RESEARCH IN PROGRESS

SUBJECTIVE KNOWLEDGE AND AI PRIVACY RISKS

DOI
https://doi.org/10.18690/um.fov.4.2026.68

ISBN
978-961-299-152-4

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Artificial Intelligence (AI) systems are increasingly used in everyday decision-making, but the adaptive and opaque nature makes them difficult to understand, creating uncertainty in evaluating risks. Prior research has examined privacy risk through factors such as trust and perceived control but lacks an explanatory mechanism for how individuals assess such risk in AI context. This study explores the role of subjective knowledge, defined as individuals' perceived understanding of a system, in shaping privacy risk perception using a pilot experiment with two modalities (text vs. voice). The results suggest that subjective knowledge is associated with privacy risk perception and usage intention, providing preliminary insight of the underlying mechanism and highlighting its importance in AI-based interaction.

Keywords:
AI assistant,
modality,
subjective knowledge,
privacy risk,
intention to use

University of Maribor Press

1 Introduction

The use of AI assistants in human decision-making has become increasingly common. However, the use of AI-based assistants involves many unidentified privacy risks due to their opaque and adaptive nature (Liu & Shi, 2025; Robin & Dandis, 2021) which may increase users' sense of uncertainty (Schneiderman, 2021). As uncertainty increases, the assessment of risks associated with using the system may increasingly rely on users' own perceptions of how the system works. Subjective knowledge is an individual's experience of their own knowledge and based on interpretations, observations, and experiences (Brucks, 1985; Flynn & Goldsmith, 1999). Thus, under conditions of uncertainty and complexity, subjective knowledge may play a vital role in how individuals evaluate privacy risks in using AI assistants.

Prior research on risk perception suggests that individuals often rely on heuristic and subjective interpretations when evaluating risks (Slovic, 1987). In the context of privacy, individuals' risk evaluations are shaped by their perceptions on concerns regarding data collection and use (Dinev & Hart, 2006; Malhotra, Kim & Agarwal, 2004; Xu, Dinev, Smith & Hart, 2011). In addition, prior studies have focused on privacy risk perception mechanisms with factors such as privacy concerns, trust, control, vulnerability, and transparent data collection (Karwatzki, Dytynko, Trenz & Veit, 2017; Liu et al., 2024; Robin et al., 2021). However, the role of subjective knowledge in privacy risk perception has received limited attention in previous privacy literature. Therefore, the significance of subjective knowledge in risk recognition in AI systems is noteworthy, as the inherent opacity of these systems makes it even more difficult to anticipate risks.

This pilot study aims to understand the role of subjective knowledge in assessing privacy risks in the use of AI assistants. This research is highly topical as the predictability of risks associated with AI systems is weak due to their adaptive nature. Study explores a mechanism whereby subjective knowledge shapes the privacy risks assessment in AI interactions and how it is associated with the intention to use AI assistant. Specifically, the study examines whether modality (text vs. voice) shapes this mechanism by influencing subjective knowledge. The pilot study provides preliminary findings of the effectiveness of the connections and enables the evaluation of the indicators used.

2 Conceptual framework

According to behavioral science, human reasoning and decision-making involve two information processing systems (e.g., Kahneman & Frederick, 2005; Schneider & Shiffrin 1977a, 1977b). System one is an automated processing mode with fast, intuitive, and reactive while system two is slower and reflective (Kahneman et al., 2003). A key concept related to intuitive information processing is processing fluency, which refers to the subjective experience of how effortless it is to understand information (Reber, Wurtz & Zimmermann, 2004). When information processing is fluent, people tend to rely on quick assessments (Kunst-Wilson & Zajonc, 1980). However, the fluency of information processing, combined with familiarity and repetition, can also lead to biases in knowledge (Alba & Hutchinson, 2000; Flynn & Goldsmith, 1999; Reber et al., 2004; Zajonc, 1968). This fluency-inducted bias in knowledge is particularly relevant in AI context, where system complexity makes objective evaluation difficulty.

Perceived understanding is closely related to the concept of subjective knowledge. According to Brucks (1985), knowledge that drives behavior can be divided into objective knowledge, i.e., what individual knows, and subjective knowledge which refers to individual's perception of their own knowledge. Subjective knowledge can strongly influence decision-making regardless of actual knowledge (Brucks, 1985; Flynn et al., 1999). When individuals perceive their understanding high, they tend to rely less on cognitive effort to process information and instead rely incorrectly on their own understanding (Alba et al., 2000; Brucks, 1985). Consequently, subjective knowledge may reinforce reliance on system one processing.

According to Hall and Mast (2007) modality refers to the channel of interaction through which information is interpreted. Different modalities can shape how individuals process information. Voice modality produces more spontaneous interpretations because it reduces cognitive load, while text modality requires the user to engage in more analytical (Hall et al., 2007; Poushneh & Gearhart, 2025). Thus, voice modality can be more interpretable and thus activates the quick information processing system one and this experience of fluency may reduce the need for analytical processing. In addition, when information is processed fluently, individuals may develop stronger perceptions that they understand the system. This perceived understanding can increase individuals' subjective knowledge, which in turn may influence how they evaluate potential risks associated with the system. This suggests that modality does not merely shape information processing but also indirectly conditions how individuals assess associated privacy risks.

In risk assessment, risk predictability plays a significant role in risk identification (Slovic,1987). When risk is impossible to identify, an individual's uncertainty increases and often leads to distorted risk assessments (Lerner et al., 2000; Slovic, 1987). In AI-based systems, data processing is opaque for users, making privacy risks particularly difficult to identify. Prior studies have shown that perceived privacy risks negatively impact on behavioral intention (Alrawad et al., 2023; Song, Xing, Duan, Cohen & Mou, 2022). The use of AI-based systems involves data loss risks as well as psychological privacy risks, such as anxiety and control, and freedom-related privacy risks, such as manipulation by algorithms (Karwatzki, Trenz & Veit, 2022; Pizzi, Scarpi & Pantano, 2021). However, these invisible risks are often misjudged, which is why the nature of the risk becomes a matter of subjective interpretation (Mitchell, 1999). Therefore, subjective knowledge may create perception of predictability and thus plays a significant role in explaining the perception of privacy risks in complex AI systems. Based on the above literature, the following hypothesis are proposed:

- H1. Modality is associated with subjective knowledge
- H2. Subjective knowledge is negatively associated with privacy risk perception
- H3. Perceived privacy risk is negatively associated with intention to use

3 Methodology

The pilot study was conducted on Qualtrics online survey platform as a scenario-based pilot experiment in which respondents (n=86) from Prolific were randomly assigned to either a text (group 1, n=40) or voice (group 2, n=46) scenario group. The aim was to evaluate scenario effectiveness, assess indicator reliability, and conduct a preliminary examination of construct relationships. Attention check questions were included to ensure that participants understood what they were responding to. Demographic data will be collected in the main study.

Measures were adapted from existing scales on a 7-point Likert scale. Subjective knowledge was measured with three items (Flynn et al., 1999), privacy risk with seven items (Karwatzki et al., 2022), intention to use with three items (Hoehle & Venkatesh, 2015). The independent variable (IV) was formed by coding the test groups with dichotomous indicators (0=text-based mode, 1=voice-based mode). Processing fluency, used as manipulation check, was measured with three items (Alter & Oppenheimer, 2009; Reber et al., 2004; Song and Schwarz, 2008.) The data was analyzed using SPSS. The effectiveness of the manipulation was assessed using T-test, which calculated the differences in modality and fluency. Linear regression analyses were performed to verify the connection between variables.

4 Results

Table 1: Descriptive statistics and correlations

Variable	α	Mean	SD	1. Group	2. SK	3. PR	4. INT
1. Group	-	1,5	.502	-			
2. SK	.792	4.39	1.195	.230**	-		
3. PR	.861	2.89	1.040	-.111	-.360***	-	
4. INT	.956	5.63	1.318	.224**	.352***	-.427***	-

**p < .005, ***p < .001, n=86 (group 1. text, n =40, group 2. voice, n= 46)
SK=Subjective knowledge, PR=Privacy risk, INT=Intention to Use

Manipulation check. The manipulation check did not produce differences in the manipulation check variable between the test groups (text: M=5.13, SD=1.21, voice: M=5.33, SD=1.06, t(78) =-.781, *p*=.437). This suggests that modality effects may be more subtle of require refine operationalization. However, differences were observed in subjective knowledge (text: M=4.09, SD=1.18, voice: M=4.64, SD=1.16, t(84) =-2.162, *p*=.017) and intention to use (text: M=5.31, SD=1.4, voice: M=5.91, SD=1.2, t(84) =-2.095, p=.039). This suggests that modality can be linked to various interpretation processes that are not necessarily directly related to fluency. As presented in Table 1, the reliability of the measures was tested using Cronbach's alpha coefficient, and all measures exceeded the criteria of ≥ 0.7. Correlations were observed between the variables (see Table 1). The group (IV, 0=text-based group, 1=voice-based group) was positively correlated with subjective knowledge (r=.230, p=.033) and intention to use (r=.224, p=.038). In addition, subjective knowledge correlated negatively with perceived privacy risk (r=-.360, p<.001) and positively with intention to use (r=.352, p<.001). Moreover, perceived privacy risk correlated negatively with intention to use (r= -.427, p<.001).

Hypotheses testing: Regression analyses were performed to confirm the constructional logic of the mechanism. Modality (IV) was associated with subjective knowledge (β =.230, p=.033, R^2 =.042), subjective knowledge was negatively associated with privacy risk (β= -.360, p<.001, R^2=.119), and privacy risk negatively predicted intention to use (β= -.427, p<.001, R^2=.172). Thus, all hypotheses were supported (see Figure 1). Additionally, subjective knowledge was directly associated with intention to use (β=.352, p<.001, R^2 =.113), suggesting a potential mediating role of privacy risk. In further explore this, we tested the combined association of subjective knowledge (β=.228, p=.031, R^2 =.208) and privacy risks (β= -.345, p<.001, R^2=.208) on the intention to use and noticed that the association of subjective knowledge on the intention to use weakens when privacy risk is included in the model. Thus, this predicts that subjective knowledge is associated with the intention to use directly and indirectly through privacy risk.

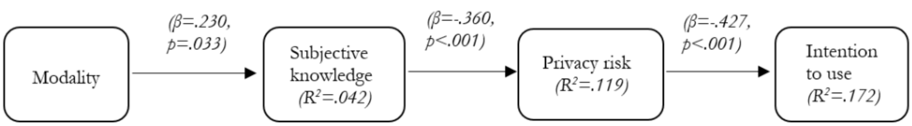

Figure 1: Research model with regression coefficients

5 Discussion

The preliminary findings provide initial insight into the relationships between modality, subjective knowledge, privacy risks, and intention to use. These findings are consistent with prior literature on subjective knowledge in risk perception (Brucks, 1985; Flynn & Goldsmith, 1999) and perceived privacy risk in behavioral intention (Alrawad et al., 2023; Song et al., 2022). The results offer tentative support for all three hypothesized relationships, suggesting that subjective knowledge plays a role in privacy risk evaluation and intentions to use AI assistants. Additionally, the findings hint at a potential mediation mechanism, where subjective knowledge influence intention to use both directly and indirectly through privacy risk, which requires further research in the main study. Although manipulation did not produce the intended difference between conditions, the pilot study helped refine the experimental setup and provides a foundation for the main study. The main study will refine the manipulation, adjust the measured variables, and collect a larger sample size to test the proposed relationship more rigorously.

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