.2a). First, prior to the recommendations, users actively selected their news preferences (Ischen, Araujo, van Noort, et al., 2020). Second, in order to consume each of the recommendations, users needed to actively click the title of the news item. This approach was implemented to enhance the similarity between the website and the CA (Xiu et al., 2023). In contrast, the CA was created as a standalone platform, using a tool kit for conversational agent research (Araujo, 2020). Similar to other CAs (e.g., ChatGPT), this CA was not embedded in a website (Figure 3.2b). Moreover, mirroring the functionality of the news website, the CA offered recommendations based on user input. The recommendations generated by the CA and the website included: the title relevant to the topic and a short summary of the news article.

Moreover, as our primary concern was evaluating the effects of the interfaces in which the news recommender was embedded (i.e., CA or a website), we decided not to include a manipulation check (O'Keefe, 2003). Instead, we included two attention-check questions to ensure complete participation. The questions incorporated were: How many topics does the news recommender present you for selecting? And does the news recommender also provide pictures of the news articles? Participants who failed the attention check were not considered for the analysis.

Measures

Perceived Ease of Use. We measure perceived ease of use by adapting 6 items from (Gefen et al., 2003). However, in this construct, we included only items loading higher than .70 in the confirmatory factor analysis. Therefore, we included only 5 items with statements such as "This news recommender is easy to use.", "It is easy to become skillful at using this news recommender.", "Learning to operate this news recommender is easy.", "My interaction with this news recommender is clear and understandable." And "It is easy to interact with this news recommender." The items used showed high reliability ($\alpha = 0.92$, $M = 5.48$, $SD = 0.89$).

Perceived Enjoyment. We measure enjoyment using 3 items adapted from (Venkatesh, 2000). These items are measured on a 7-point Likert scale ranging from 1 (Strongly disagree) to 7 (Strongly agree). The items were phrased as followed: "I find using this news recommender to be enjoyable.", "The actual process of using this news recommender is pleasant." and "I have fun using this news recommender." The scale combined showed high

reliability (α = 0.91, *M* = 4.65, *SD* = 1.21).

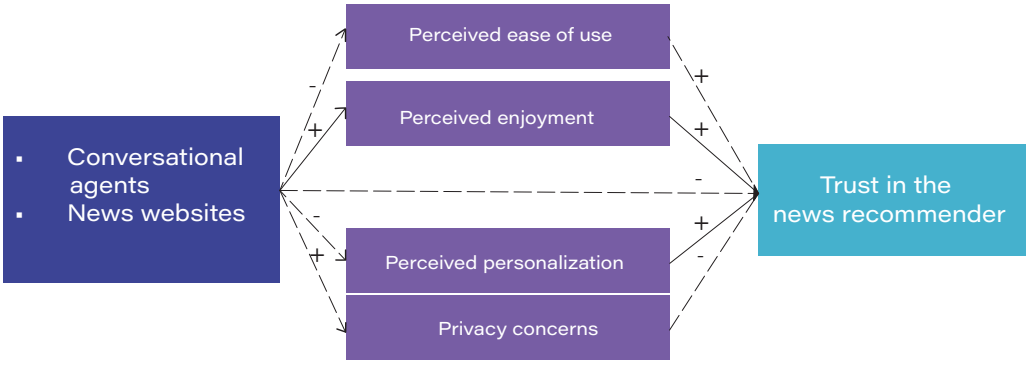
Perceived Personalization. Perceived personalization was measured using 3 items (Alimamy & Kuhail, 2023). We included statements such as: "This system understands my needs", "This system knows what I want". These items were measured on a 7-point Likert scale ranging from 1 (Strongly disagree) to 7 (Strongly agree). After combining the items, we see high reliability on these items (α = 0.91, *M* = 4.33, *SD* = 1.23).

Privacy Concerns. We used 4 items to measure privacy concerns (Dinev et al., 2017). Some of the items were: "I am concerned that the information I submit on the news recommender could be misused" and "I am concerned about submitting information on the news recommender because it could be used in a way I did not foresee"We combined the items to create the construct. The items used showed high reliability (α = 0.95, *M* = 3.52, *SD* = 1.44). Trust. We measured trust in the news recommender using 11 items (Komiak & Benbasat, 2006). However, in this construct, we included only items loading higher than .70 in the confirmatory factor analysis. Therefore, we included only 7 items with statements such as "This news recommender wants to understand my needs and preferences." The details of the statements included and the construct can be found in the OSF link: t.ly/2y2wL. The items combined showed high reliability (α = .93, *M* = 4.44, *SD* = 1.06).

Results

To address the research question and test the hypotheses (H1, H2, H3, H4,H5) we used the constructs measured and conducted a parallel

Figure 3.3.
Summary of the results



mediation (Model 4, using PROCESS macro for IBM SPSS version 29) (Hayes, 2017). This model included bootstrapping to generate 95% bias-corrected confidence intervals for the indirect effect. In addition, we included age and education as co-variates in our model to control for co-founding effects from the differences in the group. An overview of the results is presented in table 3.2 and Figure 3.3.

Direct and Indirect Effects

First, Hypothesis 1a suggested that exposure to a CA would lead to greater perceived ease of use than exposure to a website. However, the findings indicate a non-significant effect of CA on perceived ease of use (B = −0.038, SE = 0.074, *95% CI* [−0.185, 0.108]). Thus, Hypothesis 1a is not supported. Hypothesis 1b proposed that individuals with higher perceived ease of use would have more trust in the news recommender. The results indicate a non-significant effect of perceived ease of use on trust in the news recommender (B = 0.042, SE = 0.033, *95% CI* [−0.023, 0.107]). Therefore, Hypothesis 1b is not supported.

Second, Hypothesis 2a predicted that individuals exposed to a CA would have a higher level of perceived enjoyment than those exposed to a website. The results reveal that participants exposed to the conversational agents had a negative effect on perceived enjoyment in comparison to those exposed to the website (B = −0.255, SE = 0.100, *95% CI* [−0.453, −0.058]). Thus, exposure to a conversational agent decreases perceived enjoyment. As a result, Hypothesis 2a is not supported. Hypothesis 2b suggested that individuals with higher levels of perceived enjoyment would have more trust in the news recommender. The results reveal a positive effect of perceived enjoyment on trust in the news recommender (B = 0.288, SE = 0.029, *95% CI* [0.231, 0.346]). Consequently, Hypothesis 2b is supported.

Third, Hypothesis 3a predicted that individuals exposed to a conversational agent would have a higher level of perceived personalization than those exposed to a website. The findings show that CAs did not influence perceived personalization (B = −0.195, SE = 0.101, *95% CI* [−0.395, 0.004]). Thus, Hypothesis 3a is not supported. Hypothesis 3b indicated that individuals with higher levels of perceived personalization would show more trust in the news recommender. The results suggest that perceived personalization had a positive influence on trust (B = 0.475, SE = 0.025, *95% CI* [0.425, 0.526]). Therefore, Hypothesis 3b is supported.

Fourth, Hypothesis 4a predicted that individuals exposed to a conversational agent would have a higher level of privacy concerns than those exposed to a website. The results indicate that the conversational agents, in comparison to the website, did not influence privacy concerns (B = 0.040, SE = 0.120, *95% CI* [−0.195, 0.277]). Hence, Hypothesis 4a is not supported. Hypothesis 4b suggested that individuals with higher

levels of privacy concerns would show less trust in the news recommender. The results reveal a non-significant effect of privacy concerns on trust (*B* = −0.001, *SE* = 0.017, *95% CI* [−0.035, 0.031]). Thus, Hypothesis 4b is not supported.

Finally, Hypothesis 5 predicted that individuals exposed to a conversational agent would have a higher level of trust in the news recommender than those exposed to a website. The results indicate a non-significant direct effect of conversational agents on trust in the news recommender (*B* = 0.026, *SE* = 0.048, *95% CI* [−0.069, 0.122]), suggesting that the type of exposure does not significantly affect trust. Instead, CAs had a total negative indirect effect on trust in the news recommender (*B* = −0.168, *SE* = 0.074, *95% CI* [−0.315, −0.020]) through perceived enjoyment (*B* = −0.073, *SE* = 0.030, *95% CI* [−0.135, −0.016]). Thus, Hypothesis 5 is not supported.

Table 3.2.
Summary of the Results for the Hypotheses

Hypothesis	B	SE	95% CI	Supported
1A	-0.038	0. 074	[-0.185, 0.108]	No
1B	0.042	0.033	[-0.023, 0.107]	No
2A	-0.255	0.100	[-0.453, -0.058]	No
2B	0.288	0.029	[0.231, 0.346]	Yes
3A	-0.195	0.101	[-0.395, 0.004]	No
3B	0.475	0.925	[0.425, 0.526]	Yes
4A	0.040	0.120	[-0.195, 0.277]	No
4B	-0.001	0.017	[-0.035, 0.031]	No
5 (Total effect)	-0.168	0.074	[-0.315, -0.020]	No

Discussion

III

The emerging use of CAs as news recommenders is transforming news delivery into a more dialogic and informal interaction, aiming to engage with unattended audiences (Ford & Hutchinson, 2021). Despite the growing adoption of CAs as recommender systems (Jannach, 2023), limited research exists focusing on their influence on trust in the news recommender (Van den Broeck et al., 2019). Our study takes an initial step to fill this gap by evaluating the antecedents that affect trust in the news recommender when interacting with either a CA or a website.

Surprisingly and contrary to our expectations, in this study, CAs have a negative effect on trust in news recommenders when compared to websites. Our findings suggest that CAs reduce trust by reducing perceived enjoyment. Contrary to prior studies, this finding might suggest that – in our context – only the exchange of dialogue between the user and CAs might not be enough to reduce boredom for users (Ischen, Araujo, van Noort, et al., 2020; Selamat & Windasari, 2021; Xiu et al., 2023). In addition, our study provides more nuance to earlier findings regarding the influence of CAs on news. Specifically, Xiu et al. (2023) suggest that interacting with CAs may increase users' attention to the content, yet their focus was on entertainment news. In our case, with general news headlines, we do not find the same effect. This might suggest that the context of the information delivered to users and the exchange of dialogue with CAs might affect how much users enjoy the interaction. Given that our study presented general news, while Xiu et al. (2023) used entertainment news, future research could investigate how different types of content (e.g., entertainment vs. general news) influence user engagement and trust when interacting with CAs. This could help identify any potential interaction effects between the content and the mode of interaction (e.g., CAs vs websites).

Additionally, in our study, there was no significant difference in privacy concerns between CAs and websites. This finding extends previous research in the context of marking (Belen Saglam et al., 2021; Ischen, Araujo, Voorveld, et al., 2020). Ischen, Araujo, Voorveld, et al. (2020) identified no effect on privacy concerns for a human-like CA, while a machine-like CA was associated with lower privacy concerns. Given that our study utilized a human-like CA within the news context, our findings expand the finding to the context of news. Moreover, this finding builds upon the research conducted by Belen Saglam et al. (2021), suggesting that interacting with CAs, as opposed to websites, does not heighten privacy concerns. This finding may suggest that the interface of the interaction is not enough to increase privacy concerns. Previous studies suggest that users might be more concern about the institution that collects and processes their information, than the interface itself. (Ischen, Araujo, Voorveld, et al., 2020; Lutz & Newlands, 2021). Future research could evaluate this further by

evaluating the relationship between user privacy concerns and the trust in institutions behind CAs.

Finally, we confirmed the findings from earlier studies in the context of e-commerce (Hwang & Kim, 2007; Komiak & Benbasat, 2006). In this study, we found perceived enjoyment and perceived personalization as antecedents of trust in the news recommender. In the context of news recommenders, a system that is entertaining and provides relevant content for the use of the technology might show users the intention to serve them (Komiak & Benbasat, 2006). This is important for the development of news recommenders, as it guides news organizations in designing interfaces that encourage trust. Moreover, considering the relevance of the context, it is important to ensure that trusted news recommenders not only meet user-centric criteria like perceived enjoyment or perceived personalization but also adhere to ethical standards in journalism (Helberger, 2021).

This study is not done without limitations. First, our study was mainly conducted in a controlled environment through a one-time experiment. In this scenario, users interacted one time with a real-time news recommender. However, since users interact with various types of recommenders in their daily lives,it is important to evaluate how over-time interactions can influence users' perceptions, including perceived enjoyment and trust in the news recommender. Second, our news recommender was intentionally designed to offer a limited selection of topics, based on the quantity (i.e., popularity) of the collected news items. This approach was implemented to simplify the technological infrastructure required and to prevent overwhelming users with too many options. However, it is important to acknowledge that users interact with more sophisticated recommenders daily. In this sense, users might expect the system to anticipate news preferences based on their behavior. Thus, future studies could evaluate the extent to which the complexity of the algorithm across various interfaces influences users' perceptions.

The rising adoption of CAs as recommenders in the news industry is transforming the delivery of information, shifting it towards more conversational and casual forms of interaction (Ford & Hutchinson, 2021; Hepp et al., 2023). This raises questions about the antecedents that influence trust in the news recommender when interacting with CAs. Our findings contribute to the literature on journalism and news recommenders by setting an initial step toward understanding the most influential antecedents that affect trust in a news recommender, such as perceived enjoyment. Additionally, our findings offer design insights for news organizations on the antecedents that are relevant when interacting with a website compared to a conversational agent. News organizations willing to provide conversational news recommendations should focus on designing enjoyable and relevant conversations, as this is key to building and maintaining trust in their news recommender systems. As the media landscape continues to evolve with emerging technologies such as the adoption of generative AI through CAs,

it is important to understand the different antecedents that influence trust when interacting with these systems. Future research should continue to explore the different specific characteristics of CAs (e.g., audio modality in virtual assistants, AI recommendations in CAs, pull vs push information) that could shape users' perceptions of news distribution. This will enhance our understanding of how to effectively engage with unattended audiences (Ford & Hutchinson, 2021).

References

Alimamy, S., & Gnoth, J. (2022). I want it my way! The effect of perceptions of personalization through augmented reality and online shopping on customer intentions to co-create value. *Computers in Human Behavior, 128*, 107105.

Alimamy, S., & Kuhail, M. A. (2023). I will be with you Alexa! The impact of intelligent virtual assistant's authenticity and personalization on user reusage intentions. *Computers in Human Behavior, 143*, 107711.

Araujo, T. (2020). Conversational agent research toolkit: An alternative for creating and managing chatbots for experimental research. *Computational Communication Research, 2*(1), 35–51.

Beldad, A., De Jong, M., & Steehouder, M. (2010). How shall I trust the faceless and the intangible? A literature review on the antecedents of online trust. *Computers in Human Behavior, 26*(5), 857–869.

Belen Saglam, R., Nurse, J. R., & Hodges, D. (2021). Privacy concerns in chatbot interactions: When to trust and when to worry. In *HCI International 2021-Posters: 23rd HCI International Conference, HCII 2021, Virtual Event, July 24–29, 2021, Proceedings, Part II* (Vol. 23, pp. 391–399).

Blut, M., Wang, C., Wünderlich, N. V., & Brock, C. (2021). Understanding anthropomorphism in service provision: A meta-analysis of physical robots, chatbots, and other AI. *Journal of the Academy of Marketing Science, 49*, 632–658.

Boerman, S. C., Kruikemeier, S., & Zuiderveen Borgesius, F. J. (2017). Online behavioral advertising: A literature review and research agenda. *Journal of Advertising, 46*(3), 363–376.

Boerman, S. C., Kruikemeier, S., & Zuiderveen Borgesius, F. J. (2021). Exploring motivations for online privacy protection behavior: Insights from panel data. *Communication Research, 48*(7), 953–977.

Bol, N., Dienlin, T., Kruikemeier, S., Sax, M., Boerman, S. C., Strycharz, J., Helberger, N., & De Vreese, C. H. (2018). Understanding the effects of personalization as a privacy calculus: Analyzing self-disclosure across health, news, and commerce contexts. *Journal of Computer-Mediated Communication, 23*(6), 370–388.

Bozdag, E. (2013). Bias in algorithmic filtering and personalization. *Ethics and Information Technology, 15*, 209–227.

Brandtzaeg, P. B., & Følstad, A. (2017). Why people use chatbots. In *Internet Science: 4th International Conference, INSCI 2017, Thessaloniki, Greece, November 22-24, 2017, Proceedings* (Vol. 4, pp. 377–392).

Choi, J., Lee, H. J., & Kim, Y. C. (2011). The influence of social presence on customer intention to reuse online recommender systems: The roles of personalization and product type. *International Journal of Electronic Commerce, 16*(1), 129–154.

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika, 16*(3), 297–334.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. *Journal of Applied Social Psychology, 22*(14), 1111–1132.

Diakopoulos, N. (2015). Algorithmic accountability: Journalistic investigation of computational power structures. *Digital Journalism, 3*(3), 398–415.

Dinev, T., Xu, H., Smith, J. H., & Hart, P. (2017). Information privacy and correlates: An empirical attempt to bridge and distinguish privacy-related concepts. *European Journal of Information Systems*. https://doi.org/10.1057/ejis.2012.2

Foehr, J., & Germelmann, C. C. (2020). Alexa, can I trust you? Exploring consumer paths to trust in smart voice-interaction technologies. *Journal of the Association for Consumer Research, 5*(2), 181–205.

Ford, H., & Hutchinson, J. (2021). Newsbots that mediate journalist and audience relationships. In *Algorithms, automation, and news* (pp. 34–52). Routledge.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, 51–90.

Griol, D., Carbó, J., & Molina, J. M. (2013). An automatic dialog simulation technique to develop and evaluate interactive conversational agents. *Applied Artificial Intelligence, 27*(9), 759–780.

Guo, X., Zhang, X., & Sun, Y. (2016). The privacy–personalization paradox in mHealth services acceptance of different age groups. *Electronic Commerce Research and Applications, 16*, 55–65.

Ha, Q.-A., Victor Chen, J., Uy Uy, H., Paolo Capistrano, E., Chi Minh City, H., & Nam, V. (2021). Exploring the privacy concerns in using intelligent virtual assistants under perspectives of information sensitivity and anthropomorphism. *International Journal of Human-Computer Interaction, 37*(6), 512–527. https://doi.org/10.1080/10447318.2020.1834728

Hair, J., Black, W., Babin, B., & Anderson, R. (2019). *Multivariate data analysis* (8th ed.). UK: Cengage Learning EMEA.

Hayes, A. F. (2017). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. Guilford Publications.

Helberger, N. (2021). On the democratic role of news recommenders. In *Algorithms, automation, and news* (pp. 14–33). Routledge.

Hepp, A., Loosen, W., Dreyer, S., Jarke, J., Kannengießer, S., Katzenbach, C., Malaka, R., Pfadenhauer, M., Puschmann, C., & Schulz, W. (2023). ChatGPT, LaMDA, and the hype around communicative AI: The automation of communication as a field of research in media and communication studies. *Human-Machine Communication, 6*(1), 4.

Hwang, Y., & Kim, D. J. (2007). Customer self-service systems: The effects of perceived web quality with service contents on enjoyment, anxiety, and e-trust. *Decision Support Systems, 43*(3), 746–760.

Ischen, C., Araujo, T., van Noort, G., Voorveld, H., & Smit, E. (2020). "I am

here to assist you today": The role of entity, interactivity and experiential perceptions in chatbot persuasion. *Journal of Broadcasting & Electronic Media, 64*(4), 615–639.

Ischen, C., Araujo, T., Voorveld, H., van Noort, G., & Smit, E. (2020). Privacy concerns in chatbot interactions. In *Chatbot Research and Design: Third International Workshop, CONVERSATIONS 2019, Amsterdam, The Netherlands, November 19–20, 2019*, Revised Selected Papers (Vol. 3, pp. 34–48).

Jannach, D. (2023). Evaluating conversational recommender systems: A landscape of research. *Artificial Intelligence Review, 56*(3), 2365–2400.

Jia, H., & Sundar, S. S. (2023). Vivid and engaging: Effects of interactive data visualization on perceptions and attitudes about social issues. *Digital Journalism*, 1–25. https://doi.org/10.1080/21670811.2023.2250815

Jones, B., & Jones, R. (2021). Public service chatbots: Automating conversation with BBC News. In *Algorithms, automation, and news* (pp. 53–74). Routledge.

Karakayali, N., Kostem, B., & Galip, I. (2018). Recommendation systems as technologies of the self: Algorithmic control and the formation of music taste. *Theory, Culture & Society, 35*(2), 3–24.

Karimi, M., Jannach, D., & Jugovac, M. (2018). News recommender systems–survey and roads ahead. *Information Processing & Management, 54*(6), 1203–1227.

Kim, Y., Kim, S. H., Peterson, R. A., & Choi, J. (2023). Privacy concern and its consequences: A meta-analysis. *Technological Forecasting and Social Change, 196*, 122

Komiak, S. Y. X., & Benbasat, I. (2006). The effects of personalization and familiarity on trust and adoption of recommendation agents. *MIS quarterly*, 941–960. https:// doi.org/ https:// doi.org/10.2307/25148760

Komiak, S. Y., Wang, W., & Benbasat, I. (2004). Trust building in virtual salespersons versus in human salespersons: Similarities and differences. *E-service, 3*(3), 49–64.

Li, C. (2016). When does web-based personalization really work? The

distinction between actual personalization and perceived personalization. *Computers in Human Behavior, 54*, 25–33. https://doi.org/10.1016/J.CHB.2015.07.049

Li, L., Lee, K. Y., Emokpae, E., & Yang, S.-B. (2021). What makes you continuously use chatbot services? Evidence from Chinese online travel agencies. *Electronic Markets*, 1–25.

Loecherbach, F., & Trilling, D. (2020). 3bij3–developing a framework for researching recommender systems and their effects. *Computational Communication Research, 2*(1), 53–79.

Lutz, C., & Newlands, G. (2021). Privacy and smart speakers: A multidimensional approach. *The Information Society, 37*(3), 147–162.

Mayer, R. C., & Davis, J. H. (1999). The effect of the performance appraisal system on trust for management: A field quasi-experiment. *Journal of Applied Psychology, 84*(1), 123.

Natale, S., & Cooke, H. (2021). Browsing with Alexa: Interrogating the impact of voice assistants as web interfaces. *Media, Culture & Society, 43*(6), 1000–1016.

Nel, J., & Boshoff, C. (2017). Development of application-based mobile-service trust and online trust transfer: An elaboration likelihood model perspective. *Behaviour & Information Technology, 36*(8), 809–826.

Nguyen, Q. N., Sidorova, A., & Torres, R. (2022). User interactions with chatbot interfaces vs. menu-based interfaces: An empirical study. *Computers in Human Behavior, 128*, 107093.

Nicolescu, L., & Tudorache, M. T. (2022). Human-computer interaction in customer service: The experience with AI chatbots—a systematic literature review. *Electronics, 11*(10), 1579.

O'Keefe, D. J. (2003). Message properties, mediating states, and manipulation checks: Claims, evidence, and data analysis in experimental persuasive message effects research. *Communication Theory, 13*(3), 251–274.

Rapp, A., Curti, L., & Boldi, A. (2021). The human side of human-chatbot interaction: A systematic literature review of ten years of research on text-based chatbots. *International Journal of Human-Computer Studies, 151*, 102630.

Resendez, V., Araujo, T., Helberger, N., & de Vreese, C. (2024). *The influence*

of conversational agents on trust in the news recommender: A comparison between a conversation and a website [Manuscript submitted for publication].

Rouibah, K., Lowry, P. B., & Hwang, Y. (2016). The effects of perceived enjoyment and perceived risks on trust formation and intentions to use online payment systems: New perspectives from an Arab country. *Electronic Commerce Research and Applications, 19*, 33–43.

Sarkar, S., Chauhan, S., & Khare, A. (2020). A meta-analysis of antecedents and consequences of trust in mobile commerce. *International Journal of Information Management, 50*, 286–301.

Schomakers, E.-M., Lidynia, C., & Ziefle, M. (2022). The role of privacy in the acceptance of smart technologies: Applying the privacy calculus to technology acceptance. *International Journal of Human-Computer Interaction, 38*(13), 1276–1289.

Selamat, M. A., & Windasari, N. A. (2021). Chatbot for SMEs: Integrating customer and business owner perspectives. *Technology in Society, 66*, 101685.

Sidlauskiene, J. (2022). What drives consumers' decisions to use intelligent agent technologies? A systematic review. *Journal of Internet Commerce, 21*(4), 438–475.

Skjuve, M., Følstad, A., Fostervold, K. I., & Brandtzaeg, P. B. (2021). My chatbot companion: A study of human-chatbot relationships. *International Journal of Human-Computer Studies, 149*, 102601.

Sundar, S. S., & Liao, M. (2023). Calling BS on ChatGPT: Reflections on AI as a communication source. *Journalism & Communication Monographs, 25*(2), 165–180.

Thurman, N., Moeller, J., Helberger, N., & Trilling, D. (2019). My friends, editors, algorithms, and I: Examining audience attitudes to news selection. *Digital Journalism, 7*(4), 447–469.

Valtolina, S., Barricelli, B. R., & Di Gaetano, S. (2020). Communicability of traditional interfaces vs chatbots in healthcare and smart home domains. *Behaviour & Information Technology, 39*(1), 108–132.

van Deursen, A. J., van der Zeeuw, A., de Boer, P., Jansen, G., & van Rompay, T. (2022). Development and validation of the internet of things skills scale (IoTSS). *Information, Communication & Society, 25*(13), 1883–1899.

Van den Broeck, E., Zarouali, B., & Poels, K. (2019). Chatbot advertising effectiveness: When does the message get through? *Computers in Human Behavior, 98*, 150–157.

Vance, A., Elie-Dit-Cosaque, C., & Straub, D. W. (2008). Examining trust in information technology artifacts: The effects of system quality and culture. *Journal of Management Information Systems, 24*(4), 73–100.

Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research, 11*(4), 342–365.

Xiu, L., Chen, Y., Yu, G., & Yang, Y. (2023). The impact of conversational interaction on users' cognitive absorption in mobile news reading context: Evidence from EEG. *Behaviour & Information Technology,* 1–14.

Zamora, J. (2017). I'm sorry, Dave, I'm afraid I can't do that: Chatbot perception and expectations. *Proceedings of the 5th International Conference on Human Agent Interaction*, 253–260.

Zanker, M., Rook, L., & Jannach, D. (2019). Measuring the impact of online personalisation: Past, present and future. *International Journal of Human-Computer Studies, 131*, 160–168.

Zarouali, B., Van den Broeck, E., Walrave, M., & Poels, K. (2018). Predicting consumer responses to a chatbot on Facebook. *Cyberpsychology, Behavior, and Social Networking, 21*(8), 491–497.

Zhao, X., Chen, L., Jin, Y., & Zhang, X. (2023). Comparing button-based chatbots with webpages for presenting fact-checking results: A case study of health information. *Information Processing & Management, 60*(2), 103203.

Appendix A

Table 3.3.
Direct and indirect effects of CAs on trust through sequential mediators (Model 6)

EFFECT TYPE	PATH DESCRIPTION	EFFECT	BOOT SE	BOOT LLCI	BOOT ULCI
DIRECT	CAs → Trust	0.026	0.048	-0.069	0.122
INDIRECT	Total	-0.168	0.073	-0.316	-0.026
INDIRECT	CAs → Perceived ease of use → Trust	-0.001	0.004	-0.011	0.006
INDIRECT	CAs → Perceived enjoyment → Trust	-0.065	0.024	-0.114	-0.017
INDIRECT	CAs → Perceived personalization → Trust	-0.015	0.036	-0.088	0.057
INDIRECT	CAs → Privacy concerns → Trust	0.000	0.002	-0.004	0.005
INDIRECT	CAs → Perceived ease of use → Perceived enjoyment → Trust	-0.008	0.017	-0.042	0.024
INDIRECT	CAs → Perceived ease of use → Perceived personalization → Trust	-0.001	0.003	-0.011	0.004
INDIRECT	CAs → Perceived ease of use → Perceived ease of use → Trust	-0.000	0.000	-0.001	0.000
INDIRECT	CAs → Perceived enjoyment → Perceived personalization → Trust	-0.067	0.026	-0.120	-0.018
INDIRECT	CAs → Perceived enjoyment → Privacy concerns → Trust	-0.000	0.000	-0.002	0.001
INDIRECT	CAs → Perceived personalization → Privacy concerns → Trust	0.000	0.000	-0.000	0.000
INDIRECT	CAs → Perceived ease of use → Perceived enjoyment → Perceived personalization → Trust	-0.009	0.017	-0.044	0.024
INDIRECT	CAs → Perceived ease of use → Perceived enjoyment → Privacy concerns → Trust	-0.000	0.000	-0.000	0.000

EFFECT TYPE	PATH DESCRIPTION	EFFECT	BOOT SE	BOOT LLCI	BOOT ULCI
INDIRECT	CAs → Perceived ease of use → Perceived personalization → Privacy concerns → Trust	0.000	0.000	-0.000	0.000
INDIRECT	CAs → Perceived enjoyment → Perceived personalization → Privacy concerns → Trust	0.000	0.000	-0.000	0.000
INDIRECT	CAs → Perceived ease of use → Perceived enjoyment → Perceived personalization → Privacy concerns → Trust	0.000	0.000	-0.000	0.000

This table summarizes the direct and total indirect effects of condition on Trust through Model 6 in PROCESS. Bootstrapped confidence intervals are reported (BOOTLLCI and BOOTULCI) for the indirect effects, with 5000 bootstrap samples. A confidence level of 95% is applied.