Vocalizing User Feedback: The Impact of Input Modality on Self-Disclosure

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This study explores how input modality — voice versus text — affects self-disclosure in user feedback, leveraging a novel approach that uses transformer-based models to detect self-disclosure per token embedded in context. In an online experiment with 122 participants, results indicate that participants using voice input engaged significantly less in self-disclosure than those using text, a finding associated with reduced perceived anonymity in voice interactions. This effect persisted after accounting for response length, suggesting that the influence of voice input on self-disclosure is not merely due to brevity but also reflects unique psychological responses to voice-based communication. These findings contribute to a deeper theoretical understanding of input modality's role in shaping disclosure behavior in user feedback contexts. Practical implications offer design guidance for voice-based feedback systems to encourage more open and authentic feedback in sensitive settings.

CCS Concepts: • **Security and privacy** → *Social aspects of security and privacy*; • **Human-centered computing** → *Social content sharing*; *Sound-based input / output*.

Additional Key Words and Phrases: Voice User Interfaces, Self-Disclosure, User Feedback, Input Modality, Privacy Concerns

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1 Introduction

Gathering user feedback is vital for organizations aiming to remain innovative and maintain or grow their user base [22]. A central aspect of such feedback is eliciting the voluntary disclosure of personal thoughts, feelings, or other user-specific information on products and services [41]. Traditionally, organizations have relied on digital tools like web forms and chatbots to facilitate this process [29, 87]. More recently, however, the rapid adoption of voice-enabled interfaces has transformed the way users interact with technology [94]. From filing insurance claims [95] to providing feedback on university courses [83], users are increasingly "speaking" rather than "writing". This shift raises critical questions about how vocal input might reshape the nature of information sharing. As voice interfaces become more common, are they changing how users disclose about themselves, and, by extension, what organizations can learn about their users?

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Speaking, unlike writing, carries distinct psychological and social characteristics that can significantly influence user behavior [48, 95]. Prior research indicates that speaking tends to be more intuitive and socially oriented than writing [40], influencing everything from search query formulation [40] to product selection [30]. In the context of web surveys, voice input can feel less burdensome, thus potentially increasing user engagement [77]. Yet, when sensitive topics arise, respondents often become less willing to use voice [34], highlighting a nuanced relationship between modality and users' willingness to disclose. The impact of voice input on self-disclosure is far from straightforward; existing findings remain mixed, with task specificity and psychological mechanisms appearing to mediate whether—and how—voice encourages or hinders disclosure [51].

To address these uncertainties, our work examines how voice compared to text input can differently shape self-disclosure in user feedback settings, offering new insights into the design and implementation of user-feedback systems. Particularly, isolating the modality assists designers in understanding the privacy implications tied to voice or text input. Thus, we conducted an online experiment with 122 participants to compare self-disclosure when providing feedback on sensitive products — that is, offerings that require sharing personal or otherwise discomfortable information (e.g., health-related applications). Because these products often touch on intimate aspects of users' lives, they heighten privacy concerns and, in turn, can significantly influence willingness to disclose [78]. Given the conflicting evidence in prior studies, we tested two competing hypotheses that each predict opposite effects of modality on disclosure. To that end, we also administered a post-experiment questionnaire to explore the technological affordances and psychological mechanisms that drive or inhibit self-disclosure in voice-based and text-based contexts.

Overall, our results indicate that participants providing feedback via voice disclosed less personal information than those using text. This effect persisted even after controlling for response length, suggesting that factors beyond brevity drive differences in self-disclosure. Reduced perceived anonymity emerged as a partial mediator that mitigates lower levels of self-disclosure induced by voice as a modality. These findings are consistent with research on benign online disinhibition, which suggests that users share more personal or sensitive information in environments where they feel less identifiable [32]. Theoretically, our results contribute to a deeper understanding of how input modalities influence self-disclosure in user feedback scenarios; practically, they provide actionable insights for designing voice assistants in sensitive or high-stakes user settings.

In the following sections, we review the literature on self-disclosure in user feedback and vocal interaction within human-computer interaction. We then propose hypotheses on how vocal input may influence self-disclosure in user feedback. Next, we detail our experimental design and present the corresponding findings. Finally, we discuss the theoretical and practical implications of adopting voice-enabled devices for user feedback and related applications.

2 Theoretical Background

2.1 Self-Disclosure in User Feedback

User feedback involves gathering perceptions and views from a large group of users about products or services [22]. In this domain, a key research thread investigates how digital interfaces—such as web forms and chatbots—shape users' willingness to provide such feedback [29, 81, 87]. These tools streamline data collection and broaden access to a diverse user base [22]. However, users often perceive them as effortful, as articulating meaningful feedback requires time and deliberation [76, 90]. In addition, users may experience these interfaces as impersonal, lacking the warmth and fluidity of natural conversation, which can hinder intuitive and expressive sharing [36].

These shortcomings can stifle candid user reflections and hinder organizations from gaining nuanced insights into user needs and preferences [29]. Consequently, a central challenge is motivating self-disclosure, which we defined as the voluntary sharing of personal thoughts, feelings, or information that may leave individuals feeling vulnerable [1, 14, 50]. In response, researchers have investigated interface designs that encourage more personal and reflective feedback [69], with evidence suggesting that conversational, dialogue-based survey formats can lower perceived effort and elicit deeper, more emotionally open feedback [82]. Meanwhile, advancements in (generative) Artificial Intelligence (AI) are making it easier to deliver natural interactions via both text and voice [25, 93]. This raises an important question of whether voice-based feedback might better support expressive self-disclosure by mimicking the immediacy of face-to-face conversation.

2.2 Vocal Input in Human-Computer Interaction

There has been a growing interest in voice technologies across various disciplines, including social computing and human-computer interaction [54, 94]. Voice interfaces leverage automatic speech recognition, speech synthesis, and natural language processing to enable spoken dialogue with computer systems [31, 67]. Much of the extant literature centers on issues related to the adoption and use of voice interfaces in smart home environments [8, 49, 61]. More recently, scholars have begun investigating the broader impact of voice interfaces on user outcomes [82, 95]. For instance, Zierau et al. [95] found that filing an insurance claim via voice (as opposed to text) led to a more immersive experience, influencing behaviors like contract renewals and conversion rates. This suggests that voice as an input modality can spark distinctive patterns of cognitive processing and decision-making.

Overall, research on communication modalities suggests that voice has a fundamental impact on how users express themselves and share information with digital systems. However, most existing work on voice-based interactions has examined speaking versus writing in contexts like search queries [40] or product choices [30]. Fewer studies focus on how voice technologies shape information sharing and self-disclosure. Among the limited investigations, findings are mixed. For example, Schober et al. [65] showed that text-based smartphone interviews yielded greater disclosure of socially undesirable information than voice-based ones, and Berger et al. [5] found that written restaurant reviews tended to be less emotional, likely due to more deliberation in writing. However, Wambsganss et al. [82] observed that voice-based university course evaluations were typically briefer. Moreover, Moon [46] found that voice input reduced the inclination to give socially desirable responses in web surveys, suggesting that the effects of vocal input on self-disclosure remain far from uniform.

2.3 The Impact of Vocal Input on Self-Disclosure

Self-disclosure involves providing personal and potentially sensitive revelations to another entity [33, 89], shaped by a mix of cognitive and affective considerations [73]. On the cognitive side, individuals typically weigh perceived risks (e.g., social judgment) against perceived benefits (e.g., product personalization) when deciding whether to provide feedback [42]. Specifically, the social orientation of voice-based compared to text-based interactions might increase the perceived risks of self-disclosure. For instance, it has been shown that the mere act of speaking out loud can automatically trigger cognitive processes that arise when talking to another person [68], potentially invoking social scripts that encourage the sharing of only socially desirable information [85]. This effect has been empirically observed in interactions with computer interfaces as well [42]. Indeed, heightened social presence can reduce the depth of self-disclosure due to fear of judgment [92]. Social presence describes the degree to which a medium conveys the presence of another person within the interaction [70]. Regarding the impact on self-disclosure, research shows rivaling effects for perceived risk and reward with respect to social presence. While increased social presence can positively influence adherence to social goals, the direction of the effect on self-disclosure depends on the closeness of the relationship with the party to whom information is to be disclosed [50]. Disclosure to close others is supposed to be rewarding, whereas to distant others it is understood as inappropriate and shall result in the opposite effect [10, 16, 42]. In the field of user feedback collection on products, we assume the relationship to be distant. Thus, as voice-based interactions with computer interfaces convey a heightened sense of social presence, users may become more hesitant to disclose sensitive information.

Moreover, compared to text, vocal input also tends to feel less anonymous. Human voices carry identifying cues, rooted in unique vocal tract characteristics [28, 71]. While written text can appear relatively generic, spoken words link directly to one's identity [42]. Crow et al. [15] found that hearing one's voice fosters a strong connection to personal identity. Thus, as individuals hear their voice while speaking, they may receive a subconscious signal that they are revealing their identity [42]. This reduced sense of anonymity diminishes the benign disinhibition effect, where users typically share more personal or sensitive information when they feel secure and unidentifiable [32]. When individuals perceive their identity as exposed, the anticipated social and reputational risks increase, leading them to withhold personal details. This phenomenon aligns with research suggesting that reduced anonymity, along with heightened privacy concerns, generally corresponds with decreased self-disclosure [9, 12, 66, 80].

Lastly, the two modalities differ in their inherent affordances for message revisability. Text-based interfaces typically offer high revisability, allowing users to pause, reflect, and edit their input before submission. In contrast, voice-based interfaces generally offer low reliability. Once speech is produced, it is often final, with limited opportunities for revision or rehearsal before submission [44, 95]. These structural differences may affect their willingness to share sensitive information. The absence of post-hoc editing in voice input is not only a theoretical distinction but also reflects the dominant paradigm in commercially deployed voice interfaces, such as those found in virtual assistants and smart speakers. Many real-world systems, such as conversational assistants, prioritize immediacy and naturalness over revisability, relying on a "single-shot" interaction model where users speak and the system immediately processes the input without offering a review step [13, 55]. Thus, this asymmetry represents a relevant boundary condition when comparing modalities with respect to self-disclosure behavior. In summary, we propose that:

H1a: Compared to written feedback, providing vocal feedback increases social presence, thus reducing self-disclosure.

H1b: Compared to written feedback, providing vocal feedback reduces perceived anonymity, thus reducing self-disclosure.

Conversely, affective states can trigger automatic behavioral responses that bypass more deliberate cognitive processes [42]. Prior studies indicate that voice interfaces can heighten affective experiences, such as flow, where individuals become deeply immersed in an activity [95]. This immersion may limit risk evaluations and foster openness, potentially increasing willingness to disclose sensitive information [63, 64]. Additionally, speaking out loud can enhance feelings of spontaneity and presence [37], which may reduce inhibition and encourage deeper sharing. Because spoken language offers immediacy and expressiveness, users might be less inclined to filter out sensitive details in real time, unlike the more methodical editing that often accompanies writing [91]. Consequently, we posit:

H2: Compared to written feedback, providing vocal feedback increases the feeling of flow, thus increasing self-disclosure.

3 Methodology

3.1 Experimental Design

We use a randomized controlled experimental design to examine the effect of input modalities on self-disclosure. Employing a between-subject design, we avoid carry-over effects in comparing the two input methods [45]. Adapted from an experiment by Melumad et al. [41], the experiment was neutrally framed as market research aimed at enabling companies to understand customer experiences with different products better. During the experiment, participants were asked to describe a private or embarrassing product experience they had experienced in the past. They were asked to indicate what led to the purchase and how they felt using the product. More specifically, after a general introduction, participants were presented with the following instructions when starting the experiment as depicted in Table 1.

Table 1. Experiment Task Instructions

Experiment Task Instructions
This survey is part of a market study aimed at helping companies better understand consumers' experiences with different types of products. Think of a product that you use, or have used in the past, which you consider to be private and possibly embarrassing — that is, something you might not want others to know about. For example, perhaps you have purchased products to prevent hair loss, or maybe you sometimes buy certain foods to binge on when you're feeling sad. Walk us through the journey of discovering the product, deciding to buy it, using it, and your feelings throughout the process (in this process, please also tell us what the product actually is). Please answer using the **textbox/microphone button** below. It is important to answer truthfully.

Key dependent variables in this experimental setting are whether participants are willing to disclose such a product and the depth of disclosure expressed in their description of the product. The type of product was left open deliberately to ensure participants report an experience they individually perceive as embarrassing or private. Thus, while the framing is broad, we collect specific, personal, and situationally rich disclosures. Moreover, restricting responses to specific product types could risk having participants without meaningful corresponding experience who potentially fabricate responses to still participate in the experiment, which is not in line with our definition of self-disclosure as a voluntary sharing of information. Thus, participants were instructed that there are no wrong answers and only their personal assessments are of interest. This approach allows us to capture a diverse range of responses from which we can draw general conclusions regarding the different impacts of the modality. Depending on the assigned condition, participants used a voice- or text-based user interface for the responses. Task instructions were presented as text prompts for all groups to avoid bias based on the different cognitive abilities required to process information through reading or listening [4]. Both conditions were presented with instructions on how to use the interface before conducting the experiment. To foster authentic information sharing of experiment participants, data handling was clearly communicated. At the beginning of the experiment, participants were informed that all answers would be treated confidentially, collected data would be used solely for research, all evaluations would be made without personal reference, and data would not be passed to third parties. Researchers stored the collected data locally and are not able to identify respondents based on it.

After the experimental task, participants were asked to complete a questionnaire that included control measures and sociodemographic characteristics described below. We restricted all participants to only accessing the experiment from a personal computer to ensure equal settings and avoid confounding effects from different device usage.

3.1.1 Participants. A total of 151 participants were recruited from the online platform Prolific. To ensure data quality, each participant's audio transcription was manually reviewed to confirm that only accurately conducted submissions were included in the analysis. Empty responses were automatically removed, and responses with three or fewer words were discarded after inspection. This resulted in a final sample of 68 participants in the text condition (out of 71 initially collected) and 54 participants in the voice condition (out of 80 initially collected). Due to technical errors and contentless audio responses, 24 participants were removed from the voice condition and one from the text condition. The remaining exclusions were due to failed manipulation (check for input modality) or attention checks. Each participant was compensated with 1.50 USD for their participation, irrespective of the responses they provided. The average age of the final number of participants was 41.45 years (SD: 14.31), with 49.18% being male.

We analyzed demographic data and control measures to confirm randomization, finding no significant differences at the 5% level across conditions. Demographic measures included gender, education, and personality traits such as openness and extraversion. We also checked for differences in user perceptions not affected by input modalities, such as privacy protection beliefs and the perceived embarrassment of the shared product experience. To further verify the accuracy of responses, we asked participants if the described product experience was genuine, and all 122 confirmed it.

3.1.2 Interface Design. Depending on their assigned group, participants either provided their response in written form via a text input or verbally via a voice input on the same page. At the start, they received instructions on how to use their assigned interface. Figure 1 shows the text input interface, as implemented in the Unipark software.

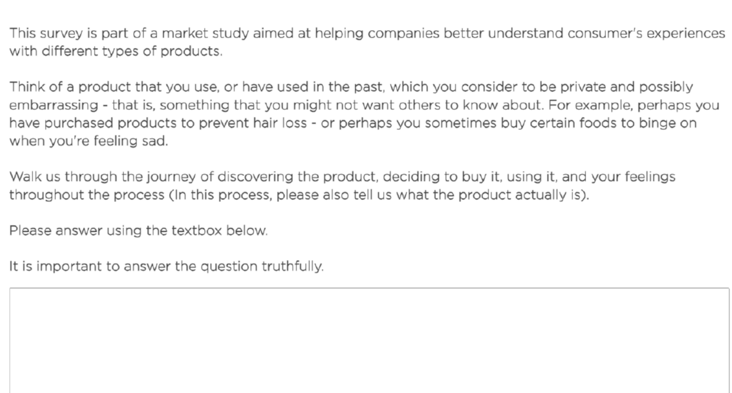

Fig. 1. Screenshot of the text user interface used in the experiment.

Both interface types presented identical task instructions. Figure 2 displays the self-developed voice input interface, where participants recorded their responses and submitted the audio file in a subsequent step. No additional design features were provided, limiting interactions strictly to the input modality. Participants did not see transcriptions of their voice inputs or receive any other form of interface feedback. The interface was designed to look neutral in order to prevent any factors that might unintentionally influence our main variables, such as an avatar's appearance or other visual design elements, and to focus solely on the predicted effects of the interface modality. As outlined in the theoretical background, a notable difference between the two modalities lies in the degree of response revisability they afford. In the text condition, participants could freely revise their responses before submission, whereas the voice condition did not allow participants to review or edit their spoken input before confirming submission. This design choice reflects a common constraint of real-world voice-based systems, which often do not offer seamless or practical options for post-hoc editing of spoken input. We acknowledge that this asymmetry in revisability could independently affect participants' comfort with disclosure. However, rather than incorporating artificial editing features not typical of deployed voice interfaces, we opted to preserve ecological validity by mirroring actual usage constraints.

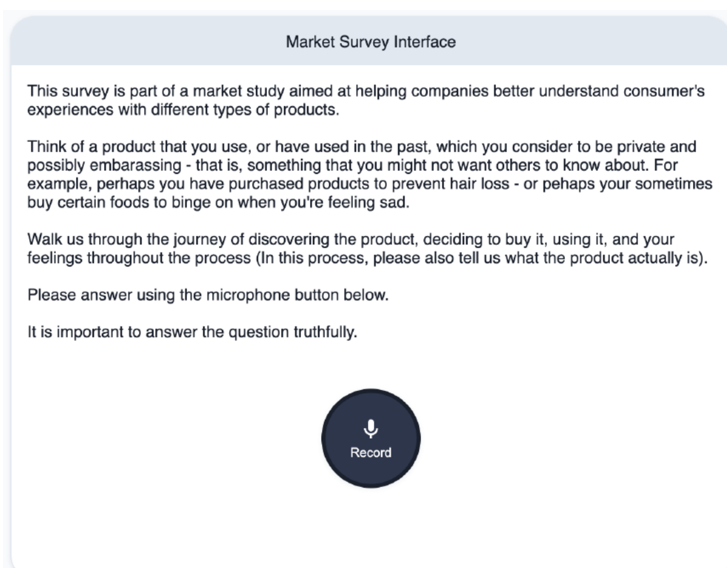

Fig. 2. Screenshot of the voice user interface used in the experiment.

After completing their responses, participants in both groups saw a thank-you message before proceeding to a follow-up questionnaire. All audio responses were transcribed using Whisper Large-v3 [58] for further analysis.

3.2 Identifying and Measuring Self-Disclosure

In line with recent studies, self-disclosure from free-text responses is evaluated using machine learning techniques rather than standardized self-reports collected via surveys. However, no widely established approach has emerged for this task [3, 41, 62, 84]. Therefore, we examine two different techniques. Our primary method relies on an open-source transformer model specifically fine-tuned for self-disclosure detection. The model, trained by Dou et al. [18], is available on HuggingFace and utilizes the DeBERTa architecture [23]. Fine-tuned on 5,761 annotated disclosure spans, the model identifies self-disclosure and classifies individual tokens into 17 categories (e.g., mental health, appearance, or sexual orientation). The fine-tuned DeBERTa model significantly outperforms GPT-4 Turbo, consistent with previous findings showing that large language models tend to underperform on span-level tasks when prompted [18]. Nevertheless, potential generalizability issues may arise across different domains and contexts [38, 62]. To check for potential deviations, we conduct a robustness check using the Linguistic Inquiry and Word Count (LIWC) tool [75]. Based on prior research on self-disclosure [7, 11, 20, 24, 41, 60, 62], we identified key LIWC categories to ensure high alignment with existing findings. The following categories have been used in at least half of the reviewed studies: "Personal Pronouns, Family, Friends, Negative Emotions, and Positive Emotions". Hence, we derive the number of words exhibiting self-disclosure based on a dictionary search with the identified categories.

Self-disclosure is assessed using DeBERTa as the primary measure and LIWC as a robustness check. Both methods identify the number of disclosure tokens (specific words that signal personal information) in each participant's response. We report both the absolute count of self-disclosure tokens and the total word count per response. This distinction between self-disclosure tokens and overall response length provides a clearer understanding of input modality effects. Using absolute measures allows us to distinguish the impact of input modality on the quantity of personal information disclosed and response length rather than relying on relative measures, which may obscure these distinct effects.

3.3 Mediation measures

In this study, we included several mediation measures to capture participants' experiences in terms of social presence, perceived anonymity, and perception of flow. These factors provide insights into the psychological mechanisms that might mediate the relationship between input modality (voice vs. text) and self-disclosure, as suggested by the theoretical background.

To measure social presence, we employed a construct developed by Gefen and Straub [19], which has been adapted for various contexts, including recent work on human-chatbot interactions [47]. Given that voice-based interactions often evoke a stronger social presence, this measure helps assess whether a heightened sense of social presence might inhibit self-disclosure by evoking social scripts that favor less personal sharing.

Perceived anonymity was assessed using the PANON scale [86], designed to gauge participants' sense of anonymity during surveys. Reduced anonymity in voice interactions can discourage free self-disclosure due to the identifiable qualities of the human voice and its link to personal identity [15, 28]. Including perceived anonymity as a mediator allows us to examine how anonymity influences disclosure behaviors, especially in voice input contexts, where users may feel a heightened risk of identifiability.

Finally, we assess the perception of flow during the interaction, for which we use the scale by Qiu & Benbasat [57], where they studied flow in real-time support communication. Voice input, known for encouraging spontaneity, may enhance flow, potentially countering inhibiting effects from perceived social presence or low anonymity. This measure explores whether voice input fosters engagement that might facilitate greater disclosure. A detailed description of the construct items can be found in the appendix.

3.4 Control Measures

While the previously mentioned measures relate to participants' experiences during the experiment, we also account for general, inherent factors that may influence self-disclosure. These factors, distinct from input modality effects, represent control variables that, while not impacted by the experimental condition, may still affect the disclosure token count in significant ways.

One such factor is privacy policy effectiveness, which reflects participants' perceptions of how well their privacy is safeguarded within the study context. Unlike perceived privacy, which may be influenced by the input modality, beliefs about privacy protection are shaped by broader, external factors such as prior experiences or general attitudes toward privacy policies [35]. Although the study and task descriptions explicitly mention confidential data handling, potential privacy concerns could still hinder self-disclosure [2]. To address this, we adapted the perceived effectiveness of the privacy policy scale from Xu et al. [88] to fit our study setting. Including this measure allows us to control for any behaviors influenced by general privacy concerns that participants bring into the experiment.

In addition to privacy concerns, perceived embarrassment is another factor that may influence disclosure tendencies. This variable accounts for an individual's perception of how embarrassing the reported experience is, which can vary significantly and affect perceived risks when making disclosure decisions. For this measure, we used a scale from Melumad and Meyer [40], capturing perceived embarrassment and controlling for differences in the nature of each participant's recorded experiences.

We also control for personality traits—specifically, openness and extraversion—since prior research has demonstrated that certain personality traits correlate with self-disclosure tendencies [6, 27, 52]. These traits are inherent characteristics of individuals, unlikely to be influenced by the input modality, yet they may still affect participants' willingness to disclose. Accordingly, we include parts of the BFI-10 scale [59] to assess openness and extraversion, capturing individual differences in self-disclosure tendencies independent of experimental condition effects.

Finally, we control for total tokens, which measures the length of each response. This variable captures the natural tendency for longer answers to increase the potential for additional disclosure tokens. Including this measure ensures that we account for variations in response length, isolating the specific effects of other factors on the disclosure token count.

4 Results

Our analysis is structured into three parts: an exploration of the gathered data, an examination of general differences in self-disclosure and control measures between the voice and text conditions, followed by an analysis of factors driving participants' self-disclosure.

4.1 Data Description

In Table 2 we show excerpts from responses we collected from participants in the experiments to provide an example of how answers looked and how the model classified the tokens. Excerpts are shown from both the text and voice conditions.

To provide a more holistic picture of all responses gathered, we present occurrences of each token classification among responses. For each response, we identified all unique token tags the model classified and aggregated them across all collected responses. Each response can have multiple unique tags of self-disclosure. Most frequently occurring disclosure tags are in the area of health and mental health, as well as appearance.

Table 2. Excerpts of model-tagged repsonses. Tokens with assigned tags are annotated inline as **token**[TAG]. All other tokens remain unannotated. Omitted non-disclosure segments are marked with `[...]` for clarity.

Excerpt Text Condition
It's not something I've openly discussed with others because it feels a bit embarrassing to admit that **I**[Mental_Health] still **deal**[Mental_Health] **with**[Mental_Health] skin **issues**[Mental_Health] as an adult. `[...]` **I**[Appearance] **had**[Appearance] **been**[Appearance] **struggling**[Appearance] **with**[Appearance] **adult**[Appearance] **acne**[Appearance] for a while, and **it**[Mental_Health] **was**[Mental_Health] **affecting**[Mental_Health] **my**[Mental_Health] **self-esteem.**[Mental_Health] `[...]` After reading reviews and doing a lot of research, I decided to buy a specific brand of acne treatment cream that had received positive feedback from other users. I was nervous about the purchase because I wasn't sure if it would work for me or if it was just another gimmick. It felt like a bit of a gamble, but I was desperate to improve my skin. Using the product was a bit of an emotional rollercoaster. At first, I felt hopeful and excited that I might finally find a solution to **my**[Mental_Health] **acne**[Mental_Health] **issues.**[Mental_Health] `[...]` However, there were moments of frustration when I experienced temporary setbacks or when I had to explain to **my**[Relationship_Status] **significant**[Relationship_Status] **other**[Relationship_Status] why I was suddenly more focused on my skincare routine.
Excerpt Voice Condition
Sometimes **I**[Appearance] **will**[Appearance] **buy**[Appearance] **tape**[Appearance] **for**[Appearance] **my**[Appearance] **fore-head**[Appearance] **to**[Appearance] **tape**[Appearance] **it**[Appearance] **up**[Appearance] **so**[Appearance] **that**[Appearance] **there**[Appearance] **are**[Appearance] **less**[Appearance] **wrinkles.**[Appearance] `[...]` I don't do this real often but I will do it for really big occasions like family weddings or something big on that order, maybe reunions, something where I really want to look my best.

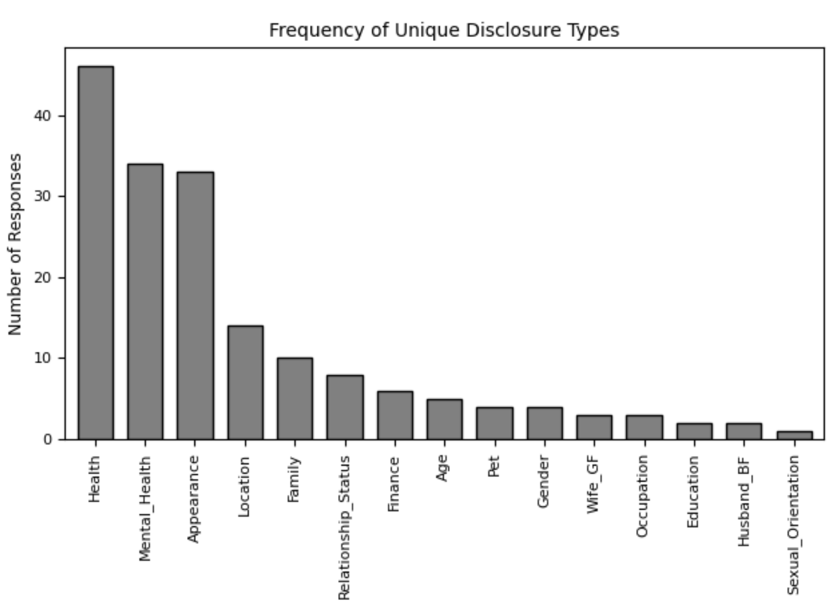

Fig. 3. Detected types of disclosure in responses

Participants were required to assess their perceived embarrassment from the reported experience. There are no statistically significant differences between the two conditions. Still, to provide readers an accurate picture of perceived embarrassment, Table 3 shows excerpts from the 10% percentile (low embarrassment), 50% percentile (median embarrassment), and 90% percentile (high embarrassment).

Table 3. Excerpts of Disclosure Responses by Perceived Embarrassment Level

Example Low Perceived Embarrassment
"The only thing I have been embarrassed about buying that I recall would be the excessive amount of a particular strawberry-flavored chocolate covered yogurt bar that I buy. I absolutely binge on these at times, and even when I'm not binging on them, I like them so much that I'll snack on a couple each day, gladly. I always get Walmart pickup, so I always have to have someone else pick my order for me in the store, and prepare it to bring it out to me. I always feel a little embarrassed about buying so many boxes of this stuff but it's literally addictive to me."
Example Median Perceived Embarrassment
"Something that I bought that I probably would be embarrassed about is a little set of cat toys. Not like cat toys for cats, but like they were little figurines that are like cat toys. And I just discovered them in a store one day and I just thought they were so adorable, but uh, I don't know, it might be a little bit embarrassing because I guess I consider myself too old to purchase toys and I just had to have them anyway so I bought them and then I set them out to look at in my room and I just thought they were adorable and had to have them."
Example High Perceived Embarrassment
"After having my children, I've had bladder issues. Sometimes when I cough or sneeze, I have a little, I pee a little bit, so I find it a little embarrassing, but I found underwear that has a little padding that's helped tremendously. It's been a little embarrassing, but hey, it's part of life and part of growing older too."

To gain a comprehensive view of all responses, we embed them in a high-dimensional vector space using Microsoft's all-mpnet-base-v2 model. This model encodes each response into a 768-dimensional dense vector that captures its semantic content. Designed for sentences and short paragraphs, the model generates embeddings that reflect the underlying meaning of the text. To visualize these semantic relationships, we project the embeddings into two dimensions using t-SNE, allowing us to visually distinguish between different conditions in Figure 4. Additionally, each response is annotated with a product type description generated by GPT-4o to provide a high-level tag.

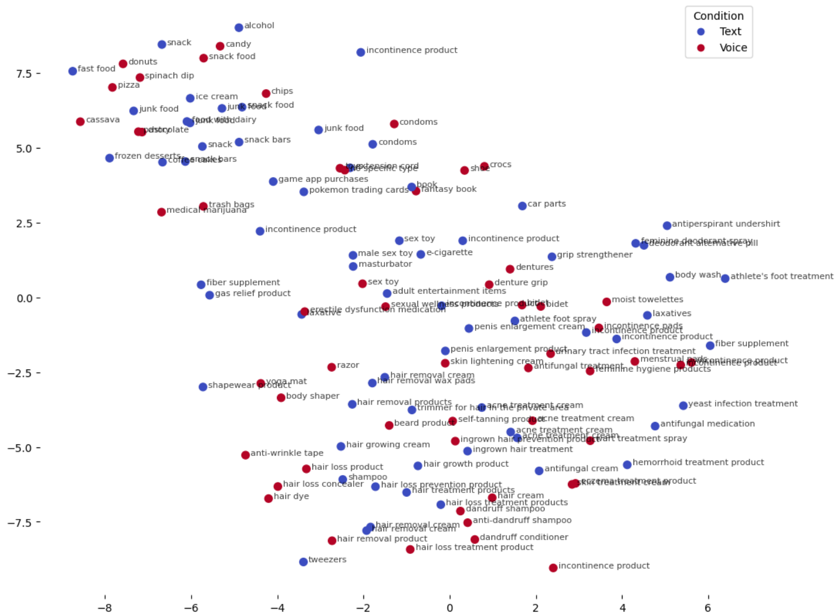

Fig. 4. Textual Embeddings of Responses By Condition

4.2 Voice Input Decreases Self-Disclosure

The results in Table 4 provide a preliminary indication of key distinctions between conditions. Given the non-normal distribution and heteroskedasticity of our variables, we employed the two-sided Mann-Whitney U Test across comparisons.

Table 4. Mann-Whitney U Tests of Variables Among Conditions

Variable	Text Mean	Voice Mean	Mean Diff.	p-value	Signif.
Dependent Variable					
# of Disclosure Tokens	15.35	7.65	7.70	0.0003	***
# of Disclosure Tokens LIWC	7.81	4.74	3.07	0.0095	**
Mediators					
Social Presence	3.68	3.56	0.12	0.7645	
Perceived Anonymity	5.28	4.48	0.79	0.0029	**
Flow	3.29	3.35	-0.07	0.7131	
Controls					
Total Tokens	93.07	73.65	19.43	0.3616	
Gender Male	0.49	0.50	-0.01	0.8747	
Privacy Policy Effectiveness	5.64	5.14	0.51	0.0571	
Perceived Embarrassment	4.76	5.04	-0.29	0.3041	
Extraversion	4.12	4.00	0.12	0.4692	
Openness	4.90	4.98	-0.08	0.5766	

Note: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

Participants in the text condition exhibited significantly higher levels of self-disclosure than those in the voice condition, indicating higher levels of personal information sharing. As seen in Table 4, this difference is evident in absolute disclosure token counts, with the voice condition associated with lower disclosure levels overall. The robustness check using LIWC to analyze disclosure content yielded an identical pattern, confirming the results from the transformer-based approach.

Among the variables hypothesized to be influenced by input modality, perceived anonymity exhibited significant differences between conditions. Participants in the text condition reported higher levels of perceived anonymity during the process. The other expected mediation variables and the control variables did not show significant differences.

We used a negative binomial regression model to further explore the factors influencing disclosure token count in more detail. This model was selected for its suitability in handling count data, which are non-negative and discrete, particularly given the overdispersion present in our data, where the variance in disclosure token counts notably exceeds the mean. Overdispersion implies that a traditional Poisson model, which assumes mean-variance equality, would likely misestimate standard errors. By introducing a dispersion parameter, the negative binomial model accommodates this variance, enabling more precise estimates and robust inferences regarding predictors of self-disclosure across input modalities. This method enhances the reliability of our results by effectively capturing the variability inherent in natural language responses. The independent variables in the model include all the presented control factors.

Table 5. Negative Binomial Regression Results for Disclosure Token Count

Variable	Estimate	Std. Error	z value	p-value	Signif.
(Intercept)	2.503	0.122	20.581	< 0.001	***
Voice Condition[2]	-0.422	0.155	-2.728	0.006	**
Total Tokens[1]	0.293	0.073	4.028	< 0.001	***
Gender Male[2]	0.052	0.149	0.346	0.729	
Privacy Policy Effectiveness[1]	0.180	0.077	2.334	0.020	*
Perceived Embarrassment[1]	0.004	0.075	0.047	0.962	
Extraversion[1]	0.076	0.075	1.011	0.312	
Openness[1]	-0.053	0.075	-0.709	0.478	

[1] Standardized and centered variable.
[2] Dummy variable.
Note: * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001.

The regression results reveal several significant predictors of disclosure token count. The voice condition shows a significant negative effect, indicating that participants in the voice condition disclosed less personal information compared to those in the text condition. By including total tokens as a predictor, we control for the natural tendency of longer responses to contain more disclosure. This allows us to isolate the specific reduction in disclosure associated with the voice condition, as any increase in disclosure solely due to response length is accounted for. Thus, the negative effect of the voice condition highlights a reduction in self-disclosure that is distinct from, and not influenced by, the overall length of participants' responses.

Privacy policy effectiveness is also a significant predictor, with a positive estimate indicating that higher trust in privacy policy effectiveness is associated with a higher count of disclosure tokens. Variables such as gender (male), perceived embarrassment, extraversion, and openness did not significantly affect the disclosure token count, suggesting that these factors do not substantially impact the amount of disclosure tokens in this model.

Total tokens naturally lead to an increased amount of self-disclosure tokens. However, further analysis revealed that the voice condition negatively affects the length of responses ($\beta = -0.229$, p-value = 0.048).

4.3 Perceived Anonymity Mitigates Voice-Related Disclosure Reduction

To evaluate our hypotheses, we explored several potential mediation effects to determine how the presented mediation measures might influence the relationship between input modality and disclosure token count. Among these, only perceived anonymity exhibited a significant mediation effect. The mediator model was estimated using linear regression, predicting the mediator variable based on the input modality and the control measures. The outcome model, predicting the self-disclosure token count, was assessed the same way as in the general analysis with a negative binomial regression, incorporating the mediation measure and the same control measures.

We applied nonparametric bootstrapping with 3,000 simulations, using bias-corrected and accelerated (BCa) confidence intervals to improve estimates' reliability and capture the input modality's indirect effect through perceived anonymity.

Table 6. Mediation Analysis Results for Perceived Identifiability

	Estimate	95% CI Lower	95% CI Upper	p-value	Signif.
Total Effect	-4.681	-8.369	-1.630	0.0067	**
ACME (average)	1.128	0.243	3.040	0.0187	*
ADE (average)	-5.808	-9.604	-2.590	0.0007	***
Prop. Mediated (average)	-0.241	-3.627	-0.070	0.0253	*

ACME = Average Causal Mediation Effect
ADE = Average Direct Effect
Prop. Mediated = Proportion Mediated.
* p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001.

The mediation analysis results in Table 6 indicate that perceived anonymity plays a significant role in mediating the relationship between input modality and self-disclosure token count. The indirect effect (ACME) indicates that participants in the voice condition, who generally reported feeling more anonymous, showed a small but significant increase in disclosure due to this perceived anonymity. This suggests that, although the voice condition tends to decrease disclosure, the increased sense of anonymity partially mitigates this reduction.

The direct effect (ADE), however, highlights the negative relationship between the voice condition and self-disclosure tokens, independent of perceived anonymity. This underscores that, even with a greater feeling of anonymity, participants in the voice condition still disclosed fewer tokens overall.

The total effect remains negative, reinforcing the overall finding that the voice condition reduces self-disclosure. The proportion mediated shows that perceived anonymity accounts for a modest portion of this reduction.

4.4 Hypothesis Assessment

Our hypotheses presented competing perspectives on how input modality might influence self-disclosure: Hypothesis 1 (with subcomponents H1a and H1b) suggested that vocal input would inhibit self-disclosure due to higher social presence and reduced perceived anonymity, while

Hypothesis 2 posited that vocal input might facilitate self-disclosure by inducing a greater sense of flow. The results provide strong support for Hypothesis 1b over the others.

Table 7. Summary of Hypothesis Assessment

Hypothesis	Description	Assessment and Outcome
H1a	Voice input increases social presence, thus decreasing self-disclosure.	**Rejected**. No significant difference in social presence was observed between voice and text conditions. Mediation analysis also indicated no significant indirect effect, suggesting that social presence is not a primary factor influencing reduced self-disclosure in voice interactions.
H1b	Voice input reduces perceived anonymity, leading to decreased self-disclosure.	**Supported**. Testing confirmed that perceived anonymity is significantly lower in the voice condition, contributing to reduced self-disclosure. Both condition comparisons and mediation analyses underscore perceived anonymity as a critical factor.
H2	Voice input increases self-disclosure by enhancing the sense of flow.	**Rejected**. Testing revealed no significant difference in flow between voice and text conditions, nor any significant indirect effect in mediation analysis, indicating that flow does not drive the observed differences in disclosure behavior.

In summary, these findings position Hypothesis 1b as the leading explanation for the reduced self-disclosure observed in the voice condition, with perceived anonymity serving as a key mediator. Voice input primarily results in lower levels of self-disclosure. Mediation analysis reinforces this conclusion, showing that while perceived anonymity partially offsets the reduction, the overall effect of voice input remains negative, highlighting the nuanced impact of anonymity in voice-based interactions.

5 Discussion

Our study broadens the understanding of voice interfaces and their influence on self-disclosure, especially within user feedback contexts where gathering honest, comprehensive input is valuable yet challenging. This research makes three contributions to the field. First, it extends the scope of voice input applications, examining the impact of vocal interactions on self-disclosure beyond common settings and into the realm of large-scale feedback collection.

Second, unlike prior studies, which frequently relied on proxies like response length, emotional sentiment, or social desirability to gauge self-disclosure levels [65, 82], this study utilizes large language models to measure self-disclosure directly. This methodological advancement allows us to capture more nuanced aspects of self-disclosure, producing insights that are more precise and directly relevant to user behaviors. As a result, our findings demonstrate not only the decrease in self-disclosure associated with voice input but also clarify that this reduction is not merely an outcome of response brevity but a distinct effect tied to the nature of voice interactions themselves.

Third, our work enhances understanding of the psychological mechanisms affecting self-disclosure in vocal versus written feedback. By examining perceived anonymity, social presence, and flow, we offer a more detailed view of factors that may encourage or inhibit self-disclosure in voice interactions. Our findings reveal that perceived anonymity significantly influences disclosure behavior, with reduced anonymity in voice interactions partially mediating the observed reduction in self-disclosure. Additionally, we found that perceptions of privacy policy effectiveness had a general impact across both conditions, suggesting that trust in data protection consistently influences users' willingness to share personal information. In contrast, social presence and flow were not significant drivers in this context, indicating that concerns around privacy and identifiability may take precedence over the immersive or engaging qualities of voice interactions when users decide the extent of their self-disclosure. Furthermore, our results indicate that participants in the voice condition tended to keep their responses shorter, possibly contributing to the observed reduction in self-disclosure. This trend underscores the importance of designing voice interactions that can encourage users to extend their responses, allowing for richer and more comprehensive feedback.

Subsequently, we relate driving factors influencing self-disclosure to previous research and derive design recommendations for mitigating the negative impact of voice as an input modality.

Perceived Risk. Multiple studies have associated the reluctance to use voice assistants with concerns around trust and privacy/data security [72]. Vimalkumar et al. [79] engage in a similar argumentation concerning voice assistant acceptance and privacy calculus, showing that users perceive a higher privacy risk when using voice-based assistants. Given the significant reduction in self-disclosure for participants in the voice condition observed in our study, these broader concerns related to voice assistants may similarly hinder users from disclosing personal information. Additionally, independent of the condition, we identified the perceived effectiveness of the privacy policy as a crucial factor in self-disclosure. Thus, factors influencing disclosure by impacting perceived risk do not have to be limited to the voice condition. An emphasis on privacy policy could mitigate general perceived risks and foster more disclosure in general.

Keep People Talking. Our results indicate that although participants disclosed more personal information when providing longer answers, those in the voice condition tended to keep their responses shorter than participants in the text condition. While there is no extensive research on user response length when interacting with voice interfaces, some findings show that in the realm of chatbots, strategic conversation design can increase conversation length without affecting conversation quality [26].

Lack of Anonymity. We identified perceived anonymity as a driving factor influencing self-disclosure. Increasing the perception of anonymity in user interaction could mitigate reduced disclosure. Low anonymity has already been determined to affect adoption rates of voice user interfaces [21]. Several technical options for anonymization techniques are under active development [43, 53, 74]. The requirement for an intermediary anonymization layer is particularly present in cloud-based services [56]. Nonetheless, user perception does not have to be entirely driven by the underlying technical solution but by how a communication platform affords anonymity [39]. These findings add to the discussion about how anonymity as a construct needs to be carefully evaluated to reflect additional parameters that might affect one's sense of anonymity in online environments [32]. When individuals perceive themselves as anonymous, they experience reduced inhibition and are more likely to disclose sensitive or personal information because the fear of negative social repercussions is diminished. In our study, the reduced anonymity inherent in voice-based interactions appears to counteract this effect, leading to lower levels of self-disclosure.

5.1 Design Recommendations for Mitigating Self-Disclosure Reduction

Based on the results and implications discussed, we derive practical design recommendations to potentially counteract self-disclosure reduction by voice as an input modality. We see three main areas for potential improvements.

Recommendation 1: Ensure Efficacy of Privacy Policy Effectiveness
Our findings underscore that participants' trust in the privacy policy's effectiveness positively influences self-disclosure. Ensuring a transparent and robust privacy policy can help alleviate privacy concerns and build user confidence. Voice interfaces should prominently communicate privacy protections, emphasizing data security measures and explaining how personal information is handled. This clarity may encourage users to share more personal insights, especially in sensitive contexts.

Recommendation 2: Design for Longer Engagement
Our analysis suggests that response length positively correlates with the depth of self-disclosure. To counteract the tendency of voice interactions to elicit shorter responses, voice interfaces can be designed with prompts and follow-ups that encourage more detailed sharing without compromising interaction quality. For instance, using conversational cues or follow-up questions could gently extend the dialogue, facilitating richer responses and enabling deeper self-disclosure.

Recommendation 3: Foster Perception of High Anonymity
Perceived anonymity emerged as a critical factor in self-disclosure. Designing voice interfaces to foster a sense of anonymity — such as by reducing the association with personal identity markers—can help alleviate privacy concerns. Clear anonymization techniques, both in perception and technology, such as voice modification or disclaimers on data usage, can make users feel less identifiable. This adjustment may encourage users to engage more openly, as anonymity can mitigate the perceived risks of sharing personal information in voice-based systems.

5.2 Limitations and Future Work

Although our findings provide valuable insights, several limitations and new research directions warrant further investigation.

First, our design employed voice input primarily for response collection, without modeling the full conversational dynamics that often characterize voice interactions. Future studies could explore multi-turn, adaptive dialogue systems to determine whether ongoing, responsive conversations foster trust and engagement, ultimately leading to greater engagement. Incorporating personalized voice feedback tailored to user behavior or needs could further enhance natural interaction and openness.

Second, our experiment assured participants of confidentiality and avoided collecting personally identifying information, which may not always reflect real-world conditions. Many feedback systems require identifiers such as usernames or phone numbers, potentially inhibiting disclosure. Varying the degree of identifiability in future experiments could illuminate how anonymity and perceived risk shape user comfort and candor when providing voice-based feedback. When feedback systems require identifiable information, users perceive a higher risk, that could tip the balance toward non-disclosure. Hence, an increased risk perception, as predicted by the privacy calculus model, leads to more cautious behavior when sharing personal data [2, 17].

Third, in our study, participants were assigned to use either voice or text input, without the option to choose their preferred channel. As multimodal systems become commonplace, it is critical to examine how self-determination in modality selection — or the ability to seamlessly switch between voice and text—might alter disclosure behaviors. Users' sense of control in choosing how they interact could foster greater comfort, satisfaction, and willingness to share sensitive information.

Fourth, a limitation of our study design concerns the asymmetry in revisability between modalities. While the text interface naturally supports reflective editing, the voice interface did not include a transcript review or editing option. This difference, although aligned with the capabilities of many current voice systems, may have introduced a confounding variable affecting participants' perceived privacy and willingness to disclose. We acknowledge that this limits the internal validity of our modality comparison and recommend that future research isolate revisability as an independent factor to disentangle its effects from those of modality alone. Nevertheless, our decision not to implement transcript review in the voice condition was made to preserve ecological validity and to reflect common affordances of real-world voice interfaces.

Finally, the open-ended nature of our task introduced variability in the types of sensitive products reported. While this flexibility provided broad insights into self-disclosure, future experiments could focus on specific sensitive domains (e.g., health or finance) to evaluate whether narrower contexts lead to different disclosure behaviors. This line of inquiry could also address how personalized or restricted domains influence the balance between privacy concerns and the benefits of sharing.

By addressing these dimensions—conversational engagement, real-world identity constraints, user choice of modality, revisability, and domain-specific contexts—researchers can further refine voice-based feedback systems to better support meaningful and user-driven self-disclosure.

6 Conclusion

In this study, we investigated the impact of voice input on self-disclosure in user feedback contexts, comparing it to text input. Using a transformer-based model to measure self-disclosure, our findings show that voice input significantly reduces self-disclosure, a result likely driven by diminished perceived anonymity associated with vocal interactions. Theoretically, this research advances the understanding of how input modality influences self-disclosure behavior, providing empirical insights into psychological mechanisms, particularly perceived anonymity, that play a critical role in voice-based feedback settings. Practically, our findings suggest design recommendations for developing voice interfaces that foster more open, detailed feedback in sensitive contexts. Together, these insights contribute to the creation of voice feedback systems that encourage richer, more authentic user interactions, supporting the broader adoption and efficacy of voice interfaces in feedback collection.

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A Questionnaire Items

A.1 Mediation Measures

Table 8. Questionnaire Constructs and Items with 7-point Likert Scales - Mediation Measures

Social Presence (Cronbach's Alpha: 0.93)
I felt a sense of human contact in the interaction with the market survey interface. I felt a sense of personalness in the interaction with the market survey interface. I felt a sense of human warmth in the interaction with the market survey interface. I felt a sense of sociability in the interaction with the market survey interface. I felt a sense of human sensitivity in the interaction with the market survey interface.
Perceived Anonymity (Cronbach's Alpha: 0.87)
While disclosing my personal experience, I felt... ...my responses are indistinguishable from the responses of other that have taken this survey. ...it would be impossible to trace my responses to this survey back to me. ...that my responses are unidentifiable from the other responses. ...my responses will blend in with the responses of other people. ...certain that this survey is anonymous. ...if someone saw my responses, they would never know who it was who filled out the survey.
Flow (Cronbach's Alpha: 0.79)
While interacting with the market survey interface... ...my imagination was aroused. ...I felt curious. ...I thought about unrelated things. ...I thought the interaction was interesting. ...I was absorbed. ...I was distracted by unrelated things. ...my curiosity was excited. ...I felt it was fun. ...I was not focused.

A.2 Control Measures

Table 9. Questionnaire Constructs and Items with 7-point Likert Scales - Control Measures

Privacy Policy Effectiveness (Cronbach's Alpha: 0.93)
While disclosing my personal experience I... ...felt confident that the experiments privacy statement reflects their commitment to protect my personal information. ...believed that my personal information will be kept private and confidential by the experiment team. ...I believed that the privacy statement was an effective way to demonstrate the experiments commitment to privacy.
Perceived Embarrassment (Cronbach's Alpha: 0.77)
I would hesitate to tell someone I just met that I use this product. This product reveals something about who I am as a person. The fact that I use this product is very private. I felt I was revealing something very personal about myself when describing this product. I find my use of this product to be embarrassing.

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