Evaluating User Preferences in Sharing Sensitive Information via Telepresence Robots

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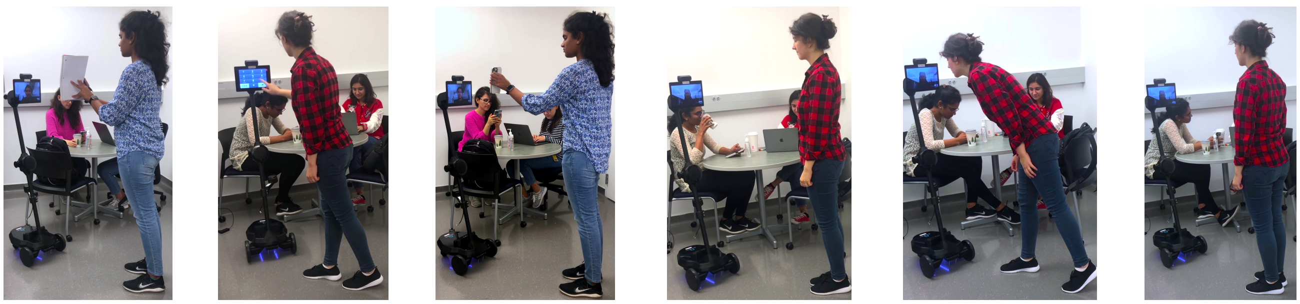

(a) Pen & Paper (b) Robot Display (c) Smartphone (d) Speech (e) Whisper (f) Silent Speech

Figure 1: The six sensitive information sharing strategies investigated in this work.

Abstract

This paper explores user preferences for sharing sensitive information via telepresence robots using six input methods: pen & paper, smartphone, robot display, speech, whisper, and silent speech. Through a crowdsourced survey and a follow-up user study, it identifies key differences in effort, convenience, privacy, security, and social acceptability. Speech is perceived as the easiest but least secure method, while pen & paper, initially favored, proves inconvenient in practice. Robot display and smartphone consistently rank as the most secure, private, and socially acceptable. Silent speech emerges as a strong alternative, offering greater privacy than other speech-based methods. These findings highlight the need for telepresence robots to support multiple input methods to accommodate diverse user needs and privacy concerns.

Keywords

Human-Robot Interaction, Privacy, Security, Speech, Whisper, Silent Speech, Smartphone, Optical Character Recognition

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1 Introduction

Telepresence robots are generally equipped with audiovisual systems that allow users to engage in two-way verbal and non-verbal communication in real-time [37]. Some telepresence robots also support textual communication through messaging systems [23]. These robots can increase accessibility for people with limited mobility and those in rural areas with limited transportation options, while also expanding access to education, healthcare, rehabilitation, and other essential services for economically disadvantaged communities [13, 34, 38]. However, privacy and security concerns, particularly in public settings, remain a challenge for the widespread adoption of these robots [29, 33]. Users typically communicate with telepresence operators verbally, which increases the risk of sensitive information being overheard by bystanders [17, 18].

Humans use different methods to share sensitive information, depending on the context and level of privacy needed [32]. Common approaches include whispering directly into someone's ear [6, 10], moving to a quiet, secure location for a private conversation, using non-verbal cues like facial expressions or written notes [7], and relying on digital media, such as encrypted messaging apps or secure email services [15, 31]. While previous research has focused on data protection measures such as encryption [29] for telepresence robots, effective methods for private communication remain largely unexplored. To address this gap, this paper examines six information-sharing methods inspired by interpersonal communication: pen & paper, smartphone, robot display, speech, whisper, and silent speech.

2 Related Work

Studies have highlighted potential privacy risks associated with telepresence robots [18]. Research suggests that the privacy and security of remote operators, local users, and nearby bystanders may be compromised, particularly due to the continuous recording and transmission of audio and video [17]. Rueben et al. [30] found that local users' perceptions of privacy and security vary depending on whether they are communicating with a stranger or a close acquaintance. Balali et al. [3] discovered that users prefer to conceal personal and financial information when robots are present in their homes. Heshmat et al. [12] observed that the lack of physical embodiment in telepresence robots during outdoor activities heightened operators' privacy concerns in interactions with bystanders. Consequently, Such [33] emphasized the need for stronger privacy measures in autonomous systems. However, most research in this area has focused on precautionary or preventive measures aimed at reducing the risk of sensitive information being exposed or leaked.

Some have focused exclusively on the audio channel. Lee and Takayama [19] demonstrated that privacy and security are improved when both the operator and the users can adjust the volume during communication. In contrast, Hayamizu et al. [11] proposed automatic volume adjustments to ensure that the operator's voice is only audible to those standing close to the robot. Jouppi [14] explored the use of whispering between operators and users in public spaces. Some studies have focused on video streams, such as Butler et al. [4], who used an intermediate filter to reduce the quantity and quality of visual information transmitted by the telepresence robot, while still providing enough information for users to complete tasks. Alternative preventive measures have also been proposed, focusing primarily on creating virtual boundaries. Kaptelinin [16] proposed an approach in which the robot automatically determines which data to transmit or collect by distinguishing between active and inactive communication between the operator and others. Similarly, Loza-Matovelle et al. [20] introduced active and passive interaction modes, where all data are transmitted in the active mode, and only the robot status and location are shared in the passive mode. Cardenas and Kim [5] focused on differentiating between the physical states of multiple operators to alert secondary operators when the primary operator exhibits inadequate physical signs. Wu et al. [36] took a direct approach, preventing the robot from entering private areas such as bedrooms and bathrooms. In a related work, Patompak et al. [28] designed the robot to maintain a safe distance from humans to respect their personal space.

3 Methodology

This work explores six methods for sharing sensitive information via telepresence robots (Fig. 1). Method 4 involves speech, which serves as a baseline for comparison in this investigation. Methods 1, 3, and 5 are based on three of the most commonly used approaches in interpersonal communication. Method 2 is specifically designed to take advantage of the unique characteristics of telepresence robots, while Method 6 introduces a novel approach that enhances the security of speech-based interactions.

(1) **Pen & paper**: In this approach, users write down sensitive information on paper and then show it to the telepresence robot operator by positioning it in front of the robot's camera. This method helps to prevent bystanders from overhearing the information.
(2) **Robot display**: In this approach, users enter details directly on the robot's touch-sensitive display using a virtual keyboard or keypad, allowing the operator to see the information immediately.
(3) **Smartphone**: This approach is similar to the pen & paper method. However, instead of writing on paper, users type information on a smartphone and then hold it in front of the camera to show the operator. This method was included because smartphones have become ubiquitous, making them more readily available than pen and paper in many situations. In addition, it spares users the need to safely dispose of paper containing private information.
(4) **Speech**: In this approach, users share sensitive information in a naturally spoken manner, without altering tone or volume. This method was included as a baseline condition in our evaluations.
(5) **Whisper**: In this approach, users whisper sensitive information to the robot, typically by leaning toward the microphone, similar to how one would whisper into another person's ear.
(6) **Silent speech**: In this approach, users convey sensitive information by mouthing words without vocalizing, a technique known as silent speech [24, 26]. This method has gained significant attention in recent years as a private, secure, and accessible way to communicate with computers [27]. However, in this context, it is used for human-to-human communication, where the robot's camera captures the speaker's lip movements, converts them into text, and displays the output on the operator's screen.

The first four methods are analog or manual, which means that they do not require recognition technologies. Users either speak, write, or input information directly into digital devices. In contrast, the last two methods rely on recognition systems to process whispered or silently spoken input. To maintain consistency across all methods in the study, we envision using recognition technologies for each method, such as optical character recognition (OCR) for pen & paper and smartphone inputs, and speech recognition, while informing participants that these technologies are not strictly necessary for the methods to function.

4 Online Survey

We conducted an online survey to explore user perceptions of effort, comfort, privacy and security, usability, convenience, and social acceptability[1] in different approaches to communicating sensitive information via telepresence robots. The survey was created using Qualtrics and posted as a task on Amazon Mechanical Turk (MTurk). To ensure data quality, participants were required to have native or bilingual English proficiency and a minimum Human Intelligence Task (HIT) approval rate of 70%. Participants were compensated with US $1.50 in Mechanical Turk Credits.

4.1 Design & Procedure

The survey was self-paced. It began with images of various telepresence robots, accompanied by descriptions of their primary functions

[1] Social acceptability reflects how appropriate a technology is based on social norms. It is usually measured by asking participants to rate their comfort using a method in public from both user and observer perspectives on a 5-point Likert scale [27].

and purposes. This was followed by textual descriptions and short video clips, ranging from 13 to 22 seconds, demonstrating each communication method. It had four sections. *Informed consent* ensured that participants agreed to take part in the study. *Demographics* included eight questions on background and experience with technologies. *Perception assessment* included seven 5-point Likert scale questions per method to evaluate user perceptions of effort, comfort, privacy, security, usability, convenience, and social acceptability. *General preference* asked two open-ended questions about their preferred methods. Crowdworkers were instructed to watch the video clips for each method before answering the questions. Participants who did not fully view the videos were excluded from the study. In addition, an attention check question was included to ensure that participants were truly engaged in the survey.

4.2 Participants

The survey initially collected 252 responses. A preliminary analysis was conducted to exclude unreliable entries by removing responses that failed the attention-check question, were completed in under three minutes, were incomplete, came from duplicate IP addresses, contained inconsistent or irrelevant open-ended answers, or showed straight-lining or patterned responses. This yielded a final sample of 79 participants for analysis.

Participants' ages ranged from 19 to 70 years, with an average age of 35.13 years (SD = 9.68). Among them, 38% (N = 30) identified as women, 58.2% (N = 46) as men, 2.5% (N = 2) as non-binary, and 1.3% (N = 1) chose not to disclose their gender. The majority were from the United States (83.5%, N = 66), while the remaining participants were from Brazil (10.1%, N = 8), India (2.5%, N = 2), Estonia (1.3%, N = 1), Georgia (1.3%, N = 1), and Italy (1.3%, N = 1). All participants had a native or bilingual proficiency in English. Most had a bachelor's degree (60. 8%, N = 48), followed by a master's degree (19%, N = 15), a high school diploma (17.7%, N = 14), and a Ph.D. (1. 3%, N = 1). One participant (1.3%) chose not to disclose their level of education.

Most participants were experienced smartphone users (97.5%, N = 77), with an average of 9.6 years of experience (SD = 3.8). Two were relatively new to smartphones, having less than one year of experience. The majority (88.6%, N = 70) had no prior experience with telepresence robots, while 11.4% (N = 9) had used one on a few occasions. Almost all participants (97. 5%, N = 77) were frequent users of voice assistants like Google Assistant or Apple Siri, with an average of 4 years of experience (SD = 2.3). Two participants did not use voice assistants but were familiar with them.

4.3 Results

We used a Friedman test for Likert scale responses and a chi-square test for nominal data.

4.3.1 Perceived Effort. Participants rated the ease of use of each method by responding to the statement: *"The method is physically and cognitively easy to use, requiring minimal physical and mental effort."* A Friedman test indicated a significant difference in perceived effort between the methods ($\chi^2 = 50.35, df = 5, p < .0001$). A Tukey-Kramer test revealed that the robot display and smartphone methods were perceived to be significantly easier to use, requiring less effort than the other methods (Fig. 2a).

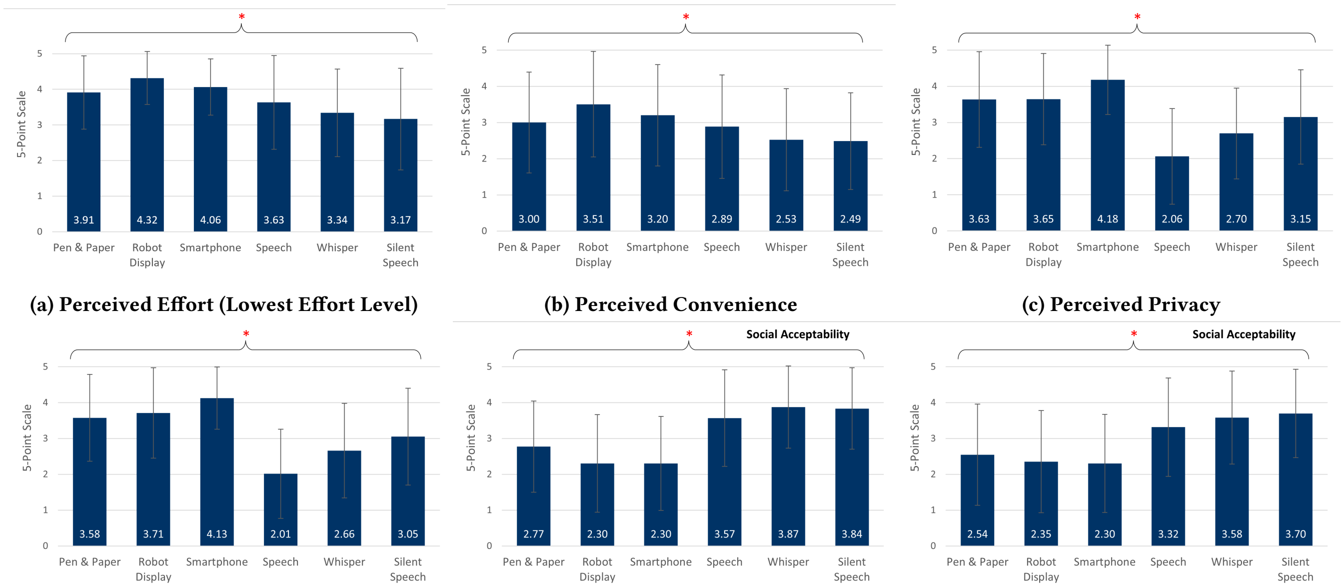
4.3.2 Perceived Convenience. Participants rated the perceived convenience of using the methods in public settings. A Friedman test revealed a significant effect of method on their comfort level ($\chi^2 = 26.03, df = 5, p < .0001$). A Tukey-Kramer test identified three distinct groups: {smartphone, robot display}, {pen & paper}, and {speech, whisper, silent speech}. The smartphone and robot display methods were rated as significantly more convenient, while the speech-related methods were rated as significantly less convenient compared to the others (Fig. 2b).

4.3.3 Perceived Privacy. Participants rated the privacy of the six methods, where privacy was defined as the protection of personal and sensitive information. A Friedman test revealed a significant effect of method on perceived privacy ($\chi^2 = 113.35, df = 5, p < .0001$). A Tukey-Kramer test identified three distinct groups: {smartphone}, {pen & paper, robot display, silent speech}, and {speech, whisper}. The smartphone method was perceived to provide significantly higher privacy, while audible speech-related methods were perceived to offer significantly lower privacy compared to the other methods (Fig. 2c).

4.3.4 Perceived Security. Participants were also asked to rate the security of each method, defined as the protection of sensitive data from unauthorized access, attacks, and damage. A Friedman test revealed a significant effect of method on perceived security ($\chi^2 = 103.95, df = 5, p < .0001$). A Tukey-Kramer test identified three distinct groups, mirroring the results for privacy: {smartphone}, {pen & paper, robot display, silent speech}, and {speech, whisper}. The smartphone method was rated as providing significantly higher security, whereas the audible speech-related methods were perceived as offering the lowest level of security compared to the others (Fig. 2d).

4.3.5 Social Acceptability. A Friedman test revealed a significant effect of method on social acceptability from the performers' perspective ($\chi^2 = 108.03, df = 5, p < .0001$). A Tukey-Kramer test identified two distinct groups: {pen & paper, robot display, smartphone} and {speech, whisper, silent speech}, with the latter group being perceived as significantly more socially acceptable to perform than the former (Fig. 2e). Similarly, a Friedman test showed a significant effect of method on social acceptability from the observers' perspective ($\chi^2 = 77.57, df = 5, p < .0001$). A Tukey-Kramer test identified two distinct groups: {pen & paper, robot display, smartphone} and {speech, whisper, silent speech}, with the latter group being perceived as significantly more socially acceptable than the former (Fig. 2f). A Spearman rank correlation test identified a significant and strong correlation between performers' and observers' perceptions of social acceptability for all methods: pen & paper ($\rho = 0.71, p < .001$), robot display ($\rho = 0.78, p < .001$), smartphone ($\rho = 0.73, p < .001$), speech ($\rho = 0.70, p < .001$), whisper ($\rho = 0.60, p < .001$), and silent speech ($\rho = 0.67, p < .001$). This suggests that the perspectives are closely aligned.

4.3.6 Overall Preference. A chi-square test revealed a significant difference in the general preference of the users for the methods ($\chi^2 = 63.67, df = 5, p < .0001$). The results showed that most of the participants preferred the use of the robot display (40.5%, N = 32) and the smartphone (34. 2%, N = 27), followed by pen & paper (11.4%, N = 9). Speech-based methods were less preferred (Fig. 3).



(a) Perceived Effort (Lowest Effort Level) **(b) Perceived Convenience** **(c) Perceived Privacy**

(d) Perceived Security **(e) Performers' Perspective** **(f) Observers' Perspective**

Figure 2: Average user ratings in the survey for effort, convenience, privacy, security, and social acceptability of the methods from both performers' and observers' perspectives on a 5-point scale (1 = strongly disagree, 5 = strongly agree). Error bars represent ±1 standard deviation. red asterisks indicate statistically significant differences.

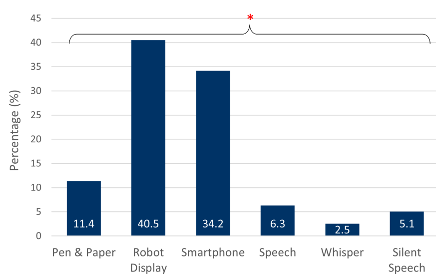


Figure 3: Percentage of participants preferring each method for sharing sensitive information via telepresence robots. The red asterisk indicates statistically significant differences.

4.4 Discussion

The results showed that participants found the robot display and smartphone methods to be the most effortless and convenient, followed by pen & paper. This was unexpected, as we initially anticipated these methods to be perceived as more effortful and inconvenient due to their multiple steps, some of which could be complex or stressful if not executed smoothly. For example, the smartphone method requires users to locate, pick up, and unlock the device, find an appropriate app (which might need to be downloaded and installed), and then hold the device up to the robot's camera. Similarly, the pen & paper method involves finding a pen and paper (which may not always be available), writing the information, positioning the paper in front of the robot's camera, and securely disposing of it to prevent unauthorized access. In contrast, speech-based methods involve fewer steps, requiring only verbal input. We speculate that participants envisioned an ideal scenario where all necessary tools were readily available. While we provided method descriptions in the survey, we deliberately avoided emphasizing specific scenarios to reduce bias in participant responses.

Participants rated the smartphone method as the most private and secure, followed by the robot display and pen & paper methods. While we expected the first two to be perceived as more secure due to their digital nature, we were surprised that pen & paper also ranked highly, given the need for secure disposal of the paper. Some participants noted they could keep the paper safe (N = 9) or shred it later (N = 3), which may explain this perception. Among speech-based methods, silent speech was rated the most private and secure, aligning with expectations and prior findings [27], as it eliminates vocalization. Interestingly, participants' ratings for privacy and security were closely aligned, which suggests that they perceive these factors as strongly related or even interchangeable.

Participants found the speech-based methods to be significantly more socially acceptable to perform than the other methods, from both the performers' and observers' perspectives. Among speech-based methods, whisper and silent speech were perceived as relatively more socially acceptable than regular speech. Among non-speech methods, participants showed a preference for pen & paper over robot display and smartphone, although the differences were not statistically significant. This preference may have been influenced by the high effort and convenience ratings of the pen & paper method, as discussed earlier. Additionally, similar to the findings on privacy and security, there was a strong correlation between performers' and observers' views on social acceptability. This suggests that in the survey where participants did not directly interact with the technology, these two perspectives were closely related and can most probably be predicted from one another.

When asked to select their preferred method for sharing sensitive information with telepresence robots, only 6.3% (N = 5) chose speech, reinforcing our assumption that users are generally uncomfortable sharing sensitive information verbally, particularly in public settings. In fact, only 13.9% (N = 11) of the participants preferred any of the speech-based methods, with whisper being the least favored, probably due to the inconvenience of leaning towards the robot's microphone. Most participants preferred robot display (40.5%, N = 32) and smartphone (34.2%, N = 27) methods, followed by pen & paper (11.4%, N = 9). Those who favored the robot display cited reasons such as greater privacy and security (N = 26), noting that *"information can be shielded from other people seeing what I'm typing."* They also appreciated the method's ease (N = 16) and convenience (N = 11), as it *"doesn't require any additional items to convey information,"* and found it faster (N = 6) and *"not awkward"* in public places (N = 3). Participants who preferred the smartphone method valued its superior privacy and security (N = 30), with comments like *"no one can see what I type."* They also found it easier (N = 8), more convenient (N = 6), and familiar (N = 2), as they frequently carry and use smartphones. Some participants also found it more socially acceptable (N = 4). Those who preferred pen & paper did so because of its perceived privacy and security (N = 13), with remarks like *"I can shred (or destroy) the info later."* Some participants found it easy to use (N = 4), while others preferred it for personal reasons (N = 4), with comments such as *"I'm a writer and I've always got pen/paper"* or *"I like the physicality of it."* However, a few participants expressed their dislike for this method, noting, *"I'm not used to writing on paper."* Participants who preferred whisper or silent speech cited similar reasons, including ease of use (N = 2) and greater privacy and security (N = 4). However, they also raised concerns about the precision of these methods, with comments like *"It may misunderstand the info."* Those who preferred to use speech primarily did so for convenience (N = 4), although they also expressed concerns about the risks involved in public settings, describing it as potentially *"dangerous."*

5 Follow-up User Study

The most surprising finding of the survey was the higher ratings for non-speech methods, particularly smartphone and pen & paper, despite their multiple steps and reliance on additional tools. We had expected these methods to be less favored due to their potential inconvenience when items were not readily available. To determine whether this preference was influenced by participants evaluating the methods without using them firsthand [21], we conducted a follow-up Wizard of Oz (WOz) study. This study allowed us to compare perceptions before and after direct interaction with the methods, examining whether actual use affects preferences.

5.1 Equipment

The study used an Ohmni telepresence robot, which stands 4'8" tall, an optimal height for standing conversations. The robot is equipped with a 4K camera featuring 13-megapixel Snapshot and Superzoom capabilities, and a 10.1" HD IPS touchscreen. For the purposes of the study, however, we replaced the Ohmni's touchscreen display with a Microsoft Surface Go tablet, available with 4GB or 8GB RAM, which has a comparable 10" PixelSense touchscreen display. The robot's interface on the tablet was kept identical to Ohmni's default interface. The tablet was chosen over the default display because it runs on the Windows 10 Pro, which allowed the wizard to control the robot interface remotely from a separate room using a Web interface. Both the robot interface and the control interface were developed using HTML and JavaScript. The wizard operated the robot using the default Ohmni application on an Inspiron 13 7000 Series laptop running on Ubuntu 18.04.6 LTS.

5.2 User Interface

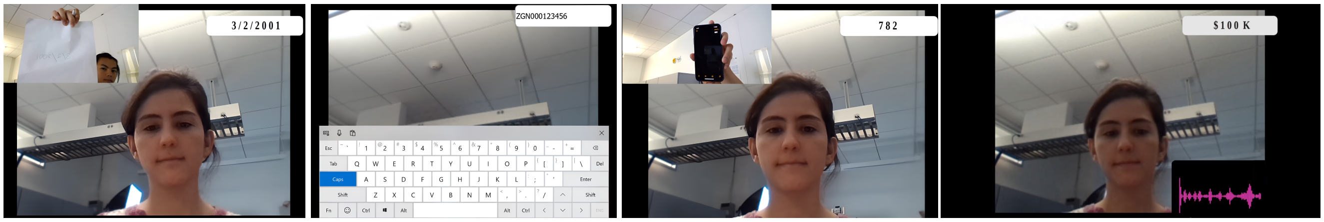
We developed custom interfaces for the six interaction methods, all of which followed a consistent structure (Fig. 4). The main screen showed the operator's face, with a front camera view in the top left corner to display the paper or the smartphone held up in front of it. For the robot display method, the default Windows onscreen keyboard appeared automatically when users touched the screen, allowing them to input information directly. In contrast, for speech-based methods, the front camera view was omitted and instead a waveform appeared in the bottom right corner of the screen to indicate that the system detected speech, whisper, or silent speech. We carefully considered whether to display recognized sensitive information on the robot's screen, as it could pose security risks if visible to bystanders. However, we implemented this feature across all methods to enable users to verify accuracy, ensuring consistency and eliminating it as a potential confounding variable in the study.

5.3 Synthetic Sensitive Information

We generated fictitious sensitive information for participants to share with the operator via the telepresence robot. This information was based on Milne et al. [22]'s categorization of the six most perceived sensitive data types: basic demographics (e.g., date of birth), personal preferences (e.g., auto insurance), contact information (e.g., phone number, email address), community interaction (e.g., friends' and family's phone numbers), financial information (e.g., bank account number, credit score), and secure identifiers (e.g., social security number, passport number, driver's license number, vehicle registration numbers). The final data set included ten examples from each category, resulting in 60 pieces of sensitive information. These elements were also strategically selected to vary in length (ranging from 3 to 12 characters) and format, including only digits, only letters, and alphanumeric combinations, following US conventions.

5.4 Participants

Twelve participants took part in the study. Their ages ranged from 21 to 38 years, with an average of 27.9 years (SD = 7.2). Five participants identified themselves as female and seven as male. Using the 5-point Interagency Language Roundtable (ILR) scale [9], eight participants rated their English proficiency as *Level 5: Native or bilingual proficiency*, while the remaining four rated themselves at *Level 4: Full professional proficiency*. All participants were experienced smartphone users with an average of 13.7 years of experience (SD = 5.0 years). None had any prior experience with telepresence robots. Each participant received US $15 for their participation.



(a) Pen & Paper **(b) Robot Display** **(c) Smartphone** **(d) Speech, Whisper, Silent Speech**

Figure 4: User interfaces for the interaction methods examined. Recognized information is displayed in the top right corner of the screen. All speech-based methods utilize the same interface.

5.5 Design

We used a within-subjects design for the user study. Participants shared one piece of sensitive information from each of the ten categories using all six methods ($6 \times 10 = 60$ entries). As a result, all participants entered exactly the same number of characters per method (79 characters, including digits, letters, and symbols). The order of the methods and the information shared were counterbalanced using a balanced Latin square. The independent variable was the *method* used, and the dependent variables were as follows:

- **Preparation time** (seconds): The average time participants took to prepare for sharing information with each method, such as picking up pen and paper, taking out a smartphone, or leaning toward the robot's microphone.
- **Input time** (seconds): The average time participants took to actually share the information with the operator, such as speaking the information or typing it on the display.
- **Verification time** (seconds): The average time participants took to confirm the accuracy of the information recognized by the system.
- **Questionnaire**: We also used the same effort, convenience, privacy, security, and social acceptability questionnaire on a 5-point Likert scale as in the crowdsourced study.

5.6 Procedure

The study was carried out in a laboratory. Upon arrival, participants were introduced to the Ohmni robot and its primary functions. After explaining the research objectives, we obtained informed consent and collected demographic data. Participants then watched short video clips (13–30 seconds) introducing the methods.

Once participants understood the methods, the study began. In the study, participants used each method to share six types of sensitive information. Unaware of the WOz setup, they were told all methods were fully functional and were instructed to verify recognized information and correct any errors, though no mistakes were actually introduced. The wizard, controlling the robot from a separate room, requested information (e.g., *"What is your social security number?"*), which participants provided using the assigned method. The information was printed on flashcards and given to participants in the order requested by the wizard to avoid any delays or confusion during the study. The robot and wizard interfaces automatically logged all interactions, while the wizard kept a separate manual log of user interactions with the systems. In addition, another researcher discreetly observed and recorded participant behavior. For the pen & paper method, only three participants had their own materials, so others were provided with them. For the smartphone method, participants without a suitable app were assisted in locating one. After the study, participants completed a questionnaire and were debriefed about the WOz methodology.

5.7 Quantitative Results

A Shapiro-Wilk test confirmed that the residuals of the response variables were normally distributed. In addition, Mauchly's test indicated that the assumption of sphericity was met, suggesting equal variances across populations. Therefore, we applied repeated measures ANOVA for all quantitative within-subject factors.

5.7.1 Preparation Time. An ANOVA did not reveal a significant effect of method on preparation time ($F_{5,11} = 1.88, p = .11$). Users took an average of 1.5 seconds to prepare for the methods (Fig. 5a).

5.7.2 Input Time. An ANOVA identified a significant effect of method on input time ($F_{5,11} = 5.38, p < .0005$). Evidently, input times differed significantly between methods (Fig. 5b). A Tukey-Kramer test revealed four distinct groups, with {speech} yielding the fastest input time, followed by {pen & paper, smartphone, robot display}, and {whisper, silent speech}.

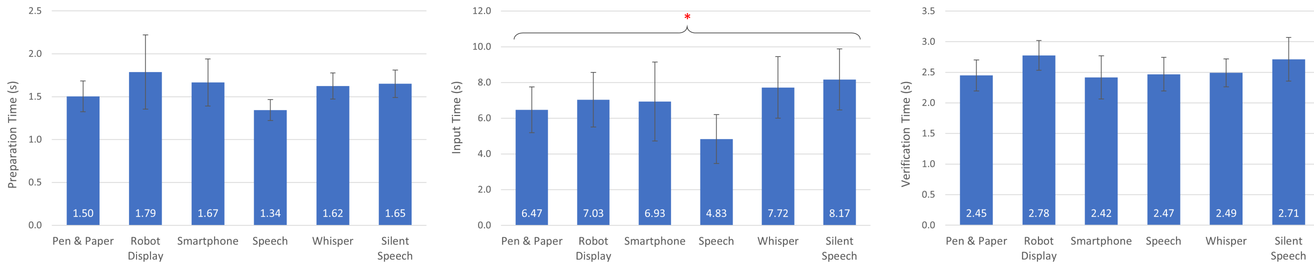
5.7.3 Verification Time. An ANOVA did not identify a significant effect of method on verification time ($F_{5,11} = 1.65, p = .16$). Participants took an average of about 2.5 seconds to verify the information shared across all methods (Fig. 5c).

5.8 Qualitative Results

We used a Friedman test to analyze responses to the questionnaire.

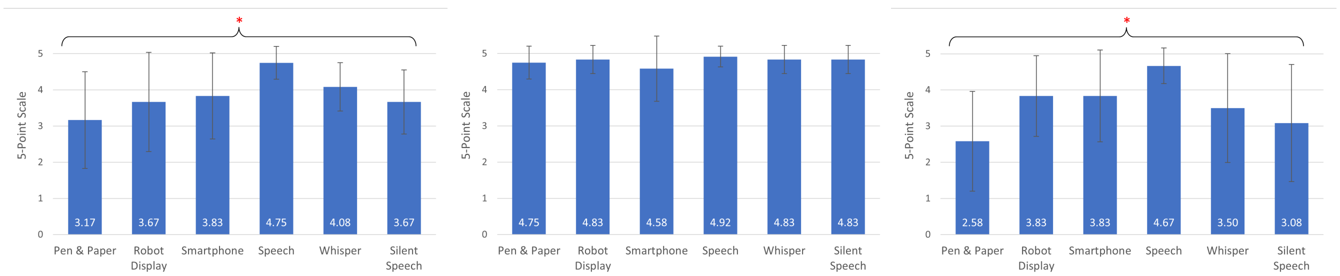
5.8.1 Perceived Speed & Accuracy. We asked participants to rate the speed and accuracy of all methods using a 5-point Likert scale. A Friedman test revealed a significant effect of method on perceived speed ($\chi^2 = 13.02, df = 5, p < .05$). A Tukey-Kramer test showed that participants perceived the speech method as significantly faster than the pen & paper method, while perceptions of the other methods were relatively similar (Fig. 6a).

In contrast, a Friedman test did not identify a significant effect of method on perceived accuracy ($\chi^2 = 4.67, df = 5, p = .46$). In fact, all methods yielded comparable accuracy ratings (Fig. 6b).

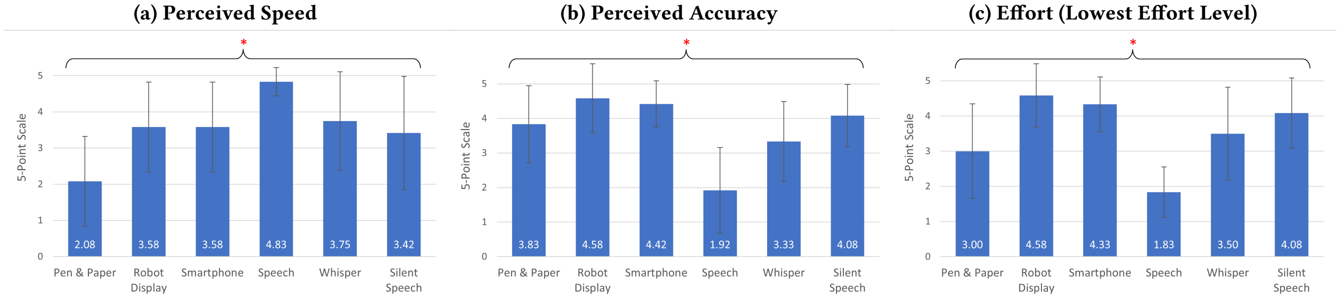


(a) Preparation Time (b) Input Time (c) Verification Time

Figure 5: Average preparation, input, and verification times per method in the user study. Error bars represent ±1 standard deviation. A red asterisk indicates statistically significant differences.



(a) Perceived Speed (b) Perceived Accuracy (c) Effort (Lowest Effort Level)



(d) Convenience (e) Privacy (f) Security

Figure 6: Average user ratings for the speed, accuracy, effort, convenience, privacy, and security of the examined methods on a 5-point scale (1 = strongly disagree, 5 = strongly agree) in the user study. Error bars represent ±1 standard deviation. Red asterisks indicate statistically significant differences.

5.8.2 *Effort.*

A Friedman test revealed a significant effect of method on effort ($\chi^2 = 17.06, df = 5, p < .005$). A Tukey-Kramer test suggested that the speech method required significantly less effort than both the pen & paper and silent speech methods (Fig. 6c).

5.8.3 *Convenience.*

A Friedman test revealed a significant effect of method on comfort ($\chi^2 = 25.77, df = 5, p < .001$). A Tukey-Kramer test showed that users found the pen & paper method to be more uncomfortable to use than the other methods (Fig. 6d).

5.8.4 *Privacy.*

A Friedman test identified a significant effect of method on privacy ($\chi^2 = 35.15, df = 5, p < .001$). A Tukey-Kramer test revealed that participants found the speech and whisper methods to be significantly less secure than the other methods (Fig. 6e).

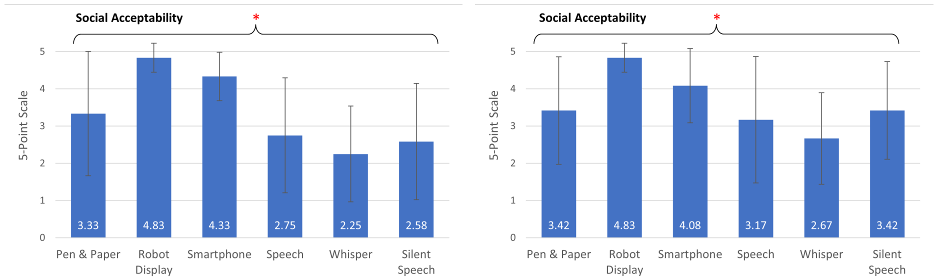
5.8.5 *Security.*

A Friedman test found a significant effect of method on security ($\chi^2 = 36.66, df = 5, p < .001$). A Tukey-Kramer test identified three distinct groups: {speech}, {pen & paper, whisper}, and {robot display, smartphone, silent speech}, with the latter group being rated as significantly more secure than the others (Fig. 6f).

5.8.6 *Social Acceptability.*

A Friedman test revealed a significant effect of method on social acceptability from the performers' perspective ($\chi^2 = 25.45, df = 5, p < .001$). A Tukey-Kramer test identified two distinct groups: {pen & paper, robot display, smartphone} and {speech, whisper, silent speech}, with the former group being perceived as significantly more socially acceptable to perform (Fig. 7a).

Similarly, a significant effect was identified from the observers' perspective ($\chi^2 = 20.34, df = 5, p < .001$). A Tukey-Kramer test



(a) Performers' Perspective **(b) Observers' Perspective**

Figure 7: Average user ratings for the social acceptability of the examined methods from both the performers' and observers' perspectives on a 5-point scale (1 = strongly disagree, 5 = strongly agree). Error bars represent ±1 standard deviation. Red asterisks indicate statistically significant differences.

identified three distinct groups: {robot display}, {smartphone, pen & paper, silent speech}, and {speech, whisper}, with the robot display method perceived as significantly more socially acceptable than speech and whisper (Fig. 7b).

5.9 Discussion

Speech was the fastest of all methods, followed by pen & paper, smartphone, robot display, whisper, and silent speech. Interestingly, the whisper and silent speech methods were 60% to 69% slower than speech, despite involving the same process. The observer's log revealed that many participants slowed down their speaking speed and inserted extra pauses between digits. This behavior is consistent with findings from previous studies [25], in which users adjusted their speech rate and pronounced phonemes more clearly in an effort to improve recognition accuracy. Preparation and verification times were generally comparable across the methods. However, the robot display method had slightly longer preparation and verification times on average. This was expected, as users had to approach the robot and touch the display to access the keyboard, then manually type the input, contributing to the increased verification time. Verifying typed text is a common behavior in text entry tasks [2].

Participants accurately perceived speech as the fastest method. Interestingly, they perceived pen & paper as the slowest method, although it was the second fastest in reality. We speculate that the physical and embodied nature of the pen & paper method may have led users to feel that it took more time than it actually did [8]. In terms of accuracy, participants perceived all methods as mostly comparable, which is consistent with the fact that no errors were introduced in the study. However, a few participants rated the smartphone and robot display methods lower in terms of accuracy due to the potential for mistyping information.

Participants found speech to be the most effortless method, followed by robot display and smartphone, then whisper, and silent speech. Pen & paper was considered the most effortful method, requiring 45% more effort than speech. User ratings for convenience mirrored those for effort, with speech rated as the most convenient, followed by robot display and smartphone, then whisper, and silent speech. Pen & paper was also rated the least convenient method, with a significant 57% decrease in the convenience rating.

These findings contradict the survey results, where pen & paper was rated as more effortless and convenient than all speech-based methods. The fact that most of the participants (75%) did not bring pen and paper to the study likely made them consider real-world scenarios, contributing to lower ratings. Additionally, those who had pen and paper struggled to write due to the absence of a flat surface (participants interacted with the robot while standing). A clipboard was provided when needed, but this added inconvenience led to comments such as (male, 22 years) *"The paper method felt a little uncomfortable."* It is striking how user opinions shifted dramatically between the crowdsourced survey and the study once participants had the opportunity to try the methods. The method rated as most effortless and convenient in the survey (pen & paper) was rated the most effortful and inconvenient in the study. This highlights the importance of letting participants use and experience a system first-hand before gathering their opinions, particularly when dealing with new and unfamiliar technologies like robots.

Another interesting observation from the study is that, although the pen & paper, smartphone, and speech methods did not require recognition systems as the operator could see the text written on paper or a smartphone and hear the user speak, the participants appreciated that the system displayed the "recognized" input on the screen. They found it particularly helpful in situations where the paper or the smartphone was too close or too far from the camera, or when reflections or glare made the text illegible to the human eye, yet the system recognized and presented the data to the operator. Participants also noted that the pen & paper method is not particularly accessible. One participant with a minor motor disability (female, 21 years) commented that this method was difficult for her to perform (*"I have wrist issues, so it's uncomfortable."*). However, in both the survey and the study, the robot display and smartphone methods received high ratings for ease of use and convenience (ranked second or third in both), suggesting that these two methods are generally preferred.

Participants rated the robot display as the most private and secure method, followed closely by smartphone and silent speech. Speech was perceived as the least secure, followed by whisper and pen & paper. Unlike effort and convenience ratings, these results closely aligned with the crowdsourced study, where the robot display and smartphone also ranked highest in privacy and security.

Those who favored the robot display cited its ability to keep information discreet, stating it is *"difficult for other people to see the typed information on the screen"* (male, 21 years). However, some raised concerns that *"people around you can see the information on the screen or take pictures of it"* (female, 36 years). Many who preferred the smartphone method argued that *"personal information is already saved on my phone"* (male, 22 years), reducing exposure. In both studies, speech and whisper consistently ranked lowest in privacy and security, while silent speech emerged as a strong alternative, appreciated for its discretion, as *"others cannot hear you speak, while with other methods people can still see you [writing or typing]"* (female, 25 years). Another notable difference is that, unlike in the crowdsourced study, participants rated pen & paper significantly lower in privacy and security, citing concerns such as *"you might throw it away, and other people can find it and access your information"* (male, 21 years).

Participants found the robot display method to be significantly more socially acceptable than the other methods from both the performers' and observers' perspectives. The social acceptability of the smartphone and pen & paper methods followed closely. Participants commented that these methods felt more socially acceptable because typing on touchscreens or writing on paper are common everyday tasks that do not appear awkward to perform in public. In contrast, speech-based methods were deemed the least socially acceptable, especially whispering. Participants found leaning toward the robot and whispering into its microphone awkward. Speech and silent speech received comparable ratings, although some participants found silent speech challenging at first. One participant noted (male, 22 years), *"[I was] feeling uncomfortable while using silent speech… [as I usually wouldn't] speak without voice. I felt I had to consciously avoid making any sound while speaking."* These results contradict the survey findings, where participants rated the speech-based methods as significantly more socially acceptable than the other methods from both the performers' and observers' perspectives. In both studies, participants consistently found robot display, smartphone, and silent speech to be more socially acceptable from both the performers' and observers' viewpoints.

6 Design Recommendations

Both studies strongly indicate that users are uncomfortable sharing sensitive information with telepresence robots using spoken methods. We recommend that designers offer alternative input options for such tasks. The findings also underscore the importance of letting participants try new technologies before evaluating them, as user perceptions can change significantly through hands-on experience compared to reading descriptions or watching videos.

In both studies, participants consistently rated the robot display, smartphone, and silent speech methods highest in terms of effort, comfort, privacy, security, and social acceptability. We recommend these as viable options for enabling secure and user-friendly information sharing. Based on these findings, we propose the following design recommendations for the community.

(1) *Enable typing on the robot display.* This feature, often disabled in telepresence robots, should be activated, as it consistently ranks among the most effortless, convenient, private, secure, and socially acceptable methods.
(2) *Offer multiple methods for sharing sensitive information.* Providing a variety of options increases accessibility, particularly for individuals with motor disabilities who may find writing or typing challenging. It also allows users to adapt to situational impairments [1, 35] or specific scenarios, such as switching to an alternative method in noisy environments.
(3) *Incorporate recognition features.* Although pen & paper, smartphone, and speech methods do not inherently require recognition systems to function, we recommend providing this option to address practical or environmental challenges. For instance, when the paper or smartphone is too close or far from the camera, when writing is illegible due to reflections, glare, or low light, or when speech is difficult to hear in noisy environments. Further, this allows the operator to copy and paste the information rather than retyping it on their end.

7 Conclusion

The findings revealed that while speech was considered the easiest method, it was also perceived as the least secure, highlighting a trade-off between usability and security. Methods like pen & paper, initially favored in theory, proved inconvenient in practice, emphasizing the role of real-world experience in shaping preferences. The robot display and smartphone were rated as the most secure, private, and socially acceptable options, with silent speech showing promise as a speech-based alternative. These results suggest that telepresence robot designers should incorporate multiple input methods to accommodate diverse user needs. Furthermore, the study underscored the importance of hands-on user testing for accurately assessing preferences, especially for novel technologies.

In future work, we will explore additional input methods, such as gesture-based interfaces, to improve security, convenience, and usability in telepresence robots. We will also investigate how environmental factors, including background noise, lighting, and bystanders, influence user perceptions of privacy and security.

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