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Information Overload in Information Seeking with Conversational Agents: A Survey and Design Considerations

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Abstract

Conversational agents and related systems enable more flexible and elaborate information seeking and retrieval than earlier search strategies, such as conventional web search engines. However, these systems sometimes produce responses that are excessively long or complex, not always aligning with the needs of their human interaction partners and potentially leading to information overload (IO). IO is associated with negative affect in humans and is known to reduce information effectiveness, thereby limiting the usability of information-seeking systems. In this paper, I briefly discuss psychological effects of IO and present the results of a survey examining self-reported experiences of IO when using conversational agents for information seeking in a German sample (n = 50). The paper concludes with suggestions for how conversational agents could be adapted and modified to become more sensitive to humans' affective experiences, with the goal of mitigating the effects of IO.

CCS Concepts

• **Information systems → Users and interactive retrieval**; • **Human-centered computing → Empirical studies in HCI**.

Keywords

conversational information seeking, information overload, human-agent interaction, conversational agent, affect

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1 Introduction

Starting with customer assistants on commercial websites and, ultimately, with the public release of ChatGPT 3.5 [48], as well as the subsequent release of other chat-based large language model (LLM) interfaces (e.g., Google's Gemini [25]), LLM-driven conversational agents are becoming increasingly common for solving problems and tasks, including information seeking and retrieval.

It is probably fair to say that we are currently on the brink of these newer forms of conversational information seeking (CIS [16, 17]) gradually replacing conventional web search engines [64, 65]. This is further evidenced by the recent trend of integrating conversational search features into traditional web search engines (such as the incorporation of Gemini into Google Search, for example).

CIS is, in some respects, superior to conventional web searching because it typically provides more elaborate and nuanced answers and allows users to ask follow-up questions that take into account the initial query or prompt as well as the subsequent conversation. At the same time, many people struggle to adapt to these new search strategies, either due to the required change in habits or because of system-inherent factors. For this reason, it is crucial to expand our understanding of the user experience in CIS using LLM-backed transformer models [39], particularly from psychological and interactional perspectives. In contrast to previous information systems, CIS represents a specific form of human–agent interaction (HAI), in which socio-affective processes and the establishment of rapport between humans and agents play a more vital role [27].

One prominent observation in CIS with LLMs is that these systems sometimes produce responses that are excessively long or complex, and thus do not always align with human-to-human conversational norms or the needs of human interaction partners, posing a risk of information overload (IO [4, 8, 9]). From a psychological perspective, IO is problematic because it is associated with negative affect in humans and is known to reduce information effectiveness, potentially limiting the usability of an information-seeking system.

To address this issue, I briefly discuss psychological effects of IO in Section 2 and then present the results of a survey examining self-reported experiences of information overload when using conversational agents for information seeking in a German sample in Section 3. This analysis aims to provide insights into the occurrence and form of this phenomenon in the context of CIS. Section 4 concludes with suggestions for how conversational agents could be adapted and modified to become more sensitive to the affective experience of humans in information-seeking contexts, with the specific goal of mitigating the effects of IO in HAI. Furthermore, investigating IO in HAI also contributes to our broader understanding of the phenomenon in human cognition, with implications for other domains such as education or health communication.

2 Information Overload and its Consequences

2.1 Information Overload and the Digital Era

Closely related to the concept of cognitive overload [59], information overload (IO) is defined as "the state that occurs when the amount or intensity of information exceeds the individual's processing capacity" [4]. As emphasized by Bawden (1999), this poses a paradox to some extent, as it refers to situations in which "information received becomes a hindrance rather than a help, even though the information is potentially useful" [8].

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Critically, the occurrence of information overload has increased in the digital age with the widespread use of digital communication (e.g., emails, team chats, communication platforms), search engines, and databases [6]. The impact of these organizational changes has been widely discussed in the fields of business studies and organizational psychology (for an overview, see [5], for instance). More recently, with the advent and public release of chatbot-based interaction interfaces (e.g., ChatGPT, currently integrating GPT-5 [49]), as well as expanded forms of search engines—such as the implementation of Gemini [25] into Google's classical search interface-the ways in which people seek and retrieve information are shifting. Without a doubt, the use of conversational agents will continue to increase in the near future, given their greater flexibility, more nuanced responses, and the possibility of posing follow-up queries.

So far, several researchers have explored how conversational agents can help mitigate information overload. As an early example, Maes (1995) discussed in an overview article how the use of autonomous agents (in the form of computer programs) can reduce the effects of IO in daily life [41]. Goddard, in a recently published dissertation [24], examined how a personal LLM-backed agent can help alleviate IO across multiple platforms (see also [38]).

At the same time, the occurrence of IO during the use of conversational agents for information seeking has received comparatively little attention and warrants further investigation, particularly because IO can have significant effects on humans' emotional experiences and cognitive processing. In the context of conversational agents, users can particularly experience communication overload, a subform of information overload (IO), defined as "a condition in which more information is presented to a person or a computer system than can be processed or otherwise effectively utilized" [3] (see also [15, 33]). In other words, the sheer volume of information presented might impair a user's ability to effectively process it.

2.2 Psychological Effects

IO is associated with a range of negative affective (e.g., stress, negative mood, anxiety) and cognitive (e.g., poor decision-making, reduced cognitive processing) consequences (for overviews, see [6, 26, 32, 45, 56]). IO has been investigated in a variety of contexts, including healthcare [28, 62], health information [57, 58], patient education [61], social media use [11, 23, 54], workplace environments [18, 63], decision-making [51], the COVID-19 pandemic [10, 60], and, more recently, in interaction with LLMs [38]. At the socio-affective level, IO is associated with increased stress and anxiety [8, 42], depression and reduced emotional well-being [43], as well as emotional exhaustion [23]. Moreover, IO is linked to a number of health issues, including increased strain, stress, and burnout [6]. Also, IO has been shown to impair cognitive processes [13, 47], including attention [40], memory [14, 35], and cognitive processing efficiency, thereby negatively affecting decision making [12, 13, 50].

In addition to studies focusing on the psychological effects of IO, only a few studies have examined psychophysiological and neurophysiological markers associated with its impact on emotional and cognitive processing, reflecting a clear gap in IO research [26]. Research in this area is increasingly feasible with accessible techniques such as wearables, which allow objective measurement of physiological responses. Because humans may not have full awareness of IO but immediately experience its effects, focusing on psychophysiological markers offers a promising approach — both for understanding IO and for improving CIS systems. For example, Mizin et al. (2014) observed increased sympathetic activity in students under higher information load using heart rate (HR) assessment via wearables [46]. Similarly, Abdullah et al. (2019) found rapid HR increases in response to rising information load [1]. Higher attentional engagement, even after a decision is made, has been reflected in neurophysiological patterns [50].

Consequently, in interactive settings, IO can also have significant interpersonal effects, such as reduced group cohesion [7, 19] and interpersonal bias [2, 44]. Beyond these psychological factors, research in organizational psychology has widely discussed the negative effects of IO on information effectiveness [6, 28, 31] and work productivity [34, 55, 56] (but see counterevidence by [36]).

This brief summary illustrates some of the significant effects that IO can have on human cognition, affective experience, and interpersonal behavior. Likewise, the ability to access and manage information is vital in a post-modern information society, a concern that has become even more pronounced in the digital era. Given the ongoing major shift in how we seek and retrieve information online, it is crucial to understand IO in the context of newer forms of CIS and the associated psychological aspects of this form of HAI.

3 Information Overload in Information Seeking with Conversational Agents: A Survey

3.1 Sample, Procedure, and Data Analysis

In the present research, 50 participants (16 women, 32 men, 1 non-binary participant, and 1 participant who did not disclose their gender) with a mean age: 40.24, SD = 14.27 recruited online via Prolific (www.prolific.com) provided minimal demographic information and then completed the German versions of the Affinity for Technology Interaction Scale (ATI) [22] and the Need to Belong Scale [37, 53]. They subsequently answered questions about their technical expertise, frequency of digital media use in general, and their use of conversational agents and chatbots in particular.

The survey on information seeking and IO in the use of conversational agents was divided into three parts. The first part focused on the use of conversational agents for information seeking in general. The second part addressed the user experience when seeking information with these agents, considering both the effectiveness and the affective experience of CIS. In the third part, participants were asked how they handle problems encountered in CIS. After that, participants answered questions about their affective experience and relationship with conversational agents (not discussed here).

The survey primarily consisted of 7-point Likert scale ratings but also included multiple-choice and open-ended questions. Due to a scripting error affecting the first five participants, only the last selected answer was recorded for multiple-choice questions, so for these questions only data from the remaining 45 participants were included. Data preprocessing and analyses were conducted in R [52]. Means and standard deviations were calculated for each scale and for age. For the relevant dimensions associated with IO, Spearman correlations were computed, all of which were non-normally distributed based on Shapiro-Wilk tests. In a few cases, interaction effects were assessed using R's base lm() function, with significance testing performed via the anova() function from the car package [21]. Counts were calculated for multiple-choice responses, and open-ended questions were qualitatively analyzed.

3.2 Results

Means, standard deviations, and correlations with the three central variables—information overload (IO), processing difficulty (Pro. Diff.), and negative affect (Neg. Aff.) are reported in Table 1.

3.2.1 Tech Expertise and HAI User Experience. As shown in Table 1, participants' scores on the ATI [22] were relatively low. In contrast, self-reported ratings for general experience and competence in using modern technology were above the scale midpoint, and interest in using technology was reported as high.

With respect to conversational agents, the majority of participants (47; 94%) reported having used such agents for a variety of purposes and with varying frequencies of use. When asked which commonly available conversational agents they had interacted with, most participants mentioned ChatGPT (40 participants; 80%), followed by Gemini (24; 48%) and the voice assistant Siri (14; 28%).

For the analysis of multiple-choice responses, only the 45 participants whose answers were successfully recorded were included. Based on this smaller sample (n = 45), the main purpose for using conversational agents reported by 37 participants (82.2%) was information seeking, followed by learning and educational purposes (30 participants; 66.7%) as well as entertainment (18 participants; 40%).

3.2.2 Information Seeking with Conversational Agents. Notably, the number of participants using conversational agents specifically for information seeking was lower than for general use with only 41 participants reporting having used agents for for this purpose.

Based on the smaller sample of 45 participants whose multiple-choice responses were recorded, the majority reported having used or currently using ChatGPT (n = 33; 73.3%), followed by Gemini (n = 18; 40.0%) and Microsoft Copilot (n = 11; 24.4%) for conversational information seeking. When asked about use cases, the most frequently selected responses were: tech support (28 participants; 62.2%), understanding complex topics (26; 57.8%), looking up facts (25; 55.6%), creative support (20; 44.4%), and learning (18; 40.0%).

3.2.3 Information Overload in CIS. When asked about the experience of IO while seeking information with conversational agents, participants reported a mean of 3.74 (SD = 1.03) on the 7-point Likert scale. This suggests that IO is present in these interactions, although not at a severe level. Regarding the types of situations in which IO was experienced: 28 participants (62.2%) reported encountering responses with irrelevant details, 24 participants (53.3%) reported incorrect information, and 19 (42.2%) reported contradictory information. Interestingly, 16 participants (35.6%) indicated that responses were too short in some cases.

IO was positively correlated with reports of irrelevant information and excessive detail, and was also significantly associated with participants' likelihood of stopping or interrupting use of the respective tool. Negative effects of inadequate or imperfect responses were reported, but the mean ratings were in the moderate range (see Table 1). The highest average rating was observed for difficulties in processing the information, followed by frustration. In comparison, stress and anger received relatively lower ratings. Ratings for processing difficulty, negative affect, and frustration were significantly correlated with each other and were also associated with anger.

Table 1: Results of the Likert-Rating-Scales and the ATI

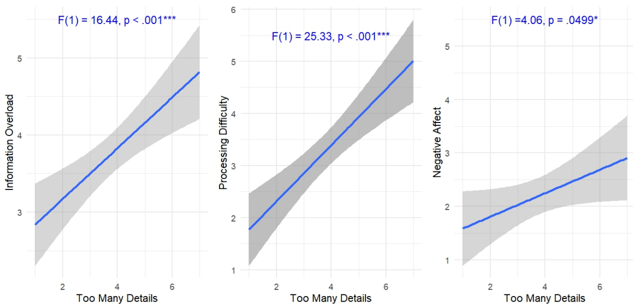
	M	SD	IO	Pro. Diff.	Neg. Aff.
General Tech Affinity					
ATI Score	2.57	0.30	0.17	-0.08	-0.06
Experience	5.34	1.14	0	0.02	-0.26
Competence	5.46	1.18	0.03	-0.22	-0.49^{***}
Interest	5.24	1.48	0.11	0.03	-0.14
Use of Agents for Information Search					
Frequency of Use					
... in General	4.44	1.76	0.27	0.06	-0.09
... for CIS	3.90	1.72	0.22	0.2	0.12
Evaluation of Responses in CIS					
Sufficient Info	4.75	1.39	0.17	-0.14	-0.18
Clear Response	5.17	1.37	0.13	-0.1	-0.23
Adequate Length	4.79	1.49	-0.12	-0.2	-0.21
Relevant Key points	4.79	1.40	-0.04	-0.09	-0.14
Clear Language	5.66	1.27	0.03	-0.22	-0.26
Irrelevant Details	4.45	1.57	0.41^{**}	0.32^{*}	-0.1
Too Many Details	3.74	1.58	0.44^{**}	0.56^{***}	0.32^{*}
Effects of Overly Complex CA Responses					
Information Overload	3.74	1.03		0.28	-0.04
Processing Difficulty	3.26	1.44	0.28		0.59^{***}
Negative Affect	2.19	1.21	-0.04	0.59^{***}	
Frustration	2.89	1.46	0.03	0.55^{***}	0.56^{***}
Anger	1.85	1.18	0.15	0.36^{*}	0.45^{**}
Response to Too Detailed Responses					
Interrupt Use	3.40	1.23	0.33^{*}	0.37^{*}	0.33^{*}
Rephrasing	4.26	1.24	0.12	0.14	-0.16
Switch Tool	3.83	1.25	0.04	0.37^{*}	0.23
Opinions Toward Solutions					
Cross-Chat Memory	3.84	1.92	0.18	0.29^{*}	0.06
Affect inferred					
...from Language	2.75	1.67	0.07	0.39^{**}	0.25
...from Physiology	2.29	1.38	0.05	0.38^{**}	0.2
Automatic Summaries	4.96	1.70	0.21	0.28	0.17
Simplified Language	4.80	1.73	0.27	0.26	0

Interestingly, processing difficulties were positively associated with both irrelevant information and excessive detail, and also correlated with participants' likelihood of interrupting the use of the conversational agent or switching to a traditional search strategy. In contrast, negative affect was only associated with excessive detail and interrupted use but showed no significant correlation with IO.

Linear regression revealed significant main effects of perceiving responses as containing too many details on IO, processing difficulty, and negative affect (see Figure 1), but not of irrelevant details, suggesting that the volume of information plays a role here. Another noteworthy observation is that self-reported competence in technology use was negatively correlated with negative affect.

3.2.4 Coping with Complex Responses. When participants encountered overly complex or misleading responses from conversational agents, they reported using several strategies to cope. The most common approach was asking follow-up questions (29 participants; 64.4%), followed by shortening the answer (25; 55.6%), selecting only the relevant parts of the response (12; 26.7%), requesting sources (11; 24.4%), or using bullet points (10; 22.2%). Only a few participants reported stopping use entirely (8; 17.8%) or asking the agent to simplify the language of their queries (6; 13.3%).

Figure 1: Main Effect of Response on IO Parameter



A final set of questions addressed potential strategies, and participants were asked to provide their opinions on these approaches. As shown in the bottom section of Table 1, the idea of adding summaries after longer prompts or simplifying the language of responses was rated positively, above the scale midpoint. Using the agent's memory to link information across chats was also supported, with mean ratings above the midpoint. In contrast, strategies involving the extraction of emotional characteristics from language patterns or physiological signals received lower ratings, below the midpoint, and were generally not endorsed by participants.

4 Some Design Considerations

The small survey suggests that IO in CIS is not extreme, but nonetheless present. Given its association with processing difficulties and negative affect, IO may, under certain conditions, hinder information seeking and retrieval with conversational agents, potentially diminishing information effectiveness and user engagement. It is therefore worthwhile to consider design characteristics that could mitigate these effects, ideally by reducing the occurrence of IO in CIS from the outset. In the remainder of this contribution, I discuss potential solutions with focus on the affective experience in HAI.

Beyond adaptation of the underlying model itself and model-specific fine-tuning, models could be constrained to produce shorter responses—for example, by adjusting temperature or defining a maximum token length. Models could also be globally prompted to respond more concisely or adapted through targeted Low-Rank Adaptation [30] to encourage more focused answers. Additionally, the length of the user's prompt could serve as a parameter indicating whether a shorter or longer response is desired. According to the survey, the simple, user-driven solution to provide prompts explicitly requesting concise answers is already commonly employed.

The last solution, however, illustrates the central challenge that users typically do not anticipate information overload and may only experience it during the information search, along with its negative consequences. Therefore, a viable alternative is to explore approaches in which the model's responses are dynamically adapted to the user's experiential state. Several avenues exist for evaluating and integrating the emotional experience of the human interaction partner. Under the assumption that IO is associated with increased negative affect, the system could be designed to detect elevated negative affect and respond with shorter or modified answers.

For this purpose, affect could be assessed directly by adding feedback-oriented questions (e.g., "Was this helpful?"), an approach that is already partly implemented in some platforms. However, this approach can counteract the intended effect by generating additional information overload. A more effective approach would be more indirect assessments, allowing the system to estimate the user's affect and adapt responses accordingly. This can be achieved either by extracting features from the user's language or by monitoring psychophysiological arousal—for example, using a wearable device. An additional analysis loop could infer emotional arousal from the user's linguistic style, similar to the approach employed in EmpathyEar [20], an empathetic conversational agent.

While the use of psychophysiological measures may initially appear excessive and was the least preferred option according to the survey, it offers practical advantages, especially considering that such signals can now be measured easily via wearables (e.g., photoplethysmography) and increasingly through camera-based methods [29]. Integrating physiological measures could improve the effectiveness of information seeking in CIS by constraining IO in these contexts. For instance, heart rate (HR) monitoring from a wearable during the overall interaction with a given chatbot (requiring repeated or longer interactions) could be used to derive a specific index of the current arousal in response to a given answer. That value could then be fed into the model as a new command prompting the system to rephrase the response or as an add-on prompt to the next user query, adapting the subsequent response (e.g., shortening the answer in response to relative HR increases). Put simply, the basic idea is that a second signal type in addition to textual input is used to modulate the response.

Aside from data protection concerns when combining multiple data streams, this raises the question of whether people should adapt to new technologies or whether technologies should better support human (social and cognitive) needs. LLM-based chatbots increasingly enable the latter, and developing clear linguistic or psychophysiological markers to guide adaptive responses could improve interactions with conversational agents. In particular, agents that are sensitive to the affective experiences of humans and that are linked physiology-based feedback loops that detect emotionally relevant features could mitigate IO in CIS and enhance HAI.

5 Conclusion

While information seeking and retrieval with conversational agents allows for more elaborate and reflective engagement with information from diverse sources, information overload in conversational information seeking can undermine these benefits. In this brief contribution, I discussed IO from a psychological perspective and examined, based on survey data, its occurrence in CIS, as well as its association with negative affect and reduced processing efficiency.

Importantly, developing and evaluating new HAI design characteristics may not only improve CIS but also provide insights for enhancing information seeking and retrieval in other contexts. Ultimately, understanding information processing in HAI deepens our understanding of information processing in human cognition.

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