

1 Assessing Human Reactions in a Virtual Crowd Based on Crowd
2 Disposition, Perceived Agency, and User Traits

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10 Immersive virtual environments populated by real and virtual humans provide valuable insights into human decision-making
11 processes under controlled conditions. Existing literature indicates elevated comfort, higher presence, and a more positive user
12 experience when virtual humans exhibit rich behaviors. Based on this knowledge, we conducted a web-based, interactive study,
13 in which participants were embodied within a virtual crowd with complex behaviors driven by an underlying psychological
14 model. While participants interacted with a group of autonomous humanoid agents in a shopping scenario similar to Black
15 Friday, the platform recorded their non-verbal behaviors. In this independent-subjects study, we investigated behavioral and
16 emotional variances across participants with diverse backgrounds focusing on two conditions: perceived agency and the
17 crowd's emotional disposition. For perceived agency, one group of participants was told that the other crowd members were
18 avatars controlled by humans, while another group was told that they were artificial agents. For emotional disposition, the
19 crowd behaved either in a docile or hostile manner. The results suggest that the crowd's disposition and specific participant
20 traits significantly affected certain emotions and behaviors. For instance, participants collected fewer items and reported a
21 higher increase of negative emotions when placed in a hostile crowd. However, perceived agency did not yield any statistically
22 significant effects.

22 CCS Concepts: • Computing methodologies → Animation.

24 Additional Key Words and Phrases: crowd simulation

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29 1 INTRODUCTION

31 The growing integration of digital technologies into our daily lives necessitates an in-depth understanding
32 of our interactions within virtual environments. Exploring our relationship with virtual humans and crowds
33 that populate these environments presents opportunities and challenges across various domains such as social
34 psychology, human-computer interaction, emergency management, and gaming. One such opportunity involves

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48 the ability to conduct controlled studies that would be unattainable or non-replicable in real-life settings. For
 49 instance, when examining events that involve crowds, such as those characterized by emergent behaviors like
 50 panic, stampedes, or riots, the consequences of irrational behavior are discernible; yet the underlying mechanisms
 51 can only be approximated through retrospective analyses or field observations. Given the realistic responses of
 52 people in immersive virtual worlds [Slater et al. 2020; Slater and Sanchez-Vives 2016] and the high ecological
 53 validity of virtual social interactions [Bombari et al. 2015], we can gain critical insights into human decision-
 54 making processes through controlled virtual crowd experiments in a low-risk and efficient manner.

55 Existing approaches that integrate humans into virtual crowds predominantly focus on crowd or human
 56 movement characteristics [Kim et al. 2016; Moussaïd et al. 2016; Nelson et al. 2020], or consider a limited set
 57 of other parameters such as crowd density [Dickinson et al. 2019], eye gazes of agents [Narang et al. 2016], or
 58 character appearance [Nelson et al. 2020]. However, a holistic approach needs to consider nuanced behaviors
 59 rooted in the complexities of human psychology. Understanding the reactions of a user when embodied in a
 60 crowd simulation system that portrays the psychological nuances of its agents remains a promising area for
 61 exploration. Such an understanding can elucidate human psychology and decision-making patterns in virtual or
 62 real crowds, depending on the level of immersion.

63 In this paper, we explore the impact of a virtual crowd's emotional disposition and perceived agency of
 64 crowd members on human emotions and non-verbal behaviors. We assess emotional disposition on two levels:
 65 hostile versus docile crowds. Perceived agency also involves two levels that indicate whether users believe crowd
 66 members to be human-controlled avatars or autonomous agents. The literature does not have consensus on the
 67 effects of perceived agency [Oh et al. 2018]. While some works suggest that avatars and agents elicit similar
 68 responses in users [Von der Pütten et al. 2010], others report stronger emotional responses toward avatars [Fox
 69 et al. 2015; Kothgassner et al. 2017]. However, existing studies only involve interactions with individual virtual
 70 humans, and do not extend to crowds.

71 We introduce an independent-subjects study where users were embodied in a web-based 3D platform involving
 72 emotionally expressive virtual crowds exhibiting complex behaviors. The web-based nature of the study allowed
 73 us to efficiently recruit a diverse set of participants. We designed a scenario mirroring a shopping event resembling
 74 Black Friday. The participants were told to collect as many items as they could from a virtual store. We introduced
 75 a reward strategy directly mapped from real life, where participants earned additional compensation based on
 76 the number of items they collected. While each person engaged with the environment as a crowd member, the
 77 platform collected data regarding their simulation behaviors and affective states.

78 In addition to crowd disposition and perceived agency, we explored the impact of individual differences across
 79 participants on their emotional and behavioral responses. Specifically, we considered their age, gender, personality
 80 traits, and familiarity with 3D virtual environments. This work poses the following research questions:

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- 82 **RQ1.** How does the virtual crowd's emotional disposition towards aggression affect user emotions and behavior?
- 83 **RQ2.** How does perceived agency affect user emotions and behavior? Specifically, do user behaviors and
 84 emotions vary when they perceive the other crowd members as avatars controlled by real individuals as
 85 opposed to artificial agents?
- 86 **RQ3.** How do users' demographics affect their emotions and behavior when interacting with virtual crowds?
- 87 **RQ4.** Are there any correlations between users' personality traits and their emotions and behaviors in the
 88 simulation?
- 89

90 Our work, expanding upon traditional approaches to crowd simulation research, holds the potential to advance
 91 the understanding of human behavior in social environments while contributing to the development of more
 92 effective and adaptable crowd simulation strategies.

93

95 2 RELATED WORK

96 2.1 Interactions with Crowds in Virtual Environments

98 The promise of immersive virtual environment technologies to support social experiments has long been es-
 99 tablished [Blascovich et al. 2002; Loomis et al. 1999]. This can be attributed to the high ecological validity of
 100 virtual social interactions [Bombari et al. 2015]. Multiple studies have shown that people treat and communicate
 101 with virtual humans naturally as if they were real humans [de Borst and de Gelder 2015; Nass and Reeves 2003].
 102 Virtual humans increase the sense of immersion in virtual worlds [Llobera et al. 2010; Pelechano et al. 2008],
 103 provide standardization for social experiments, and offer low-cost solutions for training applications [Bombari
 104 et al. 2015].

105 Besides individual exchanges with virtual humans, understanding human interactions in multi-agent scenarios
 106 carries a significant potential to advance both our knowledge of human psychology and the state of the art in
 107 crowd simulation research [Pelechano and Allbeck 2016]. Since Pelechano et al.’s seminal work that evaluated
 108 user presence in a virtual crowd [Pelechano et al. 2008], many studies have explored human behaviors when
 109 embodied in virtual crowds, especially in VR environments. These studies have predominantly examined the
 110 steering or walking behaviors of human participants in crowds. Nelson et al. [Nelson et al. 2019], evaluated
 111 walking within a virtual crowd where the participant was actually walking in a motion capture studio. They found
 112 that an extremely dense virtual crowd significantly altered the movement behavior of participants in terms of
 113 their speed and walking time. This finding was also supported by Koiliias et al. [Koiliias et al. 2020a], who reported
 114 a high impact of density, low speed, and diagonal direction on the speed, deviation, and trajectory lengths of
 115 participants. In a separate work, Nelson et al. found participant movement speed, deviation, and interpersonal
 116 distance to be significantly affected by the appearance of the virtual characters [Nelson et al. 2020]. Bruneau et
 117 al. [Bruneau et al. 2015] studied the interactions between individual walkers and groups by applying the Principle
 118 of Minimum Energy (PME) and found that humans behaved as predicted by the PME. For instance, participants
 119 preferred to go through large and sparse groups and go around small and dense groups. The study took place in a
 120 CAVE environment where the participants navigated with a joystick. The work demonstrated the promise of VR
 121 experiments to guide the improvement of crowd simulations by directly designing an algorithm to imitate human
 122 behavior. Olivier et al. [Olivier et al. 2017] also performed CAVE experiments to show that collision avoidance
 123 trajectories and levels of perception in VR were sufficiently realistic for human locomotion studies.

124 Jiang et al. [Jiang et al. 2018] investigated the coordination of joint actions on road-crossing in VR, which
 125 provides a safe environment for such tests. They observed that participants’ impulses to move in coordination
 126 when crossing a virtual road were consistent with real-world studies. Koiliias et al. [Koiliias et al. 2020b] evaluated
 127 the movement coordination of participants with virtual crowd members and found significant differences between
 128 the movements of participants and crowd agents. Particularly, the participants moved slower, followed longer
 129 paths, performed less smooth motions, and had higher interpersonal distance. Although they found moderate
 130 associations, the crowd’s influence was not enough to make the participant become a part of it.

131 Studies show proxemics to be an influential factor in user experience. In an early work by Llobera et al. [Llobera
 132 et al. 2010], virtual characters approached a stationary participant in groups of one to four agents. The authors
 133 measured electrodermal activity to evaluate participant arousal and found that skin conductance levels increased
 134 more the closer the virtual characters approached the participants. Christou et al. [Christou et al. 2015] also
 135 evaluated proxemics and found similar results by measuring electrodermal activity, again with a stationary
 136 participant and groups of agents. Additionally, they showed a declined cognitive performance under close
 137 proximity. Different from earlier works, Dickinson et al. [Dickinson et al. 2019] designed an experiment where the
 138 participant was allowed to navigate naturally in the environment with dynamically tracked handheld controllers
 139 and a head-mounted display. They found high density to increase the difficulty of participants’ carrying out the
 140 given task and negatively impact their affective states as measured by PANAS self-reports.

142 Instead of employing crowds of virtual humans, Moussaïd et al. [Moussaïd et al. 2016] conducted a study
 143 with multiple human participants, demonstrating the efficacy of virtual platforms for social experiments. They
 144 replicated a high-stress emergency situation from a real-life experiment on a screen-based study involving the
 145 simultaneous participation of multiple human subjects. An important observation they report is that herding
 146 resulted from the high density and not from a change in the individual tendency to imitate neighbors.

147 Gaze and gestures positively affect user experience by increasing perceived realism and feeling of comfort.
 148 Narang et al. [Narang et al. 2016] introduced PedVR, a VR framework that couples crowd simulations with realistic
 149 3D body movements and gestures of a large number of virtual characters. Their within-subjects experiments
 150 indicated that the gaze behavior of agents through eye contact with the user improved perceived believability.
 151 Kyrikou et al. [Kyriakou et al. 2017] suggested that in addition to collision avoidance with the participant,
 152 interactions such as verbal salutations, gaze, waving, and other gestures should be employed to enhance the
 153 sense of presence.

154 Volonte et al. [Volonte et al. 2020] developed an agent-based crowd model with rich behaviors including eye
 155 gaze, facial expressions, body motion, verbal, and non-verbal behaviors. They evaluated the impact of a crowd of
 156 emotional virtual humans on users' affective and non-verbal behaviors in a VR setting and found that participants
 157 interacted with the positive emotional crowds more than the negative ones. Our work shares similarities with
 158 this study in the exploration of complex virtual human behaviors and the emphasis on affective and non-verbal
 159 behaviors. Differently, our crowd simulation system is controlled by a multi-layered parametric psychological
 160 model that incorporates personality and emotions to control low and high-level agent behaviors. Additionally,
 161 the experimental settings, scenarios, and research questions diverge significantly, which demonstrates the
 162 applicability and breadth of virtual social interactions for understanding human reactions.

163 Although undoubtedly more immersive, VR with head-mounted displays or in CAVE is more restrictive
 164 than desktop environments regarding participant recruitment. The aforementioned studies typically involved a
 165 small number of participants, ranging from 13 [Bruneau et al. 2015] to 18 [Nelson et al. 2019, 2020]. Given our
 166 primary emphasis on high-level behavioral parameters and emotional outcomes rather than steering behaviors,
 167 precise locomotion control was not a pressing requirement for our work. Thus, we preferred a browser-based
 168 environment, which facilitated access to a broader participant base.

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173 2.2 Perception of Aggression in Crowds and Virtual Humans

174 Several studies have examined the perception of emotions in crowds. For example, Hansen and Hansen [Hansen
 175 and Hansen 1988] showed an anger superiority effect, where angry faces were more easily detected in crowds of
 176 happy faces compared to happy faces in crowds of angry ones. Bucher and Voss [Bucher and Voss 2019] asked
 177 participants to rate the overall mood of the crowd and found that happy faces were more likely to be attended
 178 to and their predominance was assessed more accurately than the predominance of angry faces. Mihalache
 179 evaluated anger bias towards crowds with varying ratios of angry to happy faces and found that anger bias
 180 emerges particularly in the context of perceptual uncertainty, i.e. with low intensities of expressions [Mihalache
 181 et al. 2021]. It is important to note that in these studies, crowds were composed of static images of real or
 182 computer-generated faces, not real or simulated crowds. Also, the participants were merely observers.

183 Studies involving individual virtual humans also confirm anger bias. For instance, participants took longer
 184 times to recognize patterns when presented with angry faces [Rapuano et al. 2023], tended to increase spatial
 185 distances, and reacted with increased emotional arousal [Ruggiero et al. 2021].

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189 2.3 Perceived Agency

190 Perceived agency, or “agency belief”, is a concept for which there is no clear consensus in the literature regarding
 191 its effects. There are many studies that did not find any differences towards agents vs. avatars in social judg-
 192 ments [Nowak 2004; Von der Pütten et al. 2010]. This can be explained by the “ethopoeia” concept, introduced by
 193 Nass and Moon, which indicates that systems elicit social responses as long as they provide social cues [Nass and
 194 Moon 2000]. Von der Pütten et al. later discussed that the strength of reactions would depend on the amount or
 195 strength of the social cues [Von der Pütten et al. 2010] and demonstrated that higher behavioral realism led to
 196 stronger social effects.

197 Contrary to these works, in a study by Guadagno et al., subjects assessed a virtual human’s behaviors as
 198 more realistic and reported higher levels of social presence when they believed that it was controlled by a
 199 human [Guadagno et al. 2007]. The authors also found interaction effects of agency with the gender of the virtual
 200 human, indicating in-group favoritism and stereotypical effects. Other studies also support the relationship
 201 between social presence and agency in a similar way, reporting stronger effects when others were perceived as
 202 avatars instead of agents [Appel et al. 2012; Fox et al. 2015; Gajadhar et al. 2008; Weibel et al. 2008]. Poinsot et al.
 203 discussed the interaction effects of emotional communication and perceived agency, reporting that emotional
 204 communication led computer-controlled opponents to elicit a stronger sense of co-presence than human-controlled
 205 ones [Poinsot et al. 2022].

206 In the opposite direction, Williams and Clippinger found higher levels of aggression toward computer opponents
 207 than humans [Williams and Clippinger 2002]. Lim and Reeves [Lim and Reeves 2010] later showed interaction
 208 effects of agency with the type of game activity (cooperative vs. competitive). Thus, the apparent contradictions
 209 in research results toward agency may be a result of other factors such as visual and behavioral fidelity, type of
 210 interaction, and in-group effects.

212 3 METHOD

213 3.1 Stimuli Creation

215 We developed an interactive, browser-based platform using Unity¹ and WebGL, building upon an existing crowd
 216 simulation system that models crowd behavior using social psychology theories and features autonomous
 217 humanoid agents with controllable psychological states [Durupinar et al. 2016a]. The system allows authoring
 218 scenarios by initializing agents with social roles, cognition, and personalities, which determine the agents’
 219 emotions, decision-making, and actions. Agents interact with each other and the environment; have emotional
 220 facial expressions and body postures; and exhibit complex behaviors. The system uses the Five-Factor model of
 221 personality [Goldberg 1990a] to indirectly influence all these features and directly control low-level dynamics
 222 parameters such as velocities, forces, and local steering choices. The system also employs an epidemiological
 223 emotional contagion model, simulating a phenomenon that causes emotions to propagate among the crowd,
 224 which potentially yields irrational emergent behavior, turning regular crowds into emotional mobs. Our extended
 225 platform incorporates the human user as a crowd member with a 3D body who can navigate the environment
 226 with a first-person perspective.

227 We launched the platform’s Unity WebGL build on a public-facing server that employs Express², a Node.js
 228 application framework. The collected user data was managed on a MySQL server. Our platform’s web support
 229 facilitates deployment on crowdsourcing websites like MTurk. Users accessed the study’s website, which was
 230 embedded in an HTML inline frame (iFrame) as part of the MTurk Human Intelligence Task (HIT). Worker IDs
 231 and HIT information were automatically transmitted to our server (Figure 1). As a quality assurance measure, we
 232 hid the “submit” button until a study completion token was sent from the server.

233 ¹<https://unity.com/>

234 ²<https://expressjs.com/>



Fig. 1. Platform architecture for the study

The scene involved a big sale event in a store offering discounts, with the goal of purchasing iPads. There were 20 virtual agents and a human user. Participants were told that they would receive bonuses based on the number of iPads they collected, incentivizing them with a direct mapping to the scenario's theme. Both the human user and the computer agents could navigate the store, collecting iPads from the shelves and paying at the counter. Users were given the option to start fights with virtual humans, with the winner collecting the loser's iPads. Users could interact with the environment through keyboard controls using the arrows for navigation, the 'C' key for collecting iPads, 'F' for fighting, and 'P' for paying at the counter (Figure 2). We preferred keyboard controls over mouse or touchpad for accessibility.

Each press of 'F' animated a punching clip on the human's avatar and included a punching sound. To enhance immersion, we also assigned footstep sounds to the participant's walking. We used freely available Mixamo ³ and Adobe Fuse ⁴ virtual human models with facial blendshapes.

3.2 Study Design

We conducted a study with a 2×2 factorial design model with independent subjects on MTurk. Each task consisted of six scenes: a warm-up scenario, demographic data survey, participant personality assessment, pre-study participant emotional state assessment, the main scenario, and post-study participant emotional state assessment (Figure 3). The warm-up scene displayed the environment without any virtual humans, where the participants were instructed to collect iPads. The study started with a warmup so that the workers could decide whether to continue the study or not. We assessed personality by a brief Five-Factor personality measure, the Ten Item Personality Inventory (TIPI) [Gosling et al. 2003]. For the emotional state assessment, we used a short version of PANAS [Watson et al. 1988] for brevity: the International Positive and Negative Affect Schedule Short-Form (I-PANAS-SF) [Karim et al. 2011]. At the end of the study, we presented a questionnaire with the following questions:

- Please rate your overall experience during the iPad collection task on a scale of 1 to 7, where 1 indicates "Not at all like interacting with real persons" and 7 indicates "Exactly like interacting with real persons."

³<https://www.mixamo.com/>

⁴<https://www.adobe.com/tr/products/fuse.html>



Fig. 2. A first-person view of the environment at the beginning of the study.

- Did you feel that the behaviors of others during the task were consistent and predictable? Please explain your answer.
- How would you describe the personalities of others based on your interactions? (e.g., friendly, helpful, competitive, cooperative)
- Did you notice any emotional responses from other characters during the task? If yes, please describe the emotions you observed.
- To what extent did you feel that other characters understood your perspective and communicated effectively? Rate on a scale of 1 to 7, where 1 indicates "Not at all" and 7 indicates "Completely."
- Were there any moments during the task that made you doubt or suspect that other characters might not be other MTurkers but artificial characters? If yes, please describe those moments. (Question reworded as "Were there any moments during the task that made you doubt or suspect that other characters might not be artificial characters but other MTurkers? for the "Agent" condition.)
- Please provide any additional comments or observations about your experience during the task, including any thoughts or feelings you had.

The study conditions included the emotional disposition of the crowd (*docile* vs. *hostile*) and whether the participants were told the others in the crowd were *virtual agents* or *avatars controlled by other MTurk workers*. In the *docile* scenario, crowd agents were assigned neutral personalities (with all the five factors set as 0, e.g., neither introvert nor extrovert), so they only walked around the store, collecting iPads and not showing strong emotions or fighting (Fig. 4(a)). In the *hostile* scenario, the personalities were assigned as unconscientious, extroverted, disagreeable, and neurotic (*openness* = 0, *conscientiousness* = -1, *extroversion* = 1, *agreeableness* = -1, *neuroticism* = 1), so that the agents would be more assertive and prone to starting fights with the human participant and other agents, displaying negative emotions such as angry facial expressions, and exiting the store without paying [Durupinar et al. 2016b] (Fig. 4(b)). During each scenario, we recorded the total time, average speed, the number of fights, punches, iPads grabbed from others, and the total number iPads (collected from

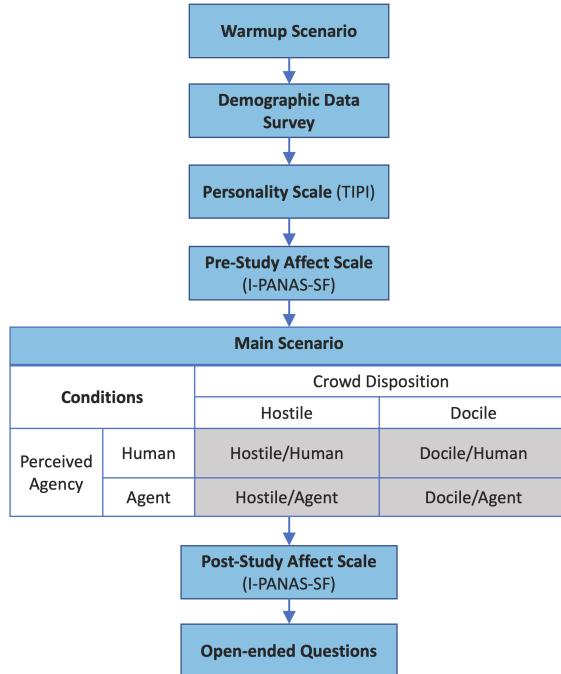


Fig. 3. Independent-subjects study procedure



Fig. 4. (a) A docile crowd; (b) a hostile crowd. Participant fights with an agent.

shelves and grabbed in a fight). The University Institutional Review Board approved the experiment protocol. The participants were paid \$1 per task and an additional \$0.02 bonus per iPad they collected.

3.3 Participants

We set participation requirements as having an acceptance rate of > 95% and experience of more than 100 HITs and Masters qualifications. To ensure quality, we placed attention-checking questions in the questionnaires and discarded the responses of participants who did not pass these tests. For a medium effect size (Cohen's $d = 0.25$)

³⁷⁷ for both main effects and their interaction and power of 0.80 at a significance level of 0.05, we collected 30
³⁷⁸ participant responses per group (120 in total).

³⁷⁹ Of the 120 unique participants (83M/37F/0 other), the average age was $= 37.083 \pm 11.41$. The ethnic distribution
³⁸⁰ was 81 White, 25 Asian, 6 Black, and 7 Hispanic/LatinX, and 1 other. We also asked about familiarity with
³⁸¹ first-person view video games on a scale of 0 (“not familiar at all”) to 5 (“highly familiar”). The mean familiarity
³⁸² level was 1.533 with a standard deviation of 1.66.

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³⁸⁵ 3.4 Analysis

³⁸⁶ *³⁸⁷ 3.4.1 The Effects of Study Conditions on Participant Emotions and Behaviors.* We collected the emotional states of
³⁸⁸ participants before and after the study using a short and international version of PANAS. We collected scores
³⁸⁹ for ten emotions, five positive and five negative, on a 5-point Likert scale. The positive emotion items were
³⁹⁰ *active, determined, attentive, inspired, alert*, and the negative emotion items were *afraid, nervous, upset, hostile,*
³⁹¹ and *ashamed*. To test for differential effects, we subtracted the pre-study scores from post-study scores. Figure 5
³⁹² shows the frequency histograms of the positive and negative affect differences scores, indicating approximately
³⁹³ normal distributions.

³⁹⁴ As behavioral parameters, we collected the number of fights (*fightCnt*) each participant involved, punches
³⁹⁵ administered (*punchCnt*), iPads collected from the shelves (*collectedItemCnt*), and iPads stolen from others
³⁹⁶ (*stolenItemCnt*), as well as the time spent (*timeSpent*), average speed (*avgSpeed*), and the total distance covered
³⁹⁷ during the simulation (*totalDist*). Figure 6 shows the frequency histograms of the behavior parameters for the
³⁹⁸ whole study.

³⁹⁹ To analyze the effects of the perceived agency (whether participants believe others are humans vs. agents) and
⁴⁰⁰ crowd disposition (docile vs. hostile) on emotional state changes, we designated these two factors as independent
⁴⁰¹ variables with two levels each, and the affect score differences as the response variables. With a lack of evidence
⁴⁰² for unequal variances across conditions (with Levene’s test) we employed a two-way independent subjects
⁴⁰³ Analysis of Variance (ANOVA) to test the effects of the study conditions on affective differences.

⁴⁰⁴ The ANOVA test returned a statistically significant main effect of crowd disposition on *afraid* $F(1, 116) =$
⁴⁰⁵ $4.545, p = 0.035$, *upset* $F(1, 116) = 4.474, p = 0.037$, *hostile* $F(1, 116) = 12.865, p = 0.0005$, and *ashamed*
⁴⁰⁶ $F(1, 116) = 9.901, p = 0.002$. We did not find any main effects of agency or interaction effects. To control
⁴⁰⁷ for potential inflation of the Type I error rate, we employed Benjamini-Hochberg (BH) procedure for False
⁴⁰⁸ Discovery Rate (FDR) detection. After FDR correction, only *hostile* and *ashamed* remained statistically significant.
⁴⁰⁹ Figure 7 illustrates the comparative distributions of affect score differences between post and pre-study responses
⁴¹⁰ across the study conditions. We also calculated the composite positive and negative affect scores as the means of
⁴¹¹ the positive and negative items respectively as dictated by PANAS. ANOVA yielded a significant main effect
⁴¹² of post and pre-study negative affect score difference with $F(1, 116) = 13.954, p = 0.0003$. The effect remained
⁴¹³ statistically significant after the BH procedure. Table 1 summarizes the statistically significant results after
⁴¹⁴ ANOVA and FDR correction.

⁴¹⁵ To measure simulation conditions on participant behaviors, we again took participant belief and crowd dispo-
⁴¹⁶sition as independent variables. Because of the ANOVA model’s robustness given independent and sufficiently
⁴¹⁷ large data (typically $n = 30$) we repeated a two-way independent subjects ANOVA to test the effects of the study
⁴¹⁸ conditions on behavior parameters. The ANOVA test yielded statistically significant main effects of crowd type
⁴¹⁹ on *fightCnt* with $F(1, 116) = 9.405, p = 0.003$, *collectedItemCnt* with $F(1, 116) = 15.917, p = 0.0001$, *timeSpent*
⁴²⁰ with $F(1, 116) = 5.299, p = 0.023$, *totalDist* with $F(1, 116) = 4.696, p = 0.032$. We did not find any main effects of
⁴²¹ agency or interaction effects. To control for potential inflation of the Type I error rate, we employed Benjamini-
⁴²² Hochberg procedure. After FDR correction, only *fightCnt* and *collectedItemCnt* remained statistically significant.

⁴²³

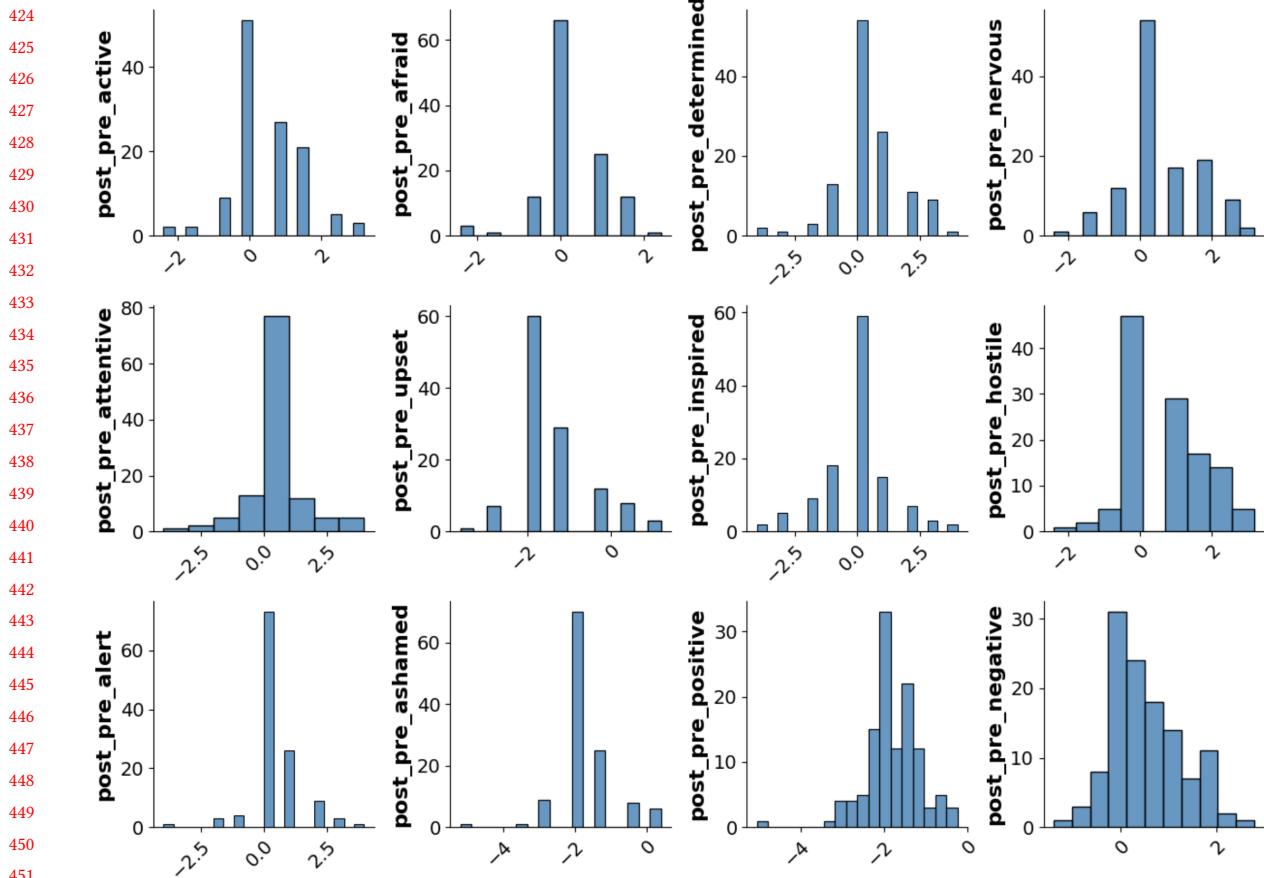


Fig. 5. Frequency histograms for the differences of the post and pre-study affect scores

Table 1. Two-way ANOVA results for crowd disposition and perceived agency on post and pre-study participant affect differences. Statistically significant factors are indicated by **, with $p < 0.01$ and * with $p < 0.5$.

Parameter	Model term	n	F value	p-value	Adjusted p-value
post_pre_afraid	crowd disposition	120	4.545	0.035	0.274
post_pre_upset	crowd disposition	120	4.474	0.037	0.274
post_pre_hostile*	crowd disposition	120	12.865	0.0005	0.015
post_pre_ashamed*	crowd disposition	120	9.901	0.002	0.031
post_pre_negative**	crowd disposition	120	13.954	0.0003	0.002

Table 2 summarizes the significant results after ANOVA and FDR correction. Figure 8 illustrates the comparative distributions of behavior parameters across the study conditions.

3.4.2 The Effects of Demographics on Participant Emotions and Behaviors. From the demographic parameters, we discarded ethnicity due to its disproportionate distribution. Additionally, a least-squares linear regression to find

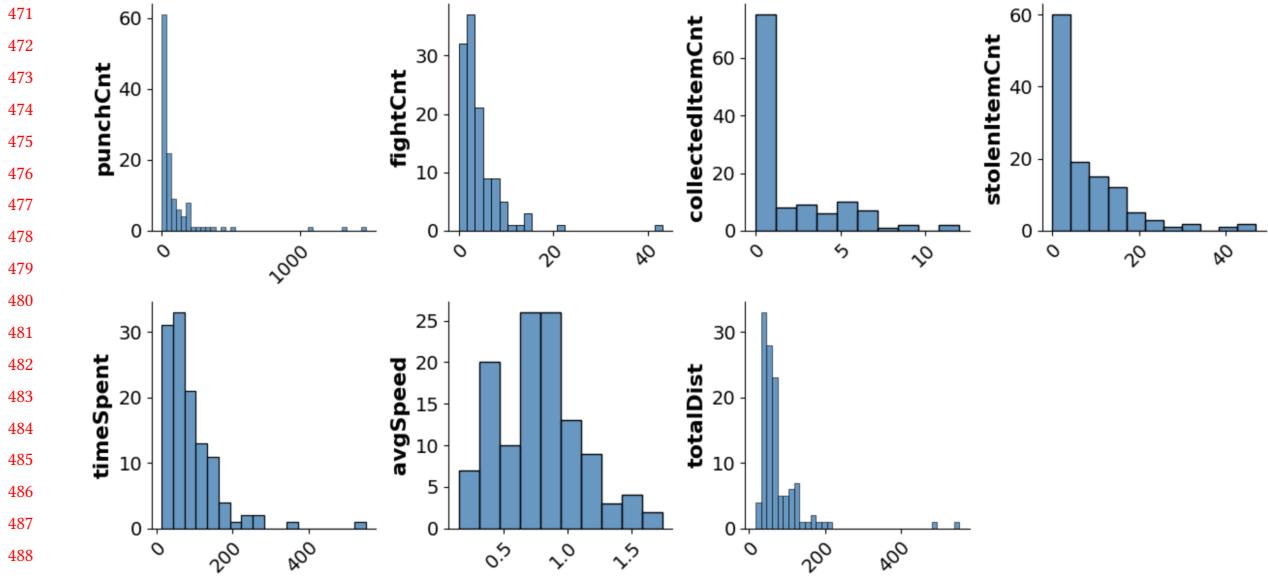


Fig. 6. Frequency histograms of participant behavior parameters

Table 2. Two-way ANOVA results for crowd disposition and perceived agency on participant behavior parameters. Statistically significant factors are indicated by **, with $p < 0.01$ and * with $p < 0.05$.

Parameter	Model Term	n	F value	p-value	Adjusted p-value
fightCnt*	crowd disposition	120	9.405	0.003	0.028
collectedItemCnt**	crowd disposition	120	15.917	0.0001	0.002
timeSpent	crowd disposition	120	5.299	0.023	0.162
totalDist	crowd disposition	120	4.696	0.032	0.169

the effects of age, a continuous variable, on emotional changes did not return any statistically significant effects. As nominal and ordinal variables respectively, we assessed the effect of gender and familiarity on participant emotions using a two-way ANOVA. Familiarity was recorded on a 7-point Likert scale ranging from “not at all” to “highly familiar”. We binned familiarity into two groups low ($n = 32$) and high ($n = 88$), corresponding to the ranges [-3,0] and [1, 3]. Thus, we treated it as a binary variable with sufficient sample sizes per category and explored its interaction effects with gender.

We ran a 2×2 ANOVA to test the effects of gender and familiarity on the differences in participants’ emotions after and before the study. The ANOVA returned a statistically significant main effect of familiarity on the differential affect scores of *afraid* with $F(1, 116) = 9.158, p = 0.003$ and *ashamed* with $F(1, 116) = 6.810, p = 0.01$. There were interaction effects of gender and familiarity on the differential affect scores of *attentive* with $F(1, 116) = 6.194, p = 0.014$. However, we did not find any statistically significant effects after BH correction. We also tested the composite affect scores, where familiarity yielded a significant main effect on differential negative emotions $F = (1, 116) = 5.088, p = 0.026$; familiarity and gender yielded a significant interaction effect on differential positive emotions $F = (1, 116) = 4.495, p = 0.036$. Again, after correcting for FDR, we did not find any significant factors. Table 3 summarizes the significant results after ANOVA and FDR correction.

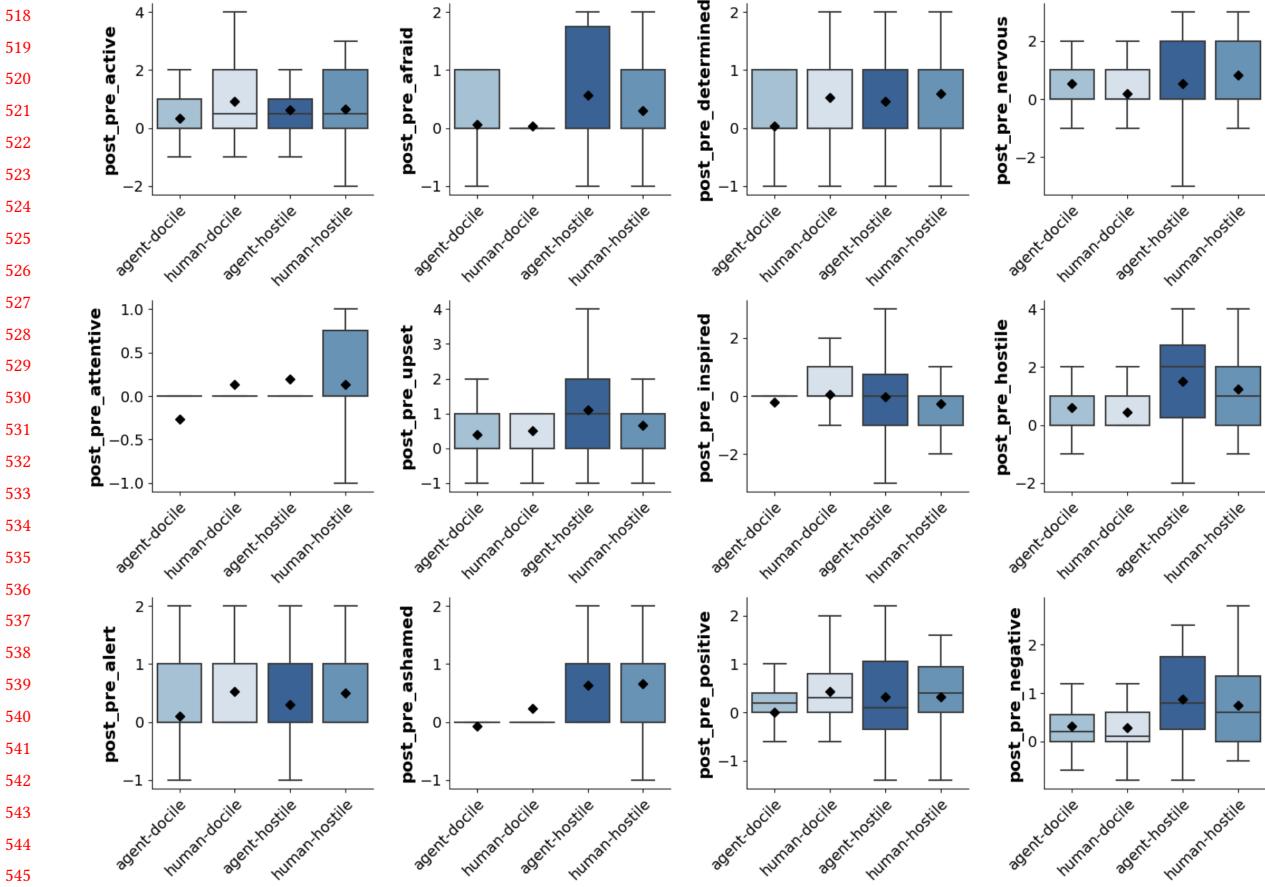


Fig. 7. Box plot diagrams for the differences between the post and pre-study affect scores by study condition

Figure 9 shows the distributions of affect score differences for gender and familiarity, respectively.

Table 3. Two-way ANOVA results for gender and familiarity on participant post and pre-study participant affect differences.

Parameter	Model Term	F value	p-value	Adjusted p-value
post_pre_afraid	familiarity	9.158	0.003	0.092
post_pre_attentive	gender: familiarity	6.194	0.014	0.142
post_pre_ashamed	familiarity	6.810	0.010	0.142
post_pre_positive	gender:familiarity	4.495	0.036	0.108
post_pre_negative	familiarity	5.088	0.026	0.108

We ran a 2x2 independent subjects ANOVA to test the effects of gender and familiarity on participant behavior parameters. ANOVA returned a statistically significant main effect of familiarity on *fightCnt* with $F(1, 116) = 8.677, p = 0.004$, *timeSpent* with $F(1, 116) = 13.423, p = 0.0004$, and *avgSpeed* with $F(1, 116) = 9.886, p = 0.002$. We also found an interaction effect of gender and familiarity on *totalDist* with $F(1, 116) = 3.961, p = 0.049$. BH

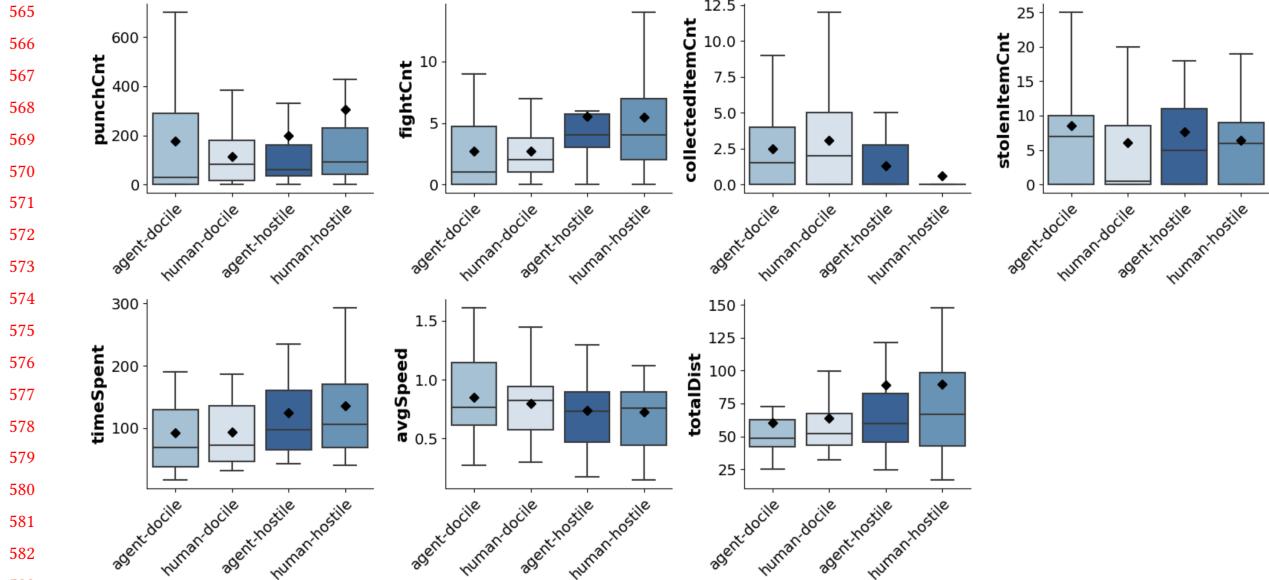


Fig. 8. Box plot diagrams for the participant behaviors by study condition

correction yielded only the main effects to be statistically significant. Table 4 summarizes the significant results after ANOVA and FDR correction. Figure 10 depicts the distributions of behavior parameter values for gender and familiarity, respectively.

Table 4. Two-way ANOVA results for gender and familiarity on participant behaviors. Statistically significant factors are indicated by **, with $p < 0.01$ and * with $p < 0.05$

Parameter	Model Term	F value	p-value	Adjusted p-value
fightCnt*	familiarity	8.677	0.004	0.027
timeSpent**	familiarity	13.423	0.0004	0.008
avgSpeed*	familiarity	9.886	0.002	0.022
totalDist	gender:familiarity	3.961	0.049	0.257

3.4.3 *Correlations of Participant Personality Factors with Their Emotions and Behaviors*. We computed the participant personality scores for the Five-Factor personality model, which defines personality on five orthogonal dimensions of (O)penness, (C)onscientiousness, (E)xtroversion, (A)greeableness, and (N)euroticism. Data was collected for each personality dimension on a 5-point scale where zero indicated “strongly disagree”, and four indicated “strongly agree”. We computed the responses per participant according to the TIPI guidelines. For instance, the agreeableness score was computed by taking the average of the responses for the question “I see myself as *sympathetic, warm*.” and the score for “I see myself as *critical, quarrelsome*” subtracted from four.

We performed Spearman rank-order correlations between personality factors and participants’ affect score differences between post and pre-study responses. To control for Type I errors, we performed FDR correction with BH procedure. We evaluated composite positive and negative affect scores separately due to their dependence on

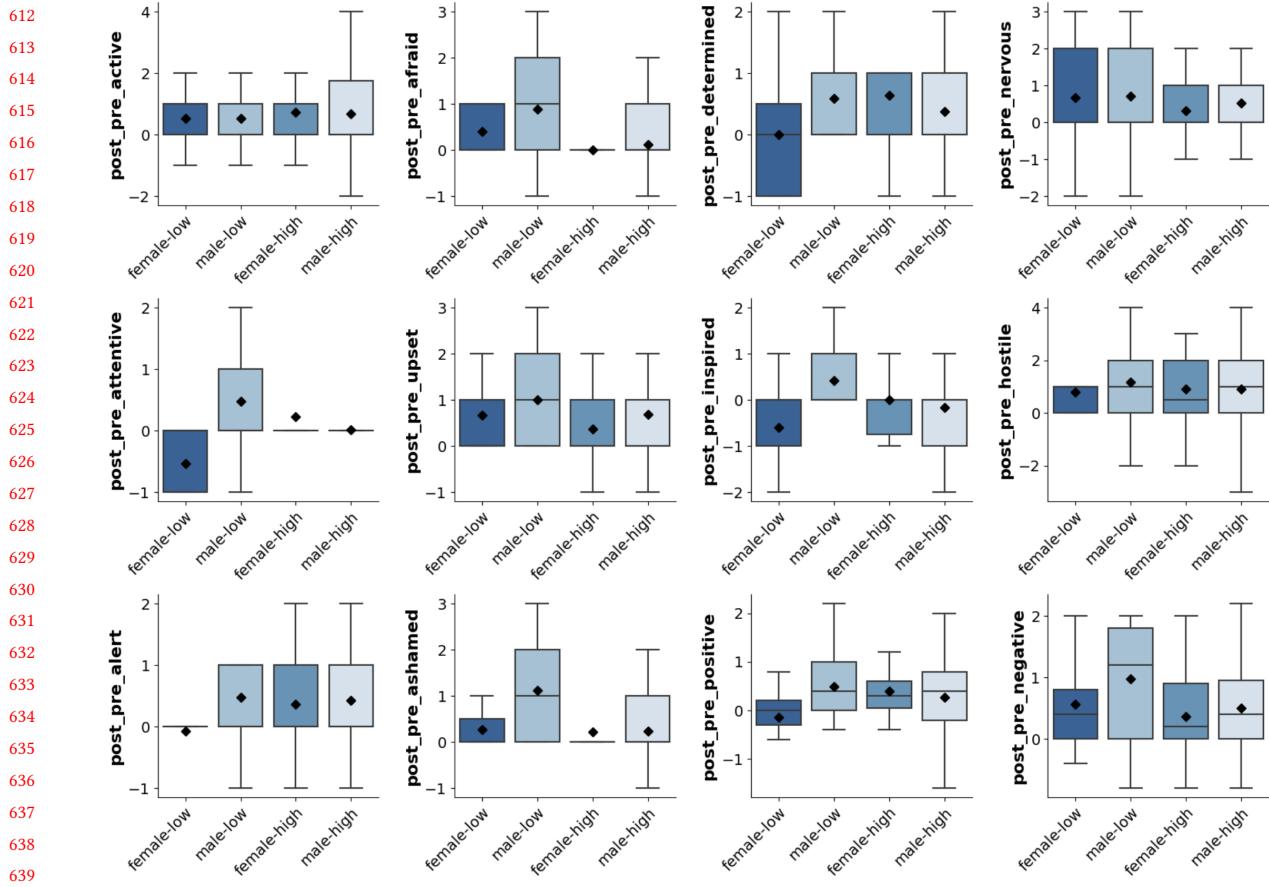


Fig. 9. Box plot diagrams for the differences between the post and pre-study affect scores by gender and familiarity

other factors, again correcting for FDR. After FDR correction, the results indicate a moderate negative correlation between extroversion and the differential score of *active* emotion ($\rho = -0.456, p < 0.001$), a low positive correlation between neuroticism and the change in *active* emotion ($\rho = -0.305, p < 0.001$), a low negative correlation between extroversion and the change in overall positive affect score ($\rho = -0.29, p = 0.0013$), and a low negative correlation between conscientiousness and the change in overall positive affect score ($\rho = -0.25, p = 0.006$). Figure 11 (a) shows the correlations between participants' differential affect scores and their personality traits, where the statistically significant correlations are highlighted with their corresponding adjusted p-values.

To further explore the relationship between initial emotions and personality scores, we also calculated Spearman rank-order correlations between personality factors and participants' pre-study affect scores and applied FDR correction with BH procedure. We observe slight to moderate positive correlations between positive affect scores (individual and composite) and the personality factors of openness, conscientiousness, extroversion, and agreeableness. In contrast, we find negative correlations between negative affect scores and neuroticism. Figure 11 (b) shows the correlations between pre-study affect scores and personality traits. The statistically significant correlations are highlighted with their corresponding adjusted p-values.

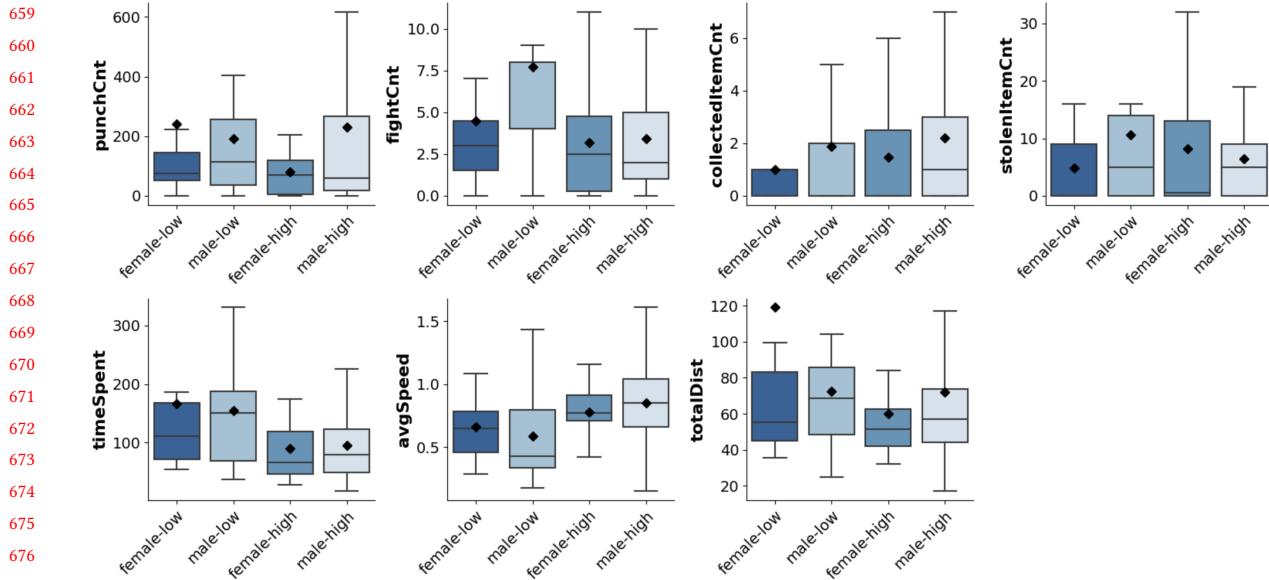


Fig. 10. Box plot diagrams for the participant behaviors by gender and familiarity

Although Spearman rank-order correlations between personality factors and participant behavior parameters returned a low positive correlation between neuroticism and *punchCnt* ($\rho = 0.202, p = 0.027$), openness and *timeSpent* ($\rho = 0.187, p = 0.041$), after FDR correction using the BH, none of these values remained statistically significant. Figure 12 shows the correlation matrix of personality factors and behaviors, where statistically significant correlations are highlighted with their corresponding adjusted p-value.

3.4.4 Post-Study Survey. The mean ratings for q1 and q5 were $\mu = 3.306 \pm 1.952$ and $\mu = 2.953 \pm 1.731$, respectively. These indicate that the participants had neutral experiences and found the character communication to be neutral. Most participants found the characters consistent and predictable.

All participants stated that they never suspected the agency when they were told that others were artificial agents.

More people believed the characters to be genuinely human-controlled in the hostile condition than the docile. Around 40% explicitly stated that they never suspected them to be artificial and 16% stated they were suspicious when agents did not attack others with more iPads or when they quickly gathered so many iPads. Others who did not believe they were avatar-controlled, mentioned robotic movements, the improbability of having the simulation start simultaneously on MTurk, and the game-like nature of the study. In the docile-human condition, only 25% believed others were humans.

When the crowd was hostile, some of the adjectives to describe the personality of the crowd included ‘greedy’, ‘rude’, ‘competitive’, ‘aggressive’, ‘hostile’, ‘primordial’, and ‘selfish’. In the docile condition, some also described the crowd as ‘competitive’, ‘greedy’, and ‘rude’ but there were also mentions of ‘(very) friendly’, ‘stoic’, ‘passive’, ‘uninterested’, and ‘cooperative’.

An interesting response for the docile-human condition, where the participant believed others were humans was “I felt pretty ashamed because I just started swinging, trying to get what I needed. I felt like I didn’t have

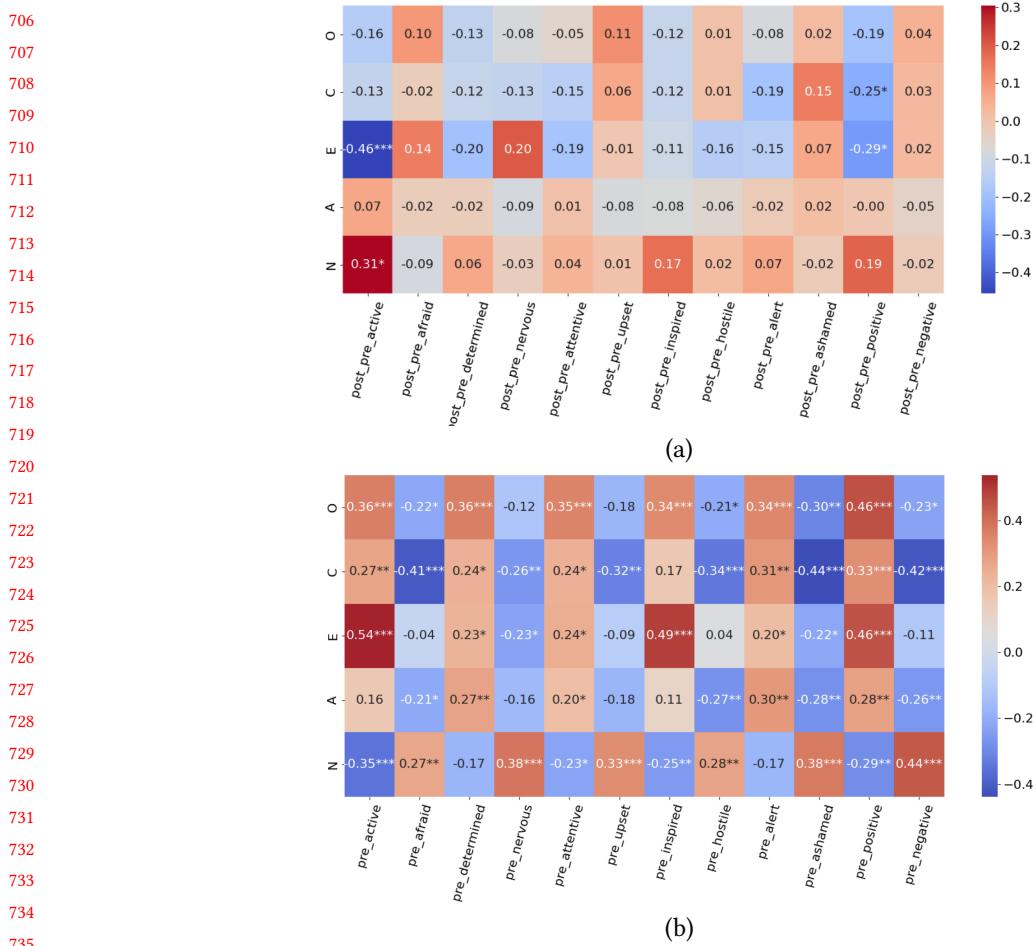


Fig. 11. Spearman correlations between participant personality and emotional changes. Statistically significant factors after FDR correction are indicated by **, with $p < 0.01$ and * with $p < 0.5$.

much of a choice because of the other players. It seemed like one of those Black Friday videos but happening in a virtual world. It was crazy.”

4 DISCUSSION

RQ1 explores the effect of the crowd’s emotional disposition on participant emotions and behaviors. We calculated the differences between the post and pre-study affect scores of participants to understand the emotional changes. Thus, the analyses compare these differential scores rather than the absolute emotions before or after the study. In the hostile crowd condition, there was a higher increase in the scores of *hostility*, *shame*, and *overall negative emotions* after the study, compared to the docile crowd condition. Additionally, the hostile condition yielded a slightly higher increase in *fear* and *upset* although the results did not remain statistically significant after the FDR correction. However, all these negative emotions have likely contributed to the combined negative affect score. There were no statistically significant differences between conditions for the changes in positive emotions.

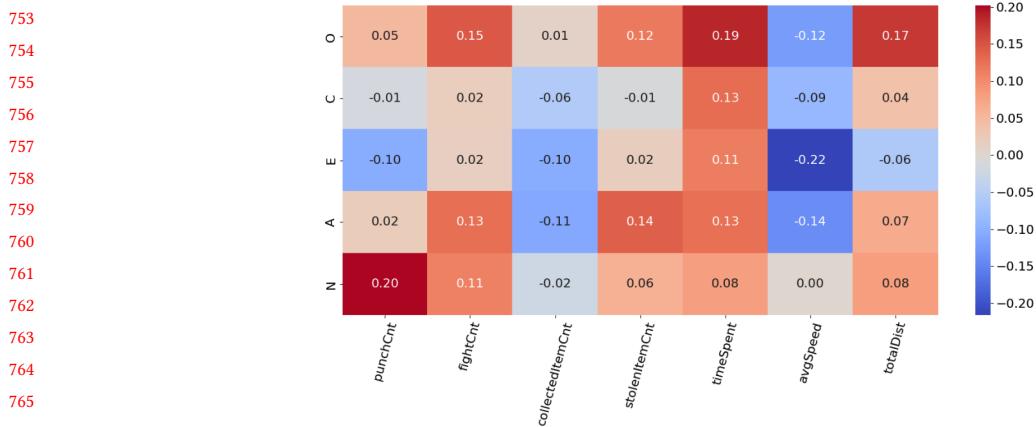


Fig. 12. Spearman correlations between participant personality and behavior parameters.

The results for emotions are in line with the participant behavior differences, showing a higher fight count in the hostile crowd than in the docile crowd condition. Yet, there was no significant difference in the number of punches they administered. Participants were attacked by crowd agents in the hostile setting. So, they had to engage in fights even when they did not initiate them. The lack of a significant difference in the number of punches between the two conditions indicates that participants generally responded to fights only when needed, which is also supported by their responses to open-ended questions. The number of collected iPads was lower in the hostile condition. This is also an expected result of the simulation setting as the hostile agents were able to attack the participants and steal their iPads. The participants spent slightly longer time and traveled longer distances in the store in the hostile setting. Regardless, reaching a definitive conclusion is challenging because these results did not retain statistical significance after the FDR correction. We can speculate that some participants might have extended their stay to recover the iPads that were stolen from them.

The results indicate that by imbuing agents with emotional behaviors dictated by personality factors, we can control users' behaviors and affective states. The increase in negative emotions, especially hostility, affirms the effectiveness of the simulation conditions in eliciting emotional responses.

In response to RQ2, we did not find any statistically significant effects of agency on human emotions or behaviors. The answers to open-ended questions hint at the main reason being the failure of the instructions and simulation to convince the participants that the agents were human-controlled. Although a considerable number of participants believed that narrative, others were skeptical, as a multi-user study that starts simultaneously on all computers is not usual on a crowdsourcing platform. Considering that the participants were selected from "Masters", i.e., people with high experience, deceiving them was especially challenging. Participants in the hostile crowd condition had a higher belief in the stated agency, possibly because the agents' actions were less predictable. The literature has mixed findings on the impact of perceived agency. Therefore, other factors than the participants' beliefs may have played a role in the lack of a difference between the two conditions of avatar vs. agent. An explanation might be the effect of the anonymity on MTurk. Because the experiment was short and did not involve further interaction other than the simulation, the participants may have distanced themselves from others, depersonalizing them, regardless of their agency [Chen and Dang 2022]. Another explanation may simply be ethopoeia, as suggested by Nass and Moon [Nass and Moon 2000].

Regarding RQ3, we did not find any significant effects of age and gender on participants' emotions or behaviors. Although high familiarity suggested higher increases in *fear*, *shame*, and *negative emotions*, the effects were not

800 found to be statistically significant after controlling for Type I errors. Regarding behaviors, familiarity was found
 801 to be related to a lower number of fights and the time spent, and an increased average speed with statistically
 802 significant effects after FDR correction. Having more experienced participants perform the study in a shorter
 803 time and with higher speed is an expected outcome. The lower number of fights was likely a result of the shorter
 804 time spent in the simulation. The lack of a significant effect of familiarity on punch count can be attributed to
 805 more effective fights for more familiar participants.

806 RQ4 explored potential correlations between the dependent variables and participants' personality traits.
 807 Although no significant correlations were observed after applying the FDR correction, we found slight positive
 808 correlations between neuroticism and punch count, and openness and time spent. Neuroticism is associated with
 809 anger, nervousness, and emotionality [Goldberg 1992] which could explain the higher punch count. Similarly,
 810 openness is described with curiosity and inquisitiveness [Goldberg 1990b], which could indicate the increased
 811 time in the environment. As these results are in line with the literature [Durupinar et al. 2011], we postulate that
 812 significant effects might be achieved with a larger sample size.

813 Although our main focus was the change in emotional states, we examined correlations between the participants'
 814 emotional states before the study and their personality traits to test the coherence of the collected data with the
 815 literature. Openness, conscientiousness, extroversion, and agreeableness, which can be considered the personality
 816 factors with "positive" connotations, were correlated with the participants' initial positive affect scores, i.e. being
 817 *alert, determined, attentive, and inspired*. In contrast, neuroticism, which is described as a tendency to experience
 818 negative affect, was correlated with the initial scores of *afraid, nervous, upset, hostile, and ashamed*. Those affinities
 819 are in alignment with the trait descriptions of the personality factors in the literature [Watson and Clark 1992;
 820 Watson et al. 1992].

821 We found statistically significant correlations between some differential affect scores and personality traits.
 822 For instance, extroversion was negatively correlated and neuroticism was positively correlated with the increase
 823 of *active* emotion. In other words, higher extroversion and emotional stability (low neuroticism) scores were
 824 linked to higher decreases in feeling active after the study. In addition, higher extroversion and conscientiousness
 825 were found to be correlated with higher decreases in positive affect scores. An explanation could be about the
 826 computer-based nature of the study, leading to lower activity and less excitement for extroverted and emotionally
 827 stable individuals. The unpredictable nature of the simulation might have caused higher distress in the more
 828 conscientious individuals. Although the correlations between individual positive emotions and conscientiousness
 829 were not statistically significant, their combination was. In addition, all the positive emotions, i.e., *activity,*
 830 *determination, attentiveness, inspiration, and alertness* were negatively correlated with conscientiousness.

831

832 5 CONCLUSION AND FUTURE WORK

833 This paper presents a web-based study to explore the effects of perceived agency and emotional disposition of
 834 virtual crowds on a human participant embodied as a crowd member. The system recorded each participant's
 835 actions during the simulation. We also collected data about their personalities and emotional states before and
 836 after the study, in addition to their demographics. We found statistically significant effects of crowd disposition
 837 and familiarity with first-person 3D games on certain behavioral parameters and differential emotion scores but
 838 did not observe any effects of perceived agency.

839 The findings provide a foundation and direction for the next phase of crowd simulation research. By incorporating
 840 the insights gained from these results, researchers can work towards more detailed, realistic, and adaptive
 841 virtual environments that mirror the intricacies of human behavior and decision-making in crowds. The clear
 842 impact of crowd disposition on individual emotions and behaviors emphasizes the promise of incorporating
 843 emotional temperaments in simulations. The absence of significant effects of perceived agency suggests that
 844 the distinction between avatars and agents might not be crucial in certain contexts. However, it also opens
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846

847 the door for more detailed research, perhaps exploring subtler nuances or different scenarios where perceived
 848 agency might have a more pronounced impact. Because not all the participants believed that the crowd was
 849 human-controlled, a more convincing study needs to be performed to reach a conclusion about the lack of
 850 significant effects for perceived agency. More diverse animations, perhaps with deliberately erratic behaviors,
 851 and a more convincing platform for multi-user studies can provide different results.

852 The findings about the effects of participant familiarity and personality on their behaviors and emotions can
 853 guide researchers and animators to design personalized simulations based on user profiles. This can increase the
 854 accuracy of predicted simulation effects and provide customized virtual experiences.

855 Our future plans include repeating the study in a VR environment. Although VR headsets provide higher
 856 immersion, their usage has limitations in terms of efficiency, diversity of the participant pool, and participant
 857 comfort. Thus, we preferred a browser-based environment instead of a lab-based VR study for this exploratory
 858 study. We expect to gather more detailed data and pronounced differences in a more immersive setting. Such a
 859 setting will also permit recording physiological responses in addition to self-reported measures. Additionally, we
 860 will explore different scenarios that analyze the attitudes of people toward virtual agents with diverse personalities
 861 and behaviors. Our study involved a single user but the platform can easily be extended to incorporate multiple
 862 participants, allowing the design of more variable scenarios.

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