Everyday-Life Information-Seeking With AI: How Insights From ELIS Can Help Design Trustworthy AI Systems.

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Abstract
As artificial intelligence (AI) systems are becoming an integral part of our everyday life, their role in shaping human information-seeking behaviors has become a crucial area of study. During the years, part of the literature on Human-Computer Interaction (HCI) that has focused on AI, concentrated on the role of trust in mediating users' reliance on the AI output. However, the experimental tasks they used in these studies did not reflect the way in which people actually seek information in their everyday life, undermining the generalization of the obtained results. Here, we posit that the way people practice information-seeking in their daily lives can influence the way in which they then decide to rely on the output of the AI. Therefore, we propose that the perspective offered by the Everyday Life Information-Seeking literature (ELIS) can help designers create more trustworthy AI systems, that can foster users' appropriate reliance.

Keywords
trustworthy AI, appropriate reliance, information-seeking, ELIS

1. Introduction

Imagine it is 10 a.m of a Sunday morning. You just woke up and while you are having breakfast, you are planning the day ahead of you. It is not a workday, but you have to run some errands, maybe fix some small things that you ignored all week, and you want to dedicate some time sewing your cosplay costume for an upcoming comic convention. One thing that is particularly bothering you is the squeaky bathroom door, which is still opens fine but let all your roommates know when you are going to the toilet. Not knowing how to fix the problem, you turn to ChatGPT to find some quick solutions. You pick one of the answer that it provided to you, and decide to rely on it. Your choice can depend on the trust that you have in ChatGPT, but also on variable like the time that it will take you to implement that solution, the tools needed, their availability, or how much do you care about the success of the solution. Since it is Sunday morning and the door is not an important problem, you can decide to rely on the given suggestions and apply just a little bit of oil on the hinges to see if it works. Later, you want to continue working on the costume for the cosplay. It is your dream cosplay, and you want to wear it at a comic convention you are really excited about. You want to do a good job, and you really value the success of your work. So when your sewing machine gives you trouble, you approach ChatGPT's suggestions more cautiously and likely rely on them differently. And it is possible that, in the end, you will decide to call your grandparents -former tailors- for help.

This imagination exercise had the purpose to highlight the connection between the reliance on AI outputs, and our information-seeking habits, specifically the one that occurs in our everyday lives. Some studies among the information-seeking literature decided to focus on this latter aspect: they investigated the ways individuals research information for everyday purposes, a phenomenon described as Everyday Life Information-Seeking (ELIS) [1]. ELIS explores the search of information that supports users' personal interests and broader life responsibilities [1][2]. This perspective can offer

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a valuable framework for understanding how users interact with AI-driven information systems, in non-professional, real-world scenarios. However, the impact of AI on ELIS (and conversely, the impact of ELIS on AI use) has not been explored yet.

While ELIS research provides insights into how individuals seek information for personal and everyday needs, another body of literature in Human-Computer Interaction (HCI) focuses on a different but related aspect: trust and reliance on AI outputs. These studies (e.g. [3] [4] [5]) have explored the topic by asking the participants to evaluate AI outputs and decide whether to rely on them in order to solve some imposed tasks in which participants do not have knowledge or interest in.

The fact that subject do not encounter these tasks in their everyday life, or worse, they would not choose to engage with them outside of the experimental settings, can probably compromise the generalization of the results in more naturalistic settings.

This paper gives a brief overview on these two literature, and aim to bridge the existing gap by examining the intersection of ELIS and reliance on AI. Specifically, we posit that users' reliance behaviors change based on the type of information they are retrieving and the values they assign to it. According to this perspective, insights from ELIS literature can be beneficial for reliance research, by giving a more comprehensive understanding of user-AI interactions, that can be used to design trustworthy AI systems that foster appropriate reliance.

2. Information-seeking and insights from ELIS

2.1. Information-seeking: definition and influential frameworks

With information-seeking we mean the activities of searching for information. This search is active and intentional, and it is usually directed to information which are salient for the seeker (e.g, information they need to solve tasks or make decisions) [6] [7].

Information seeking behaviors are varied, and can include asking questions, looking up information on books or on the internet, but also interrogate AI systems (like, for example, Large Language Models -LLMs).

During the years, research coming from the fields of psychology and information science have largely investigated the motives and antecedents of information-seeking, but also the search strategies employed by the users (specific for search engines), the use of the retrieved information, their sharing, and the discrimination between factual information and misinformation [8].

To this day a great number of frameworks and models of information-seeking exists in both literature, indeed without agreement on which one better describe the process [9] [6] [10] [7].

Other rich literature related to information-seeking include the one of curiosity, seen as an antecedent [11] [12] [8], but also information-avoidance, the counterpart of information-seeking [13] [14].

One model that has recently obtained attention is the one proposed by Sharot and Sunstein [7]. The authors propose that, in order to decide to seek information, people evaluate the instrumental, hedonic and cognitive utility of the information. *Instrumental utility* concern how much the information will allow the person to achieve a goal; *hedonic utility* correspond to the amount of positive affects minus the amount of negative affects that an information would induce; *cognitive utility* regards the role of information in strengthening the internal mental models of who is going to retrieve the information.

An estimate, that can be positive, negative or zero, will be assigned to the three dimensions. Then, these evaluations will be integrated together into a final estimation of the value of the information, that can trigger information-seeking (if positive), information-avoidance (if negative) or neither (if zero).

In general, people will end up choosing to seek information that a) help them select actions that lead to the best outcomes; b) elicit positive affective responses at the present time; and c) that will strengthen their mental models or that are related to concepts frequently activated and interconnected in the models [7]. The authors also posit the role of biases and individual differences [15] in influencing the estimation of the three utilities. Figure 1, illustrates the authors' framework.

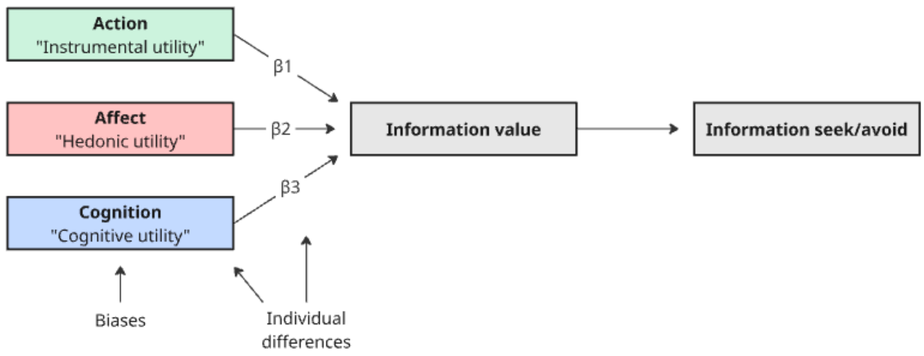

Figure 1: This is a reproduction of the framework proposed by Sharot and Sunstein [7]. On the left, we can see the three described utilities (instrumental utility, hedonic utility and cognitive utility), to which the individual attribute values. These values are integrated into the estimation of the final information, which can be positive, negative or equal to zero. The estimation can lead to information-seeking if positive, to information-avoidance if negative, and to indifference if zero. In addition, the picture shows the influence of biases on the estimation of the utilities, together with the modulating role of individual differences (which influence both the estimations and the differences in the weights - β1-3).

2.2. ELIS literature

One line of research focused on what has been defined Everyday Life Information-Seeking (ELIS) [2] [1]. ELIS has been described as a process of information-seeking that concerns knowledge useful for daily life needs, or to fulfill roles and life responsibilities. ELIS practices include searching information to solve specific problems, but also the passive receipt or monitoring of information through media and social network [1].

In one of his core papers on ELIS, Savolainen [2] introduces two captivating concepts related to the topic, namely the *way of life* and the *mastery of life*. The way of life (or the "order of things") refers to the preference (hence, the order) that an individual assigns to her daily life activities, which are not only job related. The assigned order depends both on objective (like the length of the working day and the amount of free time) and subjective evaluations (pleasantness experienced by doing some activities). On the other hand, the mastery of life (or "keeping things in order") refers to the effort that individuals make to maintain their meaningful order of activities. The core idea is that both the way of life and the mastery of life affect individuals' information-seeking practices.

What is really different about ELIS literature is its focus on a type of information seeking that interests areas of individual's life that go beyond mere duties (work or study related), but are related to personal interests, attitudes and needs. Additionally, it can be seen as an approach that gives a more ecological and naturalistic view on the information-seeking process, traditionally less explored. Finally, ELIS research takes into consideration the complexity and diversity of information-seeking behaviors: ELIS behaviors are characterized by many different factors, but also differ between people and different contexts [1].

One of the trend of ELIS research concerns how the rapid development of technologies is changing people information behaviors, now that they have become part of their everyday lives [1]. However, these line of research has not yet explored the relationship between the use of AI systems and ELIS behaviors, suggesting that this is still a potential area for investigation.

3. The impact of ELIS on reliance on AI system

The advent of AI has introduced a new type of interaction between user and system, which consequently influenced information behaviors. In the last years this interaction has been studied, with a strong focus on the concept of trust and reliance on the AI outputs, in experimental situations that are not ecologic. In the next paragraphs we give an overview on the literature on trust and reliance on AI, and explain why ELIS can give some insights on the topic.

3.1. Trust and reliance: some definitions

According to the widely used definition proposed by Lee and See [16], trust is referred to as *"the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability"*. Trust implies a relationship between a trustor, the one that trusts, and a trustee, the party that is being trusted. In the case of automation, the user is the trustor and the system is the trustee.

The concept of trust in the context of HCI has been explored in different fields (e.g. e-commerce, e-health, e-government, digital information, human-robot interaction, computer-supported cooperative work, and so on) and the process of trust formation has been investigated through different theories [17]. Moreover, several frameworks about the role of trust in the interaction between human and automation have been proposed over the years [16] [18] [19] [20] [3]. All of the proposed models share the idea that trust is a complex construct, influenced by component that are dispositional (so related to the person's tendencies, background, cognitive and emotional aspects), and external, so dependent on the context and the environment (cultural, organizational, etc.), including relational and social aspects [17].

Trust has received so much attention in the last decades in the context of HCI, because of its role in the modulation of reliance on automation. Reliance, contrary to trust, is a behavior. In the context of AI, reliance is usually intended as the frequency to which a person accepts the AI advices, so how much it "relies" on the suggestions of the machine. Usually, behaviors are influenced by the individual's attitudes, but also by other factors. For example, according to the Theory of Planned Behavior (TPB), a well known framework proposed by Ajzen [21] [22], subjective norm concerning the behavior and perceived behavioral control are as important as attitudes in influencing intention to perform it and, if the individual act on that intention, on the behavior. This adds a layer of complexity on the analysis of reliance behaviors that, to our knowledge, has not been properly addressed in literature.

So, what is really important to keep in mind is that reliance is influenced by trust, but also by other factors (like self-confidence or perceived risk). This makes reliance possible without trust, but also implies that trust does not always translate into reliance behaviors [3] [16].

3.2. The issue with overreliance

Both trust and reliance have an important role in the interaction between human and automation: a miscalibration of them, can lead to behaviors of overreliance and underreliance on the system.

As Lee and See [16] defined it, calibration consists in "*the correspondence between a person's trust in the automation and the automation's capabilities*". So, we have a calibrated trust when "*trust matches system capabilities, leading to appropriate use*" [16].

To prevent errors in decision-making when using automated systems, what matters is not the level of trust per se, but its calibration.

When trust is not well calibrated, we incur in overtrust or in distrust, respectively a situation in which "*trust exceed system capabilities*" and a one in which "*trust falls short of the automation's capabilities*" [16].

As said earlier, trust has a mediating role on reliance, so a poor trust calibration might lead to two scenarios. In the context of human-AI cooperation for instance, users can reject the AI's suggestion when it is actually correct: in this case we talk about *underreliance*. Alternatively, users can often accept incorrect AI decisions, incurring in *overreliance* [23]. This concept is visually explained in Table 1, equal in content to the one proposed in Vasconcelos et al. [23].

3.3. The problem with the study of reliance and where ELIS can help

The issue with the literature regarding trust and reliance in HCI, is related to a confusion around the terminology and, consequently, the measures employed to evaluate the constructs of trust and reliance.

Table 1
Underreliance and overreliance scenarios, as proposed by Vasconcelos and al. [23].

		AI's Decision	
		Incorrect	Correct
Human's Decision	Accept	**Overreliance**	Appropriate Reliance
	Reject	Appropriate Reliance	**Underreliance**

Usually, these two terms are used indistinctly even if they are two different construct (one is an attitude -a latent variable- and the other one is a behavior -hence, observable-), and the boundaries between the two construct tend to vanish.

This lead to a lack of agreement on the measures employed to evaluate them, which can translate in a lack of agreement on the interpretation of results.

Another issue emerges from the experimental design employed in the study of trust and reliance with AI. These studies (e.g. [3] [4] [5]) usually asks the participants to solve tasks in which they have no interest or in which they have not expertise in. This happens because the task is imposed to the participants, who cannot chose it. Here, we posit that this task imposition can potentially influence the participants' reliance behaviors (or trust behaviors, when the term is used improperly), potentially causing them to differ from the one that they would have in everyday life situations, or for tasks that they care about or are important to them. In this scenario, ELIS perspective can come at hand. By embracing the way in which people seek information with AI, we can better understand the motives that lead users to search information with this tool and, consequently, how they decide to rely on the AI output. The results that can be drawn from these observations will probably be more useful to understand the dynamic interaction between user and AI, therefore, to design trustworthy interfaces.

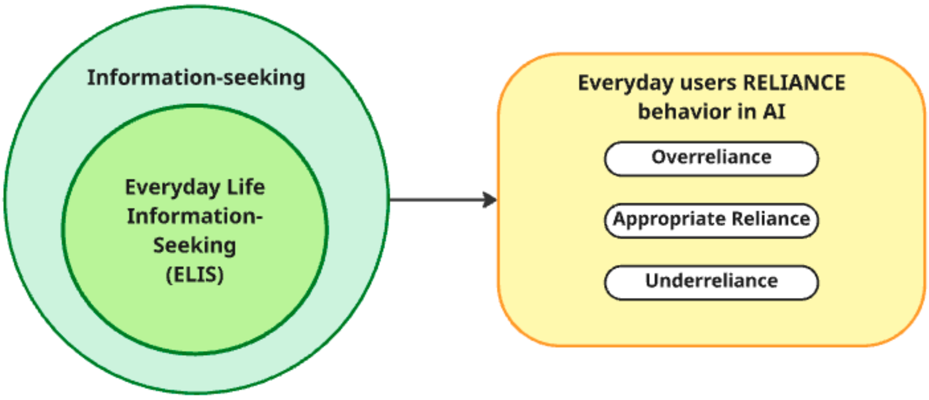

Figure 2: The diagram aim to illustrate the influence of Everyday Life Information-Seeking practices on the actual reliance behaviors of the users, less explored in literature. On the left, we can see ELIS represented as a subgroup of the larger category of information-seeking behaviors. The arrow then symbolize the influence on the everyday users reliance behaviors, which include overreliance, underreliance and appropriate reliance.

4. Open questions and insights for future works

With this new perspective in mind, illustrated by Figure 2 here we propose some research questions that can inspire future works:

- RQ1: How does the use of AI systems influence the process of everyday life information-seeking?

Given the literature gap in ELIS research, it would be useful to explore how the introduction and use of AI systems is influencing users' information seeking [1].

- RQ2: How can the way in which people seek information in their everyday-life modulate reliance behaviors on AI outputs?

As mentioned earlier, it is possible that the type of information that people choose to seek, together with the personal values that they assign to them [7] [2], have an influence on the user decision to rely or disregard the AI output. However, specific research on the topic are missing.

- RQ3: Which strategies can be implemented to foster appropriate reliance on AI outputs when engaging in everyday life information-seeking activities?

After we have investigated the users' reliance behaviors when engaged in ELIS, strategies to foster appropriate reliance should be designed, tested and implemented.

One final issue concerns the method that should be employed to investigate these research questions, and specifically to measure the information-seeking behavior.

It could be measured using quantitative measures like questionnaires [24] [25], or qualitative methods like think aloud [26] [27], use of diaries [28] [29] and interviews [30] [31] (structured and semi-structured). It needs to be clarified which one is the most suitable to measure information-seeking, or if a combination of these methodologies is needed.

We hope that the insights presented in this section can guide some future research, and allow the designers to create systems that support everyday information-seeking, tasks and decisions.

5. Conclusions

Now, let's get back for a moment to the imagination exercise that we started at the beginning of this discussion. It is Sunday again, but the day is ending. As you crawl into bed, you think about the day that has just passed. Overall you had a nice day, and you took care of all the things you neglected during the week. You encountered some problems along the way, but you actively searched for useful information to solve them. What tool did you use to search for that information? How did you decide to rely on it, based on the task you had to accomplish? Did the tools you used supported you in the research? If not, how could they be better designed to support your search and your decision to rely on the information?

In this paper we have briefly explored the literature about information-seeking and reliance in AI, in order to draw a connection between these two themes and delineate some useful research questions for future works. We suggested that studying how people seek information with AI in their everyday-life, will help design AI systems that can better suit users and support them during the process of information seeking. More importantly, the knowledge gained through the observation of this process will allow to create trustworthy AI systems that can foster user appropriate reliance.

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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