

A study on the effects of mixed explicit and implicit communications in human-virtual-agent interactions

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Abstract

Communication between humans and robots (or virtual agents) is essential for interaction and often inspired by human communication, which uses gestures, facial expressions, gaze direction, and other explicit and implicit means. This work presents an interaction experiment where humans and virtual agents interact through explicit (gestures, manual entries using mouse and keyboard, voice, sound, and information on screen) and implicit (gaze direction, location, facial expressions, and raise of eyebrows) communication to evaluate the effect of mixed explicit-implicit communication against purely explicit communication. Results obtained using Bayesian parameter estimation show that the number of errors and task execution time did not significantly change when mixed explicit and implicit communications were used, and neither the perceived efficiency of the interaction. In contrast, acceptance, sociability, and transparency of the virtual agent increased when using mixed communication modalities (88.3%, 92%, and 92.9% of the effect size posterior distribution of each variable, respectively, were above the upper limit of the region of practical equivalence). This suggests that task-related measures, such as time, number of errors, and perceived efficiency of the interaction, have not been influenced by the communication type in our particular experiment. However, the improvement of subjective measures related to the virtual agent, such as acceptance, sociability, and transparency, suggests that humans are more receptive to mixed explicit and implicit communications.

Keywords: Human-robot interaction, Human-robot communication, Explicit and implicit communications, Virtual agent

1 Introduction

Modern robots are increasingly expected to work alongside humans, such as in assembly and transportation [66, 47], collaboration with humans through physical interactions [2], housework [4], and assistance to people with disabilities [17].

In addition to performance indicators, those applications also require comprehensive analysis of human-related aspects, such as preferences, satisfaction, and burden during the human-robot interaction (HRI) [59, 27, 26].

Social robots motivate social interactions, and people tend to attribute human characteristics to

robots that communicate, cooperate, and learn [10]. Consequently, people rely on human social interaction models to understand and interact with these robots [10]. Socially interactive robots, whose main characteristic and purpose are to socially interact [23], can be receptionists [24] or play educational and companion roles [64, 57, 50].

Given the importance of shared information and intentions during collaboration [58, 6] and the need for natural communication in socially interactive robots [23], communication is an essential part of HRI. Robots should interpret human communications and convey information clearly and naturally. Therefore, it is necessary to define the communication type that best suits each context, considering human perceptions and communication performance and efficiency, to satisfactorily achieve the interaction goals in a natural, intuitive way.

To develop robots and virtual agents to interact with humans, we need an extensive study of aspects related to their interaction and communication. In their review, Natarajan *et al.* [54] included communication on the list of the grand challenges in human-robot collaboration, mentioning specifically that which modality to use is still an open question. This work investigates how the communication type affects human-virtual-agent interactions. We compare using only explicit communication with mixed explicit-implicit communications to observe the effects on task- and human-related outcomes. The goal is to provide insights, based on scientifically-sound empirical data, about human-virtual-agent interactions and experimental procedures that will serve as a stepping-stone for further works on the development of techniques for intuitive communication in HRI.

1.1 Contributions

The contributions of this work are:

- scientifically sound empirical data showing that combining explicit and implicit communications in interactions between humans and virtual agents, as opposed to using only explicit communications, can improve the acceptance, sociability, and transparency of the virtual agent; and
- estimation of parameters related to objective and subjective measures obtained through a

Bayesian approach, which can be used to inform future studies related to these types of interactions.

2 Human-robot communication

According to Mavridis [48], two aspects motivate the development of interactive robots that use natural human communications. First, we can take advantage of the human interaction and teaching capabilities so robots can learn and adapt while interacting, minimizing the need for experts to program and reprogram the robots. Second, several applications benefit from this natural communication, such as socially interactive robots assisting humans.

Humans use several means to communicate, from verbal languages and gestures to more subtle communications, such as facial expressions, speech intonation, and eye gaze, which can be cues for people's internal state and be used to estimate intentions during interactions. These different communication types can be classified as explicit and implicit. Some authors define them based on intention: explicit communications convey information deliberately (*e.g.*, pointing and head gestures) whereas in implicit communications the information is inherent to the behavior (*e.g.*, facial expressions and eye gaze) [11, 6]. Others treat deliberate and unambiguous communication as explicit (*e.g.*, haptic signals with predefined meanings), and communication where information is incorporated to a behavior or action and for which interpretation is context-dependent as implicit (*e.g.*, change of direction and speed during movement) [39, 16]. However, some modalities can be difficult to classify under these definitions. For instance, people can use and alter the intensity of facial expressions when they know they are being observed, thus serving as a communicative act [7], which could make them explicit if classified based on intention.

In an attempt to make this classification easier, in the present work, we define these communication types considering what the aforementioned definitions have in common: explicit communications are directly interpreted whereas implicit communications require more subjective inferences and interpretation. Table 1 summarizes the

Table 1 Definitions of explicit and implicit communications from the literature and the present work.

	Explicit	Implicit
[11, 6]	Information conveyed deliberately	Information inherent to the behavior
[39, 16]	Deliberate and unambiguous	Information incorporated to behavior/action, with context-dependent interpretation
Present work	Directly interpreted	Subjective inferences and interpretation

definitions of explicit and implicit communications from the literature and the present work.

Communication modalities, such as gestures, speech, gaze, haptic and physiological signals, and facial expressions, can be explored separately in HRI, enabling the robot to convey information and also perceive and interpret information conveyed by humans. However, platforms combining multiple communication modalities to perceive and produce different explicit and implicit communications might be used to create more complex systems and a richer experience. Some works use humanoids or virtual agents with abilities to speak, direct their gaze, and make gestures and facial expressions, and systems to monitor and interpret human speech, gestures, gaze direction, head orientation, eye movements, and physiological signals to investigate physical, cognitive, emotional, and behavioral aspects in HRI [44, 70, 43].

2.1 Interaction experiments and comparative studies

With all these communication possibilities, several questions arise:

1. Which communication type is more appropriate for each context?
2. Does including implicit communications improve HRI?
3. Do different communication types affect human perceptions and both agents' performance during interaction?
4. How is the robot communication interpreted?

Experiments proposing interactions between humans and robots or virtual agents aim to answer some of these questions.

Bruce *et al.* [12] investigated whether a more expressive robot with a face producing facial expressions and head movement to indicate gaze direction would affect people's willingness to interact with it. In their experiments, the number of people willing to interact with the robot increased when it used facial expressions. Breazeal *et al.* [11] explored explicit and implicit communications in a task where a person teaches the robot buttons' names and then make it press them. They compared two conditions: when the robot uses only explicit communication, such as voice to inform its internal state when requested, and another one in which the robot uses both explicit and implicit communications, such as voice, gaze, facial expressions, and eye blinking to convey vivacity. In both conditions, the person communicated only explicitly through voice and gestures. Their study indicates that participants had a better understanding of the robot and created better mental models about it when it used the two communication types. Also, in the mixed explicit-implicit condition, the task execution time was smaller and errors during the task were identified faster and better mitigated. To understand how people use and interpret seemingly unintentional cues leaked through the robot's gaze, Mutlu *et al.* [52] proposed a game where a person should find out an object the robot chooses by asking *yes* or *no* questions. In the condition including implicit communication, the robot glanced to the chosen object before answering the question. They used two humanoid robots and observed that people identified the correct object quicker and with fewer questions when the android robot leaked cues through its gaze. In a study of a long term interaction, Tanaka *et al.* [62] obtained results suggesting that the company of a communicative robot able to talk and nod can improve cognitive functions and other aspects of the daily life of elderly women living alone, when compared to the same robot without the communicative features. Huang and Mutlu [34] showed that, when the robot uses the human gaze direction to anticipate explicit commands and act accordingly, the task is better performed and the robot is perceived as more aware of the interaction.

Using their model for bidirectional gaze in human and virtual agent interactions, Andrist *et al.* [3] observed improved task performance when the virtual agent both produced gaze and responded to human gaze. Participants also perceived the virtual agent as more expressive and with greater cognitive abilities when it produced gaze, and more competent when produced and responded to it. In Buschmeier and Kopp’s work [13], an attentive speaker agent, which estimated the human mental states during the interaction and adapted its behavior, received more feedback signals from the human and was perceived as an attentive agent by them. Iwasaki *et al.* [35] observed that a robot recognizing and responding to people’s behaviors encourages them to interact with it. Che *et al.* [16] studied the communication effects when the navigation of one agent affects the navigation of another (*i.e.*, social navigation). Their experiment showed that when the robot communicated its intention explicitly and implicitly and predicted human movements, participants navigated more efficiently and it increased their trust and understanding of the robot, compared to when the robot predicted movements and communicated only explicitly, and when the robot executed only collision avoidance without prediction. Zhang *et al.* [71] showed that team performance, trust, and anthropomorphism perceived by the human are improved when the robot is able to understand implicit information conveyed by indirect speech acts. The authors also highlight that this capability can affect differently depending on the context, and therefore it should be used carefully. Six *et al.* [60] evaluated the use of animation features in virtual agents in brief cognitive behavioral therapy based mental health apps. In this context, their results suggest that a virtual agent with body movements and facial expressions can improve user experience, in contrast to a static one with blank facial expression.

It is also important to investigate how to use each available communication modality. The way the robot communicates (*e.g.*, how it speaks and engages in touch interactions, and where it directs its gaze [61, 22, 32, 1, 9]) must be carefully adjusted and can be influenced by the application context and the general profile of people interacting with the robot. Aspects such as the effects of robot’s conveyed mood, transparency, planning for communication, ethical concerns, and influence

of people’s gender, age, culture, familiarity with robots, and other factors are also concerns of HRI studies [25, 28, 65, 67, 56].

Communication is essential to interaction and studying it is paramount to develop better robots interacting with humans. In this work, we consider the literature on explicit and implicit communication in HRI, such as the works of Breazeal *et al.* [11] and Huang and Mutlu [34], to define the hypotheses presented in the next section.

3 Experimental design

We investigate the effects of communication type on human perceptions and task-related outcomes in a human-virtual-agent interaction. The literature on HRI described in Section 2.1 suggests that combining explicit and implicit communications improve the interaction. We define two communication configurations:

- EX:* Only explicit communications from human and virtual agent.
- EXIM:* Explicit and implicit communications from human and virtual agent.

3.1 Human-robot communication infrastructure

We used a human-robot communication infrastructure with selected explicit and implicit communication modalities [14]. The system is integrated in the Robot Operating System (ROS) and includes recognition and interpretation of human pointing gestures and gaze direction, and a virtual agent with voice, facial expressions, and gaze direction.

In addition to the systems described in our previous work [14], we included other communication modalities such as screen applications for the virtual agent to keep the human informed of the task progress. The human can also insert explicit information using mouse and keyboard. The virtual agent uses sound signals to indicate successes and errors, and raises its eyebrows to implicitly draw the person’s attention during interaction. The human location during the interaction implicitly indicates the current stage of the task and if instructions were followed. Table 2 summarizes the communication modalities available in our infrastructure.

Table 2 Available communication modalities for human and virtual agent.

	Human	Virtual agent
Explicit	gestures manual entries	voice sound signals information on screen
Implicit	gaze direction location	facial expressions raise of eyebrows gaze direction

Since we planned an structured interaction with well defined steps, there was a ROS node responsible for integrating the individual systems and managing the interaction. This manager node autonomously read important information and sent commands through ROS topics to each of the other modules to carry on the interaction. We also used cameras and markers to locate objects and other important elements in the environment, such as the screens to display virtual agent. The human location was also inferred using markers. Given the specific locations the human was instructed to be at each phase, we placed a marker on the floor that would be occluded whenever the human reached that specific location. After some camera frames without detection of a specific marker on the floor, we would consider that the human reached that location.

3.2 Hypotheses

We hypothesize that the combination of explicit and implicit communications makes the agents' actions more transparent and predictable, which is important to successfully achieve a collaborative goal. Hence, we postulate the following:

- H1:* The task execution time will be smaller in the EXIM configuration than in the EX configuration.
- H2:* The number of task errors will be smaller in the EXIM configuration than in the EX configuration.
- If using explicit and implicit communications makes the virtual agent more similar to human agents, we expect that humans understand it better and perceive it more as a social agent, making the interaction more natural and pleasant. Therefore, we introduce three additional hypotheses:
- H3:* The acceptance of the virtual agent will be higher in the EXIM configuration than in the EX configuration.

H4: The virtual agent will be perceived as more sociable in the EXIM configuration than in the EX configuration.

H5: The virtual agent will be perceived as more transparent in the EXIM configuration than in the EX configuration.

Lastly, we expect that the virtual agent's greater sociability and the better task performance when combining communication types will make the interaction be perceived as more efficient, resulting in our final work hypothesis:

H6: The perceived interaction efficiency will be greater in the EXIM configuration than in the EX configuration.

3.3 Human and virtual agent interaction

To evaluate our hypotheses, we chose to conduct the study in a well controlled environment, so we could isolate the factor of interest [33]. Also, to reduce the sample size needed, we decided for a within-subjects design, in which each participant completes the task twice, one for each condition [33]. We propose an activity similar to a game with two phases that include actions present in real collaborative scenarios, such as following instructions and pointing to objects.

In the first phase, after introducing itself and giving instructions, the virtual agent shows a four-color sequence. The person should then point to colored boxes in the environment in the same order as the sequence. Sound signals suggest correct and wrong indications, and the screen application shows the task progress. The color sequence works as a password for the next phase, when the person is further instructed to count the occurrence of some objects in images containing several other items. There are four images in the workspace. Given an object shown in each corner of the computer screen, the person should count it on the respective image in the workspace and type the number of occurrences on the screen application. The images' positions were chosen to encourage people to move their heads to look at them. In both phases, if a time limit is reached, the virtual agent finishes the task, adding the password or filling the remaining count fields.

Each participant completed both phases twice, once for each communication configuration (EX and EXIM). Each configuration is represented by

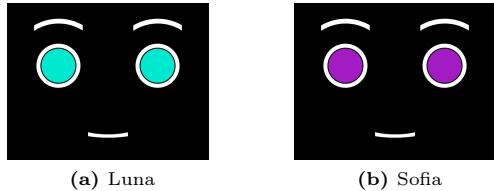


Fig. 1 Two virtual agents created to interact with people in the experiments.

a different virtual agent selected randomly by the system at the beginning of the experiment, as well as the communication configuration order for each participant. The two virtual agents, Luna and Sofia (see Fig. 1), differ by their names, eye colors, and voice tones. As described in [14], we recorded audio files with selected sentences to be the virtual agents' voices. Since participants interact with both virtual agents, there are slight differences in the sentences for each one to help differentiate them.

On the EX configuration, the virtual agent uses only voice with simulated mouth movements, sound signals, and information on screen to communicate. The agent always has a neutral expression, blinks periodically, and looks straight ahead, while the human communicates through pointing gestures in Phase 1 and manual entries by keyboard and mouse in Phase 2. On the EXIM configuration, along with the explicit communications of the EX configuration, the virtual agent uses different facial expressions according to the context, raises its eyebrows to call the human's attention, and directs its gaze through the environment. The system also uses implicit information from the location and the person's gaze in specific moments of the interaction.

During EXIM's Phase 1, the virtual agent looks at the colored box that the person should indicate. If the person makes a mistake or the password is repeated on screen after some wrong indications, the virtual agent looks at the person, raises its eyebrows, and then looks at the correct box again. After Phase 1 is finished, the virtual agent instructs the person to go to a specific location to start Phase 2.

In the EX configuration, Phase 2 starts only after the person's explicit command through the screen application. In the EXIM configuration, the system anticipates the explicit command and starts Phase 2 whenever it detects the person on

the instructed location. During Phase 2 of EXIM, if the system detects that the human is looking at one of the images of shuffled items, the virtual agent also looks at it and verbally suggests the correct counting value (*e.g.*, “[translated from Portuguese] I guess it is five there.”). Moreover, when the person opens one of the fields on the screen application to add the counting value, the virtual agent directs its gaze to the open field.

In the EXIM configuration, the virtual agent always looks at the person's face when speaking, except when it is giving a clue on Phase 2, since in this moment its gaze indicates which image/object it refers to. Fig. 2 illustrates the interaction.

3.4 Objective and subjective metrics

The outcomes related to hypotheses H1 and H2 are time and number of errors. The system registers the interaction duration, including both phases, except for initialization, verbal instructions, and audio file execution times. More specifically, the time for the phase instructions is excluded because they are only given in the first configuration. We also exclude the times for the execution of the audio files for the virtual agents' voices to prevent the differences in the sentences' length from affecting the comparison between the two communication configurations.

Errors are counted whenever the indicated colors in Phase 1 or counting values in Phase 2 are wrong. We discard system errors, such as wrong identification of a pointing gesture. When the task finishes due to timeout, we count one extra error for each color not added in Phase 1 and each counting value not inserted in Phase 2.

The hypotheses H3 to H6 are related to subjective outcomes, namely acceptance, transparency, and sociability of the virtual agents and the perceived interaction efficiency. We measure each variable with a Likert scale [46] containing a set of *items* (sentences) that people answer with one of the following options: (1) totally disagree, (2) disagree, (3) do not know, (4) agree, and (5) totally agree. Therefore, we have five response *levels* (1 to 5), and we present them to the participants always in the same order and without numbered labels.

Table 3 shows the 19 items composing the Likert scales, translated from Portuguese. They

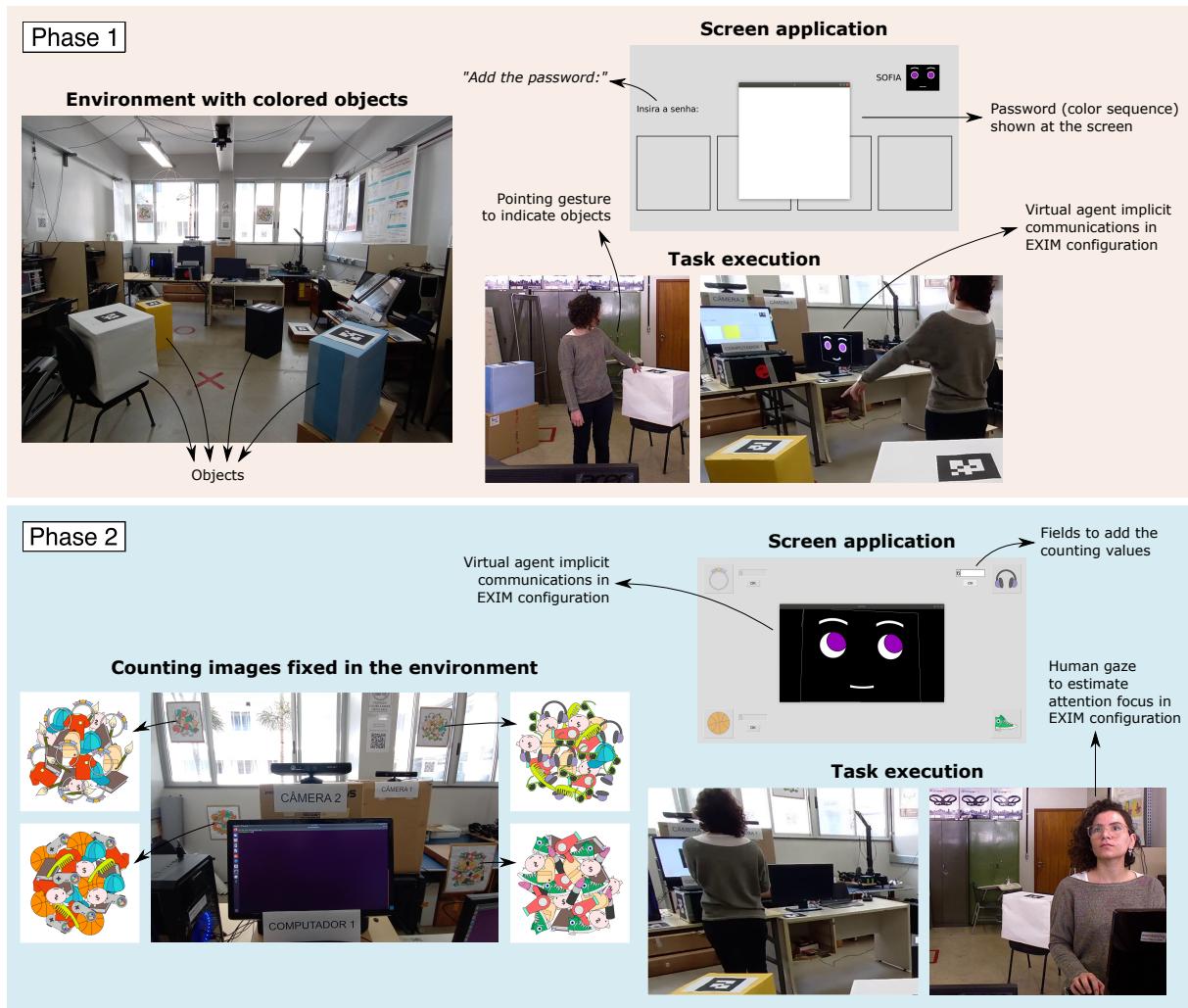


Fig. 2 Illustrations of the proposed interaction.

were defined according to our experiment, but inspired and adapted from works such as the ones by Heerink *et al.* [30] and Iwasaki *et al.* [35]. In most cases, the lowest response level (“totally disagree”) indicates a more negative perception. For instance, to disagree with the first item of the transparency scale means that the virtual agent was perceived as not very transparent. On the other hand, a low level response for the first item in the acceptance scale indicates good acceptance of the virtual agent because it uses a reverse scale. Items with a reverse scale, for which low levels indicate positive perceptions, are marked with an (R) in Table 3. The 19 items from the table are presented randomly to each participant, unlabeled and without the reverse scale indication.

4 Methodology for experimental analysis

We use Bayesian parameter estimation in our data analysis as it provides richer information when compared with frequentist analyses such as null hypothesis significance tests, maximum likelihood estimation, and confidence interval [41, 42, 69, 37]. Bayesian approaches are not so common in HRI studies as the analysis using *p*-values [8], but they allow discussions beyond the accepting or rejecting hypotheses dichotomy. In areas such as statistics and psychology, Bayesian methods have been discussed as alternatives to deal with the limitations

Table 3 Likert scales for the measurement of human perception variables. Items marked with (R) are treated with a reverse scale. The term VA is replaced by the name of the virtual agent.

Acceptance of the virtual agent	
1.	I found VA intimidating. (R)
2.	I found VA friendly.
3.	I felt comfortable while interacting with VA.
4.	I liked to interact with VA.
5.	I found unpleasant to interact with VA. (R)
6.	I would like to interact more with VA.
Sociability of the virtual agent	
1.	I felt like VA understood what I was doing.
2.	When interacting with VA, I felt like I was with a real person.
3.	Sometimes I felt like VA was really looking at me.
4.	Sometimes VA seemed to have real feelings.
5.	VA's behavior is similar to a person's.
Transparency of the virtual agent	
1.	I understood VA.
2.	I was able to know what VA was "thinking."
3.	I knew when VA was paying attention on me.
4.	During the interaction, VA's intentions were clear to me.
Perceived efficiency of the interaction	
1.	I could count with VA to help me during the task.
2.	VA helped me to execute the task.
3.	VA got in my way. (R)
4.	VA made no difference to my performance. (R)

and sometimes inadequate interpretations of p -values [40, 42, 69, 37, 38]. In the HRI context, Baxter *et al.* [8] suggest we focus on methods that can incrementally increase our knowledge about phenomena of interest; that is, a Bayesian perspective. The methods we chose to analyze our results are detailed below.

4.1 Overview

Bayesian methods rely on Bayes' rule to re-allocate credibility across possibilities, using collected information. More specifically, an initial belief on the value of a set of variables is updated after collecting new data. Let $P(\mathcal{V})$ be the prior joint probability of n parameter values $\mathcal{V} = \{v_1, v_2, \dots, v_n\}$ without the data (initial belief), $P(\mathcal{D} | \mathcal{V})$ the likelihood to obtain the data \mathcal{D} given \mathcal{V} , and $P(\mathcal{D})$ the data likelihood according to the considered model. Then, the Bayes' rule states that the posterior credibility of \mathcal{V} (updated

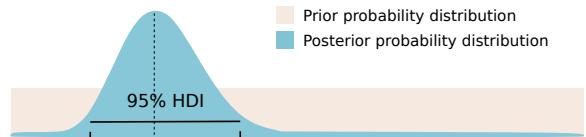


Fig. 3 Example of prior and posterior probability distributions for parameter values in the Bayesian estimation. The 95% HDI includes 95% of the posterior distribution and the most credible parameter values.

belief) is given by

$$P(\mathcal{V} | \mathcal{D}) = \frac{P(\mathcal{D} | \mathcal{V})P(\mathcal{V})}{P(\mathcal{D})}.$$

The Bayesian parameter estimation allows estimating a parameter value or the magnitude of an effect of interest. When there is few prior information about the parameter values, we usually use prior probability distributions that are vague and uninformative so that they have minimal influence on the estimation [42, 37]. Fig. 3 shows a uniform prior distribution, which assigns the same credibility for all parameter values inside an interval. The Bayes' rule provides the posterior distribution with updated credibilities for each parameter value, which are summarized using measures of central tendency, such as mean, mode, and median, and intervals such as the HDI (Highest Density Interval).

The HDI includes a percentage of the distribution, and the parameter values inside the interval are more credible than the ones outside of it. Therefore, the 95% HDI contains 95% of the distribution, and parameter values inside of it are more credible than parameter values outside of it [41] because there is a 95% probability that the true parameter value is inside this interval. Also, the 95% HDI width indicates the estimation uncertainty: the smaller the interval, the more precise is the estimation and the more certain we are about the parameter value.

The posterior distribution alone already provides information about the parameter value. Nonetheless, we can also evaluate the credibility of specific values such as a null value indicating the absence of an effect. The Region Of Practical Equivalence (ROPE) is defined around the

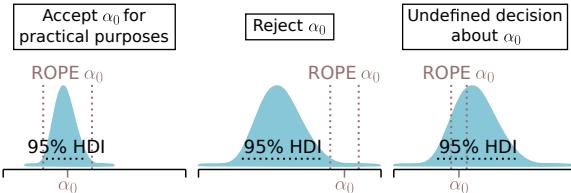


Fig. 4 Examples of possible relations between the 95% HDI of the posterior distribution and a ROPE around a value of interest, α_0 , for the parameter.

parameter value of interest to indicate a set of values that are practically equivalent to the one of interest [40]. When deciding about accepting or rejecting a specific value, Kruschke [41] proposes a decision rule, illustrated in Fig. 4, using a ROPE around the value of interest and the 95% HDI of the posterior distribution. If the entire 95% HDI is inside the ROPE, the value of interest is accepted for practical purposes. Conversely, if the entire 95% HDI is outside the ROPE, the value of interest is considered incredible and, therefore, rejected. If none of those occur, the available data set is considered insufficient to make a decision about the specific parameter value. To define the ROPE around the value of interest, the context of the application must be taken into consideration for it to reflect practical equivalence. With an adequate ROPE, a value of interest is accepted only when there is a sufficiently precise parameter estimation, which implies a sufficiently narrow 95% HDI that could fit into the ROPE.

4.2 Objective measures

In our experiment, participants interact with two virtual agents, one for each communication configuration (EX and EXIM), resulting in measurement pairs. One way commonly used to cancel individual variations is to take the difference between the two observations and run the analysis with a single group [51]. For time and number of errors, we take the differences

$$\Delta t \triangleq t_{\text{EX}} - t_{\text{EXIM}} \text{ and } \Delta e \triangleq e_{\text{EX}} - e_{\text{EXIM}}, \quad (1)$$

respectively, between the observations in each configuration, and Δt and Δe are the final measurements associated with each participant. There is no difference between the configurations when

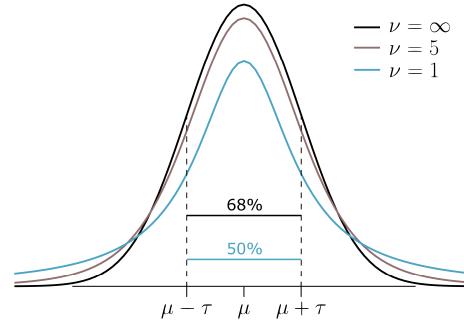


Fig. 5 Examples of t distributions with mean μ , scale τ , and different normality parameters ν . The greater ν is, the closer the t distribution is to a normal distribution. The scale τ is related to the spread of the data and covers 50% of the t distribution with $\nu = 1$ and 68% of the distribution with $\nu = \infty$.

$\Delta t = \Delta e = 0$, and positive differences ($\Delta t > 0$ and $\Delta e > 0$) favor our hypotheses.

We treat time and number of errors as metric variables in interval or ratio scales and represent them using t distributions because of the heavier (with higher probabilities) tails that accommodate outliers better than the normal distribution [41]. The distribution is described using mean μ , scale τ , and a normality parameter $\nu \in (0, \infty)$, all illustrated in Fig. 5. The scale τ is related to the spread of the data and ν determines the heaviness of the distribution tails. The greater ν is, the closer the t distribution is to a normal distribution.¹ The goal of the Bayesian inference is to estimate the parameters $\mu_{\Delta t}$, $\tau_{\Delta t}$, and $\nu_{\Delta t}$ for the time difference and $\mu_{\Delta e}$, $\tau_{\Delta e}$, and $\nu_{\Delta e}$ for the difference in the number of errors.

Since we do not have previous information about the parameters, all priors are broad and vague to minimally influence the estimation (e.g., avoid biasing). Therefore, both for Δt and Δe , the prior distributions for the mean and scale parameters are normal and uniform distributions [41], respectively. When $\nu > 30$, the t distribution closely approximates a normal. Hence, large differences between the normal and t distributions occur when ν is small (see Fig. 5), which is considered credible in the posterior distribution only if smaller values for ν are more credible in the prior

¹For more about the scale and normality parameters of the t distribution, please refer to Section 16.2 of [41].

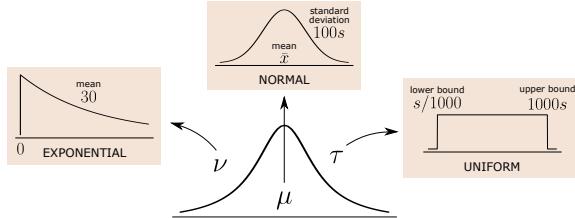


Fig. 6 Diagram of the Bayesian estimation for the metric variables Δt and Δe . A t distribution describes the data and we estimate the parameters μ , τ , and ν of each variable, using the indicated priors, where \bar{x} and s are the sample mean and standard deviation, respectively.

distribution, or if the sample contains a lot of outliers, rare by definition [41]. As a consequence, we use an exponential with mean of 30 as a prior distribution for the normality parameters to consider small values in the estimation while still allowing high values. The parameters and their priors are illustrated in Fig. 6.

4.3 Subjective measures

We obtain the subjective measures through questionnaires with Likert scales (see Section 3.4). Following Likert's original work [46], one frequently used way to deal with this type of data is using the average or the sum of the points of the items in a scale, and then treating this value as an observation from each participant. There is a discussion in the literature on whether this data set generated from the average or sum of points should be treated as interval or ordinal measures and which tests apply to them.² Liddell and Kruschke [45] show that treating ordinal data from a single item as metric leads to systematic errors of false positives, failures in detecting effects, and even the inversion of an effect. They also show that using the average points from a set of items does not solve the problems. Since there is no consensus in the literature, we treat data from subjective measures as ordinal.

Kruschke suggests a cumulative normal model (see Chapter 23 of [41]) for the analysis of ordinal data from a single item, and Liddell and Kruschke [45] extend the model to multiple items.

²Some references that discuss the subject, especially in the context of frequentist analyses (for example, comparing the t and Wilcoxon signed-rank tests) are [53, 49, 15, 29].

They treat items together but without aggregating points into a single measure. The idea is that the measured variable is in a continuous metric scale but cannot be accessed directly; that is, it is a latent variable. Therefore, the set of items in the Likert scale is a way of accessing the latent variable through a discrete and ordinal response scale. As in the metric model, using a t latent distribution instead of a normal makes the model more robust to outliers.

For a single item with $K \in \mathbb{N}$ response levels, thresholds $\theta_1, \dots, \theta_{K-1}$ divide the latent distribution into K intervals, as shown in Fig. 7 (for $K = 5$). On the ordinal model, the probability assigned to each response level is the cumulative probability of each interval, calculated as the area under the latent distribution between the respective thresholds, or between the outer thresholds (θ_1 and θ_{K-1}) and open boundaries at $-\infty$ and ∞ (i.e., $\theta_0 \triangleq -\infty$ and $\theta_K \triangleq \infty$). For a latent t distribution with mean μ , scale τ , and normality parameter ν , the probability of the ordinal response $y = k$, with $k \in \{1, \dots, K\}$, is

$$P(y = k | \mu, \tau, \nu, \theta_1, \dots, \theta_{K-1}) = \\ \Psi_{\mu, \tau, \nu}(\theta_k) - \Psi_{\mu, \tau, \nu}(\theta_{k-1}), \quad (2)$$

where $\Psi_{\mu, \tau, \nu}(u) = \int_{-\infty}^u f_{\mu, \tau, \nu}(x) dx$ is the cumulative t function with

$$f_{\mu, \tau, \nu}(x) = \\ \frac{\Gamma(\frac{\nu+1}{2})}{\Gamma(\frac{\nu}{2})} \left(\frac{1}{\tau^2 \nu \pi} \right)^{\frac{1}{2}} \left[1 + \frac{(x - \mu)^2}{\tau^2 \nu} \right]^{-\frac{(\nu+1)}{2}}$$

and Γ represents the gamma function $\Gamma(w) = \int_0^\infty z^{w-1} e^{-z} dz$ with $\text{Re}(w) > 0$ [36, p. 501-507]. The model represented by Eq. 2 applies to all ordinal levels since $\Psi_{\mu, \tau, \nu}(-\infty) = 0$ and $\Psi_{\mu, \tau, \nu}(\infty) = 1$.

The model has $K + 2$ parameters: the latent variables μ , τ , and ν and the $K - 1$ thresholds that map the latent variable into the ordinal responses. There are infinite possible combinations for these parameters that result in the same ordinal probabilities, since we can "drag," "compress," or "expand" the distribution, by changing the whole set of parameters (see Fig. 7), while keeping the probabilities associated with each level. To solve this problem, Kruschke [41] suggests fixing

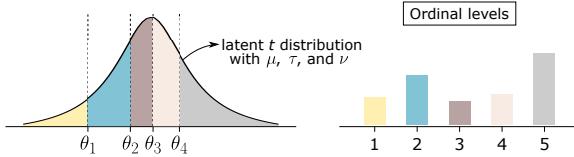


Fig. 7 The probability of the ordinal response $y = k$ is given by the cumulative probability between the thresholds θ_{k-1} and θ_k on the latent t distribution of mean μ , scale τ , and normality parameter ν , with $k \in \{1, \dots, K\}$, $\theta_0 = -\infty$ and $\theta_K = \infty$.

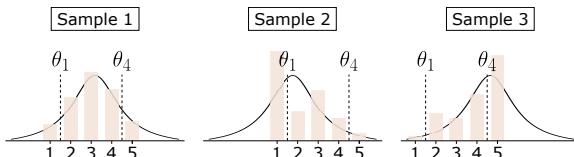


Fig. 8 Examples of sample histograms of ordinal responses with five levels and possible adequate latent distributions. Extreme thresholds are fixed at $\theta_1 = 1.5$ and $\theta_4 = 4.5$.

the extreme thresholds, θ_1 and θ_{K-1} , at meaningful values with respect to the response scale, specifically $\theta_1 = 1.5$ and $\theta_{K-1} = K - 0.5$, so these fixed values anchor the estimation. By doing it, the estimated parameters are interpreted according to the meaning of the response options. Suppose we ask people to answer an item stating “I like robots” using a scale with five response levels, from “totally disagree” to “totally agree” and with a middle answer saying “I do not know.” Fig. 8 shows examples of histograms from three possible samples and possible adequate latent distributions to each one of them, with the extreme thresholds fixed at 1.5 and 4.5. For Sample 1, the answers concentrate in the middle of the ordinal scale so the latent μ would be approximately 3, suggesting that, on average, people are not certain if they like robots or not. For Sample 2, negative answers are more frequent and the latent μ would be smaller, indicating that, on average, people do not like robots. Finally, the results from Sample 3 suggest that people do like robots, with μ having a larger value, since the higher response levels are more frequent.

Now, suppose we want to compare a variable in two different conditions (or groups), such as the acceptance of the virtual agent in EX and

EXIM communication configurations. When measuring the same latent variable (*e.g.*, acceptance) using the same questionnaire such as the Likert scale shown in Table 3, we assume that the latent variable for all groups have the same probability density function but with different parameters. Since the thresholds are related to the way we measure the variable (*i.e.*, the sentence in the Likert scale, such as “I found the virtual agent friendly”), we assume they are the same across all groups. Therefore, what differs between groups is how much people agree or disagree with the sentence and the variance of this feeling. For each group, we consider that there are common latent μ , τ , and ν for all items of the scale, but a different set of thresholds for each item, since they access the same latent variable in different ways [45].

After fixing the outer thresholds of a single item on each scale in $\theta_1 = 1.5$ and $\theta_{K-1} = K - 0.5$, as suggested by Liddell and Kruschke, we need to estimate the remaining parameters. For multiple items and multiple groups, the probability of each ordinal response $y_g^{[i]}$ of the i th item and g th group is given by [45]

$$\begin{aligned} P(y_g^{[i]} = k | \mu_g, \tau_g, \nu_g, \theta_1^{[i]}, \dots, \theta_{K-1}^{[i]}) \\ = \Psi_{\mu_g, \tau_g, \nu_g}(\theta_k^{[i]}) - \Psi_{\mu_g, \tau_g, \nu_g}(\theta_{k-1}^{[i]}), \end{aligned} \quad (3)$$

where $\theta_k^{[i]}$ is the k th threshold of the i th item (*e.g.*, “I found the virtual agent friendly”), and μ_g , τ_g , and ν_g are the mean, the scale, and the normality parameter of the latent variable (*e.g.*, acceptance) in group g (*e.g.*, EXIM).

The model states that the ordinal response $y_g^{[i]}$ comes from a categorical distribution with probabilities given by Eq. 3. As mentioned before, we fix the outer thresholds only of the first item of each scale in Table 3.³ Therefore, the goal of the Bayesian inference is to estimate the parameters μ_{EX} , μ_{EXIM} , τ_{EX} , τ_{EXIM} , ν_{EX} , and ν_{EXIM} of each variable (acceptance, sociability, transparency, and perceived efficiency) and the unfixed thresholds (*i.e.*, $(\bigcup_{i=1}^{n_i} \{\theta_1^{[i]}, \dots, \theta_{K-1}^{[i]}\}) \setminus$

³We analyze the subjective measures considering two separate groups, instead of using the difference as we do for time and errors. This is to maintain the meaning of the fixed thresholds and not to generate more empty response levels in the sample data, since they cause negative probabilities, as discussed at the end of this section and in Appendix A.

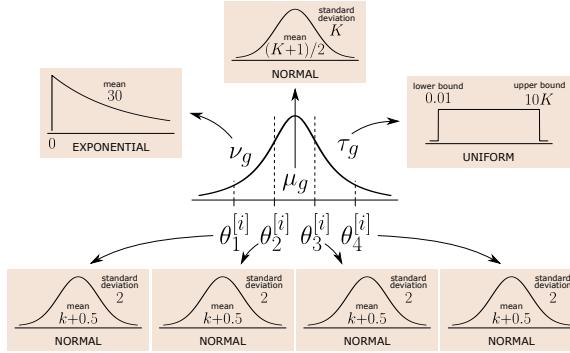


Fig. 9 Bayesian estimation for the ordinal variables. A t distribution describes the latent variable and we estimate its parameters μ_g , τ_g , and ν_g and the free thresholds $\theta_k^{[i]}$, $k \in \{1, 2, 3, 4\}$, translating the latent variable into the ordinal responses of each item i in the Likert scales. The diagram shows the prior distributions for each parameter, where $K = 5$ is the number of ordinal response levels in our scales.

$\{\theta_1^{[1]}, \theta_{K-1}^{[1]}\}$ with n_i being the number of items) associated with the items of each scale. After the estimation, we analyze the difference between the groups EX and EXIM.

Liddell and Kruschke [45] suggest using the priors shown in Fig. 9 for the parameters, with μ_g and τ_g in the neighborhood of the data, whereas the free thresholds follow normal distributions with considerable standard deviation.

There is nothing in the model to specify that the thresholds are in ascending order, *i.e.*, $\theta_1 < \theta_2 < \dots < \theta_{K-1}$. Therefore, if $\theta_{k-1} > \theta_k$, the probability of the ordinal level k is negative (see Eq. 3), which violates the first probability axiom. Kruschke works around this limitation through implementation, by considering only non-negative probabilities. However, his solution only works if the data sample has at least one answer in every level k , which can be difficult to obtain with small samples. So, together with Kruschke's proposed implementation, we decided to add one extra observation to each empty level we encounter in our samples, and use the updated data set in the Bayesian inference. In our tests with simulated data, when we added the extra observations, we observed that the estimations of the scale parameter τ gave more credibility to values greater than the real ones. This increase in the values of τ

makes it more difficult to validate our work hypotheses, since the effect size we calculate has τ in the denominator, as described in the next section. *Therefore, our strategy to mitigate empty levels due to small samples is conservative.* More details about our tests can be found in Appendix A.

5 Results

Thirty volunteers participated in the experiments but four were excluded due to significant deviation from the experimental protocol. Volunteer 4 did not finish interacting with the second virtual agent due to a technical problem, volunteer 9 did not complete the questionnaire after the first interaction, volunteer 10 asked for the researchers' help during the task, and volunteer 22 completed the task atypically, hindering the objective measures. Therefore, the final sample size is of 26 participants, summarized in Fig. 10.

5.1 Bayesian analysis results

Effect size is a measure quantifying the strength of the presence of an effect. It is calculated considering the null value, which represents an absence of effect [18]. We calculate the effect size d_{obj} for the objective measures as

$$d_{\text{obj}} = \frac{(\mu - \mu_0)}{\tau}, \quad (4)$$

considering the null value $\mu_0 = 0$ (absence of an effect) and using the estimated mean μ and scale τ of the difference between the configurations Δt and Δe , as explained in Section 4.2. Since the error and time differences are defined as in Eq. 1, positive effect sizes favor hypotheses H1 and H2, whereas negative effect sizes go against them. For the analysis of subjective measures, which estimates the parameters of each condition (*i.e.*, EX and EXIM) separately, the calculated effect size is

$$d_{\text{sub}} = \frac{(\mu_{\text{EXIM}} - \mu_{\text{EX}})}{\sqrt{0.5(\tau_{\text{EX}}^2 + \tau_{\text{EXIM}}^2)}}, \quad (5)$$

using the estimated mean and scale parameter of each group (EX e EXIM) [40, 41]. Therefore, positive effect sizes also favor hypotheses H3 to H6, whereas negative effect sizes go against those hypotheses.

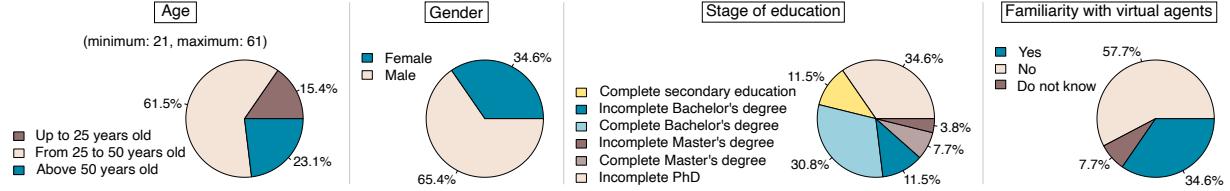


Fig. 10 Summary of the profile of the interaction experiment participants.

We define a ROPE from -0.1 to 0.1 around the null value ($d_{\text{obj}} = d_{\text{sub}} = 0$) in the effect size posterior. This interval covers values up to half of a small effect size, according to Cohen's convention [18], which is used because we do not have a clear understanding yet of what a significant effect size means in our context.

5.1.1 Implementation details

We generated the posterior distributions using Markov Chain Monte Carlo (MCMC) methods and JAGS (Just Another Gibbs Sampler) system.⁴ All scripts were written using R language and based on examples provided in the works by Kruschke [41] and Liddell & Kruschke [45].

The MCMC sample contains a large number of parameter combinations, allowing the generation of posterior distributions for each parameter and other distributions such as the difference between parameters in each group and the effect size, calculated using Eqs. 4 and 5.

5.1.2 Objective measures

For the sake of conciseness, we only show the distributions of the effect size for each measure. For the posterior distributions of mean μ , scale τ , and normality ν , please refer to the Supplementary Material accompanying the paper. The Supplementary Material also shows some credible t distributions superimposed on the data of each variable to check model adequacy. As there is no critical deviation (*e.g.*, strong asymmetry or multimodal distribution) between the data and the estimated t distributions, we conclude that the estimations fit the data well enough and the chosen model is adequate.

⁴For more details, check Chapters 7 and 8 of [41].

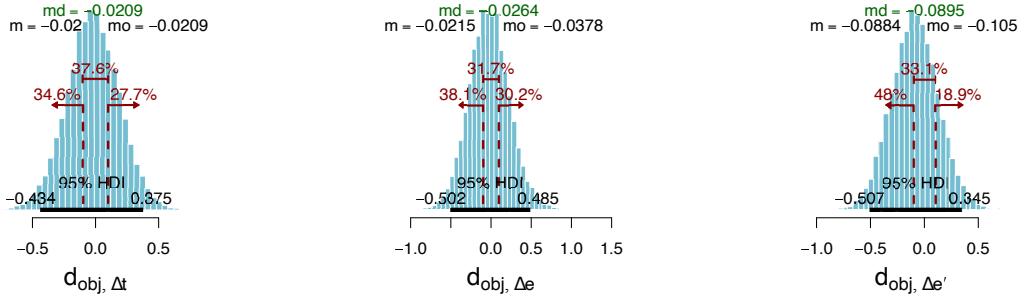
Time

Fig. 11a shows the distribution of the effect size for the time difference Δt , in seconds, between the two communication configurations. The distribution is centered close to the null value, but it has a large 95% HDI, including almost medium positive and negative effect sizes (*i.e.*, $d_{\text{obj}} = 0.5$ [18]). Positive effect sizes would favor hypothesis H1, whereas negative effect sizes would go against it. Therefore, this estimation does not allow us to reach a conclusion using the decision rule illustrated in Fig. 4 about the time difference between the two communication configurations.

Error

Owing to two possible outliers ($\Delta e = -11$ and $\Delta e = 26$),⁵ we have made the analysis for the difference in the number of errors with and without them. The effect size distributions are shown in Figs. 11b and 11c. With the outliers, more credibility is given for small values of the normality parameter ν , increasing the weight in the tails of the latent t distribution to try to accommodate the outliers. Without them, the estimations of the mean and the scale parameter became more precise (narrower 95% HDI) and the effect size posterior is slightly “compressed” to the left, reducing the percentage of the distribution above the ROPE upper limit, and giving less credibility to values favorable to our hypothesis. However, again we do not have enough precision to draw strong conclusions about the existence or not of difference in the number of errors between the two communication configurations.

⁵These two cases seem to have occurred because the participants did not understand that the first color shown on the screen (black for one participant, white for the other) was already part of the password and kept indicating the next color repeatedly, causing multiple errors to be registered.



(a) Posterior distribution of the effect size in the time difference Δt (seconds). **(b)** Posterior distribution of the effect size in the difference in number of errors Δe . **(c)** Posterior distribution of the effect size in the difference in number of errors $\Delta e'$ without outliers.

Fig. 11 Results of the Bayesian inference for the objective measures (time and number of errors). The figures show the distributions of the effect size d_{obj} (Eq. 4) calculated with the null value $\mu_0 = 0$. Mean (m), median (md), mode (mo), and the limits of the 95% HDI are annotated. Dashed vertical lines indicate the ROPE, together with the percentages of the distribution below, between and above it.

5.1.3 Subjective measures

We obtained posterior distributions for the latent parameters of each group separately and then generated posteriors for the difference between the means and the scale parameters of each group and the effect size. Positive effect sizes calculated using Eq. 5 favor our hypotheses, and their distributions are shown in Fig. 12. Other distributions, including the estimations of the thresholds θ_k , and comparisons between the data and the estimations are available in the Supplementary Material accompanying the paper. As the estimations fit the data appropriately, we conclude the model is adequate.

Acceptance

When completing the questionnaire with the Likert scales for the acceptance of the virtual agent, no participants chose ordinal level 2 for item 4 in the EX group. Furthermore, no participants from the EXIM group chose ordinal level 1 for items 1–3 and 5, ordinal level 2 for items 1, 2, and 4, and ordinal level 3 for item 5. Therefore, those levels were empty in the data set and we added one extra answer in the EX group (ordinal level 2) and eight in EXIM group (ordinal levels 1, 2, and 3) to avoid negative probabilities, as explained in Section 4.3. Thus, the estimated scales τ_{acc} might be slightly greater than the real ones, especially for the EXIM group, and the effect size slightly lower (see Appendix A for more information). The Supplementary Material shows data histograms

indicating all the levels for which we added extra answers.

Fig. 12a shows the effect size posterior of the acceptance of the virtual agents, with its median ($md = 0.264$) indicating small to medium effects (*i.e.*, 0.2 to 0.5 [18]), but without enough precision to draw a conclusion using the 95% HDI and ROPE.⁶ However, 88.3% of the distribution is above the ROPE upper limit, suggesting high credibility that there is an effect favorable to our hypotheses; namely, that the EXIM virtual agent is more accepted than the EX one.

Sociability

For the sociability data set, we added one extra answer only to level 1 of item 1 in group EXIM, as no participant chose that response. Again, the 95% HDI of the effect size posterior, shown in Fig. 12b, is not narrow enough to allow us a strong conclusion, but 92% of the distribution is above the ROPE upper limit, suggesting that the EXIM virtual agent was perceived as more sociable than the one from the EX configuration.

⁶The width of the 95% HDI of the subjective variables is smaller than the 95% HDI of the objective variables. Consequently, the estimation of subjective variables is more precise. This is because we assume in the ordinal model that the latent parameters are the same for all $Q \in \{4, 5, 6\}$ items from the Likert scales (*i.e.*, each item measures the same phenomenon). Consequently, we use all $26Q$ observations related to all 26 participants to estimate μ , τ , and ν , resulting in more precise estimations.

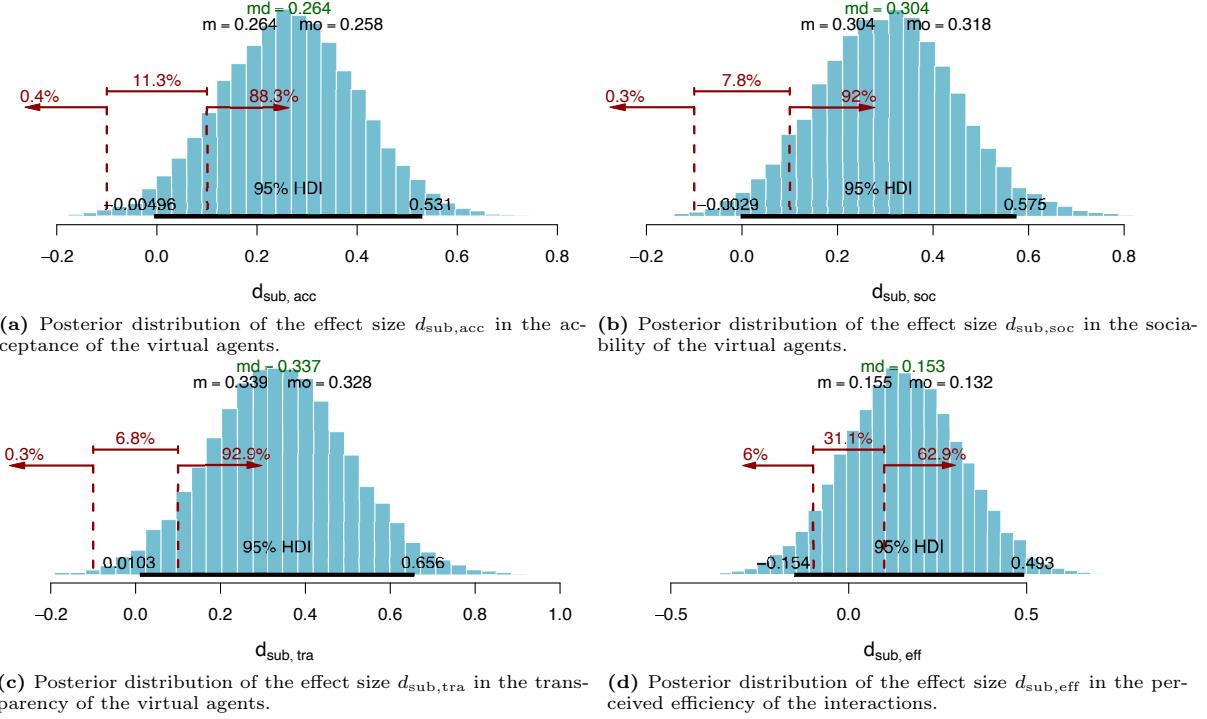


Fig. 12 Results of the Bayesian estimation of acceptance, sociability, transparency and perceived efficiency in the two communication configurations. The figures show the distribution of the effect sizes. Mean (m), median (md), mode (mo), and the limits of the 95% HDI are annotated. Dashed vertical lines indicate the ROPE, together with the percentages of the distribution below, between and above it.

Transparency

We added one extra answer on level 1 of each group to overcome the lack of participant responses in this level in item 1 for EX and item 3 for EXIM. The effect size estimation, shown in Fig. 12c, is once again not precise to fulfill Kruschke's decision criterion, but it indicates that the EXIM virtual agent might have been seen as more transparent than the EX virtual agent, with 92.9% of the distribution above the ROPE upper limit.

Perceived efficiency

Finally, for the perceived efficiency dataset, we added one extra answer in level 2 of item 3 of EX group and one in level 1 of item 3 of group EXIM because those were empty due to the lack of response. Fig. 12d shows the effect size posterior, whose median ($md = 0.153$) indicates a less than small effect (*i.e.*, lower than 0.2 [18]), with 62.9% of the distribution above the ROPE upper limit.

6 Discussions

6.1 Dealing with technical errors during the experiments

The system for human kinematic chain recognition [14] sometimes failed to detect the participant and the experimenter intervened to give additional instructions or to restart the system, sometimes remotely. Also, some participants did not understand that they would interact with two virtual agents and left the room after the first interaction and questionnaire. In these cases, the experimenter asked them to go back and continue. As long as these interventions did not happen during the task execution and interrupted the interaction flow, we took note of the occurrence and let the experiment continue and the participant was not excluded from the analysis. We excluded the system initialization times and the time to solve the aforementioned technical problems in our analyses.

All participations were recorded with the participants' knowledge and formal consent. After the experiments, we watched the videos and adjusted the data. For instance, for Phase 1, we discarded errors caused by wrong detection of pointing gestures and some delay in the sound signals indicating a correct or wrong color (sometimes, a delay happened and the participant kept pointing while waiting for the sound signal, so the system counted two gestures instead of one). Errors indirectly attributed to the system limitations, such as when a participant points to a second object after indicating the correct one, but the system fails to recognize it, were not discarded because these interpretations were subjective; therefore, we decided to follow a more conservative approach.

6.2 General discussion

The results shown in Section 5 were obtained from a sample of 26 participants. From the four participants excluded from this analysis, three completed all the steps of the interaction and the questionnaires, so they are included in the following discussion, which aims to discuss the experimental protocol and how it could be improved.

From the 29 participants that interacted with both virtual agents, 21 of them said they preferred to interact with the EXIM virtual agent, which combined explicit and implicit communications. Participants smiled at or talked to the virtual agents during the interactions and most comments made about them were positive, either on the questionnaires or to the researcher conducting the experiment. People seemed to have positive reactions to them, which was also observed in the acceptance analysis. One participant commented

"I found the interaction very interesting, and, specially after interacting with Luna [the EXIM virtual agent], I noticed that the simple fact of the virtual agent to 'look' at my direction made a difference on how I felt with respect to the task."

Another person commented that "*the voice is irritable*" and another one said to the experimenter that they did not like "*these virtual agents*".⁷

Acceptance, sociability, and transparency are variables more related to the virtual agents, whereas time, errors, and perceived efficiency of the interaction depend more directly on the task. Seven comments on questionnaires report difficulties in understanding the task, which was also mentioned by other participants directly to the experimenter, suggesting that instructions might not have been clear enough. Considering all 29 complete participations, with two interactions per people, the time limit was reached and the virtual agent had to finish the task five times in Phase 1 and eight times in Phase 2. Two of the times the time limit was reached in Phase 1 and three of the ones in Phase 2 were not considered in the analysis, since some participants were excluded from the final sample for having significantly deviated from the experimental protocol.⁸ The videos also suggest that people found Phase 2 more difficult, taking a long time to find the counting images fixed in the environment and to understand what to do. Six participants added what seems to be generic values, such as 1 for all objects, in at least one of the configurations, suggesting that they did not understand the task or did not find the images. Two people mentioned that the space used for the experiment was visually cluttered, which might have created difficulties for participants to find the counting images. The objective measures might have been influenced by these factors.

On the EXIM configuration, we used implicit communications not only to make Luna and Sofia more pleasant, sociable, and transparent. Indeed, we also hoped they would help participants during the task execution, since the virtual agents looked at the correct object they believe people would point to in Phase 1. Moreover, they used people's gaze to estimate their attention focus and give hints with the correct answers in Phase 2. In fact, based on our interpretation of the experiment recordings, we believe that at least four people might not have seen the counting images and added correct values only trusting the information provided by the virtual agent. Even when the system detected a wrong gaze direction, the virtual agent's own gaze complemented the communication and the participant could infer which object

⁷ All comments were translated from Portuguese.

⁸Please refer to Section 5 for more details about the exclusions.

it was referring to. Four other people neither understood nor considered the virtual agent’s hint and added wrong values despite being prompted with the correct answer.

In Phase 1, the videos suggest that some participants might not have seen the virtual agents’ implicit communications, as they did not seem to look at the screen displaying the virtual agent while executing the task. On the other hand, other people clearly noticed that the virtual agent looked at them because they played around with its gaze for a moment, moving their bodies to see the virtual agent following them.. People may also not have attributed meaning to its gaze, seeing it but not interpreting it. One participant seemed not to have understood that one color was from the password and, after the interaction, told the experimenter that the virtual agent kept looking the other way, without realizing it was looking at the correct object. After all, it was not necessarily a collaborative task, meaning that it did not need to be done collaboratively, although the virtual agent could help. We believe that these aspects may have influenced the perceived efficiency of the interaction, with some people attributing little or no credit to the virtual agent for the completion of the tasks.

7 Conclusions

In this work, we have investigated the effects of combining explicit and implicit communications on performance and on people’s perceptions while interacting with virtual agents. For that, we used a communication infrastructure [14] to propose an interaction experiment similar to a game. Following the HRI literature, we have hypothesized that using explicit and implicit communications from human and virtual agent would reduce time and number of errors in task execution and increase acceptance of the virtual agent, its sociability and transparency, and the perceived efficiency of the interaction.

With our relatively small sample of 26 valid participants, we cannot draw strong conclusions about the presence or absence of effects, but the results suggest that combining explicit and implicit communications have improved the subjective measures related to the virtual agent (acceptance, sociability, and transparency), favoring

three of our six hypotheses. Variables more related to the task, such as time, number of errors, and perceived efficiency, did not seem to be affected by the communication type. This may be attributed to the fact that the tasks were not necessarily collaborative and perhaps too simple, making external help unnecessary to their successful conclusion. Our results differ from works such as the one by Breazeal *et al.* [11], where they observed effects on performance measures in a task where people guided the robot to push some buttons, so they needed to work together.

According to participants’ comments and the video analysis, our instructions may not have been clear enough. From our final sample, 7.7% of the errors in Phase 1 are extra errors for not finishing including the correct colors by pointing at the right colored boxes. In Phase 2, 16.1% of the errors are due to counting values not being inserted before the timeout (see Section 3.4), indicating difficulties in completing the task. The recordings also show that people might have not perceived some of the virtual agents’ implicit communications, such as the facial expressions in Phase 1. All these factors could have influenced our comparison of task-related variables. The experimental protocol can be improved to tackle those problems, for example using a more collaborative task and giving more detailed instructions.

To measure the subjective outcomes, we used questionnaires with Likert scales. Some works propose models and instruments to measure people’s perceptions about technologies and robots [68, 5, 30], but there is no standard in the HRI area. When using Likert scales, usually a measure called Cronbach’s alpha [19] is reported to evaluate reliability and internal consistence of the scale (see [31, 52, 20, 63]), although there is some discussion about the adequacy of this measure [21, 55]. In our work, we have not made any analysis of this type, so the adequacy of our questionnaires to measure the subjective outcomes needs to be evaluated in future works.

Finally, despite some limitations of our results, which might have been caused by the relatively small sample with relatively little diversity, the posterior distributions we estimated can be used to inform prior distributions in future works considering a larger population. This is one of the reasons we chose to use a Bayesian approach to

the data analysis, so our results can more easily serve as a stepping stone to future research.

Future work will focus on improving the experimental protocol, checking the adequacy of our questionnaires, and testing the hypotheses with larger and more diverse samples. Using the data we collected about the participants' age, gender, stage of education, and familiarity with virtual agents, the influence of these factors in our objective and subjective measures can also be investigated. Our data might be used to generate new work hypotheses about these possible influences. Finally, the study can be replicated with different types of agents, such as more realistic virtual agents and humanoids, and the effects of these various embodiments can be analyzed.

8 Statements and declarations

This work was supported by the Brazilian funding agency CNPq (Conselho Nacional de Desenvolvimento Científico e Tecnológico) and by the Royal Academy of Engineering under the Research Chairs and Senior Research Fellowships programme. The authors have no competing interests to declare that are relevant to the content of this article.

Ethics approval and consent

The experiment involving human participants was approved by the ethics committee of the Federal University of Minas Gerais, and the research is identified by the number 44110621.5.0000.5149.⁹ Informed consent was obtained from all participants included in the study.

A Ordinal model limitations and adjustments due to empty levels

On the ordinal model, described in Section 4.3, there is nothing to specify that the thresholds are in ascending order, that is, $\theta_1 < \theta_2 < \dots < \theta_{K-1}$. However, if we have inverted thresholds ($\theta_{k-1} > \theta_k$), the probability of the k th ordinal level becomes negative, violating the first probability axiom. The MCMC posterior distribution

⁹The approval can be checked on the website <https://plataformabrasil.saude.gov.br/>, informing the research number on option *Confirmar Aprovação pelo CAAE ou Parecer*.

sample generator also does not prevent inverted thresholds from being generated. To solve that problem, Kruschke includes a condition that if inverted thresholds are generated at the k th level, the corresponding calculated probability would be zero and then the thresholds are discarded [41, Section 23.2.1]. This implementation solution works *as long as there is at least one answer in each level of the data sample*. When the data contains an empty level, there is nothing in the mathematical model or in the implementation that prevent the generation of inverted thresholds, and hence negative probabilities.

This model limitation is specially problematic when we have a small data sample, which increases the chance of an empty level. In his implementation, Kruschke decided to compress out the empty levels. For example, if there are five levels of response (1 to 5) but level 2 does not occur in the data sample, Kruschke's implementation changes the data set, considering only four levels (1 to 4). Then, this updated data set is used in the Bayesian inference. We can easily see that this change can alter the parameter estimation; if the original data set, with empty level 2, came from a latent distribution with mean $\mu = 4$, the compression would shift the estimated mean to a value smaller than 4.¹⁰

Because Kruschke's data compression strategy could bias our estimation and the ordinal levels are related to the actual response options in the questionnaires, we chose not to follow it. Therefore, we consider some alternatives to deal with the empty levels problem, summarized in Table 4. One option is to use more restricted priors for the thresholds, more specifically by reducing the standard deviation. That solves the problem of negative probabilities but also adds an estimation bias, since restricted priors mean a strong initial belief about the parameter value. Another reason against the restricted priors is that centering them at the same values for all items already confronts the idea that different items access the same latent variable through different thresholds. Therefore, considerable standard deviation should be used

¹⁰We discussed the matter with Prof. John Kruschke in private communication. According to him, to keep the original number of levels even when there are empty levels in the data sample, it would be necessary to change the model (using more restricted priors for the thresholds, for example) and the mechanism to select possible thresholds during the MCMC sample generation.

Table 4 Advantages and drawbacks of each method considered for the analysis of ordinal data containing empty levels.

	Advantages	Drawbacks
Keep empty levels	Original data	Possible negative probabilities
Compress empty levels	No negative probabilities	Changed data Estimation bias
Restricted prior distributions for thresholds θ_k	Original data No negative probabilities	Estimation bias
Add extra data	No negative probabilities	Changed data Inflated estimation of the latent scale parameter τ

to allow greater variability. Moreover, we do not have enough knowledge to place them at different locations for each item.

Another alternative is to add extra data to eliminate empty levels, and we consider three ways of doing it: 1) adding one extra answer in all levels, empty or not, to avoid shifting the estimation of the mean μ ; 2) adding one extra answer only in empty levels; 3) and adding one extra answer in each empty level and adding extra answers in non empty levels to keep the probability (frequency of occurrence) of each level as close to the original as possible, adding a maximum of K new answers in the data sample of each item. In our tests, when we added extra data, we observed an inflated estimation of the scale parameter τ , with greater credibility given to values higher than the real one.

Since all aforementioned alternatives to the solution of empty levels change the estimated distribution, a sensible choice must consider two main aspects: the results should be mathematical coherent (no negative probabilities) and the effects of the change in the data sample should not favor our hypotheses (that is, we seek a conservative solution). Using simulated data, we have found the best consistent results by adding extra data only to empty levels. With this method, only the estimation of the scale parameter τ was significantly hindered, making it more difficult to validate our hypotheses. The parameter τ appears on the denominator of the effect size; therefore, greater scales imply smaller effect sizes.

Another important aspect of the model is how the estimations strongly depend on the value of the fixed parameters. If we fix the latent mean

and/or scale parameter, it would be more difficult to interpret the estimations. Consequently, following Kruschke's suggestion [41], a better option is to fix the extreme thresholds of one of the items considering the response levels in the questionnaires. We arbitrarily chose to fix the extreme thresholds of the first item of each scale as shown in Table 3.

Unlike the objective measures, which do not use an ordinal model and for which we pair the observations for each participant and use the difference between the communication configurations, we estimate the parameters of each group separately for the subjective measures. This is because considering five response levels (see Section 3.4), the difference between communication configurations would assume values from -4 to 4 , which do not have a direct relation with the original five response options in the questionnaire. Remember that we fix the extreme thresholds in 1.5 and $K - 0.5$ to enable us to interpret the estimation of the latent parameters considering the actual response options presented to participants, as discussed in Section 4.3 (see Fig. 8). Moreover, more levels would increase the chance of empty ones and require more extra data in those empty levels, causing more change in the final sample and the estimations.

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Supplementary Material: *A study on the effects of mixed explicit and implicit communications in human-virtual-agent interactions*, in International Journal of Social Robotics

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This supplementary material shows the complete results of the experiment described in the main paper to compare two communication configurations, EX and EXIM. It includes the posterior distributions of all parameters estimated, and a posterior check of model adequacy, comparing the data sample with the estimations. Section 1 shows the results for the Bayesian analysis of the objective measures, namely time and number of errors. The results for the Bayesian analysis of the subjective measures, that is, acceptance, sociability, transparency of the virtual agents and perceived efficiency of the interaction, are shown in Section 2. For the discussions about the results, please refer to Sections 5 and 6 of the main paper.

As discussed in the main paper, we chose Bayesian methods because they provide richer information [6, 7, 10, 4], but also because of the subjective measures. These perceptions were assessed using Likert scales [9]. Some works suggest that if we take the average of points from the items of the scale, it can be treated as an interval scale and tests such as the t-test can be conducted, as long as its other assumptions hold [1, 2]. However, Liddell and Kruschke [8] show that treating

data from Likert scales as metric data can lead to systematic false positives, fails in detection, and even inversion of effects. They argue that data from Likert scale should be treated as ordinal, and that taking the average does not solve the problems. An option often used in the literature is a non-parametric alternative for the t-test, such as the Wilcoxon signed-rank test. Despite being a non-parametric test that does not assume data in interval or ratio scale, this test also requires taking the average of the points in the Likert scale, which is already assuming that the data can be treated as metric [8]. For any readers still interested in the results employing null hypothesis significance tests, Section 3 shows the outcome of these for each of the variables we evaluated.

1 Objective measures results

For the objective measures of time and number of errors, we use the metric model described in Section 4.2 of the main paper. We estimate the mean μ , scale τ , and normality parameter ν of the latent t distributions of the difference in time $\Delta t = t_{\text{EX}} - t_{\text{EXIM}}$ and number of errors $\Delta e =$

$e_{\text{EX}} - e_{\text{EXIM}}$, and calculate the effect sizes using Eq. 4 in the main paper. Also, some credible t distributions were superimposed on the data of each variable to check model adequacy.

Fig. 1 shows the results for difference in time and Fig. 2 for the difference in the number of errors, with and without outliers. We show the posteriors for the normality parameter ν in log scale to ease visualization, since its distribution is very asymmetric in a linear scale. Most variation in the tails of the t distribution occur for small values of ν , and values greater than $\log(\nu) = 1.47$ ($\nu = 30$ in the original scale) represent distributions very close to a normal [6].

2 Subjective measures results

Fig. 3 shows histograms with participants' responses to each item and group for all the subjective measures, namely acceptance, sociability, transparency of the virtual agents, and perceived efficiency of the interactions.

The ordinal model used for the subjective measures is described in Section 4.3 of the main paper. We estimate the mean μ , scale τ , and normality parameter ν of the latent t distributions, and the free thresholds θ_k , with $k \in \{1, \dots, K-1\}$, where $K = 5$ is the number of ordinal levels. We interpret the estimation of the mean μ considering the five ordinal levels of response (see example in Fig. 8 in Section 4.3 of the main paper). Remember that, according to the model, the ordinal response scale is a way of accessing the latent distribution, which is not limited by the response options. Thus, the estimated credible values of the mean μ of the latent distribution can be lower than 1 and higher than 5, like in some of the distributions we obtained. We also calculate the difference between the means and scales of each condition, and the effect sizes d_{sub} for each variable using Eq. 5 in the main paper.

The item thresholds, which translate the latent variable into the ordinal responses, are strongly correlated, so we present their estimations together, like Kruschke [6].¹ Fig. 4 shows example posterior distributions of the thresholds of an item, represented by the blue points clouds. The

spread of the clouds indicate the spread of the distributions and the dashed vertical lines indicate the estimated mean of each threshold. The example data sample contains more answers in the higher response levels so the estimations of the higher thresholds are more precise than the lower ones. The ellipses on Fig. 4 cover 95% of the clouds of thresholds θ_1 (on the left) and θ_4 (on the right) and the θ_1 ellipse is larger than the θ_4 ellipse, indicating that the θ_4 posterior distribution is more compact, *i.e.*, a more precise estimation.

The small blue circles in Fig. 4 represent the thresholds values in each combination of parameters in the MCMC (Markov Chain Monte Carlo) sample, and the vertical coordinate is the mean of the four thresholds in that combination. For each step of the generated MCMC sample,² the points are at the same height in the plot. The horizontal dashed lines are related to two subsequent steps in the MCMC sample generation, steps 17540 and 17541,³ and the height of the lines is the mean of the thresholds (black dots) in each step. During the generation of the MCMC sample, if a higher value is chosen for a threshold, all the other item thresholds will need to adjust and tend to be higher too, to keep the probability of each ordinal response level, calculated as the cumulative probability between two consecutive thresholds in the latent distribution (see Section 4.3 in the main paper). With that, each new step tends to shift the thresholds set up and right or down and left, as we see by the subsequent steps shown in Fig. 4.

Figs. 5 and 6 show the posterior distributions for the acceptance of the virtual agents. The extreme thresholds $\theta_1^{[1]}$ and $\theta_{K-1}^{[1]}$ of the first item of each scale are always at 1.5 and 4.5, since they were fixed at these values.

For the model adequacy check, we estimate the probability of each ordinal level using the estimated parameters. Fig. 7 shows the final acceptance data histograms (with the extra answers included, as explained in the Section 4.3 and Appendix A of the main paper) superimposed with the median of the estimated probability of

¹The figures in this document containing our results were generated using the scripts provided by Kruschke and Liddell [6, 8] and adapted to our work.

²For more information about the MCMC sample generation, please refer to Chapter 7 of [6].

³The generated MCMC sample contains 20000 combinations of parameters.

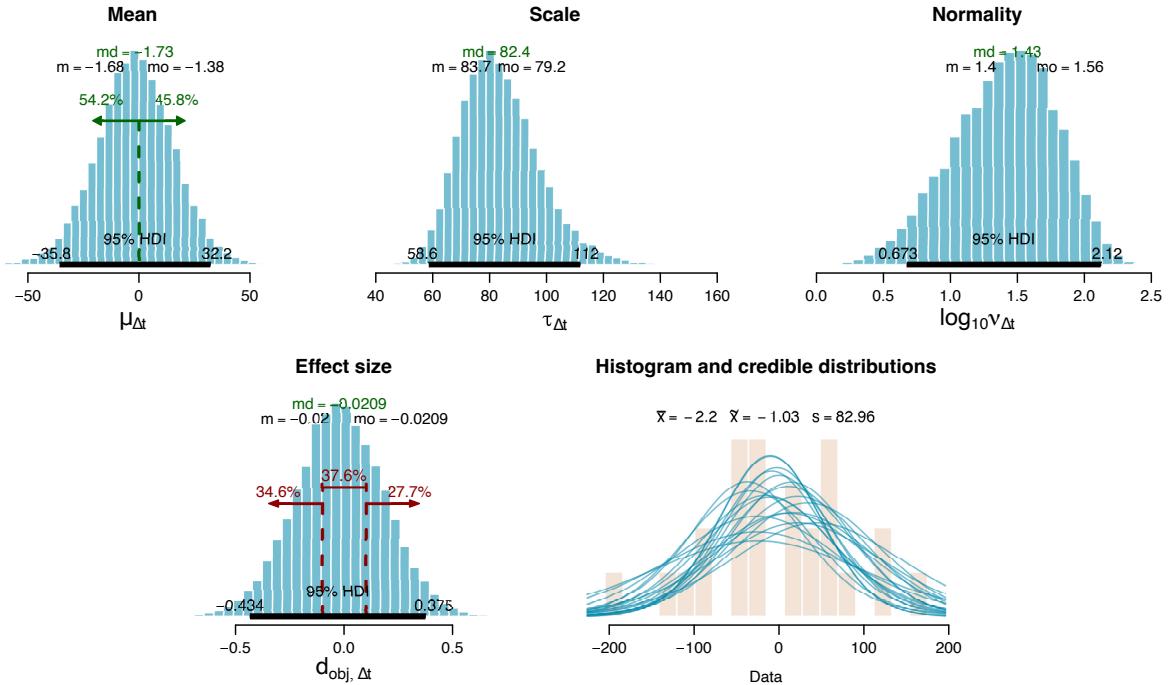


Fig. 1 Results of the Bayesian inference of the time difference Δt between EX and EXIM configurations, in seconds. The first row shows the posterior distributions of the mean μ , scale τ , and normality ν (in log scale) of the latent t distribution. On the left of the second row is the distribution of the effect size d_{obj} calculated with the null value $\mu_0 = 0$. Mean (m), median (md), mode (mo), and the limits of the 95% HDI are annotated in the distributions. Dashed vertical lines indicate the null value in the distribution of the mean μ and the ROPE in the effect size distribution together with the percentages of the distribution below, between and above the values associated with the ROPE and the null value. On the right of the second row, some credible t distributions are superimposed on the data to check model adequacy, and sample mean (\bar{x}), median ($\bar{x}\bar{\cdot}$), and standard deviation (s) are shown.

each level and its 95% HDI. Levels that were originally empty and for which we added an extra answer are indicated in Fig. 7 by asterisks.

Figs. 8 to 10 show the results for the sociability of the virtual agents, Figs. 11 to 13 show the results for their transparency, and Figs. 14 to 16 show the results for the perceived efficiency of the interactions.

3 Null hypothesis significance tests results

For the objective measures of time and number of errors, the paired t -test was used if the normality assumption was validated, and the Wilcoxon signed-rank test, if not. For the subjective measures, only the Wilcoxon signed-rank test was used

because of the reasons mentioned at the beginning of this document. This test assumes that the sample is from a symmetric population, which is already true for paired samples, according to Hollander et al [3] and Kloke and McKean [5], so this assumption was not tested.

Table 1 shows the results for the objective measures. The second column shows the normality assumption check, using the function `shapiro.test`⁴ from package `stats` (version 4.0.4) for R language. A decision was made considering a threshold of 5%, *i.e.*, when the p -value is less than 5% the normality assumption is considered not validated and therefore a nonparametric test is used. The third column shows the tests

⁴<https://stat.ethz.ch/R-manual/R-devel/library/stats/html/shapiro.test.html/>

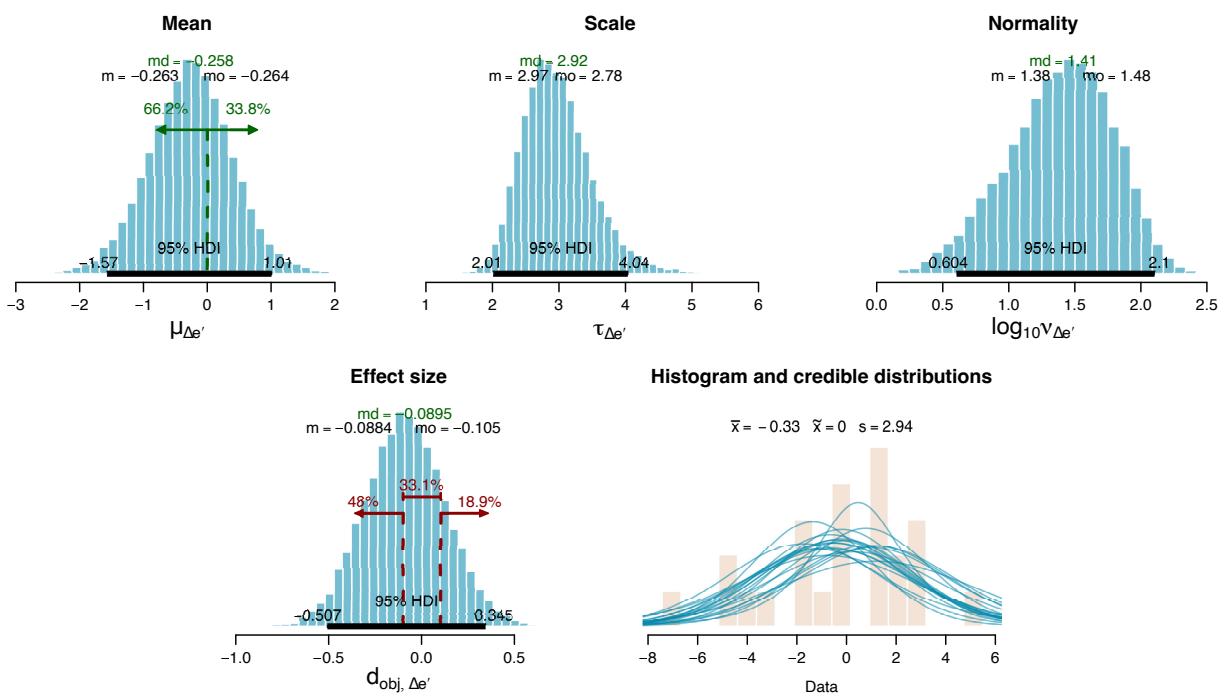
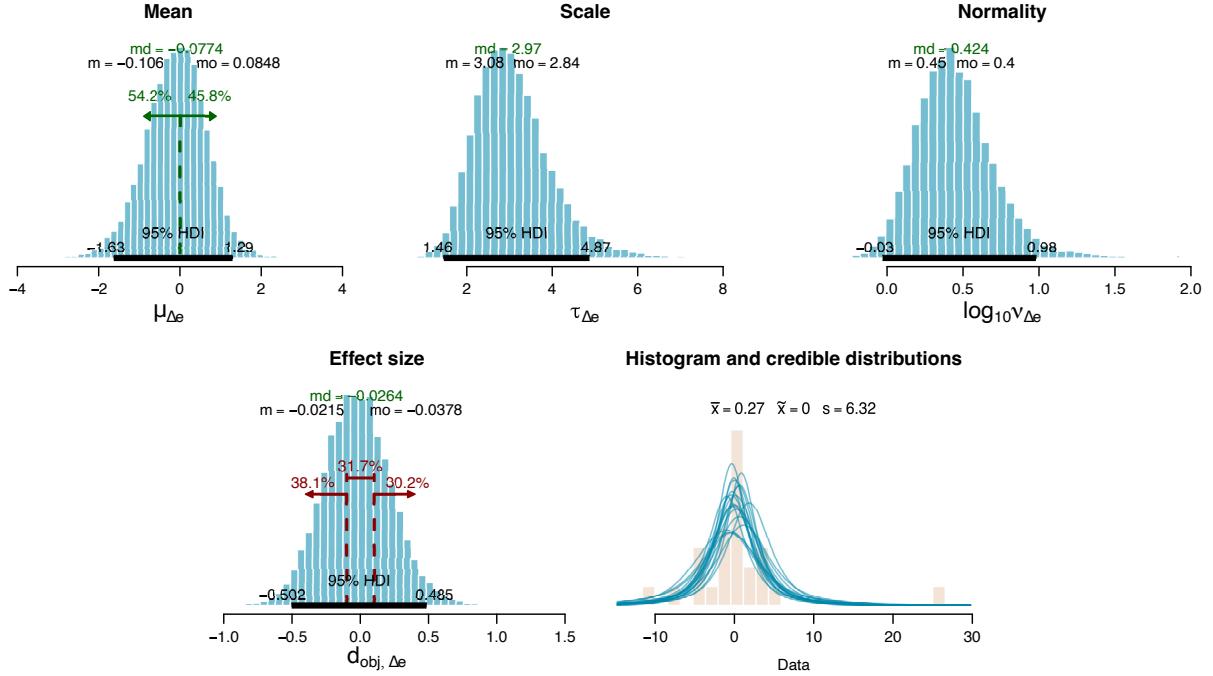


Fig. 2 Results of the Bayesian inference of the difference in the number of errors between EX and EXIM configurations, with and without outliers. In each figure, the first row shows the posterior distributions of the mean μ , scale τ , and normality ν (in log scale) of the latent t distribution. On the left of the second row of each figure is the distribution of the effect size d_{obj} calculated with the null value $\mu_0 = 0$. Mean (m), median (md), mode (mo), and the limits of the 95% HDI are annotated in the distributions. Dashed vertical lines indicate the null value in the distribution of the mean μ and the ROPE in the effect size distribution together with the percentages of the distribution below, between and above the values associated with the ROPE and the null value. On the right of the second row, some credible t distributions are superimposed on the data to check model adequacy, and sample mean (\bar{x}), median (\tilde{x}), and standard deviation (s) are shown.

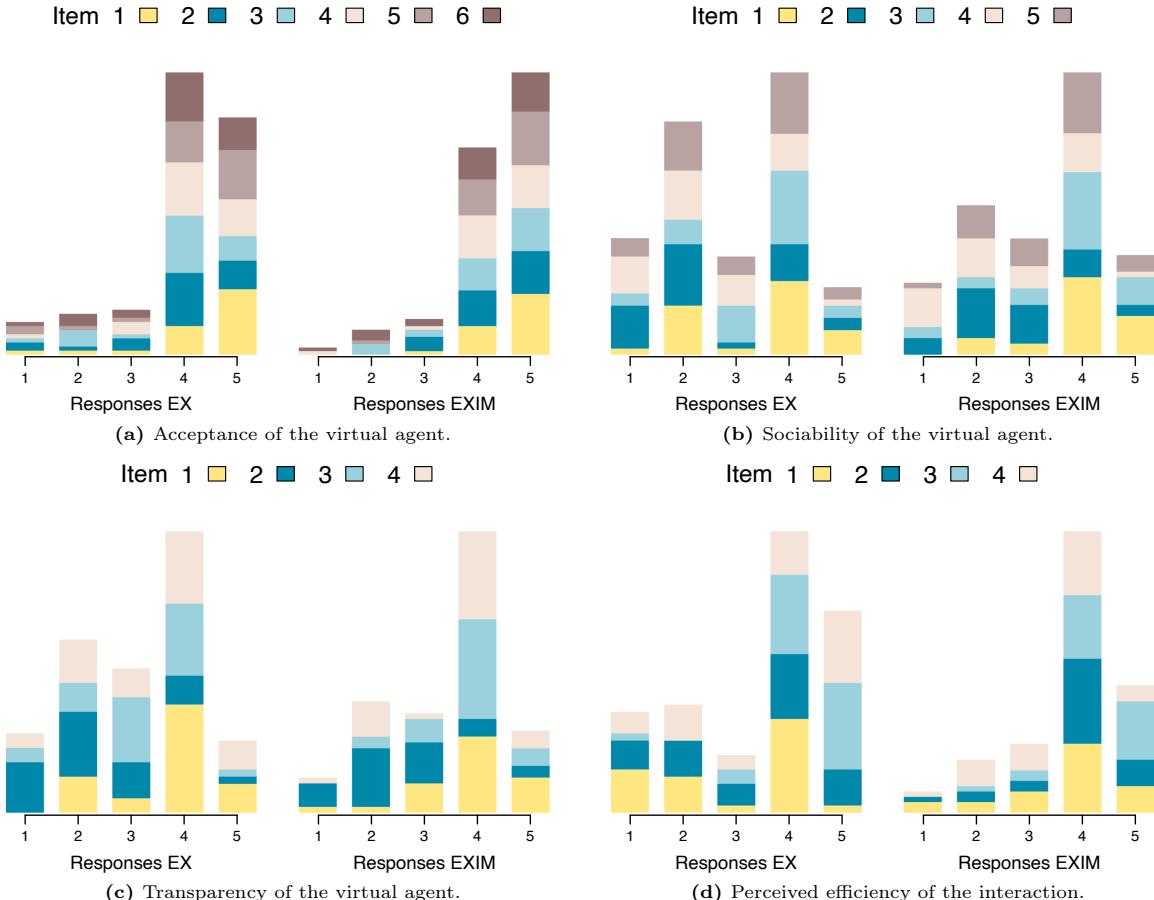


Fig. 3 Histograms of the ordinal responses (five levels) in each item of the Likert scale for the subjective measures in EX and EXIM groups.

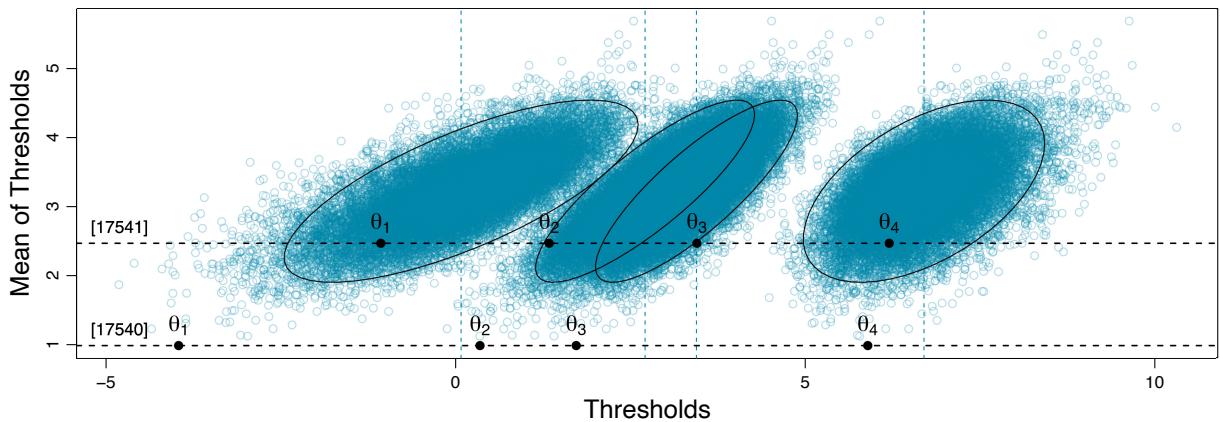


Fig. 4 Example of posterior distributions of the thresholds $\theta_1, \theta_2, \theta_3$, and θ_4 of an item.

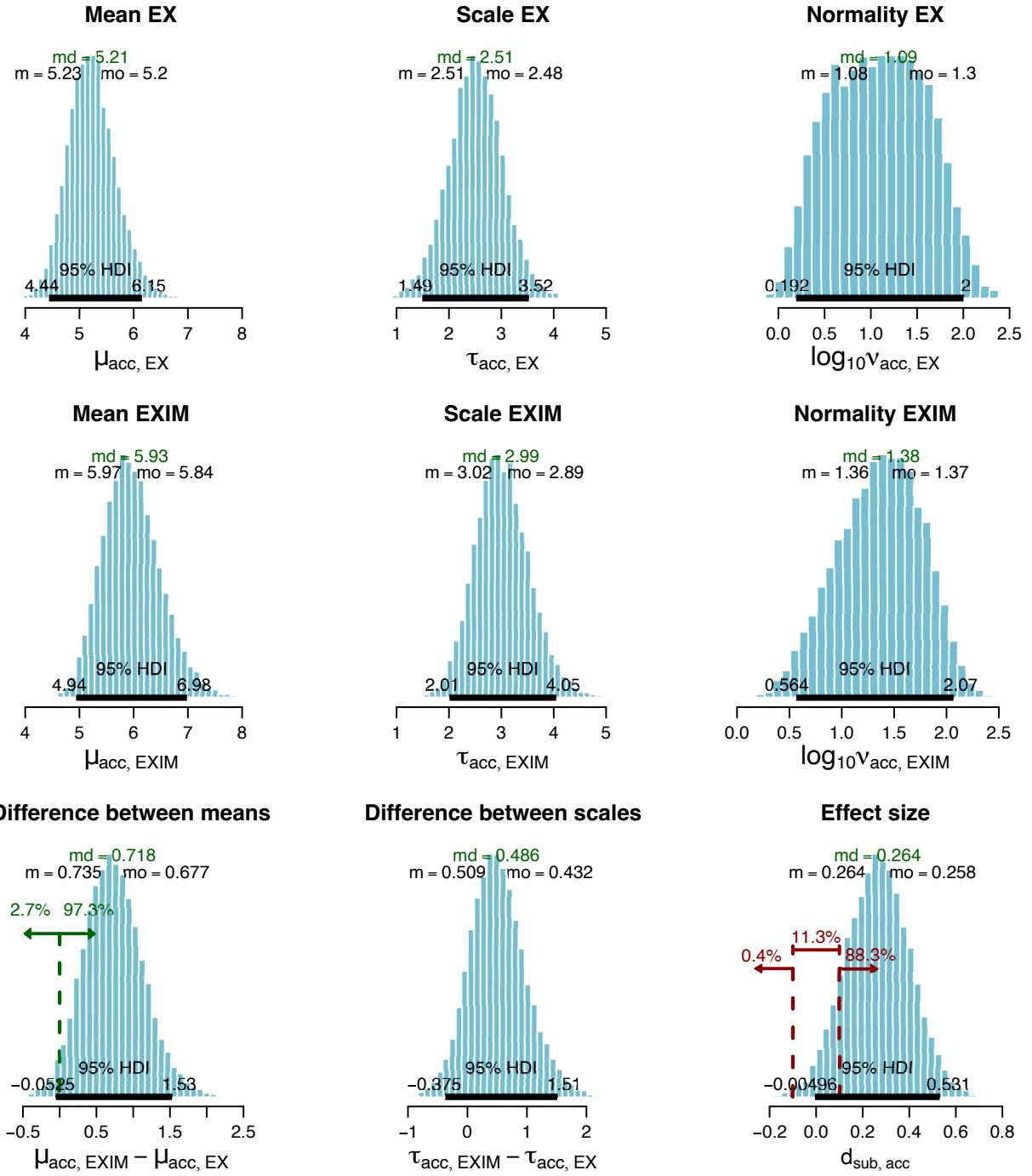


Fig. 5 Results of the Bayesian inference of the acceptance of the virtual agents in EX and EXIM configurations. The first two rows show the posterior distributions of the mean μ , scale τ , and normality ν (in log scale) of the latent t distribution of each group. On the left and center of the last row are the distributions of difference between the means and scales of the two groups, and on the right, the distribution of the effect size d_{sub} . Mean (m), median (md), mode (mo), and the limits of the 95% HDI are annotated in the distributions. Dashed vertical lines indicate the null value ($\mu_{\text{EXIM}} - \mu_{\text{EX}} = 0$) in the distribution of the difference between means and the ROPE in the effect size distribution together with the percentages of the distribution below, between and above the values associated with the ROPE and the null value.

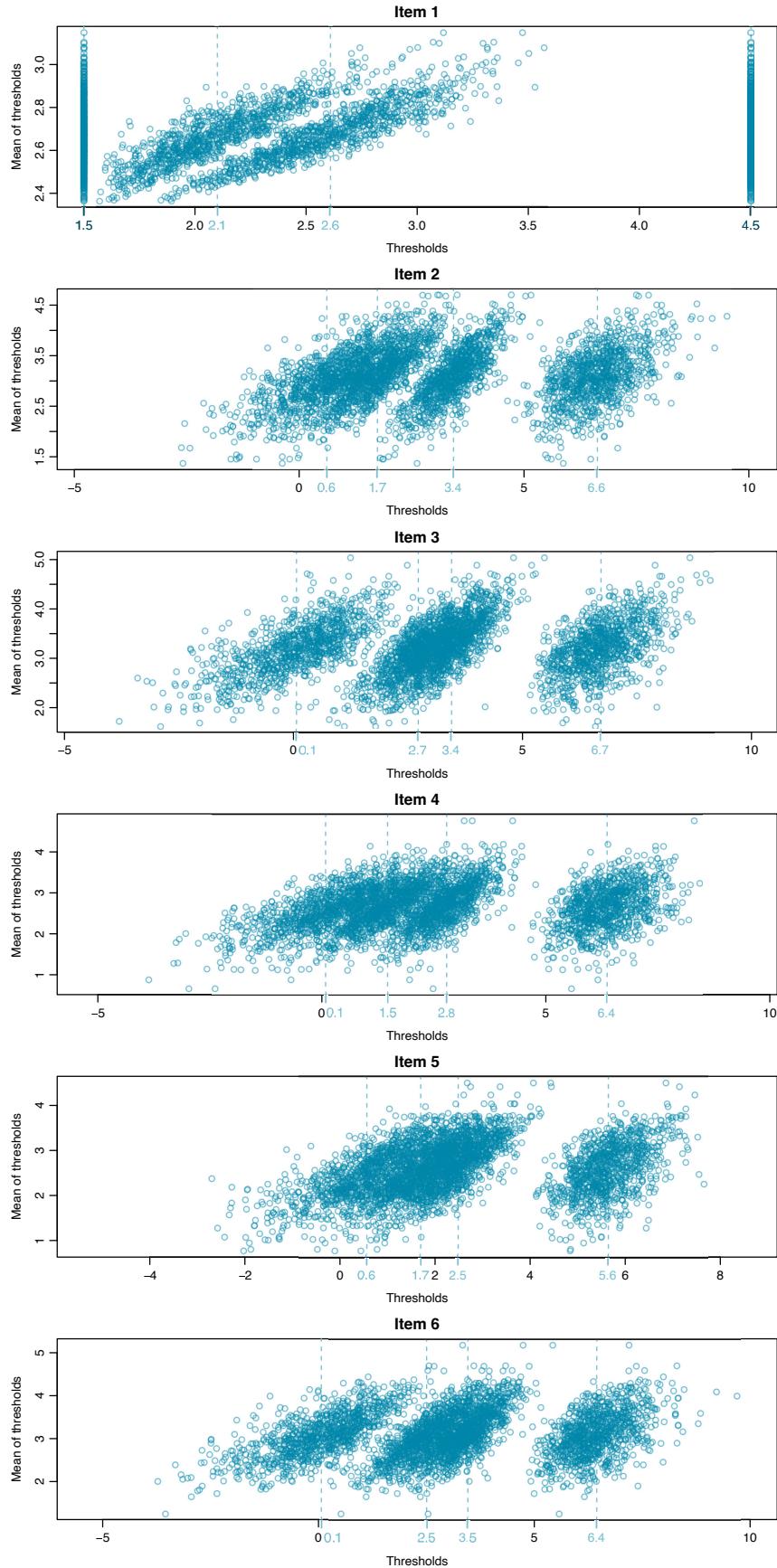


Fig. 6 Posterior distributions of each item thresholds of the Likert scale for the acceptance of the virtual agents. Dashed lines indicate the means of the thresholds estimations.

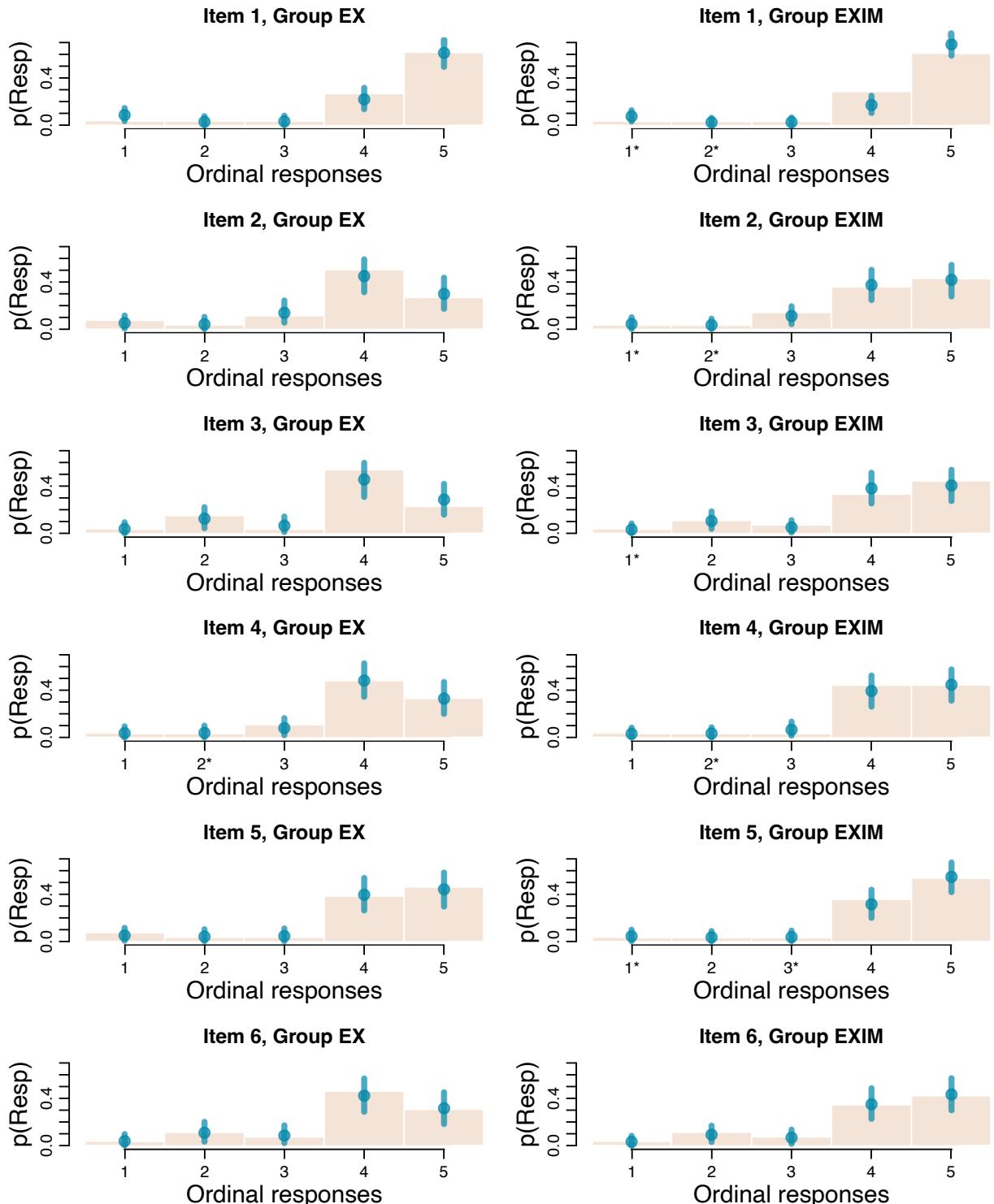


Fig. 7 Acceptance data histograms superimposed with estimated probabilities to check model adequacy. Each blue dot indicates the estimated median and the vertical line represents the 95% HDI. Levels that had extra answers added are marked with an asterisk (*).

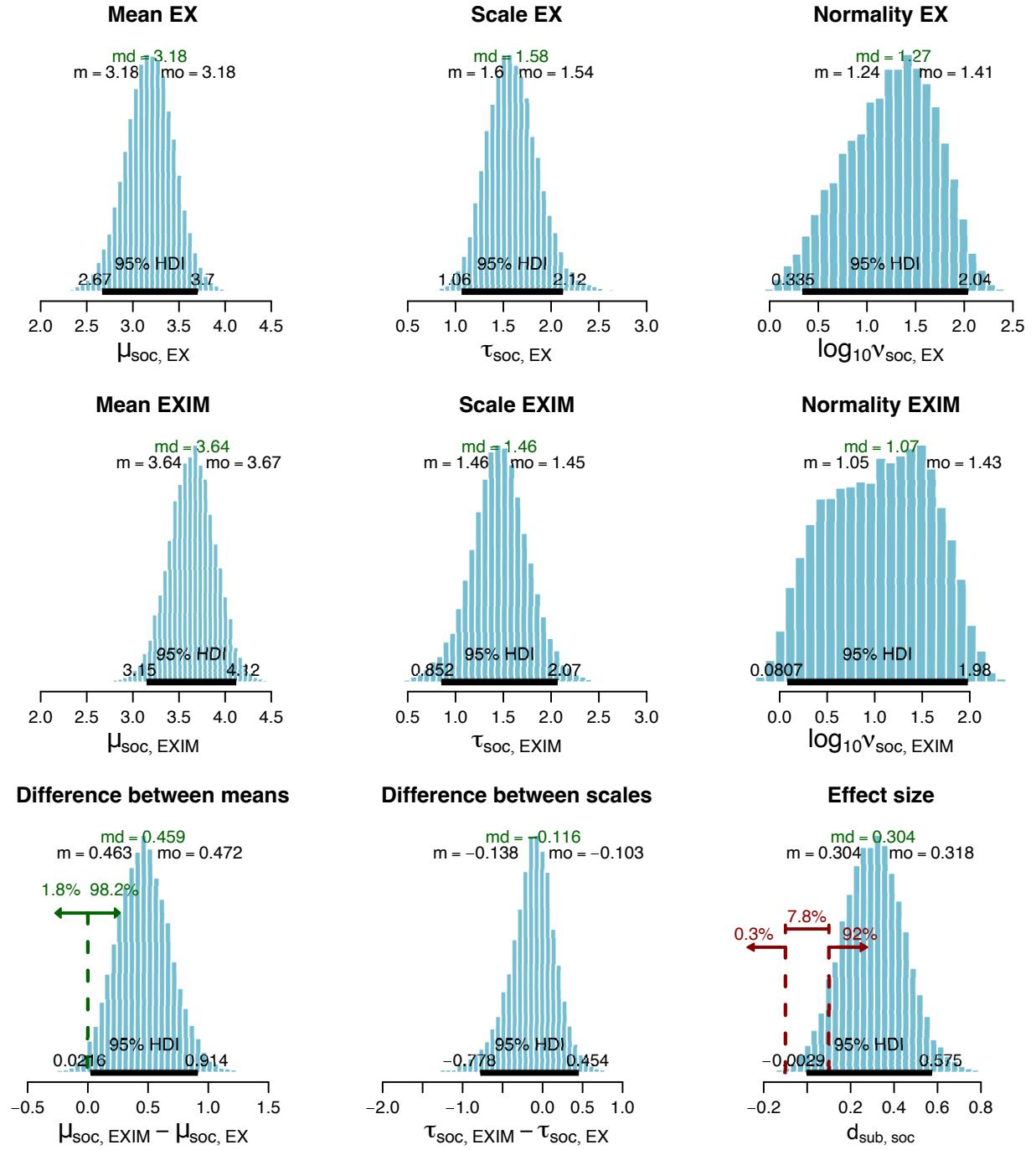


Fig. 8 Results of the Bayesian inference of the sociability of the virtual agents in EX and EXIM configurations. The first two rows show the posterior distributions of the mean μ , scale τ , and normality ν (in log scale) of the latent t distribution of each group. On the left and center of the last row are the distributions of difference between the means and scales of the two groups, and on the right, the distribution of the effect size d_{sub} . Mean (m), median (md), mode (mo), and the limits of the 95% HDI are annotated in the distributions. Dashed vertical lines indicate the null value ($\mu_{\text{EXIM}} - \mu_{\text{EX}} = 0$) in the distribution of the difference between means and the ROPE in the effect size distribution together with the percentages of the distribution below, between and above the values associated with the ROPE and the null value.

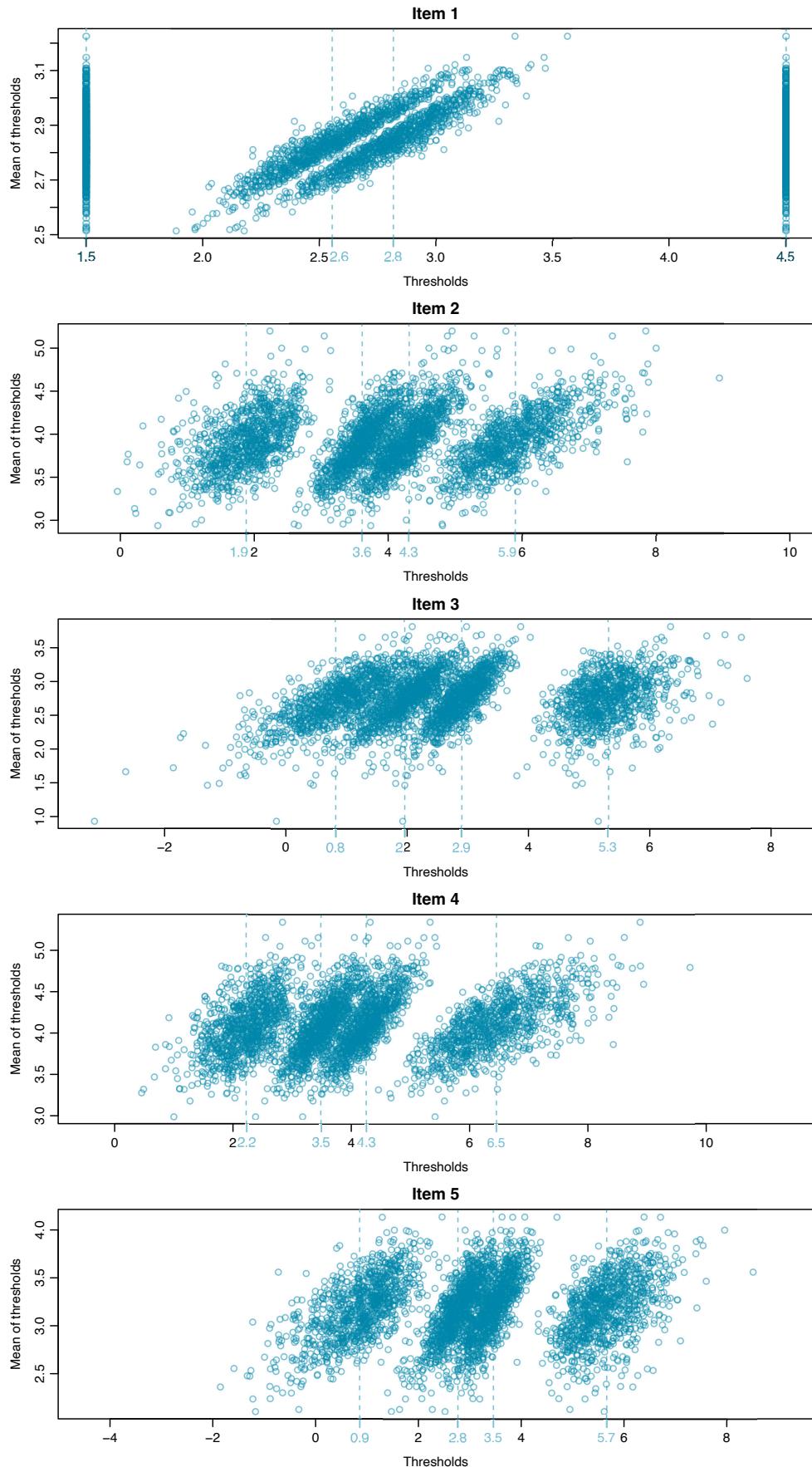


Fig. 9 Posterior distributions of each item thresholds of the Likert scale for the sociability of the virtual agents. Dashed lines indicate the means of the thresholds estimations.

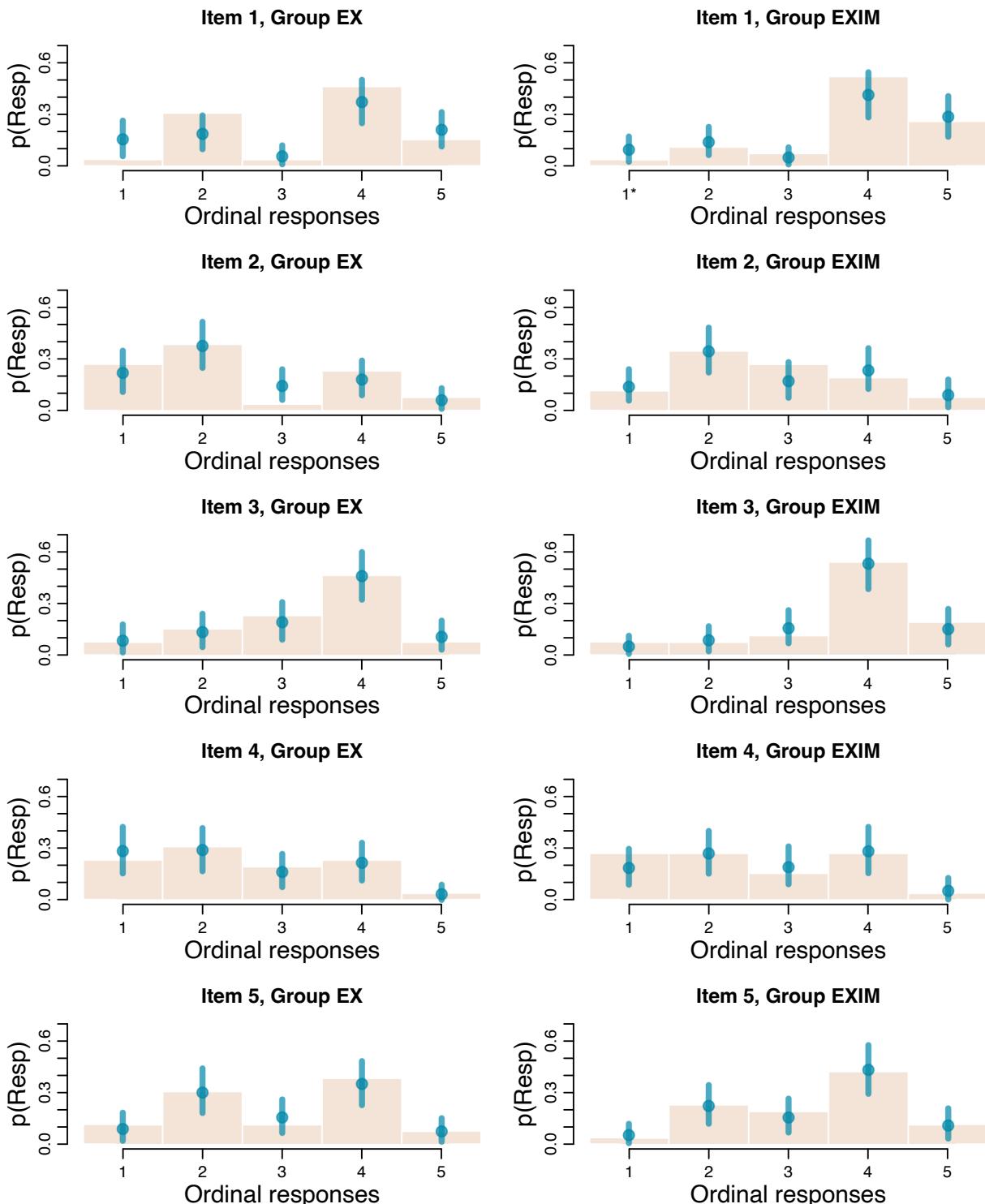


Fig. 10 Sociability data histograms superimposed to estimated probabilities to check model adequacy. Each blue dot indicates the estimated median and the vertical line the 95% HDI. Levels that had extra answers added are marked with an asterisk (*).

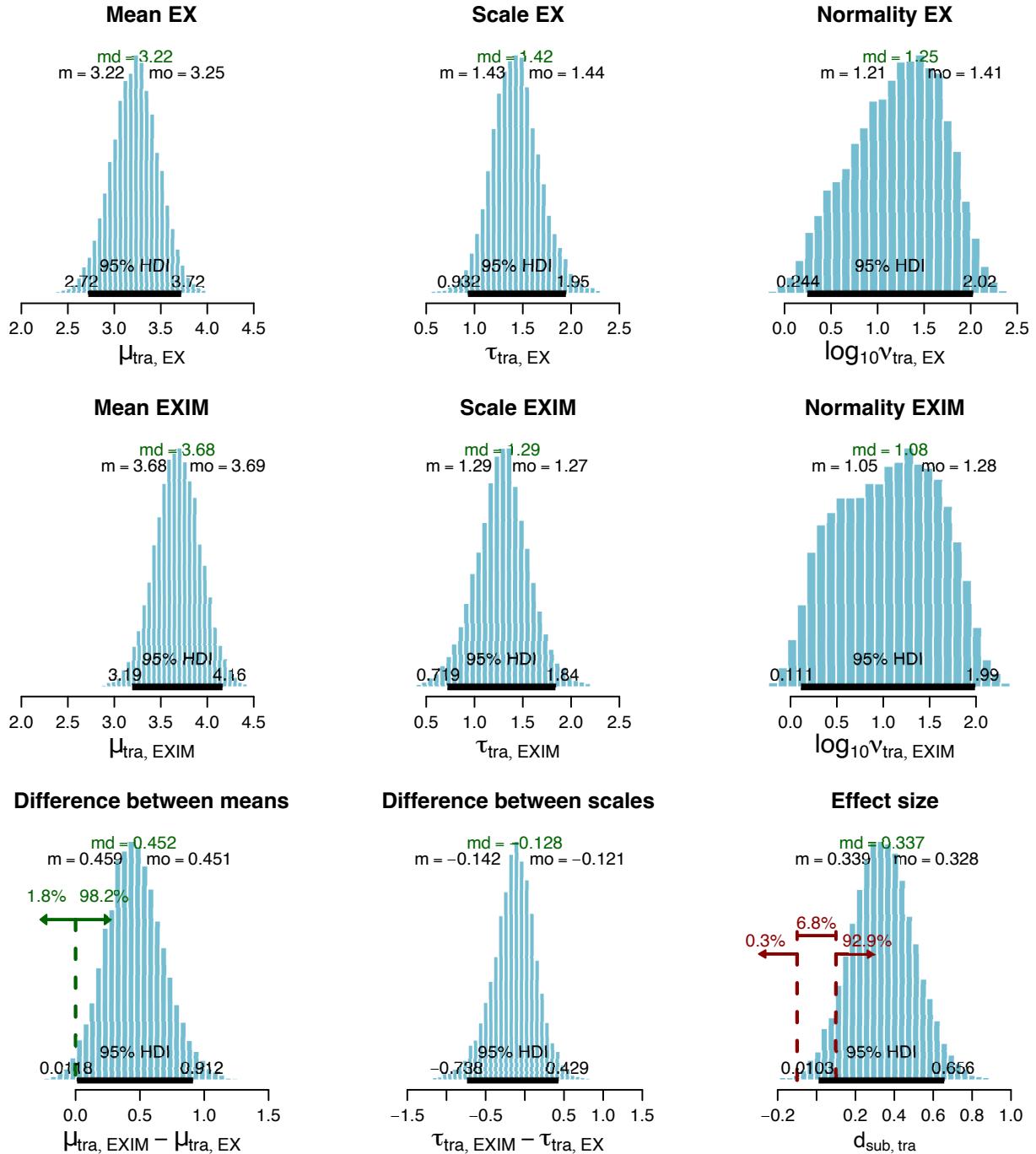


Fig. 11 Results of the Bayesian inference of the transparency of the virtual agents in EX and EXIM configurations. The first two rows show the posterior distributions of the mean μ , scale τ , and normality ν (in log scale) of the latent t distribution of each group. On the left and center of the last row are the distributions of difference between the means and scales of the two groups, and on the right, the distribution of the effect size d_{sub} . Mean (m), median (md), mode (mo), and the limits of the 95% HDI are annotated in the distributions. Dashed vertical lines indicate the null value ($\mu_{\text{EXIM}} - \mu_{\text{EX}} = 0$) in the distribution of the difference between means and the ROPE in the effect size distribution together with the percentages of the distribution below, between and above the values associated with the ROPE and the null value.

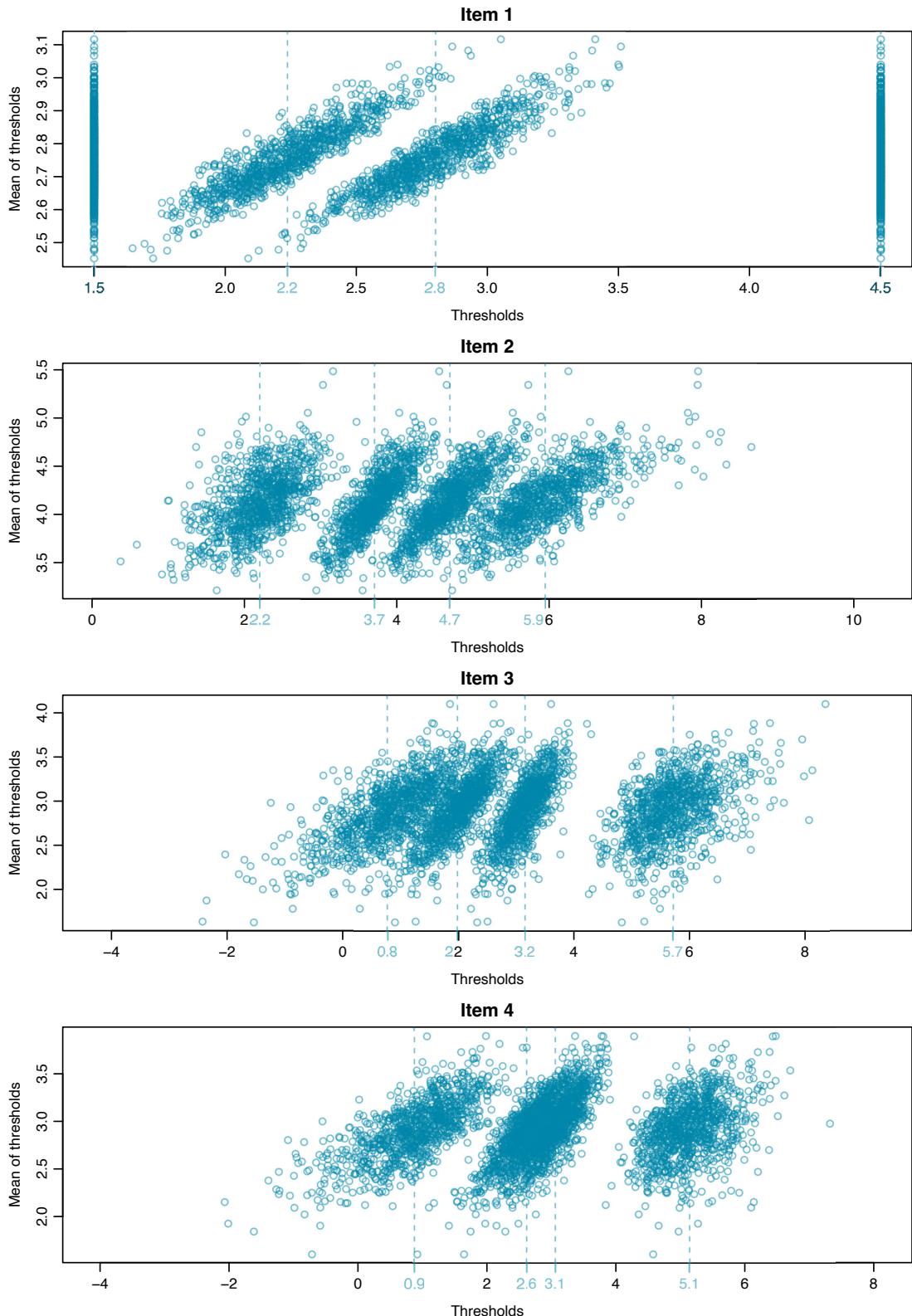


Fig. 12 Posterior distributions of each item thresholds of the Likert scale for the transparency of the virtual agents. Dashed lines indicate the means of the thresholds estimations.

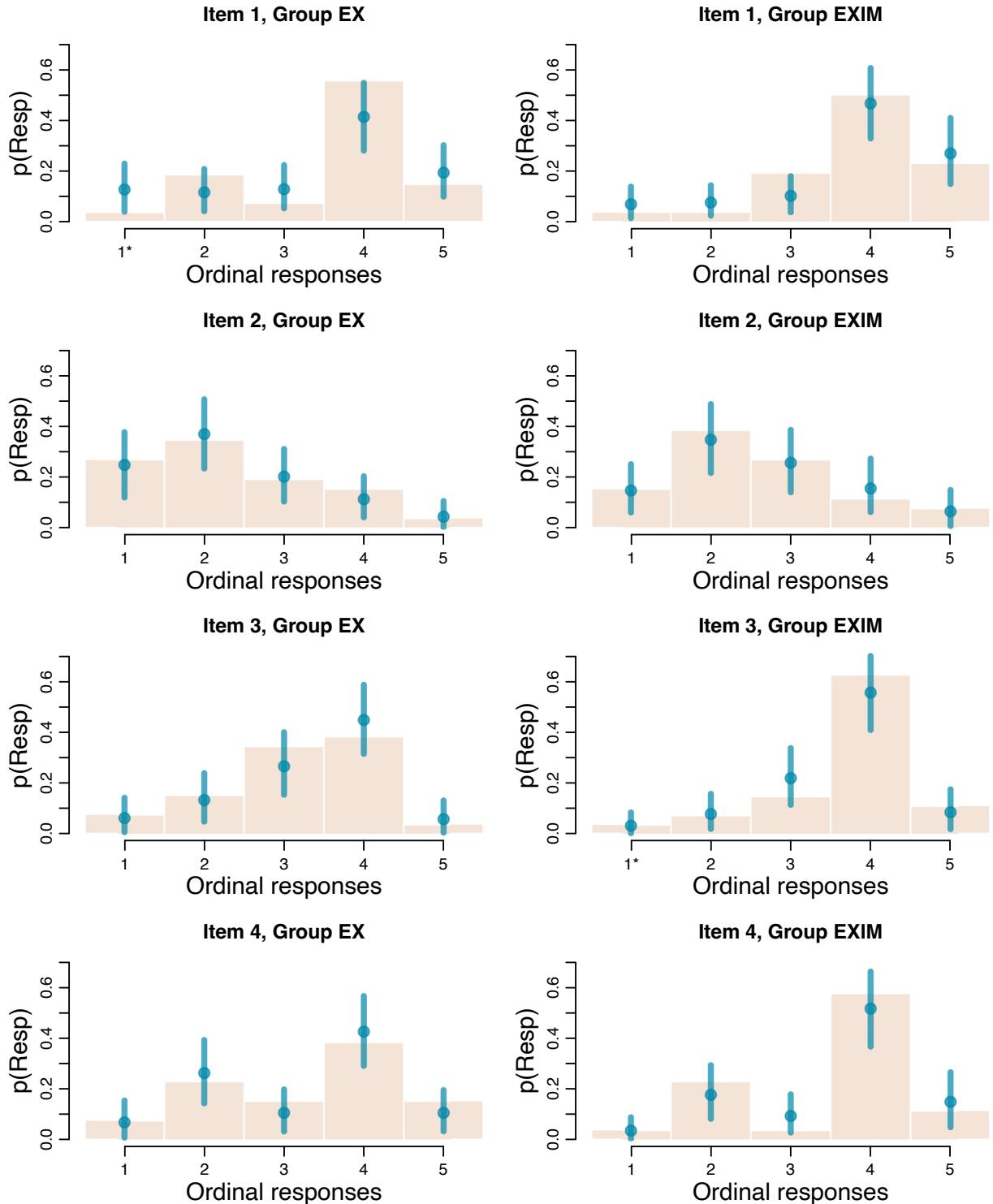


Fig. 13 Transparency data histograms superimposed to estimated probabilities to check model adequacy. Each blue dot indicates the estimated median and the vertical line the 95% HDI. Levels that had extra answers added are marked with an asterisk (*).

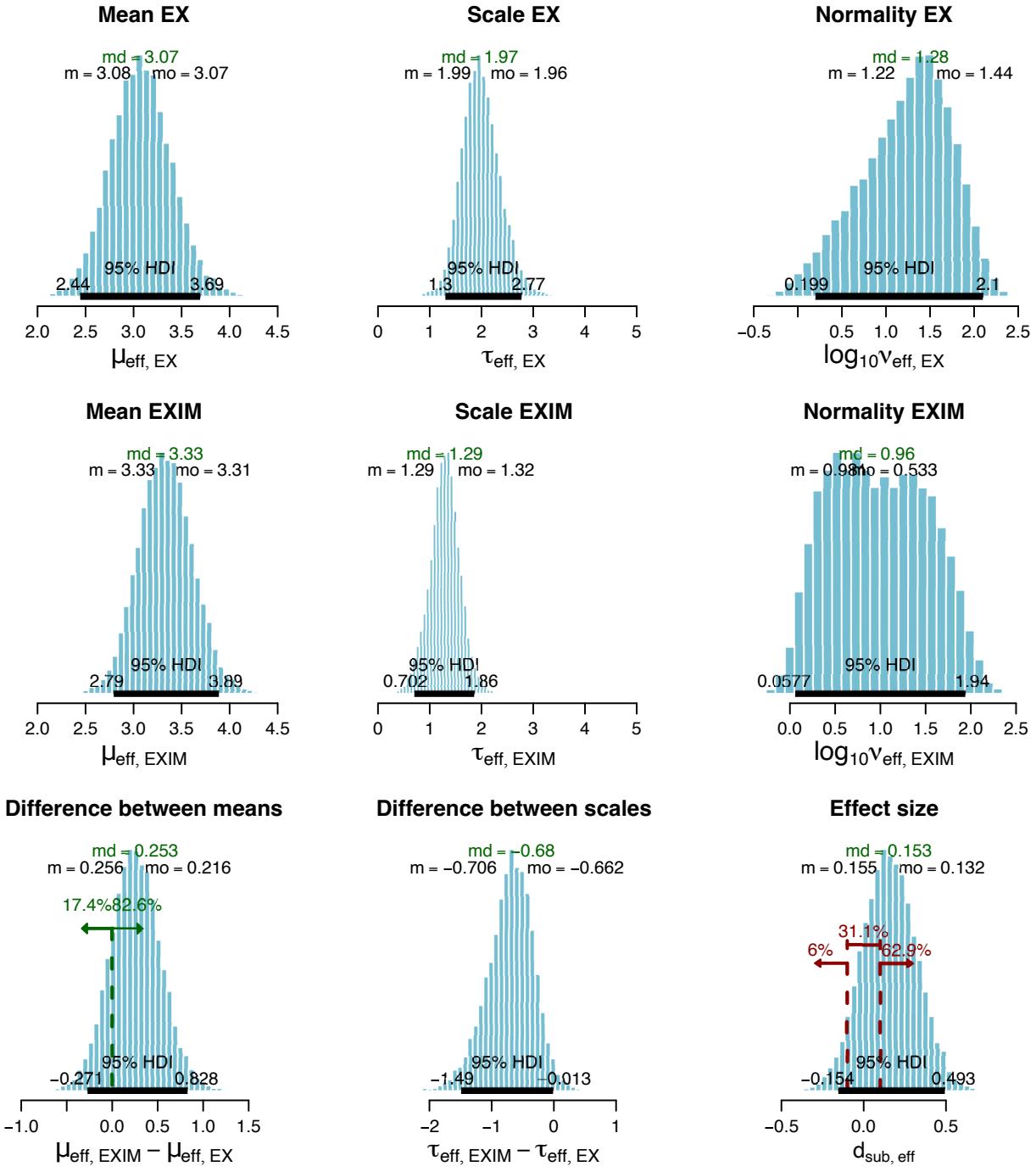


Fig. 14 Results of the Bayesian inference of the perceived efficiency of the interactions in EX and EXIM configurations. The first two rows show the posterior distributions of the mean μ , scale τ , and normality ν (in log scale) of the latent t distribution of each group. On the left and center of the last row are the distributions of difference between the means and scales of the two groups, and on the right, the distribution of the effect size d_{sub} . Mean (m), median (md), mode (mo), and the limits of the 95% HDI are annotated in the distributions. Dashed vertical lines indicate the null value ($\mu_{\text{EXIM}} - \mu_{\text{EX}} = 0$) in the distribution of the difference between means and the ROPE in the effect size distribution together with the percentages of the distribution below, between and above the values associated with the ROPE and the null value.

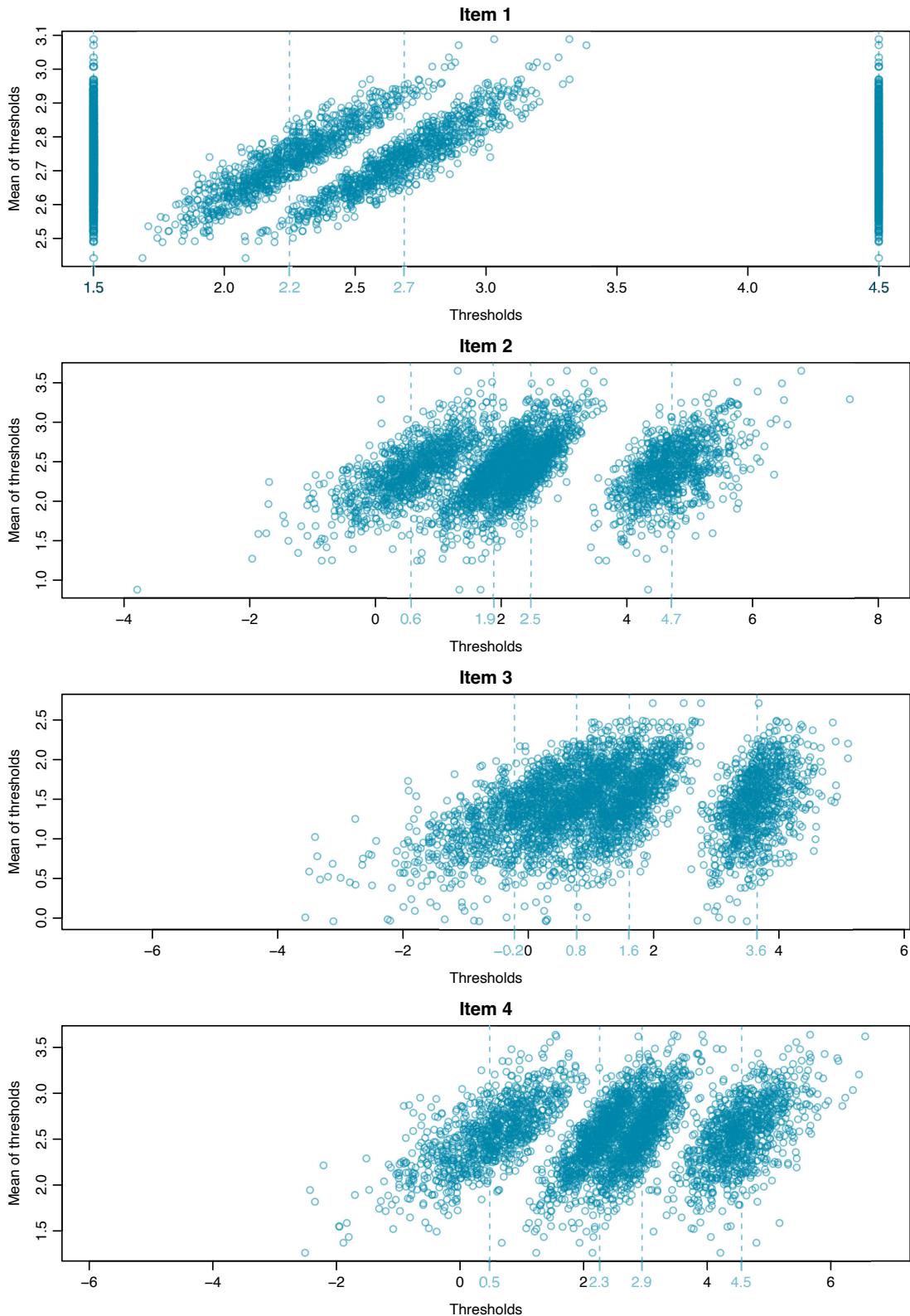


Fig. 15 Posterior distributions of each item thresholds of the Likert scale for the perceived efficiency of the interactions. Dashed lines indicate the means of the thresholds estimations.

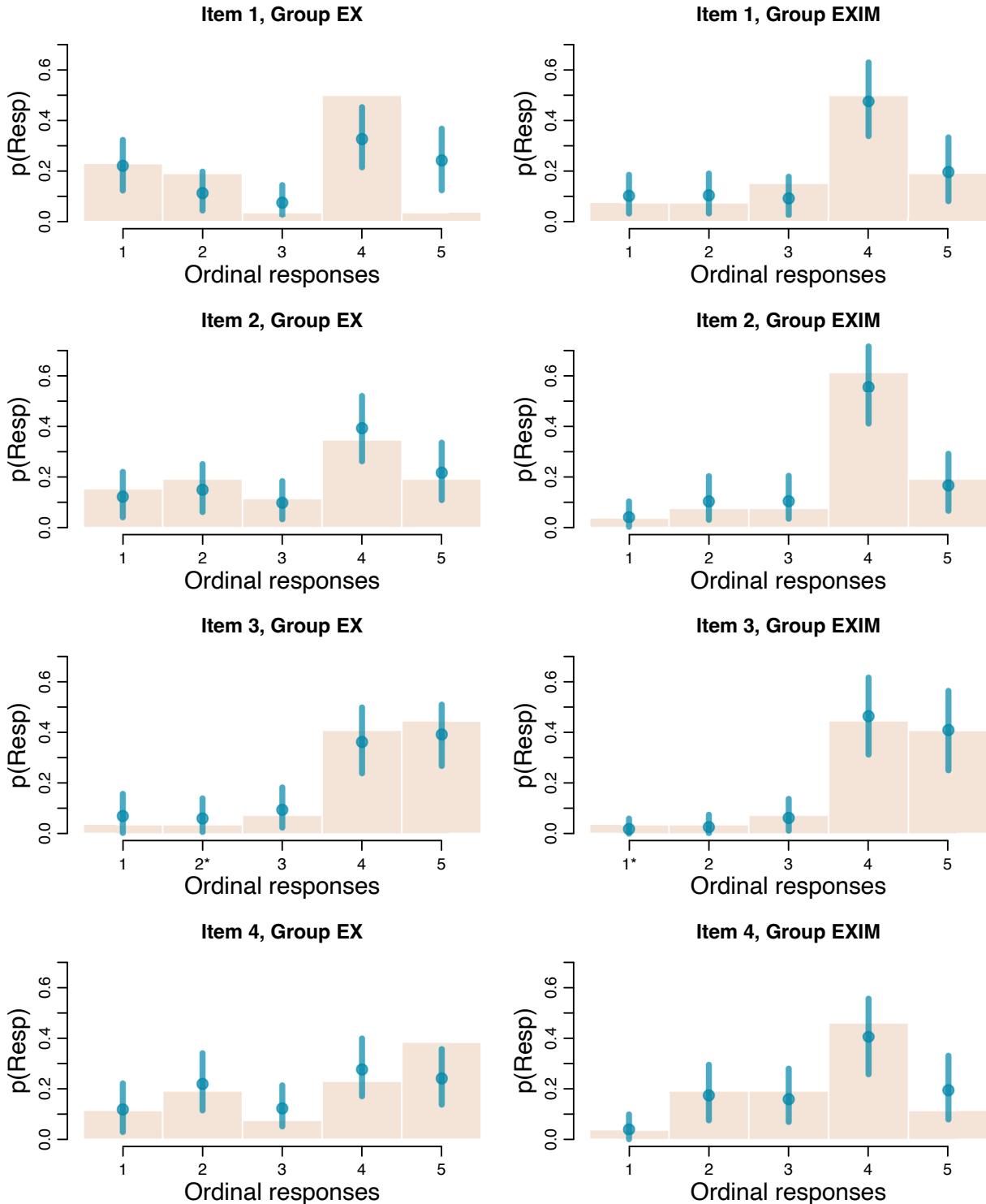


Fig. 16 Perceived efficiency data histograms superimposed to estimated probabilities to check model adequacy. Each blue dot indicates the estimated median and the vertical line the 95% HDI. Levels that had extra answers added are marked with an asterisk (*).

results for the comparison, considering an one-tailed alternative hypothesis saying that the mean (or median, for the Wilcoxon signed-rank test) is greater than zero.

For the *t*-test, the function `t.test`⁵ from package `stats` (version 4.0.4) was used, and the Wilcoxon signed-rank test was conducted using `wilcox.exact`⁶ function from package `exactRankTests` (version 0.8.32). The procedure to calculate the Wilcoxon signed-rank test statistics involves ordering the absolute values of the observations and comparing them to the null value, indicating if they are below or above it [3]. When the observations are equal to the null value, the approach applied by the function used to conduct the test is to discard them. The number of null values in the sample, which were therefore discarded when computing the test statistics, is indicated along with the results.

Table 1 shows the results for the subjective measures.

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⁵<https://stat.ethz.ch/R-manual/R-devel/library/stats/html/t.test.html>

⁶<https://www.rdocumentation.org/packages/exactRankTests/versions/0.8-32/topics/wilcox.exact>

Table 1 Results of null hypothesis significance tests for the difference in time and number of errors (with and without outliers) between the two communication configurations.

	Normality	Test result
Time	<i>Shapiro-Wilk:</i> $p\text{-value} = 0.9926 > 0.05$	<i>t-test</i> Test statistics: -0.13543 $p\text{-value}: 0.5533$
Number of errors	<i>Shapiro-Wilk:</i> $p\text{-value} = 1.482 \times 10^{-5} < 0.05$	<i>Wilcoxon signed-rank test</i> Test statistics: 116 $p\text{-value}: 0.6348$ Number of null values: 4
Number of errors without outliers	<i>Shapiro-Wilk:</i> $p\text{-value} = 0.4394 > 0.05$	<i>t-test</i> Test statistics: -0.5547 $p\text{-value}: 0.7078$

Table 2 Results of null hypothesis significance tests for the difference between the communication configurations in the mean points in the scales assessing each subjective measure.

	Wilcoxon signed-rank test
Acceptance of the virtual agent	Test statistics: 192 $p\text{-value}: 0.05121$ Number of null values: 3
Sociability of the virtual agent	Test statistics: 201.5 $p\text{-value}: 0.02642$ Number of null values: 3
Transparency of the virtual agent	Test statistics: 188.5 $p\text{-value}: 0.004566$ Number of null values: 5
Perceived efficiency of the interaction	Test statistics: 138.5 $p\text{-value}: 0.1091$ Number of null values: 6