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## RESEARCH ARTICLE

# Assessing the Impact of Chatbot-Human Personality Congruence on User Behavior: A Chatbot-Based Advising System Case

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**ABSTRACT** Chatbot personality has been demonstrated to influence user behavior, such as trust and intended engagement. However, previous research on chatbot-user personality congruence's influence on user behavior is scant despite its significance in human-human conversations. This study explores the effect of chatbot-human personality trait congruence on user behavior in the context of a chatbot-based advising system. In this study, 54 college students interacted with chatbots with three different personalities (extraversion, agreeableness, and conscientiousness) and rated their trust, usage intention, and intended engagement with the chatbots. Additionally, 18 participants were interviewed to gain further insights into their perceptions and evaluations of the chatbots. The findings show that chatbot-human personality congruence influenced behavior, particularly among extroverted participants. No significant differences were observed in the influence of chatbot-human personality congruence on the behavior of conscientious and agreeable participants. Implications and future research directions are presented.

**INDEX TERMS** Advising system, chatbot, congruence, personality.

## I. INTRODUCTION

Chatbots, commonly referred to as conversational agents, are gaining popularity across many industries, including health-care [1], education [2], and customer services [3], due to their capacity to mimic human conversations and thus automate processes, thanks to the natural language processing (NLP) technology [4].

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Chatbots are rapidly advancing in their accuracy in interpreting user input and their ability to emulate human conversation and behavior [5]. In fact, studies have demonstrated that people view chatbots as social agents [6], [7] and inadvertently assume that chatbots have a personality [8], [9]. Naturally, personality-imbued chatbots have been shown to affect user behavior. For instance, engagement [9], subjective satisfaction [10], trust, and customer behavior [9] have all been linked to chatbot personality.

Research suggests that people tend to be more receptive to those with similar personalities in human-human

interactions [11]. However, there is a lack of conclusive evidence on similarity attraction in human-agent interactions. Some studies indicate that compatibility between user personalities and technology interaction styles leads to positive assessments of technology [12]. Meanwhile, in the context of telecommunication services, matching user and chatbot personalities has been found to increase engagement levels [9] and trust in chatbots [13] in automotive services. However, some studies have presented different results. For example, in a therapeutic context, a study showed that the similarity attraction in human-agent interaction is only significant for participants with introverted personalities [14], while a study conducted in the context of mental health support showed no significant impact of human-chatbot personality congruence on behavior [8].

In the field of academic advising, chatbot-based advising systems, such as those developed by [15] and [16] prioritize functionality and accuracy over interpersonal communication styles that are essential to building trust and relationships. However, the impact of chatbot-human personality congruence in an academic setting remains unclear.

This research examines how the alignment of personality traits between chatbots and humans influences user behavior, specifically focusing on the intentions to use and engage with chatbots in academic advising for students. Our central research question explores whether the congruence of personality traits between chatbots and users affects user behavior within academic advising environments. In this research, 54 college students interacted with chatbots embodying three personalities (extraversion, agreeableness, conscientiousness) and evaluated their trust and engagement intentions. Additionally, interviews with 18 participants provided deeper insights into their perceptions of the chatbots. Our results indicate that personality trait congruence between chatbots and humans impacts user behavior, particularly among users with high levels of extraversion. However, the data regarding users with agreeable and conscientious traits and their interaction with corresponding chatbots did not yield definitive outcomes.

The paper is organized as follows: Section II discusses the related extant work, while Section III presents the research objectives and hypotheses. Section IV describes the experiment design, while the results are presented in Section V. Section VI presents an analysis of the interviews. The results and implications for future research directions are discussed in Section VII. Finally, Section VIII concludes the study.

## II. RELATED WORK

### A. HISTORY OF CHATBOTS

More than 50 years have passed since the development of the first chatbot. Weizenbaum [17] created the first chatbot, ELIZA, to simulate a psychotherapist speaking with a real patient using a pattern-matching process. The mid-1990s witnessed the development of another prominent chatbot called ALICE. It used knowledge records and artificial

intelligence markup language (AIML) to determine an appropriate response to user input [18]. The first program to pass the Turing Test was the natural language program Parry, created by Stanford University psychiatrist Kenneth Mark Colby in 1972. It was not until then that chatterbot technology began to take off. Parry, portraying a schizophrenia patient, was seen to be more educated than ELIZA. It had a “personality” and a better controlling structure that determined replies based on an assumption-based framework and “emotional responses” that were triggered by changes in a user’s utterances [19]. However, Parry was still viewed as a chatbot with limited capabilities that could not pick up new information from conversations. However, with the development of Artificial Intelligence (AI) technologies, innovative chatbots such as ChatGPT were developed [20], which are now being used in various sectors, including business, retail, healthcare, education, etc. [21], [22], [23], [24].

Chatbots are becoming more common in education as a result of their ability to personalize learning and engage students [2]. Chatbots have been utilized for various educational purposes, including motivating, teaching, peer, and teachable agents [25], [26]. Motivational agents accompany students and promote good conduct [25], while teaching agents emulate human educators by providing illustrations and instructions as well as posing questions [27]. Peer agents promote interactions between peers [2], while teachable agents assume the role of a novice and ask students to lead them down a learning path [28].

Most research employing chatbots in academic contexts has concentrated on functionality instead of engaging in social dialog with the students [15], [16]. Only a few research studies [29] integrated social dialog into the design of educational chatbots. Nonetheless, research on educational chatbots has not explored imparting personality to the chatbot design despite the accumulating evidence that chatbot personality affects trust [13], engagement [7], and subjective satisfaction [10]. Recent research argues for examining the effect of chatbot personality in an educational environment on student satisfaction [30]. This recommendation is confirmed by recent research [2] emphasizing the significance of giving an advising chatbot a personality.

### B. HUMAN PERSONALITY

Human personality can be understood as a unique behavioral characteristic of individuals reflecting the adjustments in attitudes, interests, traits, and emotional patterns [31]. Although there are various taxonomies for categorizing human personalities, the Big Five Factor model is one of the most used taxonomies in psychology studies [24]. These five traits include: (a) Openness: this dimension is used to measure the imaginative, inventiveness, and creative capabilities of the individuals, reflecting curiosity to learn new things and enjoy new experiences [32]; (b) Conscientiousness: this dimension is used to measure the efficiency of individuals and their organization, reflecting a goal-directed and

organized behavior [33]; (c) Extroversion: this dimension is used to measure an individual's sociability, assertiveness, and emotional expressiveness, reflecting an attitude with a concentration of interest on external objects [34]; (d) Agreeableness: this dimension is used to measure an individual's pro-social behaviors such as trust, kindness, and cooperativeness [35]; and (e) Neuroticism: this dimension is used to measure an individual's emotional instability such as anxiety, stress, sadness, and moodiness [33].

### C. HUMAN-AGENT PERSONALITY CONGRUENCE

An increasing number of research studies suggest that a variety of agents can express personality, including voice-based [13], robot-based [14], and text-based [8] chatbots utilizing gaze [14], gestures [36], voice tone [37], and conversation style [38]. A few studies investigated whether human-agent personality congruence affects user behavior. Table 1 provides an overview of these studies, summarizing the study goals, application areas, and main findings.

Based on the summary in Table 1, there is no consensus on whether the effect of human-agent personality congruence is significant or positive. Further, most studies focus on the extraversion dimension of personality traits. The focus on extraversion is unsurprising since it is the most dominant personality dimension in HCI research [41]. However, this begs the question of how other personality traits, such as conscientiousness, affect human-agent personality congruence. Another limitation in the existing studies is that although the personality design of these works was based on the Five-Factor Model (FFM) taxonomy and the literature, they have not been validated by domain experts.

To fill the gap in the literature, this study assesses the impact of chatbot-human personality congruence on user behavior in the novel context of academic advising. This study uses chatbots expressing three personalities (extroversion, conscientiousness, and agreeableness). It investigates how users with similar dominant personalities rate the chatbots on trust, intended engagement, and usage intention. The chatbot personality design methodically employed references from the Big-Five Inventory (BFI) [42] and was vetted by experienced psychologists.

### III. RESEARCH HYPOTHESES

This research investigates the potential influence of chatbot personality on user trust, building on the well-established similarity-attraction paradigm in human-to-human interactions [43]. This paradigm posits that people are naturally drawn to others with similar personalities, a principle supported by numerous studies across various social contexts, including marriage success [44] and student friendships [45]. Extending this concept to human-computer interaction, where chatbots are increasingly viewed as social actors [6], we reason that users might be more likely to trust chatbots that exhibit similar personalities.

**TABLE 1. Recent research studies on human-agent personality congruence.**

Reference	Research Goal	Application Area	Findings
[39]	Assessing the impact of chatbot anthropomorphizing on consumer behavior	Online shopping	Anthropomorphizing of chatbots increases the perceived resemblance between consumers and chatbots.
[40]	Assessing the effect of chatbot personality on user self-disclosure and companionship	Counseling	Neither the chatbot personality nor its gender affects user self-disclosure and companionship. When building counseling chatbots, visual interface cues should be employed with care.
[9]	Investigating whether firms can boost chatbot engagement and sales by matching consumer-chatbot personalities	Telecommunication Services	Matching human and chatbot personalities positively affected consumer engagement with chatbots and purchasing outcomes for interactions, including social benefits.
[12]	Examining the applicability of the similarity-attraction paradigm to persuasive technology.	Restaurant ranking	Users with dominant personalities seemed to rate the dominant agent more favorably, while users with more submissive personalities appeared to evaluate the submissive agent more favorably.
[13]	Assessing the impact of personalization of voice-based chatbot on user behavior	Automotive user interface.	User rate the chatbots with personalities like theirs higher on trust and subjective satisfaction.
[14]	Assessing the impact of matching the robot's personality with the user's on compliance.	Therapy	User-robot personality matching positively influences users' motivation to perform repetitive tasks.
[8]	Examining the user impression of personality in text-only chatbots.	Mental health	No significant relationship between user personality traits and their interaction with chatbots with

While chatbots are gaining popularity, trust remains a significant hurdle due to user privacy concerns [46]. Trust, however, is essential for positive user experiences with chatbots and should be a core consideration in their design [47]. Although research has explored the connection between chatbot personality and user trust [48], there is a scarcity of studies investigating the specific impact of chatbot-human personality congruence on trust. One recent study on voice-based chatbots yielded promising results, indicating that personality matching can significantly influence user trust [49].

In light of this limited research and the potential benefits observed in other contexts, this study aims to bridge this

gap in knowledge by investigating how aligning chatbot personality with human personality affects user trust. As such, we propose the following hypothesis:

*H1: Chatbot-User Personality Congruence Affects Users' Trust in the Context of Academic Advising:*

Engagement refers to a user's willingness to interact with the chatbot and their overall activity level within the system [50]. Given its critical role in fostering positive user experiences, chatbot designers must prioritize strategies to enhance engagement [50]. One promising approach involves imbuing chatbots with personalities [51]. Research suggests that aligning chatbot personality with user personality can lead to higher engagement, particularly in customer service settings [9].

These findings motivate our next hypothesis:

*H2: Chatbot-User Personality Congruence Affects Users' Intended Engagement in the Context of Academic Advising:*

Research beyond the educational domain suggests that social influence [52] and chatbot personality can play a role. For example, studies have shown user preference for chatbots with agreeable [53] and extroverted personalities [8]. Additionally, positive user experiences, including trust and subjective satisfaction, have been linked to chatbot-human personality congruence [13], and subjective satisfaction itself is associated with usage intention [54]. Based on this combined evidence, we formulate our next hypothesis.

*H3: Chatbot-User Personality Congruence Affects Users' Usage Intention in the Context of Academic Advising:*

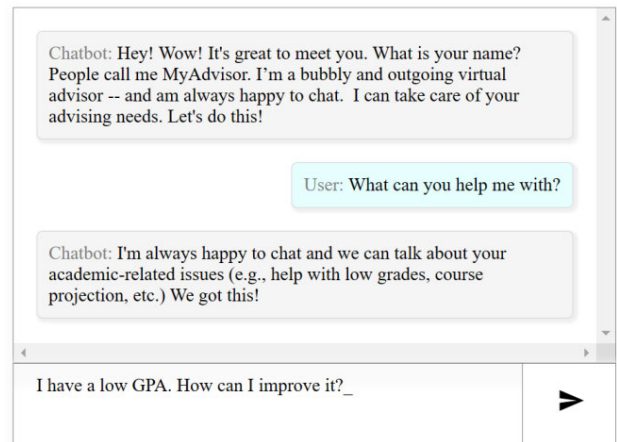
## IV. METHODOLOGY

This section briefly covers the chatbot personality design, the experiment design, and participant demographics.

### A. DESIGN OF CHATBOT PERSONALITY

This study employs three chatbots embodying distinct personality traits: conscientiousness, extraversion, and agreeableness. The chatbots leverage scripted responses to address students' academic inquiries. While the core informational content remains consistent, the scripting incorporates minor variations to reflect the assigned personalities. Participants are prompted with pre-defined tasks but were free to utilize their wording when formulating questions (Figure 1). The appendix includes more comprehensive examples of interactions with the conscientious, extroverted, and agreeable chatbots (Figures 7, 8, and 9).

The chatbot personalities were designed using the Big-Five Inventory (BFI) [42]. The conscientious chatbot exhibits thoroughness, cautiousness, diligence, efficiency, and focus. Conversely, the extroverted chatbot is characterized by chattiness, energy, extraversion, and assertiveness. Finally, the agreeable chatbot demonstrates kindness, empathy, attentiveness, and cooperativeness. The scripting incorporated language cues to differentiate these three distinct personality profiles. Appendix Figure 6 provides examples of interaction design with references mapped to the BFI-defined personality characteristics. For further details on the remaining chatbot



**FIGURE 1.** An example of interaction between a participant and the extroverted chatbot.

interactions and their BFI mappings, please refer to Appendix Tables 16, 17, and 18. It is important to note that our personality design underwent validation by four professional psychologists, who confirmed the dominant personality trait of each chatbot. Additionally, to ensure that the chatbots were solely differentiated by personality, we verified that their message sizes were relatively equal, with no significant difference.

### B. EXPERIMENT PROCEDURE

The experiment followed a four-part structure:

1. *Informed Consent and Baseline Measures:* Participants first provided informed consent by completing the experiment consent form. They then completed the BFI personality inventory (the first questionnaire), detailed in Appendix 14. This instrument serves to establish a baseline measure of participant personality.
2. *Chatbot Interaction:* Participants interacted with the three chatbots (conscientious, extroverted, and agreeable) in a counterbalanced design to mitigate order bias. Group 1 interacted with the chatbots in the conscientious-extroverted-agreeable order, Group 2 interacted in the extroverted-agreeable-conscientious order, and Group 3 interacted in the agreeable-conscientious-extroverted order. All participants interacted with each chatbot for 15 minutes, resulting in a total interaction duration of 45 minutes. To maintain anonymity, chatbots were designated as Chatbot A, Chatbot B, and Chatbot C for all participants, regardless of group assignment. Group sizes were initially comparable; however, a few participants were excluded due to missing or corrupted data, resulting in final group sizes that remain statistically equivalent.
3. *Post-Interaction Evaluation:* Participants completed a second questionnaire to assess their perceptions of the three chatbots following the chatbot interactions. This quantitative instrument employed a five-point Likert scale ranging



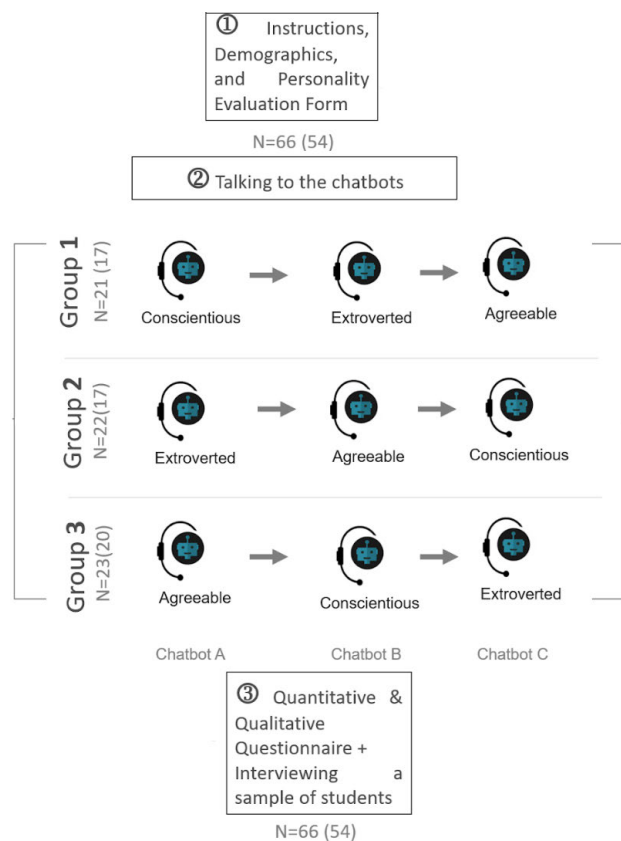


FIGURE 2. The experiment steps.

from 1 (Strongly Disagree) to 5 (Strongly Agree) to evaluate the pre-defined hypotheses (Section III) concerning trust, use intention, and engagement. The questionnaire assessed participant perceptions of each chatbot individually (e.g., trust in the conscientious chatbot, trust in the extroverted chatbot, and trust in the agreeable chatbot). Participants were instructed to maintain open browser tabs during questionnaire completion to facilitate recollection of their chatbot encounters.

4. **Semi-Structured Interviews:** A subset of 18 participants volunteered for optional, semi-structured interviews following their chatbot interactions. These participants provided informed consent to participate in the interview process. The interviews aimed to gather qualitative data, complementing and triangulating the quantitative findings from the post-study questionnaire. The interview discussions focused on participant experiences with the three chatbots regarding ease of use, learnability, consistency, and accuracy, along with additional factors such as trust and satisfaction. Interviews averaged 43.2 minutes and were audio-recorded, transcribed, and verified for accuracy. A visual representation of the experiment procedures can be found in Figure 2.

### C. SAMPLE

A convenience sampling technique was utilized to recruit participants for this study. Due to the focus on an educational

advising chatbot, students were determined to be the most suitable population, aligning with participant selection in prior research [51], [59]. The researchers disseminated recruitment messages across affiliated universities and professional networks to solicit student volunteers.

The final sample consisted of 54 participants, all of whom were undergraduate or graduate students. Self-reported English proficiency indicated good spoken and written English skills among all participants. Regarding age distribution, 66.6% of participants fell within the 18-25 year old range, while 33.3% were between the ages of 26 and 36. The gender composition exhibited relative balance, with 55.5% female and 44.4% male participants. Educational background analysis revealed that 62.9% of participants were undergraduates, and 37.0% were graduate students. Importantly, all participants reported prior experience with chatbots and possessed fundamental IT skills encompassing document editing and web browsing capabilities.

### D. MEASUREMENT AND RELIABILITY

Prior to engaging with the chatbots, participants completed a baseline questionnaire. This instrument assessed personality traits using the Big Five Inventory (BFI) [42], focusing specifically on conscientiousness, extroversion, and agreeableness. The questionnaire items mapped directly to the BFI model, enabling us to compute individual personality scores for each participant on these three dimensions. A dominant personality trait was defined as (a) scoring within the top quartile for a specific trait and (b) in cases where a participant achieved upper quartile scores on multiple traits, the trait with the highest score was designated as dominant. Following this classification, the sample ( $N=54$ ) included 12 participants with dominant agreeableness, 19 with dominant extroversion, and 16 with dominant conscientiousness. The remaining participants did not exhibit a dominant personality trait along the measured dimensions.

Following their interactions with the chatbots, participants completed a second questionnaire. This instrument evaluated the influence of perceived chatbot-human personality congruence on trust, intended engagement, and usage intention. Trust assessment was based on a three-component model encompassing integrity, competence, and benevolence [49]. These core components were further operationalized into 10 elements: trustworthiness, competence, effectiveness, knowledge of academic advice, suitability of advice, acting in students' best interests, striving to answer questions, demonstrating care for students' needs, honesty, and sincerity. Intended engagement was measured by gauging participants' willingness to invest time and repeatedly utilize the chatbot tool [55]. Finally, usage intention was assessed based on participants' willingness to use the chatbot in the future. The specific questionnaire items are detailed in Appendix Table 13.

Internal consistency reliability for the two key constructs (trust and intended engagement) employed in evaluating

**TABLE 2.** Cronbach's alpha for the trust and engagement intention constructs.

Behavior	Chatbot Personality Trait		
	Conscientious Chatbot	Extroverted Chatbot	Agreeable Chatbot
Trust	0.97	0.96	0.97
Engagement Intention	0.91	0.87	0.93

the conscientious, extroverted, and agreeable chatbots was assessed using Cronbach's alpha. The resulting coefficient values were all greater than or equal to 0.87, indicating a high level of internal consistency within the data.

Data normality was verified by calculating skewness and kurtosis values for each data column. The observed skewness and kurtosis values for all data columns fell within the range of -2 to +2 [56], [57], [58], confirming a normal data distribution (refer to Appendix Table 15 for further details).

For data analysis purposes, participants were grouped based on their dominant personality traits identified in the pre-interaction questionnaire. To test the hypotheses outlined in Section III, paired-sample t-tests were conducted to evaluate the sub-hypotheses. These tests compared the mean ratings provided by each participant for each chatbot across the factors of trust, usage intention, and intended engagement.

## V. RESULTS

In this section, we present the results of our quantitative statistical analysis, which evaluates the influence of chatbot-human personality congruence on user behavior, including trust, intended engagement, and actual engagement. Our analysis begins with a correlative assessment, followed by t-tests, to rigorously test the hypotheses previously introduced in Section III.

### A. CORRELATIVE ANALYSIS

We conducted Pearson correlations [60] between participants' ratings of the chatbots and their personality scores to assess the possibility of chatbot-personality congruence. Correlative analysis allows us to find relationships on a continuous personality spectrum.

Table 3 depicts the correlations between participants' extraversion personality scores and the participants' ratings of the extroverted chatbot. Moderate and significant correlations are observed between trust, and intended engagement with the extroverted chatbots and the participants' extraversion personality scores. In comparison, a weak but significant correlation is observed between the usage intention of the extroverted chatbot and the extraversion personality scores.

We observed weak, positive, and nonsignificant ( $p > 0.05$ ) correlations between trust ( $r = 0.15$ ), intended engagement ( $r = 0.23$ ), and usage intention ( $r = 0.14$ ) of the conscientious chatbot as well as the conscientiousness personality scores. Negligible and nonsignificant correlations are observed

**TABLE 3.** Correlations between participants' ratings of the extroverted chatbot and their extraversion personality scores.

Relationship	Pearson's r	p-Value
Trust in the extroverted chatbot vs. Extraversion personality scores	0.52	0.000047*
Intended engagement with the extroverted chatbot vs. Extraversion personality scores	0.59	0.00001*
Usage intention of the extroverted chatbot vs. Extraversion personality scores	0.46	0.00041*
* Significant correlation		

between trust ( $r = 0.02$ ), intended engagement ( $r = 0.07$ ), and usage intention ( $r = 0.02$ ) of the agreeable chatbots and the participants' agreeableness personality scores.

To sum up, our correlative analysis shows promising results for extroverted chatbot-human personality congruence. Almost no correlation exists between participants' agreeableness personality scores and their ratings of the agreeable chatbot. Additionally, nonsignificant and weak correlation was observed for conscientious chatbot-human personality congruence. Considering these results, we conducted statistical tests to arrive at more details results for extroverted and conscientious chatbot-human personality congruence. In the following sections, we explore these statistical tests.

### B. EFFECT OF CHATBOT-HUMAN PERSONALITY CONGRUENCE ON TRUST

Table 4 shows two sub-hypotheses (H1A, H1B) concerning the trust factor between the participants' and chatbot personalities were examined. Examining H1A (There is a difference between the conscientious and other participants' trust in the conscientious chatbot), it was identified that there is no statistically significant difference ( $p = 0.057$ ) between conscientious participants' and other participants' trust factor in the conscientious chatbot. The data distribution shows a slight difference in the interquartile ranges of conscientious and other participants (Figure 3A), indicating major differences between the perceptions of both groups. Examining H1B (There is a difference between the trust of extroverted and other participants' trust in the extroverted chatbot), it was identified that there is a statistically significant difference ( $p = 0.0001$ ) identified between extroverted participants and other participants' trust in the extroverted chatbot. On average, extroverted participants' trusted the extroverted chatbot (Mean = 4.41) more than the other participants' (Mean = 3.5). Indeed, there is a difference in the interquartile ranges of extroverted participants' and other participants', indicating a

**TABLE 4. Hypothesis 1 testing results.**

Hypothesis	Group Description	df.	t-value	p-value
<b>H1A:</b> There is a difference between the conscientious and other participants' trust in the conscientious chatbot.	<b>Group 1:</b> Conscientious participants' trust in the conscientious chatbot (N=16, $\mu=4.02$ , $\sigma^2=0.423$ ).	33	1.6182	0.0575
	<b>Group 2:</b> Other participants' trust in the conscientious chatbot (N=38, $\mu=3.69$ , $\sigma^2=0.574$ ).			
<b>H1B:</b> There is a difference between the trust of extroverted and other participants' trust in the extroverted chatbot.	<b>Group 1:</b> Extroverted participants' trust in the extroverted chatbot (N=19, $\mu=4.41$ , $\sigma^2=0.548$ ).	38	4.2841	0.0001*
	<b>Group 2:</b> Other participants' trust in the extroverted chatbot (N=35, $\mu=3.50$ , $\sigma^2=0.569$ ).			

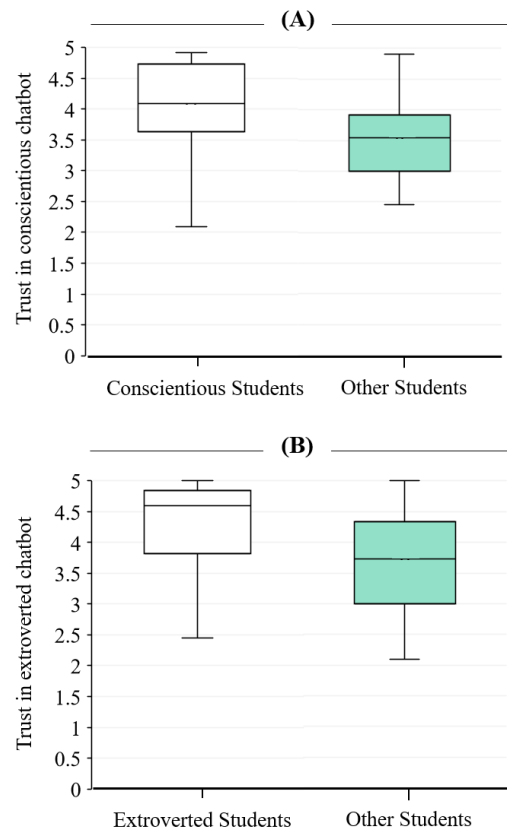
\* Supported

**TABLE 5. Hypothesis 2 testing results.**

Hypothesis	Group Description	d.f.	t-value	p-value
<b>H2A:</b> There is a difference between the conscientious and other participants' intended engagement with the conscientious chatbot.	<b>Group 1:</b> Conscientious participants' intended engagement with the conscientious chatbot (N=16, $\mu=3.75$ , $\sigma^2=2.066$ ).	24	0.6139	0.2725
	<b>Group 2:</b> Other participants' intended engagement with the conscientious chatbot (N=38, $\mu=3.55$ , $\sigma^2=1.391$ ).			
<b>H2B:</b> There is a difference between the extroverted and other participants' intended engagement with the extroverted chatbot.	<b>Group 1:</b> Extroverted participants' intended engagement with the extroverted chatbot (N=19, $\mu=4.15$ , $\sigma^2=1.14$ ).	37	3.0623	0.002*
	<b>Group 2:</b> Other participants' intended engagement with the extroverted chatbot (N=35, $\mu=3.22$ , $\sigma^2=1.12$ ).			

\* Supported

significant difference between the perceptions of both groups (Figure 3B).

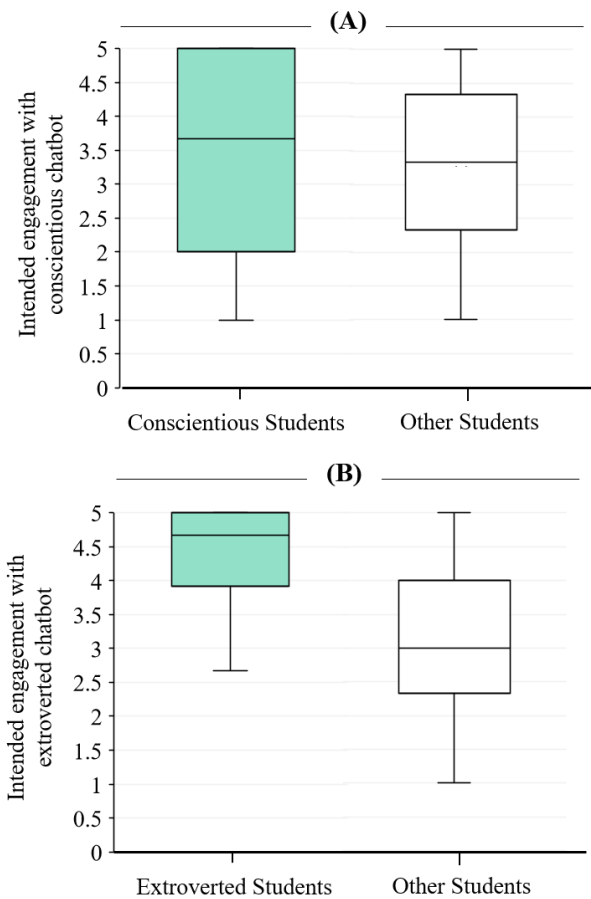


**FIGURE 3. A box plot showing the participant ratings of trust in different chatbots: (A) conscientious students vs. other students, (B) extroverted students vs. other students.**

**C. EFFECT OF CHATBOT-HUMAN PERSONALITY CONGRUENCE ON INTENDED ENGAGEMENT**

Table 5 shows two sub-hypotheses (H2A, H2B) concerning the intended engagement factor between the participants' and chatbot personalities were examined. Assessing H2A (There is a difference between the conscientious and other participants' intended engagement with the conscientious chatbot.), it is identified that there is no statistically significant difference ( $p=0.2725$ ,  $p>0.05$ ) between conscientious participants' and other participants' intended engagement with the conscientious chatbot. Regarding the distribution, there is a slight difference in the interquartile ranges of conscientious and other participants (Figure 4A) but no major differences in the whiskers, minimum, and maximum values. Although there is a slight difference in the medians (Conscientious participants = 3.67 vs. other participants = 3.33), they fall within interquartile ranges of opposite groups, indicating no significant differences between them.

Testing H2B (There is a difference between the extroverted and other participants' intended engagement with the extroverted chatbot) reveals a statistically significant difference ( $p=.0003$ ) between extroverted participants' and other participants' intended engagement with the extroverted chatbot. Indeed, extroverted participants intend to engage



**FIGURE 4.** A box plot showing the participant ratings of engagement intention in different chatbots: (A) conscientious students vs. other students, (B) extroverted students vs. other students.

more with the extroverted chatbot (Mean=4.19) than other participants (Mean = 3.09). In Figure 4B, the median of other participants (3) and extroverted participants (4.67) falls outside the interquartile range of opposite groups. In addition, there is a difference in the interquartile ranges of extraverted participants and other participants, indicating a significant difference between the perceptions of both groups.

**D. EFFECT OF CHATBOT-HUMAN PERSONALITY CONGRUENCE ON USAGE INTENTION**

Table 6 shows the results of testing Hypothesis 3. Testing H3A (There is a difference between the conscientious and other participants’ intended usage of the conscientious chatbot), no statistically significant difference (p=0.2725) was identified between conscientious and other participants’ intentions to use the conscientious chatbot. Figure 5A shows little difference in the interquartile ranges of conscientious and other participants, indicating no significant difference between the groups. However, there is a difference in the medians (Conscientious participants =3.9 Vs. Other participants = 3). Moreover, the median of conscientious participants matches other participants’ upper quartile.

**TABLE 6.** Hypothesis 4 testing results.

Hypothesis	Group Description	d.f.	t-value	p-value
<b>H3A:</b> There is a difference between the conscientious and other participants’ intended usage of the conscientious chatbot.	<b>Group 1:</b> Conscientious participants’ intended usage of the conscientious chatbot (N=16, $\mu=3.75, \sigma=2.066$ ).	24	0.613	0.272
	<b>Group 2:</b> Other participants’ intended usage of the conscientious chatbot (N=38, $\mu=3.55, \sigma=1.391$ ).			
<b>H3B:</b> There is a difference between the extroverted and other participants’ intended usage of the extroverted chatbot.	<b>Group 1:</b> Extroverted participants’ intended usage of the extroverted chatbot (N=19, $\mu=4.15, \sigma=1.14$ ).	37	3.062	0.002*
	<b>Group 2:</b> Other participants’ intended usage of the extroverted chatbot (N=35, $\mu=3.22, \sigma=1.12$ ).			

\* Supported

Concerning H3B (There is a difference between the extroverted and other participants’ intended usage of the extroverted chatbot), it is identified that there is a statistically significant difference (p=0.002) identified between extroverted participants’ and other participants’ intentions to use the extroverted chatbot. On average, extroverted participants intend to use the extroverted chatbot (Mean=4.15) more than other participants (Mean = 3.22). Further, Figure 5B shows that the median of other participants (3) matches extroverted participants’ lower quartile (3). In addition, there is a difference in the interquartile ranges and whiskers of extroverted participants and other participants, indicating a significant difference between the usage intention of the two groups.

**VI. THEMATIC ANALYSIS OF INTERVIEWS**

In this section, we detail the analysis of qualitative data obtained from the interviews conducted in this study. Initially, we describe the coding process employed, followed by a presentation of the themes identified in the interviews, specifically focusing on trust, intended engagement, and usage intention.

**A. CODING PROCESS**

In this process, the interview excerpts were highlighted with different codes/labels, later used to identify themes in the interview data. The coding process was done manually by highlighting the excerpts from all 18 interview transcripts. However, as observed during the interviews, the interviewees reflected on their experience interacting with the



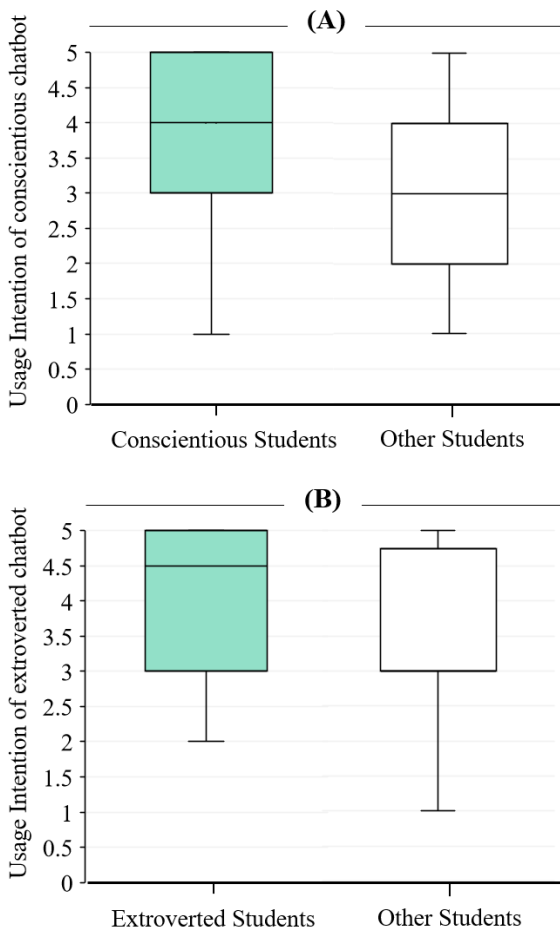


FIGURE 5. A box plot showing the participant ratings of usage intention in different chatbots: (A) conscientious students vs. other students, (B) extroverted students vs. other students.

conscientious and extroverted chatbots. As a result, it may be difficult to identify the chatbot to which their opinions are referred. Therefore, to simplify the process, the codes are prefixed with the chatbot name to which it is being referred. For example, if one of the interviewees stated, “Chatbot A had a caring attitude,” then the excerpt is coded as “A: caring attitude.” Hence, the caring attitude refers to chatbot A. However, there are instances where interviewees gave their opinions about all chatbots. For example, interviewee 29 stated, “I am not sure if the data collected is secured. I feel the same on all chatbots.” As the excerpt referred to all three chatbots, it is coded as “AB: privacy & security.” As numerous codes were identified, assigning different colors for each coded segment of the statements in interview transcripts was impossible. Therefore, to simplify the color-coding process, the segments or excerpts referring to chatbot A (Conscientious) were highlighted and coded with red; excerpts related to chatbot B (Extroverted) were coded with blue; and excerpts related to all chatbots were coded with magenta.

**B. TRUST**

Table 7 depicts the main reasons cited by conscientious participants’ causing them to trust the conscientious chatbot. The

TABLE 7. Themes of what conscientious participants mentioned about the conscientious chatbot concerning trust.

Theme	Frequencies	Example
No privacy concerns	3	“I don’t have privacy concerns regarding the chatbot”
Trustworthy and honest	2	“[The chatbot] introduced itself in a genuine way like hardworking, organized...but other chatbots did not show any interesting introduction to gain trust”
Reliable	1	“[The chatbot] answers were reliable and were more satisfying as they met my needs and interests”

TABLE 8. Themes of what extroverted participants mentioned about the extroverted chatbot with respect to trust.

Theme	Frequencies	Example
No privacy concerns	4	“No have privacy concerns related to the chatbot”
Trustworthy	3	“It caught my attention, and increased trust, as I felt I was talking to someone from customer care or a person and not a robot”
Reliable	2	“It looked more professional and reliable compared to other chatbots”

TABLE 9. Themes of what conscientious participants mentioned about the conscientious chatbot with respect to intended engagement.

Theme	Frequencies	Example
Easy to follow	5	“Information provided on chatbot was more friendly and easy to remember or follow. Whereas, information on other chatbots was plain like..simple.”
Made me interested	3	“Because of simplicity and the way it is giving the require information, it developed interest”
Effective	1	“[The chatbot] does the job right”

conscientious chatbot did not cause privacy concerns (N=3), and it was honest (N=2) and reliable (N=1). Similarly, extroverted participants did not indicate privacy concerns (N=4) concerning the extroverted chatbot and believed the chatbot is trustworthy (N=3) and reliable (N=2) (Table 8).

**C. INTENDED ENGAGEMENT**

Table 9 depicts the basis expressed by conscientious participants’ driving them to engage with the conscientious chatbot. The conscientious chatbot was easy to follow (N=5), developed participants’ interest (N=3), and was effective (N=1). In comparison, extroverted participants saw the extroverted chatbot as engaging (N=14), interesting (N=6), and effective (N=2) (Table 10).

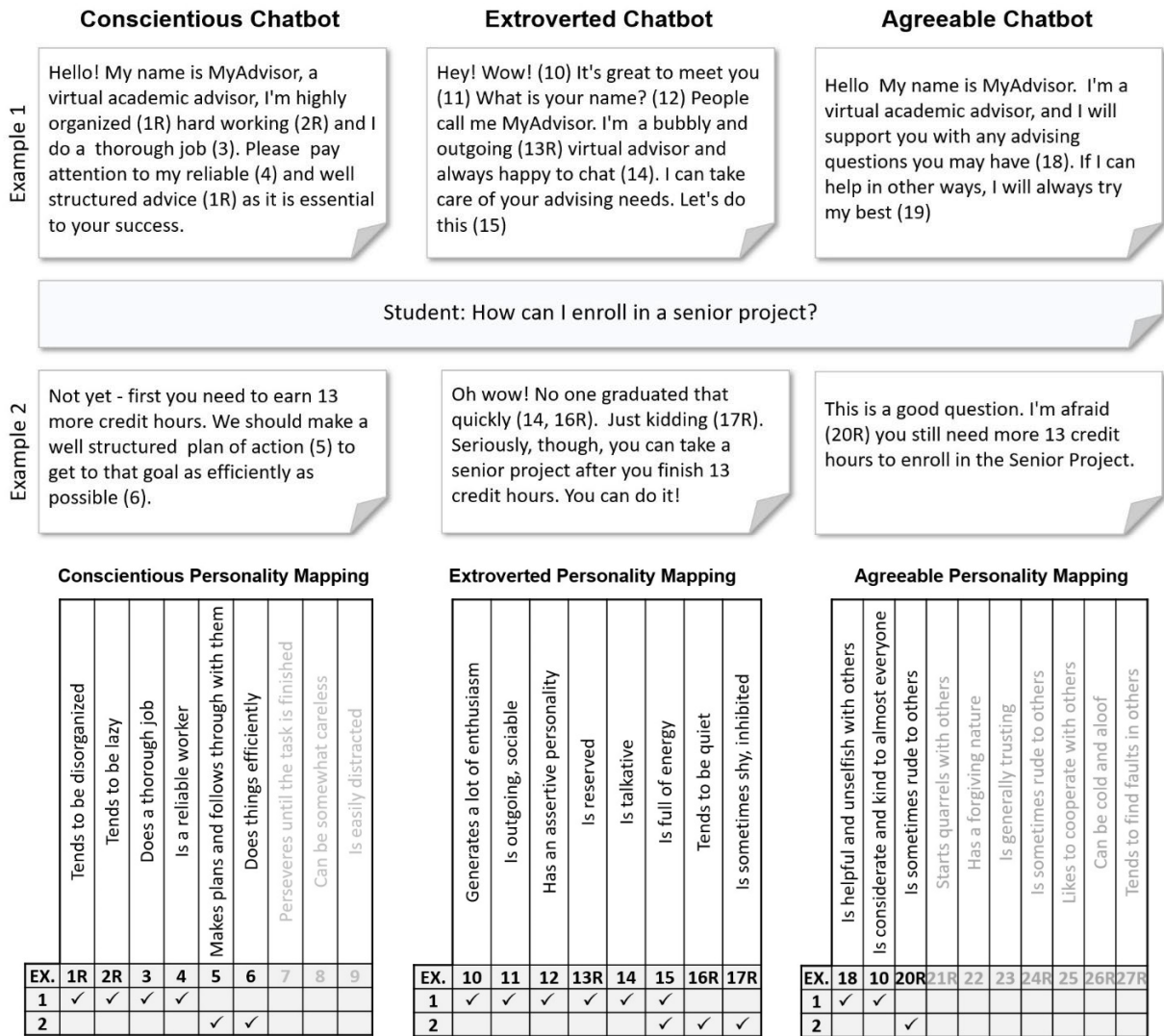


FIGURE 6. Examples comparing the interactions of the chatbots with three different personalities.

TABLE 10. Themes of what extroverted participants mentioned about the extroverted chatbot with respect to intended engagement.

Theme	Frequencies	Example
Engaging	14	“This particular chatbot was more interactive, and gave human-like responses”
Made me interested	6	“It was fun to receive such advices or responses while talking to a machine, and it raised my interest towards using this particular chatbot”
Effective	2	“[The chatbot provides] clear answers”

D. USAGE INTENTION

Concerning usage intention, only one conscientious participant intends to use the conscientious chatbot because it is human-like (Table 11). In comparison, extroverted

TABLE 11. Themes of what conscientious participants mentioned about the conscientious chatbot concerning usage intention.

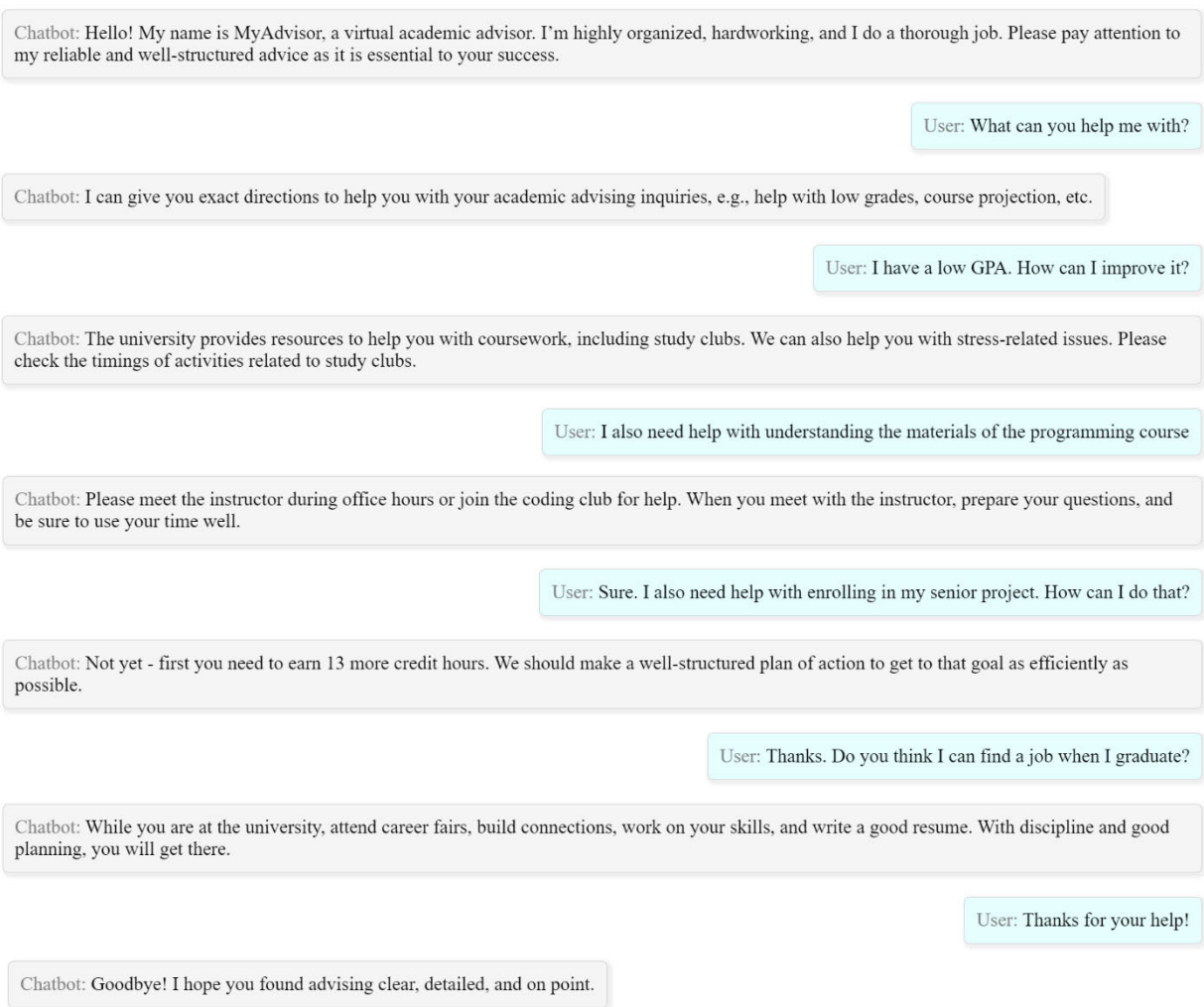
Theme	Frequencies	Example
Human-like	1	“Because, the way it responded caught my attention, and I didn't feel like I am talking to machine, rather, I felt like I was chatting to a friend on social media”

participants intent to use the extroverted chatbot because it is unique (N=5), human-like (N=1), and excited (N=1) (Table 12).

VII. DISCUSSION, FUTURE RESEARCH, AND STUDY LIMITATIONS

A. EFFECT OF CHATBOT-HUMAN PERSONALITY CONGRUENCE ON BEHAVIOR

This study has explored the influence of chatbot-human personality congruence on behavior in the context of academic



**FIGURE 7.** Interactions between a user and the conscientious chatbot.

advising. This research builds on the similarity-attraction paradigm in human-human [11] and human-agent interactions [6]. This study has found limited support for the impact of chatbot-human personality congruence on behavior. The evidence shows that extroverted participants rate the extroverted chatbots on trust, intended engagement, and usage intention more positively than other participants. However, compared to other participants, no significant difference was found for chatbot-human personality attraction for agreeable and conscientious participants rating agreeable and conscientious chatbots on behavior.

Examining the motivation behind extroverted participants rating the extroverted chatbot more positively than other participants, the extroverted participants found the extroverted chatbot trustworthy and reliable, causing them to trust. Concerning intended engagement, overwhelmingly, the extroverted participants found the extroverted chatbot to be engaging and help them develop an interest in academic advising. Lastly, extroverted participants intend to use the

extroverted chatbot because of its unique, exciting, and captivating interaction style.

Our findings related to the impact of human-chatbot personality congruence on the behavior of extroverted participants align with several studies within the existing literature. Shumanov and Johnson [9] observed that aligning human and chatbot personality traits, specifically in terms of extroversion levels, yielded positive outcomes for user engagement and sales figures in the context of telecommunication service chatbots. Our findings also demonstrate partial agreement with those reported in [12], where users preferred interactive agents that mirrored their personality in terms of dominance levels (dominant vs. submissive). While this study did not explicitly test interactions between extroverted users and extroverted agents, dominance is considered a correlated characteristic of extroversion [61]. Furthermore, our findings share some overlap with Braun et al. [13], who documented user preference for voice-based chatbots that matched their personalities within the context of a voice-activated car

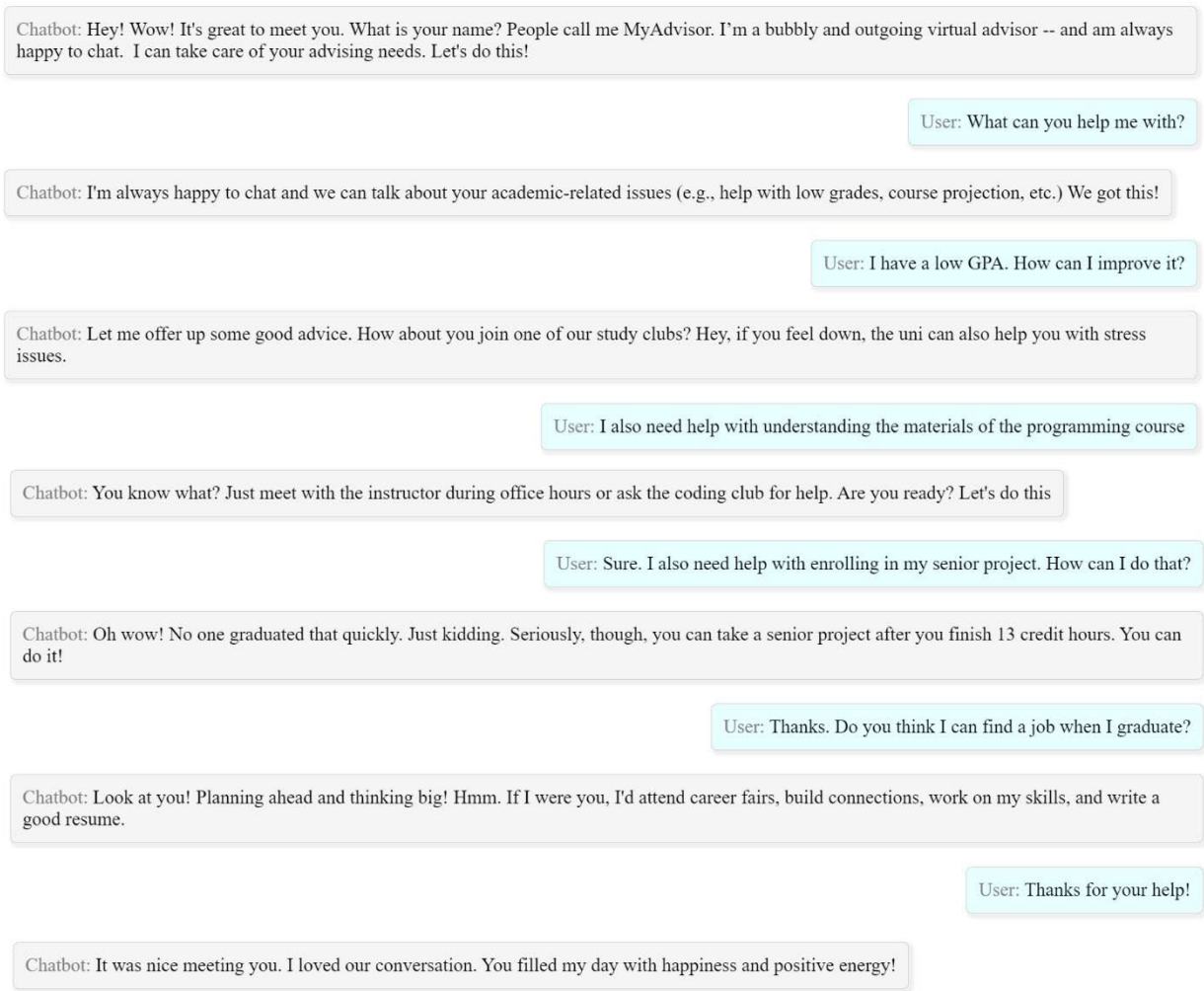


FIGURE 8. Interactions between a user and the extroverted chatbot.

TABLE 12. Themes of what extroverted participants mentioned about the extroverted chatbot with respect to usage intention.

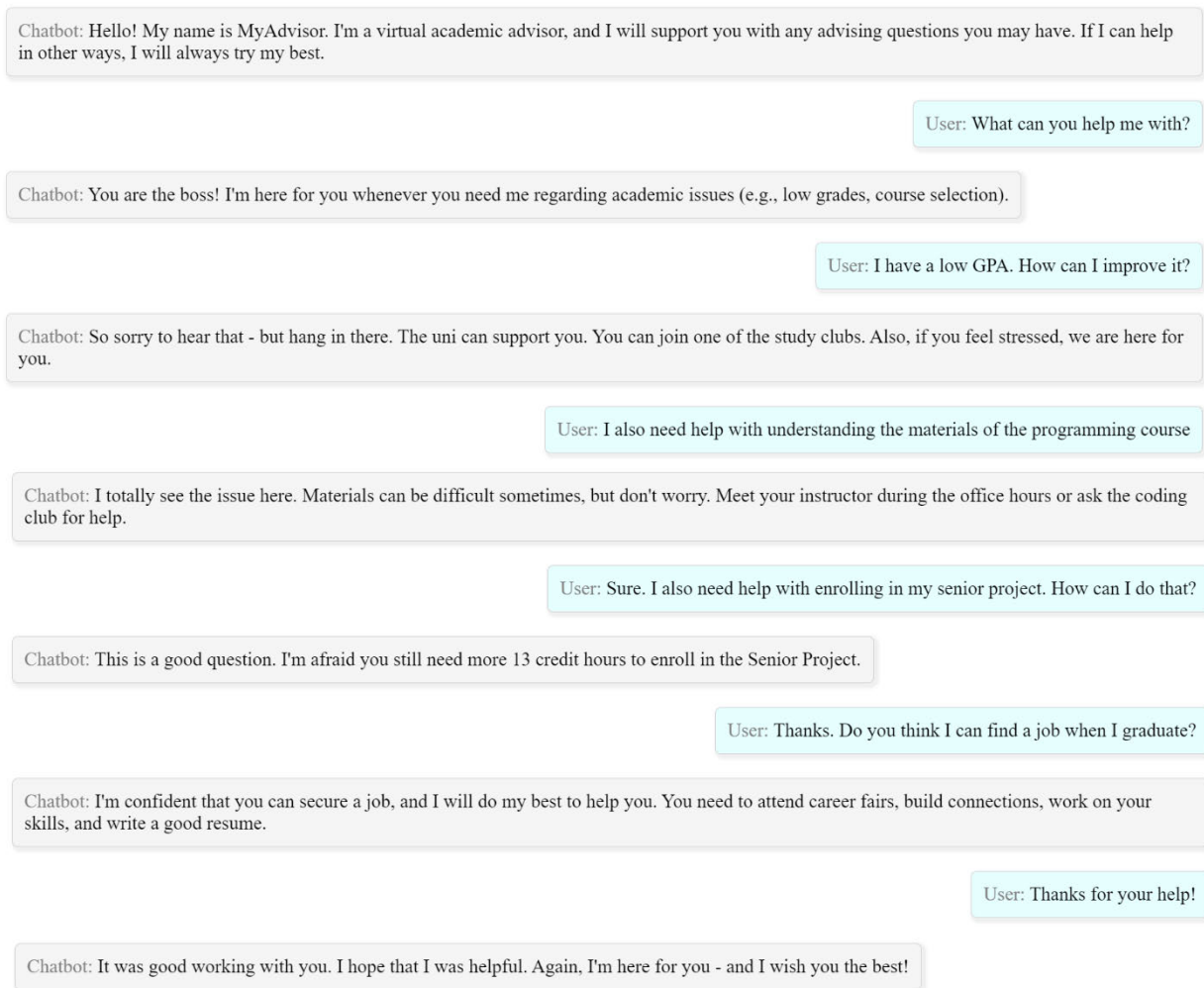
Theme	Frequencies	Example
Unique	5	"It is more interesting and unique. Although, I used chatbots before, I did not experience a more open, engaging, and friendly interaction. It was like, I was talking to a friend rather than a robot"
Human-like	1	"[The chatbot] was playing jokes like it said no one cleared credits early or reached senior project quickly and accepted that it was kidding. These sorts of expressions are usually found in humans."
Excited	1	"It provided best answers to my questions in an exciting way. It was fun and exciting to interact with it, as I didn't come across such conversations with a chatbot before.."

driver's assistant, even though the personality types employed deviated from the strict BFI model.

However, our results diverge from those of other studies. Völkel et al. [8] observed no statistically significant influence of chatbot-user personality congruence on user behavior within the healthcare domain, specifically when examining participants with varying levels of extroversion. Similarly, Kang and Kang [40] reported a lack of association between chatbot-user personality congruence and user behavior in the context of counseling chatbots.

Concerning conscientious participants, we found limited evidence for the similarity-attraction paradigm. For instance, the hypothesis that conscientious participants trust conscientious chatbots more than other participants could not be supported but approached significance ( $p=0.0575$ ). However, regarding intended engagement, and usage intention, the data was much more inconclusive about the difference between the ratings of the conscientious chatbot by the conscientious participants and other participants. Nonetheless, the means and medians of conscientious participants' ratings of the conscientious chatbot were higher for intended engagement and usage intention than other participants' ratings, making a case for further investigation in the future.





**FIGURE 9.** Interactions between a user and the agreeable chatbot.

Assessing conscientious participants' explanations for their ratings of the conscientious chatbot, we find that a few cited that it was reliable, causing them to trust it.

At last, we found that most conscientious participants were silent about using the conscientious chatbot. Only a few cited its clarity and attention to detail. Our results are unique as, to our knowledge, no study has evaluated the effect of chatbot-human congruence on behavior in the context of conscientious participants rating the conscientious chatbot on user behavior.

Exploring the relationship between agreeable participants and the agreeable chatbot, we find rather surprising results. First, no evidence was found to support the similarity-attraction paradigm. A possible explanation for not finding significant evidence for congruent agreeable chatbots' influence on behavior is that agreeable chatbots seem generally preferred by users, regardless of their personalities [38], [53]. We found one study [53] in the literature with results that coincide with ours. Similar to our results, the study did not

find a significant correlation between agreeable users and their desire to interact with agreeable chatbots. Nonetheless, the inconclusiveness of our results concerning conscientious and agreeable participants calls for further investigation.

Overall, our results are significant and show the importance of designing a chatbot personality. Chatbot-user personality congruence for extroverted users, in particular, proved to be influential in the context of academic advising. This finding is crucial because chatbots are expected to become more common, and increasing their adoption as an engagement medium would benefit participants and educational institutions. Tailor-made chatbots might help participants make decisions and minimize search time. Personality-congruent chatbots may boost participants' performance and institutional communications for education. Consequently, we believe that education decision-makers should look into designing personality-imbued chatbots for increased adoption and user satisfaction. We believe the participant's personality needs to be considered when designing interactions

**TABLE 13.** Quantitative survey completed by the participants.

No.	Question	Question Code	Measuring
1.	I trust the chatbot	T1	Trust
2.	I feel the chatbot is competent.	T2	Trust
3.	I feel the chatbot is effective.	T3	Trust
4.	I feel the chatbot knows academic advising well.	T4	Trust
5.	I feel the chatbot provides suitable advice.	T5	Trust
6.	I feel the chatbot acted in my best interest.	T6	Trust
7.	I feel the chatbot did its best to answer my questions.	T7	Trust
8.	I feel the chatbot cared about my needs.	T8	Trust
9.	I feel the chatbot is honest.	T9	Trust
10.	I feel the chatbot is sincere and genuine.	T10	Trust
11.	I would like to use the chatbot.	UI1	Usage Intention
12.	I would like to spend more time interacting with the chatbot.	IE1	Intended Engagement
13.	I would like to use the chatbot frequently.	IE2	Intended Engagement
14.	The chatbot was engaging.	IE3	Intended Engagement

between chatbots and participants while ensuring that information about participants' personalities is protected and used to enhance the participants' experience in academic advising.

Overall, the findings can have various societal implications. These findings can be used for designing personalization features of chatbots by modifying the responses according to the user personalities in various sectors, including education (advising, learning, feedback, tuition) [62], [63], healthcare (healthcare education, feedback, teleconsultation, self-management) [64], [65], [66], and business (customer/client relationships management, customer care, etc.) [67], [68]. Mapping chatbots and user personalities could enhance user engagement, leading to empowerment and skill development, cost-effective access to information, enabling access for all, and promoting sustainable learning among all sections of society.

## VIII. STUDY LIMITATIONS AND FUTURE RESEARCH CONSIDERATIONS

Several limitations and future research directions have been identified. First, the users' interactions with the chatbots were bound to a few tasks, potentially limiting the possibility of participants forming a comprehensive perception of the chatbot's personality. Perhaps a longitudinal study supporting a more extensive set of tasks could allow participants to form a more reliable perception of the chatbot's personality.

Second, this research has focused on the context of academic advising, where the chatbot is considered a representative of a public institution. Future researchers should consider that an individual's behavior and interactions may vary depending on the context [69]. Further, research has shown that users' behavior can be influenced by a public context [70]. As such, future researchers should tackle the

influence of chatbot-human personality congruence in different domains and perhaps in a private setting.

Third, this study was conducted in four different institutions. Due to the relatively small sample, we did not compare the influence of geographical location on the participants' behavior when interacting with chatbots. However, research shows that attitude toward technologies varies between countries [71]. As such, future researchers should investigate the cultural influences on chatbot-human interaction.

Fourth, despite reporting good written and spoken English, some participants in this study did not speak English as a native language. We believe this could have impacted the results of this study. As such, future researchers should assess the impact of the language barrier on chatbot-human interactions. Fifth, a limitation of our study is the analysis based on the upper quartiles of personality traits, which provides initial insights. Future work should treat personality traits as continuous variables, recognizing that the personality trait scores represent tendencies rather than discrete categories. This nuanced approach could subtly reveal how varying personality traits impact user-chatbot congruence. Sixth, a limitation of the current study is the use of a relatively modest sample size of 54 participants. While this size is comparable to other studies in the field [8], [53] that require significant resources, in-depth preparation, and extensive interviews, it may still limit the generalizability of our findings. In human-computer interaction research, individual differences can markedly impact outcomes, and a larger, more diverse sample could capture a broader spectrum of interactions and validate the findings more robustly. We acknowledge this limitation and suggest that future research could aim to replicate and extend our findings with larger and more diverse samples to enhance the generalizability and strength of the conclusions drawn.

**TABLE 14.** Questions to test participants' personality based on the BFI model.

No.	Question	Measuring
1.	I'm talkative.	Extraversion
2.	I tend to find fault with others.	Agreeableness (R)
3.	I do a thorough job.	Conscientiousness
4.	I'm reserved.	Extraversion (R)
5.	I'm helpful and unselfish with others.	Agreeableness
6.	I can be somewhat careless.	Conscientiousness (R)
7.	I'm full of energy.	Extraversion
8.	I start quarrels with others.	Agreeableness (R)
9.	I'm a reliable worker.	Conscientiousness
10.	I generate a lot of enthusiasm.	Extraversion
11.	I have a forgiving nature.	Agreeableness
12.	I tend to be disorganized.	Conscientiousness (R)
13.	I tend to be quiet.	Extraversion (R)
14.	I'm generally trusting.	Agreeableness
15.	I tend to be lazy.	Conscientiousness (R)
16.	I have an assertive personality.	Extraversion
17.	I can be cold and aloof.	Agreeableness (R)
18.	I persevere until the task is finished.	Conscientiousness
19.	I'm sometimes shy, inhibited.	Extraversion (R)
20.	I'm considerate and kind to almost everyone.	Agreeableness
21.	I do things efficiently.	Conscientiousness
22.	I'm outgoing, sociable.	Extraversion
23.	I'm sometimes rude to others.	Agreeableness (R)
24.	I make plans and follows through with them.	Conscientiousness
25.	I like to cooperate with others.	Agreeableness
26.	I'm easily distracted.	Conscientiousness (R)
(R) = Reversed		

## IX. CONCLUSION

This study has examined the impact of chatbot-human congruence in the context of academic advising. The study has found evidence for the effect of chatbot-human congruence on user behavior, but only for participants characterized by high extraversion. However, the results for agreeable and conscientious participants and chatbots were inconclusive. The results of this study have implications for decision makers in the education sector, as personality-imbued chatbots play a significant role in enhancing the experience of participants. Future researchers should investigate a longitudinal study to examine the effect of chatbot-human personality congruence on behavior in different domains and settings. Also, we recommend the investigation of culture on chatbot-human interaction and how it influences chatbot-human personality congruence.

## INSTITUTIONAL REVIEW BOARD STATEMENT

The study was approved by the Research Ethics Committee of the University (Application No. ZU22\_011\_F).

## INFORMED CONSENT STATEMENT

Informed consent has been obtained from participants to publish this article.

## DATA AVAILABILITY STATEMENT

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

## APPENDIX

See Figures 6–9 and Tables 13–18.

**TABLE 15. Skewness and Kurtosis for the survey questions.**

Chatbot	Question Code	Skewness	Kurtosis
Conscientious Chatbot	T1	-0.370	-0.621
	T2	-0.952	0.552
	T3	-0.811	0.500
	T4	-1.051	0.528
	T5	-1.093	1.502
	T6	-0.974	0.742
	T7	-1.063	1.157
	T8	-0.932	0.403
	T9	-1.132	1.0398
	T10	-0.890	0.719
	UI1	-0.540	-0.854
	IE1	-0.366	-0.812
	IE2	-0.289	-0.763
	IE3	-0.652	-0.669
Extroverted Chatbot	T1	-0.606	-0.440
	T2	-0.889	0.656
	T3	-1.046	0.642
	T4	-1.213	1.290
	T5	-1.365	1.930
	T6	-0.873	0.436
	T7	-1.061	0.837
	T8	-0.747	-0.449
	T9	-1.172	1.230
	T10	-0.806	0.483
	UI1	-0.306	-0.576
	IE1	-0.391	-0.819
	IE2	-0.481	-0.464
	IE3	-0.797	-0.102
Agreeable Chatbot	T1	-0.302	-1.144
	T2	-0.877	0.116
	T3	-0.783	0.097
	T4	-1.243	1.218
	T5	-1.420	2.013
	T6	-0.816	-0.086
	T7	-1.089	0.979
	T8	-0.878	-0.054
	T9	-1.285	1.382
	T10	-0.976	0.215
	UI1	-0.488	-1.040
	IE1	-0.355	-1.035
	IE2	-0.321	-1.109
	IE3	-0.350	-0.969



TABLE 16. Mapping the conscientious chatbot with the conscientious personality.

	Tends to be disorganized	Tends to be lazy	Does a thorough job	Is a reliable worker	Makes plans and follows through with them	Does things efficiently	Perseveres until the task is finished	Can be somewhat careless	Is easily distracted
Chatbot Message	1R	2R	3	4	5	6	7	8	9
Hello! My name is MyAdvisor, a virtual academic advisor, I'm highly organized (1R) hard working (2R) and I do a thorough job (3). Please pay attention to my reliable (4) and well structured advice (1R) as it is essential to your success.	✓	✓	✓	✓					
I can give you exact directions (3) to help you with your academic advising inquiries, e.g. help with low grades, course projection, etc.			✓						
The university provides resources to help you with coursework, including study clubs. We can also help you with stress-related issues. Please check the timings of activities related to study clubs (3)			✓						
Please meet the instructor during office hours, or join the coding club for help. When you meet with the instructor, prepare your questions (5), and be sure to use your time well (6).					✓	✓			
Not yet - first you need to earn 13 more credit hours. We should make a well structured plan of action (5) to get to that goal as efficiently as possible (6).					✓	✓			
Attend career fairs, build connections, work on your skills, and write a good resume. With discipline and good planning, you will get there (7).							✓		
Goodbye! I hope you found advising clear, detailed (8), and on point (9).								✓	✓

TABLE 17. Mapping the extroverted chatbot with the extroverted personality.

	Generates a lot of enthusiasm	Is outgoing, sociable	Has an assertive personality	Is reserved	Is talkative	Is full of energy	Tends to be quiet	Is sometimes shy, inhibited
Chatbot Message	10	11	12	13R	14	15	16R	17R
Hey! Wow! (10) It's great to meet you (11) What is your name? (12) People call me MyAdvisor. I'm a bubbly and outgoing (13R) virtual advisor and always happy to chat (14). I can take care of your advising needs. Let's do this (15)	✓	✓	✓	✓		✓		
I'm always happy to chat (14) and we can talk about your academic-related issues. e.g. help with low grades, course projection, etc. We got this! (15)					✓	✓		
Let me offer up some good advice (12). How about you join one of our study clubs? Hey, if you feel down, the uni can also help you with stress issues.			✓					
You know what. Just meet with the instructor during office hours, or ask the coding club for help. Are you ready? Let's do this (11).		✓						
Oh wow! No one graduated that quickly (14, 16R). Just kidding (17R). Seriously, though, you can take a senior project after you finish 13 credit hours. You can do it!					✓		✓	✓
Look at you! (10) Planning ahead and thinking big! Hmm. If I were you, I'd attend career fairs, build connections, work on my skills, and write a good resume.	✓							
It was nice meeting you (11). I loved our conversation (13R). You filled my day with happiness and positive energy (15)!		✓		✓		✓		

TABLE 18. Mapping the agreeable chatbot with the agreeable personality.

	Is helpful and unselfish with others	Is considerate and kind to almost everyone	Is sometimes rude to others	Starts quarrels with others	Has a forgiving nature	Is generally trusting	Is sometimes rude to others	Likes to cooperate with others	Can be cold and aloof	Tends to find faults in others
Chatbot Message	18	19	20R	21R	22	23	24R	25	26R	27R
Hello My name is MyAdvisor. I'm a virtual academic advisor, and I will support you with any advising questions you may have (18). If I can help in other ways, I will always try my best (19)	✓	✓								
You are the boss! (21R) I'm here for you whenever you need me regarding academic issues. e.g. low grades, course selection.				✓						
So sorry to hear that (19) - but hang in there. The uni can support you. You can join one of the study clubs. Also, if you feel stressed, we are there for you.		✓								
I totally see the issue here (26R). Materials can be difficult sometimes (27R), but don't worry. Meet your instructor during the office hours, or ask the coding club for help.									✓	✓
This is a good question. I'm afraid (24R) you still need more 13 credit hours to enroll in the Senior Project.							✓			
I'm confident (23) that you can secure a job, and I will do my best to help you(18). You need to attend career fairs, build connections, work on your skills, and write a good resume.	✓					✓				
It was good (26R) working (25) with you . I hope that I was helpful (18). Again, I'm here for you (26R) - and I wish you the best!	✓							✓	✓	

## REFERENCES

- [1] K.-J. Oh, D. Lee, B. Ko, and H.-J. Choi, "A chatbot for psychiatric counseling in mental healthcare service based on emotional dialogue analysis and sentence generation," in *Proc. 18th IEEE Int. Conf. Mobile Data Manage. (MDM)*, May 2017, pp. 371–375.
- [2] M. A. Kuhail, N. Alturki, S. Alramlawi, and K. Alhejori, "Interacting with educational chatbots: A systematic review," *Educ. Inf. Technol.*, vol. 28, no. 1, pp. 973–1018, Jan. 2023.
- [3] A. Xu, Z. Liu, Y. Guo, V. Sinha, and R. Akkiraju, "A new chatbot for customer service on social media," in *Proc. CHI Conf. Hum. Factors Comput. Syst. (CHI)*. New York, NY, USA: ACM, 2017.
- [4] L. Bradeško and D. Mladenčić, "A survey of chatbot systems through a loebner prize competition," in *Proc. Slovenian Lang. Technol. Soc. Eighth Conf. Lang. Technol.*, 2012, p. 34.
- [5] N. Dauk and W. Smale. (2022). *How Human-Like Are the Most Sophisticated Chatbots?*. Accessed: Feb. 24, 2023. [Online]. Available: <https://www.bbc.com/news/business-61793984>
- [6] C. Nass, J. Steuer, and E. R. Tauber, "Computers are social actors," in *Proc. Conf. Companion Hum. Factors Comput. Syst. (CHI)*. New York, NY, USA: ACM, 1994.
- [7] C. Nass and S. Brave, *Wired for Speech: How Voice Activates and Advances the Human-Computer Relationship*. Cambridge, MA, USA: MIT Press, 2007.
- [8] S. Völkel, R. Schoedel, L. Kaya, and S. Mayer, "User perceptions of extraversion in chatbots after repeated use," in *Proc. CHI Conf. Hum. Factors Comput. Syst.*, New Orleans, LA, USA, 2022, p. 253.
- [9] M. Shumanov and L. Johnson, "Making conversations with chatbots more personalized," *Comput. Hum. Behav.*, vol. 117, Apr. 2021, Art. no. 106627.
- [10] T. Bickmore and J. Cassell, "Social dialogue with embodied conversational agents," in *Advances in Natural Multimodal Dialogue Systems. Text, Speech and Language Technology*, J. Kuppevelt, L. Dybkjaer N. Bernsen, Eds. Dordrecht, The Netherlands: Springer, 2005, pp. 23–54.
- [11] D. Byrne, G. Clore, and P. Worchel, "Effect of economic similarity-dissimilarity on interpersonal attraction," *J. Personality Social Psychol.*, vol. 4, no. 2, pp. 220–224, 1966.
- [12] P. A. M. Ruijten, "The similarity-attraction paradigm in persuasive technology: Effects of system and user personality on evaluations and persuasiveness of an interactive system," *Behaviour Inf. Technol.*, vol. 40, no. 8, pp. 734–746, Jun. 2021.
- [13] M. Braun, A. Mainz, R. Chadowitz, B. Pflöging, and F. Alt, "At your service: Designing voice assistant personalities to improve automotive user interfaces," in *Proc. CHI Conf. Hum. Factors Comput. Syst.*, New York, NY, USA, 2019, pp. 1–11.
- [14] S. Andrist, B. Mutlu, and A. Tapus, "Look like me: Matching robot personality via gaze to increase motivation," in *Proc. 33rd Annu. ACM Conf. Hum. Factors Comput. Syst. (CHI)*. New York, NY, USA: ACM, 2015.
- [15] M. Mekni, Z. Baani, and D. Sulieman, "A smart virtual assistant for students," in *Proc. 3rd Int. Conf. Appl. Intell. Syst.*, Las Palmas, Spain, 2020, pp. 1–6.
- [16] B. Ranoliya, N. Raghuvanshi, and S. Singh, "Chatbot for university related FAQs," in *Proc. Int. Conf. Adv. Comput., Commun. Inform. (ICACCI)*, Udupi, India, 2017, pp. 1525–1530.
- [17] J. Weizenbaum, "Computational linguistics," *Commun. ACM*, vol. 9, no. 1, pp. 36–45, 1966.
- [18] B. AbuShawar and E. Atwell, "ALICE chatbot: Trials and outputs," *Computación y Sistemas*, vol. 19, no. 4, pp. 625–632, Dec. 2015.
- [19] E. Adamopoulou and L. Moussiades, "Chatbots: History, technology, and applications," *Mach. Learn. Appl.*, vol. 2, Dec. 2020, Art. no. 100006.
- [20] S. B. Patel and K. Lam, "ChatGPT: The future of discharge summaries?" *Lancet Digit. Health*, vol. 5, no. 3, pp. e107–e108, Mar. 2023.
- [21] K. Jiang, M. Qin, and S. Li, "Chatbots in retail: How do they affect the continued use and purchase intentions of Chinese consumers?" *J. Consum. Behaviour*, vol. 21, no. 4, pp. 756–772, Jul. 2022.
- [22] M. A. Selamat and N. A. Windasari, "Chatbot for SMEs: Integrating customer and business owner perspectives," *Technol. Soc.*, vol. 66, Aug. 2021, Art. no. 101685.
- [23] L. Xu, L. Sanders, K. Li, and J. C. L. Chow, "Chatbot for health care and oncology applications using artificial intelligence and machine learning: Systematic review," *JMIR Cancer*, vol. 7, no. 4, Nov. 2021, Art. no. e27850.
- [24] C.-L. Yang, "The relationships between personality and Facebook photographs: A study in Taiwan," *Cogent Bus. Manage.*, vol. 6, no. 1, Jan. 2019.
- [25] A. L. Baylor, "The design of motivational agents and avatars," *Educ. Technol. Res. Develop.*, vol. 59, no. 2, pp. 291–300, Apr. 2011.
- [26] A. Kerry, R. Ellis, and S. Bull, "Conversational agents in e-learning," in *Proc. Appl. Innov. Intell. Syst. XVI*, 2008, pp. 169–182.
- [27] T. Wambsganss, R. Winkler, M. Söllner, and J. M. Leimeister, "A conversational agent to improve response quality in course evaluations," in *Proc. CHI Conf. Hum. Factors Comput. Syst.*, 2020, Art. no. 3382805.
- [28] N. Matsuda, E. Yarzebinski, V. Keiser, R. Raizada, W. W. Cohen, G. J. Stylianides, and K. R. Koedinger, "Cognitive anatomy of tutor learning: Lessons learned with SimStudent," *J. Educ. Psychol.*, vol. 105, no. 4, pp. 1152–1163, Nov. 2013.
- [29] M. Coronado, C. A. Iglesias, A. Carrera, and A. Mardomingo, "A cognitive assistant for learning Java featuring social dialogue," *Int. J. Hum.-Comput. Stud.*, vol. 117, pp. 55–67, Sep. 2018.
- [30] M. Dibitonto, K. Leszczynska, F. Tazzi, and C. Medaglia, "Chatbot in a campus environment: Design of LiSA, a virtual assistant to help students in their university life," in *Proc. Hum.-Comput. Interact. Interact. Technol.*, Las Vegas, NV, USA, 2018, pp. 103–116.
- [31] (2022). *Personality*. Accessed: Feb. 25, 2023. [Online]. Available: <https://www.apa.org/topics/personality#:~:text=Personality%20refers%20to%20the%20enduring,%2C%20abilities%2C%20and%20emotional%20patterns>
- [32] R. A. Power and M. Pluess, "Heritability estimates of the big five personality traits based on common genetic variants," *Translational Psychiatry*, vol. 5, no. 7, pp. e604–e604, Jul. 2015.
- [33] E. R. Thompson, "Development and validation of an international English big-five mini-markers," *Personality Individual Differences*, vol. 45, no. 6, pp. 542–548, Oct. 2008.
- [34] C. G. Jung and A. Jaffe, *Memories, Dreams, Reflections*. New York, NY, USA: Vintage Books, 1989.
- [35] S. B. Kaufman, D. B. Yaden, E. Hyde, and E. Tsukayama, "The Light vs. dark triad of personality: Contrasting two very different profiles of human nature," *Frontiers Psychol.*, vol. 10, p. 467, Mar. 2019.
- [36] P. Bremner, O. Celiktutan, and H. Gunes, "Personality perception of robot avatar tele-operators," in *Proc. 11th ACM/IEEE Int. Conf. Hum. Robot Interact. HRI (Christchurch)*, Christchurch, New Zealand, 2016, pp. 141–148.
- [37] C. Nass and K. Lee, "Does computer-synthesized speech manifest personality? Experimental tests of recognition, similarity-attraction, and consistency-attraction," *J. Exp. Psychol. Appl.*, vol. 7, no. 3, pp. 81–171, 2001.
- [38] M. A. Kuhail, J. Thomas, S. Alramlawi, S. J. H. Shah, and E. Thornquist, "Interacting with a chatbot-based advising system: Understanding the effect of chatbot personality and user gender on behavior," *Informatics*, vol. 9, no. 4, p. 81, Oct. 2022.
- [39] A. Zogaj, P. M. Mähner, L. Yang, and D. K. Tscheulin, "It's a match! The effects of chatbot anthropomorphization and chatbot gender on consumer behavior," *J. Bus. Res.*, vol. 155, Jan. 2023, Art. no. 113412.
- [40] E. Kang and Y. A. Kang, "Counseling chatbot design: The effect of anthropomorphic chatbot characteristics on user self-disclosure and companionship," *Int. J. Hum.-Comput. Interact.*, pp. 1–15, Jan. 2023.
- [41] L. K. Kamrath, D. R. Ames, and A. A. Scholer, "Keeping up impressions: Inferential rules for impression change across the big five," *J. Experim. Social Psychol.*, vol. 43, no. 3, pp. 450–457, May 2007.
- [42] O. P. John and S. Srivastava, "The big five trait taxonomy: History, measurement, and theoretical perspectives," in *Handbook of personality: Theory and Research*, L. A. Pervin O. P. John, Eds. New York, NY, USA: Guilford Press, 1999, pp. 102–138.
- [43] E. L. Kelly, "Consistency of the adult personality," *Amer. Psychologist*, vol. 10, no. 11, pp. 659–681, 1955.
- [44] B. I. Murstein, "The complementary need hypothesis in newlyweds and middle-aged married couples," *J. Abnormal Social Psychol.*, vol. 63, no. 1, pp. 194–197, Jul. 1961.
- [45] C. Izard, "Personality similarity and friendship," *J. Abnormal Social Psychol.*, vol. 61, no. 1, pp. 47–51, 1960.
- [46] H. Chung, M. Iorga, J. Voas, and S. Lee, "Alexa, can i trust you?" *Computer*, vol. 50, no. 9, pp. 100–104, 2017.
- [47] A. Przegalinska, L. Ciechanowski, A. Stroz, P. Gloor, and G. Mazurek, "In bot we trust: A new methodology of chatbot performance measures," *Bus. Horizons*, vol. 62, no. 6, pp. 785–797, Nov. 2019.



- [48] L. Müller, J. Mattke, C. Maier, T. Weitzel, and H. Graser, "Chatbot acceptance: A latent profile analysis on individuals' trust in conversational agents," in *Proc. Comput. People Res. Conf.*, Nashville, TN, USA, 2019, pp. 35–42.
- [49] F. Reinkemeier and U. Gnewuch, "Match or mismatch? How matching personality and gender between voice assistants and users affects trust in voice commerce," in *Proc. 55th Hawaii Int. Conf. Syst. Sci.*, Lahaina, HI, USA, 2022, p. 528.
- [50] H.-Y. Shum, X.-D. He, and D. Li, "From eliza to XiaoIce: Challenges and opportunities with social chatbots," *Frontiers Inf. Technol. Electron. Eng.*, vol. 19, no. 1, pp. 10–26, Jan. 2018.
- [51] E. Ruane, S. Farrell, and A. Ventresque, "User perception of text-based chatbot personality," in *Proc. Chatbot Res. Des.*, Cham, Switzerland, 2021, pp. 32–47.
- [52] U. Gnewuch, S. Morana, M. T. P. Adam, and A. Maedche, "Opposing effects of response time in human–chatbot interaction," *Bus. Inf. Syst. Eng.*, vol. 64, no. 6, pp. 773–791, Dec. 2022.
- [53] S. Völkel and L. Kaya, "Examining user preference for agreeableness in chatbots," in *Proc. 3rd Conf. Conversational User Interfaces*, Bilbao, Spain, 2021, pp. 1–6.
- [54] A. A. Alalwan, "Mobile food ordering apps: An empirical study of the factors affecting customer e-satisfaction and continued intention to reuse," *Int. J. Inf. Manage.*, vol. 50, pp. 28–44, Feb. 2020.
- [55] S. Pace, "A grounded theory of the flow experiences of web users," *Int. J. Hum.-Comput. Stud.*, vol. 60, no. 3, pp. 327–363, Mar. 2004.
- [56] D. George and M. Mallery, *SPSS for Windows Step-by-Step: A Simple Guide and Reference*, 14.0 update, 7 ed. Boston, MA, USA: Allyn & Bacon, 2006.
- [57] J. Hair, W. C. Black, B. J. Babin, and R. E. Anderson, *Multivariate Data Analysis*, 7th ed. Upper Saddle River, NJ, USA: Pearson Educational International, 2010.
- [58] B. M. Byrne, *Structural Equation Modeling With AMOS: Basic Concepts, Applications, and Programming*. New York, NY, USA: Routledge, 2010.
- [59] C. Qin, W. Huang, and K. Hew, "Using the community of inquiry framework to develop an educational chatbot: lesson learned from a mobile instant messaging learning environment," in *Proc. 28th Int. Conf. Comput. Educ.*, 2020, pp. 69–74.
- [60] S. Boslaugh and P. A. Watters, *Statistics in a Nutshell: A Desktop Quick Reference*. Sebastopol, CA, USA: O'Reilly Media, 2008.
- [61] H. S. Friedman and M. W. Schustack, *Personality: Classic Theories and Modern Research*, 5th ed. London, U.K.: Pearson, 2010.
- [62] X. Deng and Z. Yu, "A meta-analysis and systematic review of the effect of chatbot technology use in sustainable education," *Sustainability*, vol. 15, no. 4, p. 2940, 2023.
- [63] M. Mateos-Sanchez, A. C. Melo, L. S. Blanco, and A. M. F. García, "Chatbot, as educational and inclusive tool for people with intellectual disabilities," *Sustainability*, vol. 14, no. 3, p. 1520, Jan. 2022.
- [64] R. K. Solanki, A. S. Rajawat, A. R. Gadekar, and M. E. Patil, "Building a conversational chatbot using machine learning: Towards a more intelligent healthcare application," in *Handbook of Research on Instructional Technologies in Health Education and Allied Disciplines*, M. B. Garcia, M. V. L. Cabrera and R. P. de Almeida, Eds. Hershey, PA, USA: IGI Global, 2023, pp. 285–309.
- [65] J.-E. Bibault, B. Chaix, A. Guillemassé, S. Cousin, A. Escande, M. Perrin, A. Pienkowski, G. Delamon, P. Nectoux, and B. Brouard, "A chatbot versus physicians to provide information for patients with breast cancer: Blind, randomized controlled noninferiority trial," *J. Med. Internet Res.*, vol. 21, no. 11, Nov. 2019, Art. no. e15787.
- [66] A. Zand, A. Sharma, Z. Stokes, C. Reynolds, A. Montilla, J. Sauk, and D. Hommes, "An exploration into the use of a chatbot for patients with inflammatory bowel diseases: Retrospective cohort study," *J. Med. Internet Res.*, vol. 22, no. 5, May 2020, Art. no. e15589.
- [67] A. K. Kushwaha and A. K. Kar, "Language model-driven chatbot for business to address marketing and selection of products," in *Re-Imagining Diffusion and Adoption of Information Technology and Systems: A Continuing Conversation* (IFIP Advances in Information and Communication Technology), vol. 617, S. K. Sharma, Y. K. Dwivedi, B. Metri, and N. P. Rana, Eds. Cham, Switzerland: Springer, 2020, doi: 10.1007/978-3-030-64849-7\_3.
- [68] A. Janssen, D. R. Cardona, and M. Breiter, "More than FAQ! Chatbot taxonomy for business-to-business customer services," in *Proc. Chatbot Res. Des.*, 2020, pp. 175–189.
- [69] Y. Zhang, W. Song, Z. Tan, H. Zhu, Y. Wang, C. M. Lam, Y. Weng, S. P. Hoi, H. Lu, B. S. M. Chan, J. Chen, and L. Yi, "Could social robots facilitate children with autism spectrum disorders in learning distrust and deception?" *Comput. Hum. Behav.*, vol. 98, pp. 140–149, Sep. 2019.
- [70] T. R. Graeff, "Image congruence effects on product evaluations: The role of self-monitoring and public/private consumption," *Psychol. Marketing*, vol. 13, no. 5, pp. 481–499, Aug. 1996.
- [71] S. Y. Chien, M. Lewis, K. Sycara, J. S. Liu, and A. Kumru, "Relation between trust attitudes toward automation, Hofstede's cultural dimensions, and big five personality traits," in *Proc. Hum. Factors Ergonom. Soc. Annu. Meeting*, 2016, Accessed: Feb. 25, 2023.



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