How do people intend to disclose personal information to a social robot in public spaces?

Azra Aryania[1], Ruben Huertas-Garcia[2], Santiago Forgas-Coll[2], Cecilio Angulo[1,3], Guillem Alenya[1]

***Abstract*— Social robots interacting with people in public spaces may access and collect their personal information, which raises privacy concerns regarding the disclosure of personal information. This paper aims to investigate factors impacting individuals' intention to disclose personal information to a social robot in public spaces and evaluate the actual disclosure during the interaction with the robot. For this purpose, a model is proposed to predict people's intentions to disclose information to a social robot. We conducted our experiment at a public festival with more than 100 participants using the social robot ARI. The findings reveal the substantial impact of factors including risk beliefs, trusting beliefs, perceived enjoyment, and social influence on the intention to disclose personal information. Moreover, they reveal that although only a small percentage (6.20%) of people had the intention to disclose information to the social robot, most participants (98.00%) finally disclosed their personal information.**

I. INTRODUCTION

Social robots, equipped with language, behavior patterns, and social norms, interact and communicate with people. They are utilized across diverse application contexts in public spaces, for example, museums [1], restaurants/bars [2, 3], and train stations [4], highlighting the growing importance of their acceptance among users [5, 6].

Robots interacting with individuals in public spaces may collect their personal data, raising privacy concerns and often leading users to decide whether to share their personal information when interacting with the robot [7]. Various studies highlighted individuals' willingness to share personal information, with factors like personal control and information sensitivity shaping disclosure decisions. For instance, a pan-European survey [8] reported the importance of personal control over medical files, while financial and medical data are generally considered more sensitive than lifestyle or shopping habits [9]. Although attitudes toward sharing personal data differ across income levels, receiving personalized offers and discounts can positively influence individuals' willingness to share personal data [10].

Several studies have investigated factors influencing personal information disclosure across different contexts, revealing the significance of perceived benefits as the positive effect [11, 12, 13, 14], trusting beliefs as the positive

[1]Institut de Robòtica i Informàtica Industrial, CSIC-UPC, Llorens i Artigas 4-6, 08020 Barcelona, Spain aaryania@iri.upc.edu, galenya@iri.upc.edu
[2]Faculty of Economics and Business, Universitat de Barcelona, Av Diagonal 690, 08034 Barcelona, Spain rhuertas@ub.edu, santiago.forgas@ub.edu
[3]Intelligent Data Science and Artificial Intelligence Research Centre, Universitat Politècnica de Catalunya. Jordi Girona 31, 08034 Barcelona, Spain cecilio.angulo@upc.edu

Fig. 1. ARI robot interacting with a person in Festa de la Ciencia 2023

impact [9, 15, 7], and risk perceptions as the negative influence [9, 13]. The study [7] found that service quality, enjoyment, usefulness, and trust significantly predict consumers willingness to share personal information with a fashion sales robot, with service quality and enjoyment being the most influential factors. Intentions to disclose personal information on social media are shaped by perceived benefits and subjective norms [14]. While models of intention to disclose information specifically address the willingness to share personal data, technology acceptance models offer broader insights into user behavior toward technology adoption. Cognitive models proposed in the studies [16, 17, 5] emphasized factors such as ease of use, usefulness, and compatibility with personal values, shaping user intentions towards adopting new technologies.

In this paper, we propose a new model to estimate individuals' intentions to disclose personal information to a robot. We evaluate the model's effectiveness in estimating the intention to disclose personal information based on participants' questionnaire responses. Additionally, we measure actual disclosure by analyzing participants' responses to scenario-based questions during real-world interactions with the social robot ARI. The experiment was conducted at a public science festival, involving 113 participants interacting with ARI and responding to scenario-based questions presented by the robot (see Fig. 1). The findings highlighted the significant influence of constructs including risk beliefs, trusting beliefs, perceived enjoyment, and social influence on the intention to disclose information. Furthermore, the results revealed that, while only a small portion of participants (6.20%) initially intended to disclose personal information to the robot, the majority of participants (98.00%) actually did so to some extent.

II. RELATED WORK

A. Research models on intention to disclose personal information

The Theory of Reasoned Action (TRA) is a prominent cognitive theory that explains how attitudes influence human behavior, relying on pre-existing attitudes and intentions for behavior prediction [18]. Building upon TRA, the Theory of Planned Behavior (TPB) [19] suggests that behavior stems from intentions, shaped by attitude, subjective norm, perceived behavioral control, and past behavior. TPB explains that positive attitudes, external support, and perceived control over behavior lead to a higher intention to disclose personal information.

Additionally, TPB often intersects with Privacy Calculus Theory [20]. Privacy Calculus Theory explains that individuals conduct a privacy calculus, weighing risks and benefits before deciding to disclose personal information [20]. Consequently, individuals' intention to disclose personal information rises when the perceived benefits are greater than the perceived risks [20].

Numerous studies have employed privacy calculus, TRA, and TPB to predict disclosing personal information [9, 15, 12]. Malhotra et al. [9] indicated that the presence of trusting beliefs and risk beliefs can serve as mediators in the relationship between privacy concerns and the behavioral intention to disclose personal information in a trust-risk framework. Additionally, Harborth and Pape [15] introduced a model investigating the role of trusting beliefs and risk beliefs in a marketing service provider context. Xu et al. in [12] proposed an integrated model based on privacy calculus and TPB to investigate the factors affecting information disclosure in the context of social networking sites. They revealed that both privacy concerns and perceived benets determine the self-disclosure of personal information.

Mcknight et al. [11] proposed a privacy calculus model for Facebook users, indicating that factors like trusting beliefs, privacy concerns, and information sensitivity influence information disclosure, while other factors like usefulness and enjoyment affect continuance intention. Wang et al. [13] demonstrated that self-presentation and personalized services positively impact perceived benefits, thereby positively influencing the intention to disclose personal information. Additionally, perceived severity and control affect positively perceived risks, thus influencing the intention to disclose personal information negatively. Another study [7] found that factors such as service quality, enjoyment, and usefulness, reflecting self-interest, and trust, reflecting social interaction, predict consumers' willingness to share personal information with a fashion sales robot, with service quality and enjoyment being the most influential. Furthermore, Fan et al. [14] reported that intention to disclose personal information on social media is influenced by perceived benefits and subjective norms.

B. Technology acceptance models

Cognitive models, commonly used to understand technology acceptance across various domains, could also be applied to analyze factors influencing users' intentions to disclose personal information to a system, aiming for user acceptance.

The Technology Acceptance Model (TAM) [16], originating from the TRA [18], is widely utilized in the studies of technology acceptance. It outlines key factors impacting users' willingness to adopt a system: perceived ease of use, perceived usefulness, and user attitudes. Davis et al. [21] revised TAM to include perceived enjoyment, enhancing its applicability, particularly in office settings, leading to subsequent studies [22] building upon this revised version.

In an extension of the TAM model [23], referred to as TAM2, novel theoretical elements such as social influence and cognitive instrumental processes were integrated to explain perceived usefulness. Venkatesh and Bala [24] further developed this model into TAM3 by merging TAM2 [23] with the determinants of perceived ease of use [25].

Venkatesh et al. [17] formulated the Unified Theory of Acceptance and Use of Technology (UTAUT) model, drawing from prior user acceptance theories and emphasizing pivotal factors including performance expectation, effort expectation, social influence, and facilitation conditions. In a subsequent study, Venkatesh et al. [26] extended UTAUT2 by introducing hedonic motivation, price value, and habit as novel constructs, considering their impact on behavioral intention and technology use. Their comprehensive framework integrated individual outcomes of technology acceptance, excluding moderation effects like age, gender, experience, and voluntariness from the baseline model.

Heerink et al. [5] introduced the Almere model, derived from UTAUT, to evaluate the acceptance of assistive social agents among elderly users. It incorporates factors related to functionality, such as perceived usefulness and ease of use, as well as those concerning social interaction, such as anxiety and attitudes towards technology. Applications of the Almere model in elder care platforms involving social robots have revealed various perceptions among elderly users [27, 28]. While Cobo Hurtado et al. [27] observed positive attitudes and perceived usefulness towards the robots, they also noted challenges in usability, leading to heightened anxiety. Extending the Almere model, the RAM-care model [28] suggested additional factors such as perceived compatibility with personal values and technological unemployment, with attitudes and perceived enjoyment emerging as significant predictors of robot usage intention.

III. RESEARCH MODEL AND HYPOTHESES

We propose a new research model (see Fig. 2) to predict users' intention to disclose personal information to a robot, taking inspiration from established models [7, 9, 11], and an adapted version of the UTAUT model [5, 29]. In the following, we explain the model and present the hypotheses.

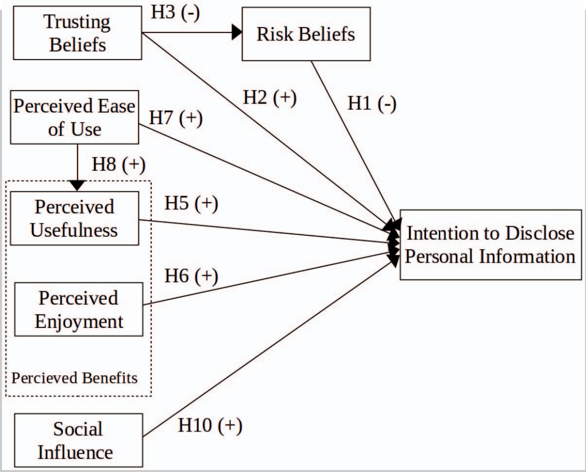

Fig. 2. The proposed new research model to predict *intention to disclose personal information*. Direct hypothesis and their positive/negative influence are shown.

A. Risk Beliefs (RB)

Risk beliefs (see Fig. 2) refer to users' perceptions of potential losses related to the disclosure of personal information [9, 12, 13, 14]. According to the privacy calculus theory, individuals weigh perceived benefits against risk when disclosing personal data [20]. Those worried about sharing information are concerned about who might access it, which could reduce their willingness to share [9]. Several studies have demonstrated a negative relationship between perceived risk and the intention to disclose personal information [9, 13, 20]. In other words, when users perceive higher risks, they tend to have lower intentions to disclose personal information. Thus, we hypothesize that:

H1: Risk beliefs negatively influence the intention to disclose personal information.

B. Trusting Beliefs (TB)

Trusting beliefs refer to users' beliefs in the robot's protection of their personal data [7, 9]. Trusting beliefs serve as crucial predictors of personal data disclosure, positively impacting the intention to disclose personal information [7, 9, 30]. Moreover, in several studies, risk was found to mediate the effect of trust on consumer purchase intentions [31, 32] and intention to disclose [9, 15] through a negative relationship. Therefore, we can expect that:

H2: Trusting beliefs positively influence the intention to disclose personal information.

H3: Trusting beliefs negatively influence risk beliefs.

H4: Trusting beliefs will have an indirect effect on the intention to disclose personal information, mediated by the risk beliefs.

C. Perceived Benefits (PB)

Privacy calculus involves consumers assessing risk-benefit analysis before disclosing personal information, ensuring that benefits exceed risks [20]. Studies consistently show a positive correlation between perceived benefits and personal information disclosure, highlighting the importance of users' perceived benefits in this decision-making process [7, 12, 13, 14]. Our study focuses on two key benefits of social robots: perceived enjoyment and perceived usefulness [7, 29].

1) Perceived Usefulness (PU): It measures a user's belief in a product's effectiveness in improving performance [5]. Explored in diverse contexts like social networks and social robots, it suggests that disclosing information enhances effectiveness, potentially boosting the intention to disclose personal data [7, 13, 14].

2) Perceived Enjoyment (PENJ): It represents the pleasure derived from using a product, regardless of its expected performance [22]. Enjoyment is a key motivator for utilizing social robots [5, 29], influencing users to engage and disclose personal information. Studies suggest that enjoying interactions with robots increases the likelihood of disclosing information [7], similar to the effect observed in social networks [33].

Therefore, we can propose that:

H5: Perceived usefulness positively influences the intention to disclose personal information.

H6: Perceived enjoyment positively influences the intention to disclose personal information.

D. Perceived Ease of Use (PEOU)

Perceived ease of use refers to the user's perception of the simplicity of using a product [5]. If using a robot is perceived as uncomplicated and doesn't require significant technical skills, users are more willing to engage with it [5, 27], which can lead to increased usefulness [5, 29] and the intention to disclose information [7]. Additionally, perceived ease of use can indirectly impact intention to use through its influence on perceived usefulness [5, 29]. Thus, we propose that:

H7: Perceived ease of use positively influences the intention to disclose personal information.

H8: Perceived ease of use positively influences perceived usefulness.

H9: Perceived ease of use will have an indirect effect on the intention to disclose personal information, mediated by perceived usefulness.

E. Social Influence (SI)

Social influence, derived from subjective norms, reflects how social factors affect an individual's decision-making process [19]. Integrated into the UTAUT model [17], it examines how perceived social context influences technology adoption. Studies on information disclosure suggest that social influence positively correlates with disclosure intentions [14], especially when driven by perceived benefits like monetary rewards [34]. Therefore, we can anticipate:

H10: Social influence positively affects the intention to disclose personal information.

IV. EXPERIMENTAL DESIGN

To achieve the study's objectives, we evaluate the proposed research model, estimating how the constructs impact the intention to disclose personal information, and assessing the

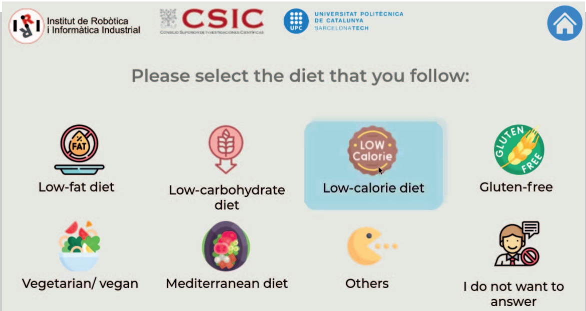

Fig. 3. An example of the questions presented to the participants

actual disclosure of personal information during interaction with the social robot ARI [35].

A. Participants

The experiment took place at a public festival in Barcelona, open to visitors over the age of 18. The experiment had 113 participants, comprising 46.9% females, 51.3% males, and 1.8% who proffered not to mention it. They were distributed across age ranges: 4.4% aged 18-24, 15.0% aged 25-34, 31.9% aged 35-44, 39.0% aged 45-54, and 9.7% aged over 54.

B. Procedure and Measurements

The experimental procedure involved three phases: first, participants were informed about the study and asked to sign consent forms. In the second phase, ARI provided two services: presenting a list of recommended restaurants (Scenario 1) and taking selfies with participants (Scenario 2). The robot posed scenario-related questions to the participants and offered different possible answers (see Fig. 3). The participants interacted with the robot's touch screen. Notably, one of the answers was "*No answer*". To evaluate actual personal information disclosure, the robot gathers responses from each participant and calculates a measurement named Disclosure Index (DI), which is the ratio of answered questions to the total questions asked by the robot for each participant individually. Note that as the robot used one response to decide the subsequent questions, the total number of questions presented to each participant can differ.

In the third phase, participants completed a questionnaire on a separate laptop assessing factors affecting their intention to disclose personal information (following the proposed model). We utilized a questionnaire comprising 32 statements grouped into eight constructs, each rated on a 7-point Likert scale from "*strongly disagree*" (1) to "*strongly agree*" (7) [9, 5, 13, 29]. The questionnaire, the scenarios questions, and a video of the interaction with the robot are available at: `https://www.iri.upc.edu/groups/perception/#SecuRoPS`.

V. EXPERIMENTAL RESULTS

The intention to disclose personal information was analyzed using Structural Equation Modeling (SEM) [36], which assessed the psychometric properties of items, modified the

TABLE I

CAUSAL RELATIONS IN THE MODEL

Independent variable	Dependent variable	Beta (T)	R^2
TB	RB	-0.036^{ns} (-0.376)	0.008
PEOU	PU	0.425^{***} (4.940)	0.173
RB	ITDPI	-0.332^{***} (-3.856)	0.203
TB		0.251^{*} (2.328)	
PU		-0.231^{ns} (-1.847)	
PENJ		0.232^{*} (1.996)	
PEOU		-0.211^{ns} (-1.751)	
SI		0.236^{*} (2.098)	

Note: ns denotes no significance, * denotes $p < 0.05$, ** denotes $p < 0.01$, and *** denotes $p < 0.001$.

TABLE II

HYPOTHESES VALIDATION FOR THE MODEL

Hypothesis	Beta (T)	Result
H1	-0.332^{***} (-3.856)	✓
H2	0.251^{*} (2.328)	✓
H3	-0.036^{ns} (-0.376)	✗
H5	-0.231^{ns} (-1.847)	✗
H6	0.232^{*} (1.996)	✓
H7	-0.211^{ns} (-1.751)	✗
H8	0.425^{***} (4.940)	✓
H10	0.236^{*} (2.098)	✓

Note: ns denotes no significance, * denotes $p < 0.05$, ** denotes $p < 0.01$, and *** denotes $p < 0.001$

model, examined causal relationships between constructs, and evaluated proposed hypotheses. Using the EQS 6 structural equations [37], we estimated an SEM model based on variance and covariance matrices through maximum likelihood estimation (MLE). Fundamentally, SEM assesses how various constructs affect their corresponding dependent variables.

Table. 1 displays the causal relationships within the proposed model. The SEM model obtained goodness-of-fit R^2 values for RB ($R^2 = 0.008$), PU ($R^2 = 0.173$), and ITDPI ($R^2 = 0.203$). The findings reveal that out of the ten relations between constructs in the model, five reached statistical significance ($p < 0.05$), confirming hypotheses H1, H2, H6, H8, and H10 (see Table. 2. However, three relations, TB$\rightarrow$RB ($\beta = -0.036$), PU$\rightarrow$ITDPI ($\beta = -0.231$), and PEOU$\rightarrow$ ITDPI ($\beta = -0.211$) did not achieve statistical significance. Consequently, hypotheses H3, H4, H5, H7, and H9 were were not supported. While PEOU held the highest weight value in the relation ($\beta = 0.425$, $p < 0.001$), it did not directly impact ITDPI, thus it cannot be considered an influential construct. Therefore, the most influential constructs directly impacting ITDPI are RB ($\beta = -0.332$, $p < 0.001$), followed by TB ($\beta = 0.251$, $p < 0.05$), SI ($\beta = 0.236$, $p < 0.05$), and PENJ ($\beta = 0.232$, $p < 0.05$).

To analyze the actual disclosure of the participants, we computed the disclosure index (DI) for each individual, as outlined in subsection IV-B. Additionally, we utilized the responses of the ITDPI construct from the questionnaire to compare ITDPI with the actual disclosure. Histograms showing DI and ITDPI are depicted in Fig. 4 and Fig. 5, respectively. The results for DI, with a mean of 0.998 and standard deviation of 0.02, indicate that 111 individu-

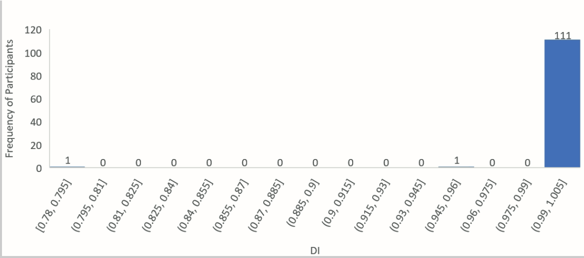

Fig. 4. Histogram for disclosure index (DI). Observe that almost all participants effectively disclosed information in all questions presented to them.

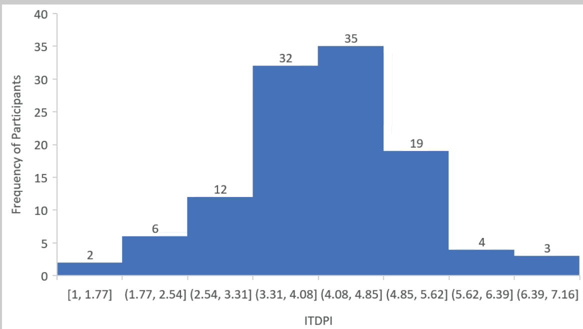

Fig. 5. Histogram for *intention to disclosure personal information* (ITDPI).

als (98.2%) responded to all presented questions, whereas only 2 participants (1.8%) did not answer some questions (One person answered 18 questions out of the 23 questions presented, and another answered 21 questions out of the 22 questions.). However, results for ITDPI, with a mean of 4.14 and standard deviation of 1.06, demonstrate that 67 individuals (60.00%) were in the middle range [3.31-4.85], while only 7 participants (6.20%) were in the range [5.62-7.16], indicating agreement (or strong agreement) with the ITDPI questions and thus a high level of intention to disclose personal information to the robot. Therefore, despite only 6.20% of participants showing agreement (or strong agreement) with the intention to disclose personal information to the robot, the interaction with the robot reveals that the majority of participants (98.00%) actually disclose their information to the robot during the interaction.

VI. CONCLUSIONS AND DISCUSSION

In this paper, we have addressed the people's intention to disclose personal information to a robot in public spaces. For this purpose, we introduced a new model to predict the individual's intention based on six constructs: trusting beliefs, risk beliefs, perceived usefulness, perceived enjoyment, perceived ease of use, and social influence. We conducted our experiment on 113 participants to assess both the model and participants' actual disclosure behavior during interactions with the robot.

The experimental results demonstrated variations in the impacts of the factors on their dependent variables, identifying those that reached statistical significance, determining whether their influence was positive or negative, and quantifying the weight values. In the SEM model, RB emerges as the most influential construct, confirming hypothesis H1 with a negative weight value. This finding aligns with the studies [9, 13, 20], exhibiting an intermediate significance level, greater than in [13, 20], and lesser than in [9]. Nonetheless, the studies [15, 14, 12, 38] did not reach a significant value for the same construct. TB is the second most significant construct, confirming hypothesis H2. Its weight is in line with [9], although less substantial than in [20]. However, TB did not attain statistical significance in [15, 34] and achieved a negative weight according to [11]. Furthermore, the results indicated that TB did not influence RB, thus not supporting H3 and H4. Neither PEOU nor PU influenced ITDPI, thereby not supporting hypotheses H5, H6, and H7. This is consistent with findings from studies [7, 11]. However, PU played a mediating role between PEOU and ITDPI, aligning with results from [5, 29] and supporting hypothesis H8. PENJ with a positive weight aligns with hypothesis H6, which is in line with the results of [7, 33]. However, PENJ did not reach statistical significance in [11]. SI, as another influential construct, supports the hypothesis H10, consistent with findings from studies [14, 34]. Nonetheless, the studies [12, 39] reported that SI did not attain statistical significance.

Moreover, the results of the questionnaire revealed that most participants (60.00%) fell within a mid-range on the ITDPI scale, indicating a medium level of intention to disclose information to the robot, and a smaller portion (6.20%) agreed (strongly agreed) with the ITDPI question. Despite this, during interaction with the robot, almost all participants (98.00%) answered all questions and actually disclosed their information, with only a small percentage (1.80%) skipping some questions.

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