

Master's Thesis

# Personalized Personality Virtual Agents

Stephen Harianto



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# Personalized Personality Virtual Agents

Assessing the impacts of virtual agent's personality match on user's trust, personal attachment, perceived risk and purchase intention in e-commerce

## MASTER'S THESIS



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## Preface

Over the course of 17 years and 16 bombings, the UNABOMB (UNiversity and Airline BOMber) case had become the longest and costliest investigation of FBI's history. Homemade bombs were sent via US mail services, killing three people and injured 23 others in an attempt to start a revolution against technology and industrialization. Investigators had been left in despair with untraceable evidences, no fingerprints nor DNA, but the mastermind's letters and grand manifestation. It was only in 1995 that James R. Fitzgerald was tasked to help profile the wrongdoer. He started analyzing the writings to help pinpoint demographic profile of the suspect, pioneering a new field of *linguistic forensic* in the history of criminal profiling. Fitzgerald successfully identified the word cues to derive many things that finally led to the arrest of Ted Kaczynski in 1996. The research of language, however, has been long studied in the academic world, but the immense application has only been extensively developed in recent decades. Unplanned, I found myself both surprised and honored that I would stumble into this field and be performing research in a similar domain for my master's thesis. For the past six months, I had been conducting research in the field of psycholinguistics, investigating the effects of chatbot personality matching to different user personality for e-commerce. The nuances in their language signal the distinctive personalities and participants were asked to assess their interaction during an online purchase scenario. I have consequently become the father of five chatbots, each blessed with different personalities, along with their silly emoticons, GIFs and remarks. After six tireless months, I have come at the end of my research and I bid my farewell to these chatbots.

In celebration of this important milestone, I would like to acknowledge the most influential actors along this journey. First and foremost, I would like to extend my deepest gratitude to my parents. This master's title is the first ever education achievement that is self-funded without their 'scholarship'. While I may be proud of this accomplishment, I could still never repay their never-ending prayers, support and encouragement from 11,340 kilometers away. Second, my acknowledgement goes to my graduation committee, Dr. Laurens Rook as my main supervisor and Dr. Stephan Lukosch as my second supervisor and chairman. I am mostly thankful to Dr. Rook for his guidance and such thoughtful insights into the research methods that played the most crucial role in my research and nobody else deserves a higher credit for this research than him. Our Skype and cubicle meetings will surely be missed.

Third, I am hugely indebted for Dennis de Vries as my company supervisor. He has been very helpful in giving me insights into the world of technology consulting. His critical feedback has proved to be a great aid from time to time and he has become such a good friend at Deloitte. I am also thankful to Tim Crone who has done similar research in the past and has given his insightful lessons-learned. This opportunity would also not have been possible without Deloitte and the Cognitive Engagement team, for giving me the opportunity to do my thesis at this wonderful consulting environment. Under the leadership of Hugo van den Berg, I could not have asked for a better team and the team's hospitality during my tenure at the company. Last, I wish to thank all my friends with whom we struggled together for the past two years.

Going back to school after working was not a small price to pay. This thesis marks the end of my two-year journey and let this thesis be an emblematic reminder of the sacrifice and achievement. The end of this milestone might be imminent, but a new milestone is just right around the corner. Graduation, here I come!

Den Haag, September 2018

Stephen Harianto

## Executive Summary

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The ever-increasing competition has led firms to higher adoption rate of technology to drive business efficiency and operation. One of the disruptive technologies of this century is Artificial Intelligence (AI), with virtual agents as one of its application. To get the maximum value of virtual agents, businesses attempt to personalize their chatbots by understanding their customers, using e.g. big data and machine learning. Together with the need for more humanlike cognitive agents, this study has proposed to approach personalization of chatbots through the matching of personality between users and chatbots. Surprisingly, personalization through chatbots personality (botsanality) has escaped the attention of the academic world. To date, this research is the first and only research in this specific topic. Therefore, the present research also hopes to be able to provide an important benchmark for future research. With participating collaborators that consist of TU Delft and Deloitte, it was decided that the testing scenario of this research would be focused for e-commerce application, where participants would ask for a product recommendation.

As a way to match personality, the Big Five personality theory (i.e. extraversion (E), agreeableness (A), conscientiousness (C), openness (O) and neuroticism (N)) was chosen as the personality model for this research. The research hinged on the similarity theory, which posits that individuals are more attracted to other individuals with similar traits and personalities. Therefore, it was hypothesized that when the personality is matched, it would result in increased purchase intention of the recommended product, that is mediated by increased trust and decreased perceived risk towards the chatbot.

Five different chatbots with each different personality combinations were created (OCEAN, OCEA, CEA, CE and C) and randomly assigned to the list of participants. The personality was projected linguistically through the words in recorded conversations (movies). In total, there had been two experiments for this study. First, participants were collected from a range of personal network and Amazon Mechanical Turk service. However, due to poor data quality, the first experiment's result was deemed unfit for further analysis. A second experiment was therefore conducted with different list of participants, as well as improved with methodology.

Among all main and interaction effects analyzed, the present research did not result in statistically significant results, which consequently meant that the hypotheses had to be rejected. Matched personality did not bring about any significant effects. Trust was the only factor that significantly resulted in increased purchase intention. Alternatively, the research also looked into the independent effects of chatbot personalities. The combination of trust and two chatbot personalities (OCEA and C) showed significant results towards purchase intention.

By being the first in the topic, the findings from this research have several implications. First, the lessons learned from the methodology would be of great contribution for future research. Second, the study showed the complexity in personality matching, from the side of the users, as well as the projection of chatbot personalities into the conversations. Therefore, this paper also invites future research to join and structurally come up with better methodologies and technology with better foundation in psychology and computer science (artificial intelligence).

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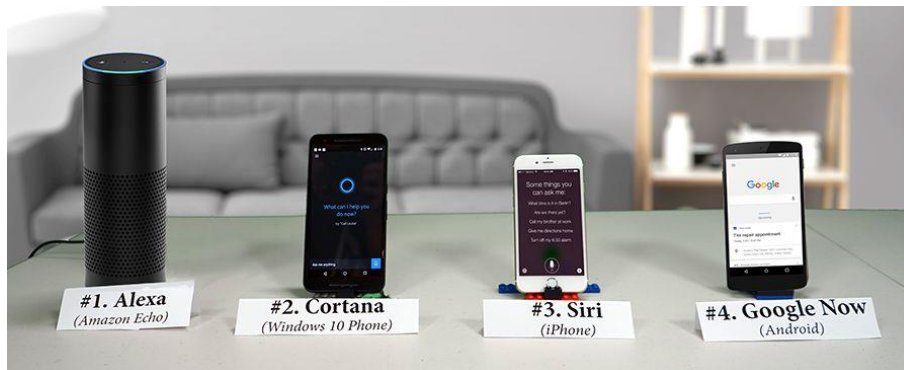
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## 1. Introduction

### 1.1. Background

In order to stay competitive in the current fast-paced, ever-increasing competition and global environment, organizations continually look for ways to implement effective business operations, while adding values into their business. For the past decades, organizations have resorted to technology in gaining the competitive advantage they need, with one of the disruptive technologies being Artificial Intelligence (AI). AI has been the driving force behind many transformations in sophisticated sectors which involves a substantial portion of knowledge work, such as finance and healthcare. As its name would imply, AI is complex computer program that is capable of mimicking and performing complex human tasks. These tasks might include detecting medical conditions, information search, image recognition, and many more. As we speak, its capabilities are kept being extended and never stop to amaze humans.

What used to be one of the main challenges in AI, i.e. to understand human language, we can already find an abundance of well-developed natural language technology in recent decades. From airline reservation to product catalogs, these so-called virtual assistants act as individual's personal assistant to perform tasks or services, e.g. Apple's Siri or Amazon's Alexa. Another similar variant of virtual assistants, called **virtual agents**, is a software agent that performs tasks at customer service centers or helpdesks. They are also known as **chatbots**, where the main medium of communication is served through instant messaging (IM). While many focus their services through instant messaging, it is not rare to see these cognitive agents also being deployed in other popular media, such as e-mail clients, social networking websites and online games (Varnhagen et al., 2009).

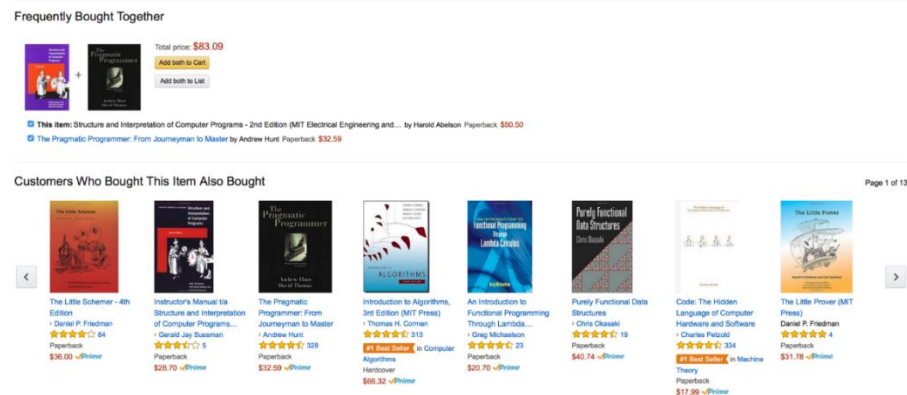


**Figure 1** Some examples of well-known virtual assistants (USA Today, 2016)

Meanwhile, the consumer shift towards messaging platforms make chatbots increasingly essential in providing fast and smart service/assistance to consumers or employees in any fields. The convergence of market forces such as slow growth in mobile apps and changing consumer demographics towards communicating using commands has directly contributed to the rise of virtual agents (Yuan, 2016). Consequently, virtual agents increasingly play a role in human-computer interaction, assisting users in various areas such as education, marketing, health care and daily tasks. In fact, experts predicted that by 2020, 85% of all customer interactions will be handled by virtual agents. As it becomes a dominant force in our society, the interests are now shifting towards building intelligent systems that are more human-aware and trustworthy (IBM, 2017a).

At the same time, companies have started to add values in their business by personalizing their services, tailoring to each user's needs. Personalization greatly empowers firms to predict and identify customer needs, as well as reacting to queries more effectively, thereby improving the interaction, customer satisfaction, improve sales conversion and promote repeat purchases (Shahin & Jamshidian, 2006). With

the abundance of data available nowadays, managers and marketers are able to make more informed and insightful decisions through a more personalized and focused service for customers. What used to be that advertisers could easily determine their next move with standard market research, the future in communication success highly hinges on their ability to make the brand experience more personalized. The level of personalization can range from simple product recommendations based on past purchases, to websites that are tailored real-time to an individual customer's reading level and even personality (Tkalcic & Chen, 2015)



**Figure 2** Amazon's recommender system (Valencia, 2017)

Despite the many attempts to personalize various services, personalization in virtual agents are seldom observed. This can be well understood with virtual agents' lifecycle still in its infancy. Nevertheless, there still have been some studies that pioneered the research in virtual agent's personalization. One of such studies, for instance from Shamekhi, et al. (2017), has investigated different user preferences towards virtual agents' conversational style.

Meanwhile, marketers are also increasingly learning about users' personalities as a way to understand and personalize their target audience better. Instead of focusing on stereotypes, they would like to understand the personality of each individual consumers, in order to know the factors that make their target tick and therefore develop a more targeted marketing campaign. As an example, IBM (2017b) have managed to use customer text-based data (e.g. social media), to derive a user profile that can be used to understand the customers and increase the level of personalization.

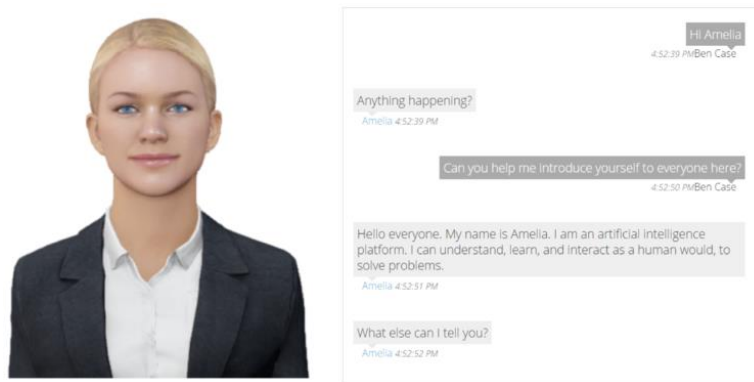
Personality could be described as one of the major deciding factors in social interaction. Whether the communication will run efficiently or muddly, often depends on the personality of its parties. Nass and Lee (2001) revealed that people consider computers as another social actor, applying social rules such as norms, personality attraction and gender differences. According to studies by Byrne and Griffitt (1973), people are generally most attracted to others with whom they share similar attitudes and styles. These studies would then imply that customers would want to interact with virtual agents with similar personality. This line of reasoning led the researcher to design an experiment to investigate the role of matching the virtual agent's personality (also known as *botsanality*) in human-agent interaction, as a crucial step towards personalization.

The significant amount of attention and investment in the design of realistic virtual agents offers a promising future in which virtual agents (and robots) will be able to provide a wide range of personalized and humanlike behaviors in social interaction. Addressing these research gaps will improve our understanding in the impact of personalized botsanality in improving the overall quality of human-agent interaction.

## 1.2. Scope

The research is conducted as a master thesis in Management of Technology at Technical University of Delft. The thesis is also a part of a six-month internship at Deloitte Digital in Amsterdam, specifically within the Cognitive Engagement (CE) team and under the Customer Solutions (CS) service line. While the CS service line generally deals with delivering technology-related added-value solutions to the customers, the CE team works on advising its customers on virtual agents strategy as well as its implementation.

The market for virtual agents could be generally categorized into three segments: first, Virtual Personal Assistants (VPAs), such as Apple's Siri or Amazon's Alexa (Kěpuska & Bohouta, 2018); second, Cognitive Virtual Agents (CVAs) that represent a company while assisting customers, e.g. KLM's Messenger chatbot; and third, CVAs that assist employees of a firm internally, e.g. Ubisend's HR chatbot (Lacity, Willcocks & Craig, 2017). Due to the larger business opportunity and expertise that the Deloitte team is focusing on, the main focus of this research will be on the Cognitive Virtual Agents.



**Figure 3** IPsoft's Amelia (virtual agent/chatbot) in action (Business Insider, 2016)

Deloitte is particularly interested in investigating the impact of the mentioned research for e-commerce application. Due to the rapid e-commerce growth, purchase decisions are increasingly made in an online environment, which offers consumers great convenience, extended product choice, and an abundance amount of product-related information. However, as a result of the cognitive constraints of human information processing and ever complex online environment, finding products that meet their needs has become a difficult task. For this reason, quite a few online stores have made virtual agents available to assist consumers in the effort to improve customer loyalty and increase sales (Detlor and Arsenault, 2002). Therefore, the researcher would like to focus his research on e-commerce for supporting product search and evaluation. Moreover, the research will only investigate one personality profile of the users, i.e. extraversion, as a way to keep the research simple, yet still acts as a reference for future research.

## 1.3. Problem Definition

### 1.3.1. The Humanness of Computers, Its Personalities and the Big Five

As virtual agent applications widely spread into everyday state of affairs, there is a rapidly growing need for humanlike autonomous agents (Lortie & Guitton, 2011). Research studying human-computer interaction found that humans tend to anthropomorphize computers (Breazeal, 2002). In other words, it suggested how people attribute human qualities to those machines and prefer to interact with more humanlike computers (Lee & Nass, 2004). This paradigm is also called the "CASA" or "Computers Are Social Actors" (Nass, Steuer & Tauber, 1994). For example, they found that people apply politeness norms to computers, as well as applying gender stereotypes to computers.



These findings then enforce the humanization of machines as one of the top imperatives in the near future. This ambition has therefore brought researchers to equip computers with various features and capacities that can make them persuasively more ‘humanlike’. For instance, one of the key focal points of the human factor is to focus on the way the computers communicate with humans, more specifically virtual agents. However, communication between humans and virtual agents is rarely studied and has thus received minimal empirical attention (Holtgraves et al., 2007). There have only been a small number of studies that improved virtual agents by controlling specific aspects in human-computer interactions, such as, facial cues (Giard & Guitton, 2010), avatar (Alissandrakis, Nehaniv & Dautenhahn, 2004), physical movements (Bailenson & Yee, 2005), or voice (Nass, Moon & Green, 1997) in recent decades. Still, endeavors to convince users of the humanness of such agents have been met with nominal success (Korukonda, 2003).

Nevertheless, those studies concluded physical factors as just one of the elements in determining the humanness of such artificial agent (Lortie & Guitton, 2011). They implied that the behavior of such agents as the central component of humanlikeness. Humanlike agents, therefore, should be able to demonstrate cutting-edge cognitive capabilities, e.g. language skills, in order to be seen as dependable communication companion (Dautenhahn, 2007). This rings well with early research in Artificial Intelligence that has been focusing on language as the main output of the humanness factor (French, 2000).

Language in this context may be redefined as a way one expresses his/her thoughts and feelings. Upon thinking the factors that affect language use, one can think of culture, intelligence and personality as the main influences (Lee et al., 2007; Sanford, 1942). Not surprisingly, each person differs considerably from each other in their language use. From the many factors, many have especially linked language use to different personality traits (Sanford, 1942; Fast & Funder, 2008; Hirsh & Peterson, 2009; Yarkoni, 2010). Those systematic research has shown that word usage seems to be characterized by the individual’s personality. Linguistic differences have therefore become an important constant in personality psychology (Hirsh & Peterson, 2009). It is clear that those who would like to improve the language use of virtual agents should pay attention to these personality traits.

Nevertheless, there has been minimal attention spent on developing virtual agent’s (linguistic) personalities. Personality is a stable set of characteristics that determine one’s commonalities and differences with others in thoughts, feelings, and actions (Maddi, 1989). As Nass et al. (1995) well put it: “Personality affects both the *nature* of, and the *responses* to, the interaction”. From the many individual personality dimensions that have been identified, the “Big Five”: extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience, theoretically and empirically captures the essence of one’s personality (Digman, 1990). Among the many Big Five research, its main focus has always been found on the humans, but non-existent on the virtual agents side. Meanwhile, a few research have suggested how chatbots or computers are perceived to have certain personalities (Nass et al., 1995; Dautenhahn, Ogden & Quick, 2002). Up to this point, enterprises have designed virtual agents personality using generic brand personality or by copying human personalities.

To the author’s knowledge, there has not been any Big Five studies or structural academic attempts on the design or impacts chatbots/computer personalities. This knowledge gap is rather surprising, imagining the many benefit of giving well-defined personality traits to chatbots. As explained earlier, personality plays an important role in word/language use, which in turn anthropomorphizes objects (virtual agents). Many questions would then arise when chatbot personalities come into the equation, such as the type of botsanalties that would be the most powerful to achieve a task or to communicate effectively with a consumer. These questions would require us to investigate the design of botsanalties, along with its theoretical and practical implications. For now, there is simply too little to know about botsanalties, let alone the optimal botsanalties.

### 1.3.2. The Relationship Between Personality and Interpersonal Interaction

Knowing that computers are perceived to have some degree of personalities, the next question would be to ask if humans would respond the same way to computers, as they would to other fellow humans. A good starting line would be to first see how personality affects human-human interaction and compare that to human-computer interaction. As a start, the author has set his eyes on the similarity attraction theory. The theory posits that individuals are attracted to other people who are similar to themselves (Byrne & Griffitt, 1973). For instance, studies have demonstrated that people prefer strangers who have similar personalities to their own, compared to strangers with different personalities (Byrne & Griffitt, 1973). This theory has also been found true on other relationships, such as friends, roommate, and spouses (Bruch & Gilligan, 1980; Eysenck & Wakefield, 1981). Fortunately, Nass et al. (1995) found that while true for human-human interaction, the similarity attraction theory has also been found to be true in human-computer interaction, e.g. dominant users are more attracted to more ‘dominant’ computer and the opposite is true for submissive users in the Desert Survival Problem case. Moreover, another similar research for the News and Entertainment Guide application also found that when the personality of a computer is matched with the users’ personalities, users found that the humor, music, and health advice (which was undistinguishable for all participants) to be perceived better (Moon, 1998). Another study also found it true in synthesized voice (Nass & Lee, 2001).

Nevertheless, those findings are concluded on the basis of basic and simple computers that are really different from the complexity of virtual agents. However, they still share the common textual-based medium and therefore should resemble similar results when adjusted to the context of virtual agents. Therefore, it would be interesting to see if such paradigm would also be found in human-chatbots interaction, more specifically in the context of e-commerce. Would matched personalities result in more sales and consumer satisfaction? These are the problems that the present study is aiming to answer.

### 1.4. Research Objectives

The problems presented above trigger the need for this present study. The research therefore aims to deliver three objectives. First, it intends to shed some light to the fact how different people should be approached differently if we want to communicate effectively. This allows any virtual agents to adapt her personalities accordingly so that (s)he could deliver a personal service to every customer, leading to a personalized chatbot. We would do this by exploring the difference in impact between every chatbots personalities and by focusing only on one personality (i.e. extraversion). The end result of this objective would be to present the ‘best’ personality matching, by measuring trust, personal attachment, perceived risk and purchase intention, which will be explained in future chapters.

Second, there have been no virtual agents that are equipped with personality adaptation at the time of writing. The two most advanced virtual agents: IBM Watson personalizes the responds and suggestions through customers’ data, while Amelia adapts her responses to the client’s emotional responses. Personality of chatbot is still developed manually by a team of programmers and poets/screen writers/marketers, at the beginning of its development (Dwoskin, 2016). The botsanalities are built according to the job description and how it should represent the company. By being the frontrunner on this specific topic, this research will then lay the ground or a starting line for future improvements, as well as an important reference for future research on how personalities can be designed and projected in ‘artificial’ conversations. Hence, the researcher hopes to deliver a set of recommendations and lessons learned from designing artificial personalities and the projected conversations.

Additionally, any technology advances will require certain resources, be it money, supporting technology, facility or expertise, depending on its level of complexity. The decision by firms to pursue a path of technology will be based on the expected return and the required resources/investments. Therefore, the



results of this research will answer whether personality development by matching the botsanality to its users' personality is worth the time and investment.

### 1.5. Research Question

Based on the research problem and objectives that have been laid out, the main research question of this research would therefore be:

*RQ: What impacts would a personalized botsanality have on its customer experience?*

In order to answer the main research question, the study has broken it down into several sub-research questions. First, to be able to come up with new insights in the field of artificial intelligence, artificial psychology and the human-computer interaction, a personified chatbot has to be simulated and experimented on. Therefore, the author needs to decide on the best way to conduct the experiment, based on the available time and resources. An option is to conduct the research with real experiment, in which participants would be interacting with a real chatbot. That would mean two things; a robust design of a chatbot needs to be built, or a moderately designed chatbot needs to be built and interacted with in a controlled and restricted environment. Another option is to conduct a vignette, where a recorded conversation between the chatbot and the user will be shown, and the participants will be asked to imagine themselves as the user. Upon deciding between the two options, the author has to decide on the advantages and disadvantages of each options and possibly compare the method of experiments from other similar research, if any. Sub-RQ1 is then arranged as follows:

*Sub-RQ1: What are the possible ways to design a robust human-virtual agents interaction experiment?*

After choosing an option to design the chatbot experiment, the author needs to gain a deeper understanding in designing the chatbot personalities. One of the contributions and main challenge of this research is on projecting the different personalities in the artificial conversations. To create the desired botsanality, knowing exactly how the different botsanalties will be concretely projected through words in the chats is of utmost importance. Exploring this question will also give an insight on the current existing process in developing botsanalties and provide a suggestive direction on how to improve the process. Sub-RQ2 is then arranged as follows:

*Sub-RQ2: How do we design artificial conversations to correctly project the desired personalities?*

Yet after having the chatbots designed to have certain "supposedly desired" personalities, it is expected that it is still highly subjective and biased towards the maker of the chatbots. There needs to be a pretest which tests these chatbots personalities objectively. First, textual AI-powered services like IBM Personality Insight can provide an easy way to analyze the conversations and ultimately provide the Big Five personalities. A second option is to present the chatbots to some users and see how they perceive them, by answering the Big Five scale. There is strong evidence that by the time people reach adulthood, they have no problem in recognizing and describing other people's personalities (Feldman & Ruble, 1981). Personality researchers would also agree that there must be some consensus between the observers' perceptions and the target's personality (Kenrick & Funder, 1988). This is also supported by the finding that humans do find certain degree of personalities in computers (Nass et al., 1995). Sub-RQ3 is then arranged as follows:

*Sub-RQ3: How do we objectively pretest the designed chatbot personalities?*

As it will be explained in future chapters, the answer to the main RQ will be quantitatively measured by four variables: trust, personal attachment, perceived risk and purchase intention. The last sub-RQ is meant to validate the scales and results statistically. This question will be answered by performing the experiment and eventually confirmed by statistical analyses. Sub-RQ4 is then arranged as follows:

*Sub-RQ4: What would be the effect(s) of matched and unmatched extraversion traits?*

## 1.6. Research Approach

The above research objectives and questions can only be respectively achieved and answered with a proper and well-designed approach. This research approach is laid out as follows. First, the literature review will cover a large majority in the early phase of the research. The first sub-RQ leaves the author with the option of building a real chatbot versus recorded chatbots. From various literatures and existing studies, the author has compared various existing methods in chatbot experiments. The former requires an extensive amount of time and accumulated knowledge in a specific bot platform to be able to build a chatbot that can endure experiments in a robust manner. Experiments done in this manner have always been strictly controlled and have small degree of freedom in terms of the way the respondents can respond. Meanwhile, the latter is admittedly easier to implement and requires the author to focus on the important variables at play. Rather than focusing on the technicality of building a robust chatbot, the researchers can focus on the main variables of interest. Depending on the availability of resources (time and skills) as well as the types of research question and research, both methods are equally popular in existing studies.

**Table 1** Research Strategy

Sub-RQ		Research Action(s)	Deliverable(s)
1	What are the possible ways to design a robust human-virtual agents interaction experiment?	Literature Review	A robust method to design a chatbot experiment
2	How do we design artificial conversations to correctly project the desired personalities?	Literature Review	Literature-backed chatbots with personalities in the form of artificial conversations
3	How do we objectively pretest the designed chatbot personalities?	Literature Review Qualitative Analysis	Pretest methodology and objectively measured chatbots
4	What would be the result of matched and unmatched extraversion traits?	Statistical Analysis	Statistically analyzed and validated results

As it will be explained in future chapters, this research selects the second approach and approaches personality from a psychological, that is linguistic personality, rather than technological perspective. The idea that the creation of personality requires richly defined agents and advanced natural language processing is a prevalent one in the field of human-computer interaction. In contrast, this research demonstrated that personality can be created using a simple, simulated scripted responses (Nass et al., 1995). At the same time, this approach will save a lot of time rather than risking building frail chatbots with such limited time and resources.

Second, further literature review will provide reasonings in deciding whether projecting the personalities on the conversations should either be approached using the Linguistic Inquiry and Word Count (LIWC) dictionary, ordinary literatures on linguistic personalities or a mix of both approaches. This is also highly related and will in fact go on reciprocity with the pretest approach (sub-RQ3). In the event of using

participants for the pretest, the inputs from the participants will be qualitatively evaluated. Last, subsequent to building a supposedly objectively-validated chatbots with personalities, the real experiment will be conducted and followed by statistical analysis. The research approach overview is shown in **Table 1**.

### 1.7. Research Relevance

Artificial Intelligence offers the ability to amplify the current capacity of companies' economic growth and individuals' productivity. Not only does the technology present the possibility of replacing human labor, it can also complement it. A study by Accenture and Frontier Economics has projected a 10-40% labor productivity increase by 2035 with the use of Artificial Intelligence (Accenture, 2018).

Meanwhile, the use of virtual agents is also not to be underestimated. Not only does it play a role in helping businesses save costs, it also drives revenue and customer satisfaction. There are over 270 billion service calls annually, from which 50% of first calls went unresolved (IBM, 2013). Before the implementation of virtual agents, the average Mean Time to Resolve (MTTR) is 18.2 minutes, while the Average Speed of Answer (ASA) is 55 seconds. In the case of Amelia, both the MTTR and ASA have been reduced to 4.5 minutes and 2 seconds, respectively (IPsoft, 2017). Furthermore, cost of live agents could range from \$5 to \$35 per call (5-7 minutes per call), not to mention its lack of scalability and expensive training up to \$5000 per agent (Inteliwise, 2016). A study from IBM (2017c) stated a 60-80% of cost savings when virtual agents is used. Another common problem is employee turn-over, something that can be mitigated with the use of virtual agents. A recent study by Salesforce (2015) stated that 72% of millennials believe that phone call is not the best way to resolve their issues. The tech-savvy generation often turns into self-service solutions, e.g. social media, FAQ, or online chatbot. Along with the rise of messaging applications, all these factors have converged to imply the potential and market size of cognitive agents. Further development of virtual agents therefore makes a lot of economic sense.

Moreover, companies that have been striving for digital transformation, find values in digitizing and strengthening customer relationships across multichannel to develop a simpler and more personal relationship with the brand. It goes as far as fundamentally transforming the company's business to ensure lower cost, agility and leanness. Digitized business enables data to be used in many meaningful ways. However, in the midst of information overload, an understanding and accurate virtual agent will serve an important function of recommender systems in helping people make better decisions. Personalization in general provides businesses with better lead generation, finer-grained customer segmentation and more effective (focused) marketing that is more relevant and personalized.

In the context of e-commerce, by providing recommendation based on user-specified preferences, shopping history, or other consumers with similar profiles, virtual agents help to reduce information overload and search complexity, while improving their decision quality (Chiasson et al., 2002). Users' awareness about the degree to which the virtual agents are personalized and understand them are key contributing factors in the adoption path (Komiak & Benbasat, 2006). At the same time, marketers, designer and product owners also are thinking hard about how they differentiate and personalize the user experience. Incorporating personalities into virtual agents might then play a major role in differentiating their product, through more entertaining, engaging, personal and life-like conversations.

The current study therefore serves to understand the complex behavior of individual consumers. In addition, Jacob (2017) mentioned the importance of botsanality on how it could provide a much richer and more memorable experience, projecting the company's image and brand. By showing the need for both personalization and botsanality, the researcher hopes to have argued for the significance of the research. Findings from this research will also benefit Deloitte in their understanding of the crucial underlying factors when implementing chatbots.

## 1.8. Report Structure

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This report is organized as follows. As seen, the first chapter of this report has provided the necessary introduction related to this research, along with several rationales why the present study is relevant and important. Next, literature is reviewed in **Chapter 2**. This chapter explains the important variables at play and serves an extremely crucial role as the theoretical foundation for the design of chatbot personalities. This chapter is then followed up by **Chapter 3** that describes the research methodology, including the design of its participants, data collection, sampling, research process (answering Sub-RQ 1, 2, and 3) and data analysis. Subsequently, **Chapter 4** lays out the results, which includes data analysis and data validation. The data is then followed up by **Chapter 5** that discusses and analyzes the empirical findings and its consequences in a meaningful way, as well as its scientific, practical contributions, and the limitations of the present study. Last, **Chapter 6** provides a conclusion that covers summary of the findings and suggestion for future studies. The report is ended with the references of this research and the appendices that contains the questionnaire questions, conversation script, pretest interview transcript and the raw SPSS data.

## 2. Literature Review

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This chapter discusses the literatures that have been reviewed, in elaborating a solid foundation and understanding of the theories and constructs at stake, as well as providing sufficient evidence to back the research. The chapter is ended with the conceptual framework and the hypothesis development.

### 2.1. Virtual Agents and The Humanness Factor

Much of the communication in the digital age has been mediated by Computer-Mediated Communication (CMC). With the rise of digital communication, CMC has become the breeding ground of research in which to explore the human language, with Instant Messaging (IM) as one of the popular form (Tagliamonte & Denis, 2008; Hill, Ford & Farreras, 2015). Compared to other forms of communication, CMC distinguished itself through its informal, shortened-form language, abbreviations and more words. When compared to spoken communication, CMC lacks cues from vocal tones, body language and communicative pauses (Hentschel, 1998). Despite the absence of these cues, CMC has been found to be able to communicate emotion or personalities just as well or better than normal communications (Derks, Fischer & Bos, 2008).

One widespread application of CMC that is in line with this research is chatbot. A chatbot is “a machine conversation system which interacts with human users via natural conversational language” (Shawar & Atwell, 2005, page 489). They can also be defined as “software that accepts natural language as input and generates natural language as output” (Griol, Carbo & Molina, 2013, page 2). Users primarily interact with them to mostly engage in small talk or to perform various simple tasks as flight rescheduling or more complex undertakings such as giving shopping, financial or health advice. Over the years, a number of new chatbot architectures and technologies, such as ALICE, Jabberwacky, Poncho, Cleverbot, etc., have risen with improving accuracy in natural language processing (Wallace, Tomabechei & Aimless, 2003; Shawar & Atwell, 2007). Chatbots for e-commerce may appear as a pop-up window through websites like Amazon, Bol.com or on apps like New York Pizza. Like any other text messaging interfaces, the questions and remarks that the customers put up show in text bubbles, while the chatbot is reacting in separate text bubbles.

With all the popularity and hype in chatbots today, existing studies have mainly focused on developing their skills and knowledge to interpret and respond to human language meaningfully (Shawar & Atwell, 2005), along with their robustness (Coniam, 2008). Thanks to these ongoing developments in natural language processing, chatbots these days have gotten significantly better in maintaining conversations (Shah et al., 2016). With sufficient technology advances and its clear added value to companies and consumers, more than 100,000 chatbots have been launched in less than one year on Facebook Messenger (Johnson, 2017). Moreover, the Computers Are Social Actors (CASA) studies concluded how people, in similar ways to other humans, socially respond to computers. While earlier experiments focused on computers and media, this pattern has also been successfully replicated in websites (Kim & Sundar, 2012), Twitter bots (Edwards et al., 2014), physical robots (Edwards et al., 2016) and last, virtual agents (Hasler, Tuchman & Friedman, 2013). These findings implied the existence of computer anthropomorphication, which is the tendency to attribute human traits or emotions to non-human entities.

Only until recent decade that there have been more trends towards more research in anthropomorphication of computers (virtual agents). This has mainly been due to consumers’ skepticism towards the technology (Elsner, 2017). Consumers are observed to show preferences towards humans over the alternative, suggesting a general struggle against chatbot technology (Araujo, 2018). Therefore, two critical challenges in real-life implementation are implied with the skepticism against chatbots. First, designers and companies must assess and possess a good level of understanding on how to best present the new agents to consumers, along with the level of anthropomorphism. Second, it is also critical to comprehend how designing

humanlike attributes (e.g., language style, avatars, human names, gender, emotions, or even personalities) influence the perceptions about the agents, services and companies deploying these agents.

From the many ways to humanize computers, Lortie and Guittion (2011) suggested the behavior of such agents to be the central component of the human factor. They implied how humanlike agents should be able to exhibit sophisticated cognitive skills, especially intelligence and language skills, in order to be seen as credible human communication partner. This aligns well with early research that has been focusing on *language as the main output of the humanness factor* (French, 2000). Furthermore, Lortie and Guittion (2011), studied how humans would distinguish linguistic conversations made by humans and computers. Their results suggested that the humanness of a conversation was determined by the higher number of words per message, higher percentage of articles, and longer words.

Based on those findings, language skills play a crucial role in the development of humanlike agents and therefore cannot be neglected. Language may be formulated as a way one expresses his/her thoughts and feelings, influenced by the individual's background, culture, intelligence and personality (Sanford, 1942). The many and unique factors therefore explain how each person differs considerably from each other in their language use. Among the mentioned factors, personality traits greatly affect language use (Hirsh & Peterson, 2009; Yarkoni, 2010; Fast & Funder, 2008). The idea that language and personality (linguistic personality) are related is not novel and it goes back as research from the 1940s (Sanford, 1942). However, researchers have only recently started to systematically scrutinize how word or textual use relates to personalities, especially with the increasing trends towards more text-heavy services (text messages, instant messaging, blogs, tweets, etc.).

The above-mentioned arguments are then summarized as follows. With the anthropomorphication of computers, humans long for more humanlike computer agents. Among the many factors of humanness, language skills arise as one of the important factors in text-based interactions. Consequently, one's language skill is heavily determined by various factors, with personality being one of the prominent factors. It could then be implied that those who would like to improve the humanness of virtual agents should pay attention to these personality traits. Nevertheless, there has been minimal attention spent on developing virtual agent's personalities (botsanilities).

Among the abundant amount of personality research, a great majority of the focus has always been directed towards studying humans, but almost non-existent on the virtual agents' side, let alone an adapting botsanality. From the few research, some have suggested how chatbots or computers are perceived to have certain personalities (Nass et al., 1995; Dautenhahn, Ogden & Quick, 2002). Up to this point, enterprises have designed virtual agent's personality using generic brand personality, by copying human personalities, or by using any of the systemized personality tools (Frommer, Rosner, Lange & Haase, 2014). None have focused on investigating the effective matching between botsanality and user personality. In the following sub-chapters, the author will attempt to explain more about personalities and the used personality tool that will be used to design the botsanilities in this study.

## 2.2. Similarity Attraction Theory

Byrne and Griffitt (1973) posit that individuals are more attracted to other individuals with similar traits, characteristics and personalities. The research further explained that sharing similar attitudes provides reassurance that a person is not alone in his or her belief and that they might be correct to stay the way they are. Knowledge of similar attitudes may also help people to predict others' future behaviors and that people have a greater chance in understanding each other. In fact, people choose to associate with certain others because they have similar personalities. Another study by Berscheid and Walster (1969) mentioned examples such as friends that are more likely to share personality traits than nonfriends, marital partners



that share more similar personalities than people in randomly assigned pairs, concluded with how personality similarity may play a key role in marital happiness and longevity. This theory also explains social homophily, where contacts tend to be found more frequent among similar ones than among dissimilar ones (Currarini, Matheson & Vega-Redondo, 2016). Nevertheless, there have been numerous studies that found that not all matched personalities will deliver positive results. Depending on the situation (marriage, work, social, attitudes toward machines), different similar personalities will deliver various results (Antonioni & Park, 2001; Gattis et al., 2004; Day & Bedeian, 1995; Sigurdsoon, 1991).

### 2.3. Personalities

Humans differ substantially from each other in their patterns of thought, feeling and action. Personality refers to the lasting and distinct psychological characteristics of feeling, thinking, and behaving (Deniz, 2011; Pervin & Cervone, 2010) and plays an important role in individual's decision-making. In a given situation, personality forms a specific tendency towards certain characteristic reactions; making personality regarded as a key driver of human behavior (Heinström, 2003). How one communicates through their choice of language, mood, tone and style reflect their personalities (Yarkoni, 2010). This insight also applies in written assignments, including chats, blogs, tweets etc. (Hirst & Peterson, 2009).

At the same time, in recent years, there has been an increasing research interest in more user-oriented approaches, as a way towards achieving personalization and better accuracy. From the many various ways towards personalization, only a few research has set their eyes to use consumers' personalities as a way to achieve that (IBM, 2017b; To et al., 2007). In the context of this research, personalization by adjusting the personalities of the virtual agents to the personalities of the consumers should bring about more effective communication, increasing user satisfaction, more sales and bear other useful fruits.

The next question that comes up is how we can concretize personalities in more tangible forms. Fortunately, decades of research on personalities have resulted in the number of personality concepts and scales (Goldberg, 1971), often leaving researchers with a bewildering number from which to choose. From the many personality scales, the author argues how one of the scales stands out from the crowd and ends up being chosen for this research.

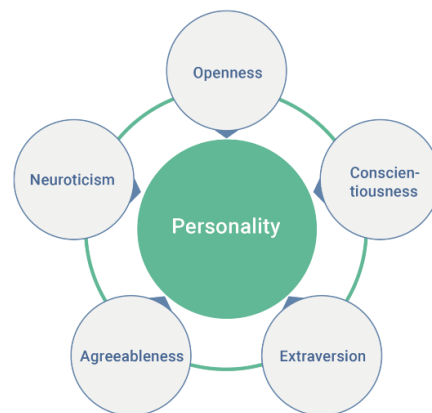
#### 2.3.1. Big Five Personality Traits

Reliable assessment of personality has been a major concern of psychological research (Goldberg, 1990). In the early days of personality research, McDougall (1932) has been credited to systematically establish a taxonomy of personality (Barrick & Mount, 1991). He came up with the earlier version of the five factors: intellect, character, temperament, disposition and temper (McDougall, 1932). For the next four decades, researchers continued the efforts to expand on his work, to find their data fitting well with the model (Norman, 1963; Borgatta, 1964). Norman (1963) was the first to formally label the five dimensions as extraversion, agreeableness, conscientiousness, culture (openness) and emotional stability (opposite of neuroticism). Since then, the model has been referred to as the '**Big Five**' or the '**Five Factor Model**'.

Since the last few decades, various research has observed compelling proof for the robustness of the Big Five across different professional categories (Barrick and Mount, 1991), theoretical frameworks (Goldberg, 1981), and different instruments (McCrae & Costa, 1985; 1989). Among the diverse personality models, the Big Five has dominated the research and occupational world (McCrae and Costa, 1999). They are shown to account for differences between people across many cultures and languages, therefore thought to be representative of the basic human personality dimensions (McCrae & Costa, 1999). Biological basis of the model has also been long-established within various fields, including developmental psychology (McCrae et al., 2000), neuropsychology (DeYoung, 2010), behavior genetics (Pedersen et al., 1988; Riemann, Angleitner & Strelau, 1997), genetic epidemiology (De Moor et al., 2012) and evolutionary psychology

(Gosling & John, 1999). Furthermore, many studies have shown the powerful predictive power of Big Five in various fields (Costa et al., 1984; Barrick & Mount, 1991; Seibert & Kraimer, 2001). Last, there is a steady-growing amount of research focusing on Big-Five's influences on social relationships (DeYoung, 2014; Jensen-Campbell et al., 2002) and interpersonal behaviors (Funder & Sneed, 1993).

The Big Five categorizes the primary factors of personalities as five main “chunks”: i.e. openness (to experience), conscientiousness, extraversion, agreeableness, and neuroticism, or OCEAN in short (Goldberg, 1990). The Big Five is actually a factor analysis of personalities, which therefore captures the commonalities among the existing systems of personality description (John and Srivastava, 1999). This model has become the ‘gold standard’ of personality model, with over two million studies on Google scholar search. However, despite its robustness and reliability, the Big Five factor models are still found to have varied across various studies (Paunonen & Jackson, 2000). In fact, plenty of lexical research have failed to find the expected five-factor structure, but even indicated the presence of sixth (Hough, 1992; Ashton et al., 2004; Saucier, 2009) or even seventh trait (Simms, 2007). Other research has also found deeper facets/lower level dimensions that share common elements and could complement the Big Five traits (Paunonen & Ashton, 2001). Moreover, some also concern the observers’ self-rate mechanism (Hogan & Hogan, 1991).



**Figure 4** Big Five personality traits (Wikipedia, 2018)

Each of the Big Five traits is composed of more specific traits as the following; openness to experience (or often called Intellect (Peabody & Goldberg, 1989)) is often related to an individual with wide range of interests with high creativity, imaginative, original and constantly curious. It includes facets like Fantasy, Aesthetics, Feelings, Actions and Ideas (Paunonen & Ashton, 2001). Next, Conscientiousness (or also called Will to Achieve or Will (Digman, 1989)) is mostly linked to intelligent and organized individuals that are dependable, careful, thorough, organized and responsible (Hogan, 1983; John, 1989). In addition, others have also suggested the trait to include volitional aspects such as being hard-working, achievement-oriented and persevering (Peabody & Goldberg, 1989). Neuroticism is the extent to which someone is insecure, anxious, depressed, sensitive and self-pitying. It that may also include facets like Angry, Hostility, Impulsiveness and Vulnerability (Paunonen & Ashton, 2001). Low scores on these personalities will reflect the opposite traits (McCrae and Costa, 1999).

The last two represents the social dimensions of the five-factor model. Extraversion (also often called Surgency (Hogan, 1983; John, 1989)) refers to the extent to which an individual is sociable, talkative, energetic, assertive and outgoing. Hogan (1986) further interpreted this dimension into two components, Ambition and Sociability. Last, agreeableness refers to the individual's level of empathy, compassion, forgiving, tolerance and cooperativeness. The trait has been labeled as Friendliness (Guilford & Zimmerman, 1949), Social Conformity (Fiske, 1949), Love (Peabody & Goldberg, 1989). It includes deeper



facets such as Trust, Altruism, Straightforwardness, Compliance, Modesty and Tender-Mindedness (Paunonen & Ashton, 2001).

With personality in the spotlight, the research must now think of a way to robustly and objectively capture the personality of the users, as well as those of the chatbots. Therefore, various ways to measure personalities will be discussed next.

### 2.3.2. Language-based Big Five

For decades, a great majority of the academic world has agreed that measuring personality with self-report questionnaires is the gold standard (Boyd & Pennebaker, 2017). Surveys are inexpensive, fast, and exhibit powerful psychometric properties. However, a considerable problem with this method, is that self-reports only reflect their own perception of what they think they are like. Most personality experts have expressed occasional doubts about the degree to which people's self-reflection truly reflects who they really are (McCrae & Costa, 1982). They found that even widely-used and well-validated self-report measures are often insufficient when it comes to forming an accurate comprehension of basic human patterns like behaviors (Morgeson et al., 2007), physical activity (Rhodes & Smith, 2006), and other emotional states (Stiles, 1992).

At the same time, the increasing availability of textual/language data and advances in data statistical methods and processing power are rapidly creating new opportunities. With more than 350,000 tweets, 3 million Facebook posts, 4 million Google searches and over 170 million e-mails every minute (Micro Focus, 2016), the amount of textual data generated by humans is nothing but staggering. For this specific reason, there have been proposals to draw on a big data solution, which is to analyze other cues that can imply human personality. For example, it has been found that there are significant correlations between personality and users' characteristics like music preferences and social media behavior (Tkalcic & Chen, 2015). In terms of communication, the ways in which people use words was also found to be reliable over time, consistent, predictive of a broad range of behaviors and are considerably different from person to person (Pennebaker & King, 1999; Boyd & Pennebaker, 2017). The words we use daily reflect what we are thinking/talking about, our feelings, our social processes and how we are organizing/analyzing our worlds (Tausczik & Pennebaker, 2009). Clues are stored in the use of pronouns, verbs, nouns and word count, among others (Tausczik & Pennebaker, 2009).

With this in mind, language-based measures of personality can be useful for capturing personality that are more closely related with objective behavioral outcomes than the traditional self-reflection personality measures. Consequently, a computerized text-analysis program that counts and analyses words as well as psychologically classifies them into more than 70 categories, called the Linguistic Inquiry and Word Count (LIWC), was developed by James W. Pennebaker (Tausczik & Pennebaker, 2009). The program represents a transition from a more traditional language analysis to a new era of language analysis. The LIWC heavily relies on the built-in dictionary that is maintained by several groups of judges (Tausczik & Pennebaker, 2009). Over time, a considerable amount of research in different languages within LIWC has established word-counting method as a strong tool for measuring individual differences. These research then documented specific categories that are well linked to certain personality traits (Tausczik & Pennebaker, 2009). For example, each Big Five personality was found to talk more about certain topics or use certain words (Hirsh & Peterson, 2009; Yarkoni, 2010; Qiu, 2012), as shown in **Table 2**.

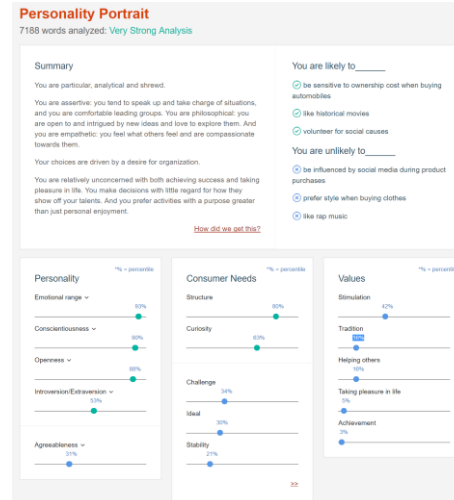
**Table 2** The associated Big Five personalities and its LIWC categories

Personality Factor	LIWC Categories	Personality Factor	LIWC Categories
High Extraversion	You, social, family, affect, assent, space, sexual, verb, work, number of words, question marks	High Conscientiousness	You, they, discrep, incl, achieve, work, preps, cogproc, social, human, achieve, article, colons, exclamation marks, links, length of words
High Agreeableness	I, you, conj, work, friend, incl, conj, posemo, ingest, certain, articles	High Openness	Hear, work, leisure, tentat, quant, humans, causation, certain, motion, number of sentences, personal pronoun, articles
High Neuroticism	Negemo, anger, swear, anxiety, sexual, bio, negate, affect, hearing, feeling, religion, ingestion, pronoun, exclamation marks		

Nevertheless, the LIWC is not without its limitations. The program still ignores context, irony, sarcasm and idioms (Tausczik & Pennebaker, 2009). Rather than providing information about the context in which these words are used, the program simply counts and categorizes them. Style words convey 55% of the message, yet only little is understood using the LIWC (Tausczik & Pennebaker, 2009). Moreover, the findings may not hold consistently with different groups of people in different cultures or settings (e.g. speakers speaking foreign languages). After all, LIWC's heart is based on probability systems, like any computerized program (Tausczik & Pennebaker, 2009). The misinterpretation of word meaning themselves should provide a disclaimer for those relying too heavily on accurately detecting one's true personality using word usage.

Meanwhile, IBM Personality Insight, a more recent and supposedly more powerful alternative, has also been developed as a text analysis program to measure the Big Five personality. Rather than counting words from an enclosed dictionary like the LIWC, the service infers the personality from an open-vocabulary approach (GloVe) and combines it a machine-learning algorithm (IBM, 2018). IBM further claimed that the LIWC approach (despite combined with the machine-learning algorithm) to still be lacking from the open-vocabulary approach, which also understands the context of the words used.

After understanding how language or word use is directly correlated to personality, this research can benefit from textual-analysis program or classic questionnaire to derive user's personality. Nevertheless, another objective of the research is to also create chatbot conversations that represent certain personalities. Therefore, it is imperative to also gain a deeper understanding on how we can project all five personalities into chatbot conversations.



**Figure 5** IBM's Personality Insight

### 2.3.2.1. Extraversion

Extraversion is deemed particularly related to people's social behavior (John, 1990; John & Srivastava, 1999; Loehlin et al., 1998). Funder and Sneed (1993) as well as Cuperman and Ickes (2009) have performed extensive studies to find extraversion to be the most accountable for the dynamic behavior in dyadic social interactions. A high score on extraversion represents individuals that are more active, cheerful and energetic to engage in social interactions (McCrae & John, 1992). Naturally, highly extraverted people have the tendency to care about their own image and other social consequences of behaviors (Devaraja et al., 2008). Those high in extraversion seem natural, smooth, dominant and loud in conversations and are positively correlated with the amount of talking, personal self-disclosure (Funder & Sneed, 1993). Many studies are also consistent with Carl Jung's studies (1921) that view extraverts as individuals with outward attention, eager to interact (assertive), as opposed to introverts. Ashton, Lee and Paunonen (2002) also found that extraverts are inclined in behaviors that attract social attention. Extraverted personalities are usually high performers in jobs with social element, such as marketing, sales or management (Barrick and Mount, 1991). This trait is particularly interesting because it is one of the most important and easily distinguishable social trait, which is relevant for our study that puts an extra emphasis on its social interaction.

In terms of linguistic personality, extraversion is most often associated with words related to humans, family and social processes (Yarkoni, 2010). These discoveries are in line with the fact that extraverted individuals are active social actors (Hirsh & Peterson, 2009). They are also positively correlated with positive emotions, such as 'fabulous', 'like', 'proud', 'funny', and etc. (Yarkoni, 2010). They also often use social settings or experiences words such as 'bar', 'restaurant', 'drinking', 'dancing', 'crowd', 'sing' and many more (Yarkoni, 2010). Another research also concluded that extraversion is negatively correlated with articles (Pennebaker and King, 1999), this reflects the extraverts' desire for social engagement and preference for reduced complexity.

Moreover, we live in a digital society that provides a range of opportunities for virtual interaction. Consequently, emoticons/emojis and GIFs (Graphics Interchange Format) have become popular for clarifying and self-expression during online communication. Emoticons/emojis are graphical representations of emotions that are extensively used in virtual or textual communication. Emoticons are made up of ASCII characters combinations, such as ':)', ':(', ':D', '.\_.' and many more, while emojis are the graphical representation of those emotions (Baron, 2003). They both possess great potential to replace, at least partially, the conventional tools in assessing individual personality differences since they also

represent the personality behind the users (Marengo, Giannotta & Settanni, 2017). Emojis are most consistent with traits that are full of emotion and affection, i.e. extraversion, agreeableness, neuroticism (Elliot & Thrash, 2002; Robinson, 2007). Extraverted individuals are more correlated with positive emotion emojis, e.g. party, laughing, happy, love, etc. (Marengo, Giannotta & Settanni, 2017). Meanwhile, GIF is a bitmap image format that is used for e.g. small animations of memes. The use of GIFs is also positively correlated with the extraversion trait (Miltner & Highfield, 2017). The artificial conversation of extravert chatbots will be projected using the discussed literature.



**Figure 6** Examples of emojis and GIFs

### 2.3.2.2. Agreeableness

Graziano and Eisenberg (1997) defined the trait of agreeableness as "a compassionate interpersonal orientation towards being kind, caring, considerate, altruistic, likable, cooperative and helpful". Agreeableness is reflected through its interpersonal friendliness, warmth, respect, sympathy and positive affect (Funder & Sneed, 1993). These behaviors also include smiling, laughing and verbal acknowledgements (Cuperman & Ickes, 2009). The altruistic trait is characterized with the propensity to demonstrate the thoughts and act of helping behaviors (Graziano et al., 2007). To the contrary, disagreeable individuals are proud of themselves, unkind, and suspicious of others (Blumer & Doering, 2012). Barrick, et al. (2001) specified how agreeables do well in jobs that include considerable social interaction and teamwork.

From the linguistic personality perspective, agreeableness, is often related to words around the topic of family and inclusiveness, which is consistent with its association with empathy and relational concern (Hirsh & Peterson, 2009). It is also found to be positively correlated with affection words, such as 'love', 'hug' and negatively correlated with angry and sexual words like 'porn', 'gay', and swear words. The negative relationship with angry and swearing words is also supported by previous research (Meier, Robinson & Wilkowski, 2006; Yarkoni, 2010).

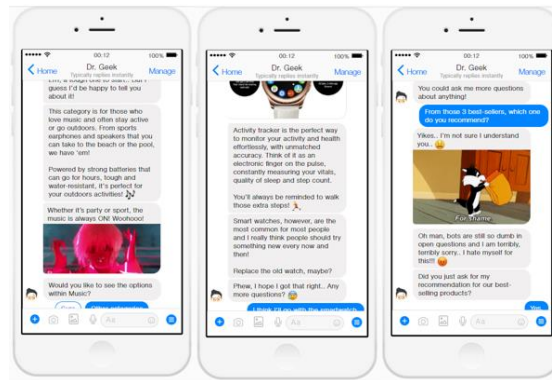
Meanwhile, emojis portraying blushing faces are associated with the agreeableness trait (Marengo, Giannotta & Settanni, 2017). The study hypothesized how specific association may be interpreted as an indication endorsing positive social communications. As shown in other literatures, sincerity (Dijk, de Jong & Peters, 2009), flirtation (Elliot & Niesta, 2008) and mitigation of negative social impression (Keltner, Young & Buswell, 1997) has been conveyed by blushing. Hence, it reflects their tendency to see themselves as others-focused, which is a distinctive characteristic of the agreeables.

### 2.3.2.3. Conscientiousness

Conscientiousness refers to the individual differences in impulse/self-control, determination and level of thoughtfulness (McCrae and Costa, 1999). Highly conscientious people tend to be organized and have a strong sense of purpose, as well as reliable, confident, dependable and self-controlled (McCrae and Costa,

1999). Among the Big Five traits, there is consensus that this trait appears to show the strongest and most consistent correlation with job performance (Barrick & Mount, 1991).

Conscientiousness is positively correlated with achievement and work-related words (Hirsh & Peterson, 2009). It is consistent with the stereotypical strong work ethic and achievement-oriented traits of highly conscientious individuals (Barrick & Mount, 1991). Meanwhile, there is no association between emoji and conscientiousness (Elliot & Thrash, 2002; Robinson, 2007). This might be explained with the fact that because they show strong links with general cognitive ability and are not typically linked with emotional expression (Moutafi, Furnham & Crump, 2006).



**Figure 7** Screenshots of conversations, showing the trait Extraversion (left), agreeableness and openness (middle), and neuroticism (right)

#### 2.3.2.4. Openness to Experience

Openness to experience is described as the extent to which individuals are imaginative, adventurous, curious, and creative (McCrae and Costa, 1999). It is often found that highly open individuals could think independently from unconventional perspectives. They have flexibility of thought and readily challenge authority, therefore preferring novelty, variety and depth of experience over traditional, routine and familiar things (McCrae and Costa, 1999). High scorers have greater access to a variety of feelings, thoughts, perspectives and ideas, as well as more adaptable to changing circumstances or challenge the status quo (McCrae and Costa, 1997). Low scorers, meanwhile, are more conservative, consistent to routines and have common interests (Blumer & Doering, 2012).

Openness is strongly related to perceptual/sensing processes, e.g. words related to touching, hearing, tasting and seeing (Yarkoni, 2010). It is also strongly (positive) correlated with words associated with intellectual or cultural experience, such as culture, art, narrative, universe and literature. On the contrary, it is negatively associated with second-person pronouns, adverbs, swear words, affect words and past tense words (Yarkoni, 2010). Last, it is positively correlated to prepositions words, indicating its ability to handle and express the spatial domain (Qiu et al., 2012). Like conscientiousness, there is no association between emoji and openness (Elliot & Thrash, 2002; Robinson, 2007).

#### 2.3.2.5. Neuroticism

Finally, neuroticism is reflected through its different emotional reactions, specifically in response to negative events (Canli, 2008). Individuals higher on this personality trait tend to regard events around them as more threatening, distrustful and distressing (Chan et al., 2007). They experience various negative emotional statuses more often and more intensely, e.g. depression, paranoia and anxiety (Watson et al., 1994). Neurotics are often considered a major red flag indicator for a variety of common psychiatric disorders (Ormel et al., 2013). Neuroticism is known to also modulate risk-related behavior, such that high scorers e.g. will take fewer risks when making investments.



In a study by Hirsh and Peterson (2009), the trait of Neuroticism was reflected in the sample's writing as negative emotion words related with sad, anger and anxiety. The trait is also clearly positively correlated with negative emotion words, such as awful, lazy, depressing, terrible and stressful (Yarkoni, 2010). The study also showed extensive first-person singular pronouns, indicating possible self-insecurity (Hirsh & Peterson, 2009). Meanwhile, the fact that highly neurotic individuals tend to experience higher levels of worry and negative affect (Elliot & Thrash, 2002) comes in accordance with the amount of pensive face, disappointed face, crying face, face with cold sweat, weary face, fearful face, worried face and negative emojis typically used (Marengo, Giannotta & Settanni, 2017).

### **2.3.3. Botsanality**

The research by Nass and Lee (2001) that revealed how people regard computers as social actors sheds a new light on human-computer interaction. Humans are known to mindlessly apply social rules such as politeness norms, personality attraction and gender differences while interacting with computers (Nass & Moon, 2000). This paradigm is also often referred to as Computers Are Social Actors or CASA (Nass, Steuer & Tauber, 1994; Nass et al., 1995). In fact, in the age where interaction with computers is as ubiquitous as any other interactions, humans are found to prefer to interact with more humanlike computers (Lee & Nass, 2004).

The preference for more manlike computers has enforced the humanization of artificial agents as one of the top to-do things for cognitive science. This ambition has therefore brought researchers to equip computers with various features and capacities that can make them persuasively more human. There have been numerous studies that attempted to do so by modifying specific aspects in human-computer interactions, e.g. physical appearance (Giard & Guitton, 2010), avatar (Alissandrakis, Nehaniv & Dautenhahn, 2004), movements (Bailenson & Yee, 2005), or voice (Nass, Moon & Green, 1997).

Those studies, however, concluded such “physical” factors as not the only elements in determining the humanness of such artificial agent (Lortie & Guitton, 2011). As discussed earlier, language skills in fact, is seen as an important component to be perceived as credible communication partner (French, 2000). Earlier literature review also showed personality to be one of the factors that affect one's language skills (Tausczik & Pennebaker, 2009). Therefore, it implies that personality, through language skills, may hold an important key towards more humanlike chatbots. Aware of the importance of personality in chatbots, it is logical to expect a number of studies being in the field. Nevertheless, there has been minimal attention spent on developing virtual agent's personalities. Designing botsanality is not new, however, as companies have attempted to design famous agents like Siri or Alexa, usually by mimicking brand personality or creating a persona. To the author's knowledge, there has not been any structural academic attempts on the design or impacts of chatbots personalities.

Many questions would then arise when chatbot personalities come into the equation, such as the type of botsanality that would be the most powerful to achieve a task or to communicate effectively with a consumer. These questions would require us to investigate the design of botsanality, along with its theoretical and practical implications. In relation with the reviewed similarity theory, it is therefore of high interest to see what would happen when we match the personalities of virtual agent and user in the context of e-commerce. It is hypothesized that when personalities are matched, we would see an increased level of trust and decreased level of purchase intention, that ultimately leads to increased purchase intention. These variables will be discussed in the following sub-chapters.

## **2.4. Trust and Perceived Risks**

The concept of trust and perceived risks are deemed to be the two important factors in forecasting the consumer's purchase intention (Chau et al., 2007; Lim, 2003; Chang & Chen, 2008). Chang et al. (2005)

found these variables to be the most researched mediating factors in investigating relations in online shopping. As trust increases because of the decreasing perceived risk, it will in turn further decrease the perceived risk, and would be repeated in a sort of feedback loop, thus mutual in nature (Chang & Chen, 2008). This finding suggests that the causal relationship between trust and perceived risk could possibly be bi-directional, which is consistent with the findings of Rousseau et al. (1998) and Mitchell (1999). Consequently, the present study then adopted both trust and perceived risk as the organismic (mediator) variables in the research framework.

#### **2.4.1. Trust**

Trust is a social psychological state and concept that has been studied extensively by numerous researchers (Rousseau et al., 1998). Trust is defined as “the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party” (Mayer et al., 1995). A lack of trust exists when a party does not possess the faith in the competencies of another or questions the motivation of others (Van der Smagt, 2000). In other words, trust is a relationship between multiple individuals in which individuals perceive that the others are capable and will make a sincere effort to meet their agreed commitments (Furumo, de Pillis & Green, 2009).

Scholars have found trust to play a crucial role in social interactions and relationship between individuals (Good, 2000), as well as individuals and organizations (Rousseau & Parks, 1993; Kramer, 1999) or between fellow organizations (Rousseau & Parks, 1993; Kramer, 1999). Trust predicts performance (Dirks, 2000) and lowers transaction costs in communication (Watson-Mannheim & Belanger, 2002). Trust is found to be the foundation of many systems that we know: financial system, economy, brands, communities and relationships (Creed & Miles, 1996). Trust can be found across multiple disciplines from psychology, marketing, business/finance, management, to even information systems (Arnott, 2007). The trending virtual communication in the age of internet, has put trust in the central spotlight. Trust grows even more important, when communicating with unknown, less-known individuals/teams, often separated by physical distance (Snow et al., 1996). In the context of e-commerce, trust (e-trust) also plays a central role in e-commerce systems adoption (Hwang & Kim, 2006).

Trust is a multi-faceted notion that consists of cognitive and affective trust (Riegelsberger et al., 2003). Cognitive trust is defined as one’s confidence or willingness to lean on the trustee’s competence (Johnson & Grayson, 2005). Meanwhile, affective trust is basing its judgment on the trustee’s kindness and compassion, often also called faith (Riegelsberger et al., 2003; Madsen & Gregor, 2000). In this research, the researcher has also taken the liberty to add another dimension – personal attachment – to the overall trust. Personal attachment is derived from one’s emotional attachment to a system and how it suits to their liking (Merritt, 2011). Personal attachment is also often grouped under affective trust (Madsen & Gregor, 2000). In the end, all the multi-faceted concepts within trust are typically intertwined, therefore concluding the necessity to measure all elements. In relation to personality similarity, Bauer and Green (1996) argued how it also plays an important role in trust, especially in the early phases of relationships. In the present study, it is hypothesized that matched personality will increase the level of trust that ultimately leads to increased purchase intention.

#### **2.4.2. Perceived Risk**

The theory of perceived risk has been applied again and again to explain consumers’ behavior since the 1960s (Chang & Chen, 2008) and seen as the powerful factor in explaining how consumers are more avoiding mistakes when purchasing (Mitchell, 1999). In the past, perceived risk was mainly considered to revolve around fraud and product quality (Wu & Wang, 2005), but it has since become popular since online transactions. It has since then evolved to refer to the consumers’ belief or biased statement about certain

types of financial, social, product performance, and time risks when transacting online (Chang, 2008; Corbitt et al., 2003; Kim et al., 2008), therefore making it relevant to our research.

With perceived risk considered as an organism variable, the research would like to investigate the impact caused by the stimuli (matched personalities) during online transactions with chatbots. Moreover, while the amount of studies that investigated personalities' role in perceived risks has been somewhat abundant, there have only been a limited amount of studies when investigating inter-personalities' role in perceived risks to the author's knowledge (Weber & Hsee, 1998; Lepp & Gibson, 2003; Schaninger, 1976). In the present study, it is hypothesized that matched personality will decrease the level of perceived risk that ultimately leads to increased purchase intention.

## 2.5. Conceptual Model and Hypotheses Development

The field of consumer purchase behavior has enjoyed increasing research and managerial attention in the age of online commerce (Davis et al., 2007). Various research in understanding the nature of purchase behavior has been studied by a number of researchers and marketers, to e.g. assess the factors in creating pleasant shopping experiences or increasing purchase intention (Bettman, 1979).

During his time, Oxenfeldt (1974) was one of the first to suggest how customers' opinions and feelings towards certain (physical) stores could influence their perceptions. Until then, customers' feelings were not considered as a variable of concern in consumer research (Sherman, Mathur & Smith, 1997). The works of researchers from the past decades have then concluded that an individual's feeling do influence consumer behavior (Clark & Isen, 1982; Holbrook & Westbrook, 1989).



**Figure 8** Stimulus-organism-response paradigm (Eroglu et al., 2001)

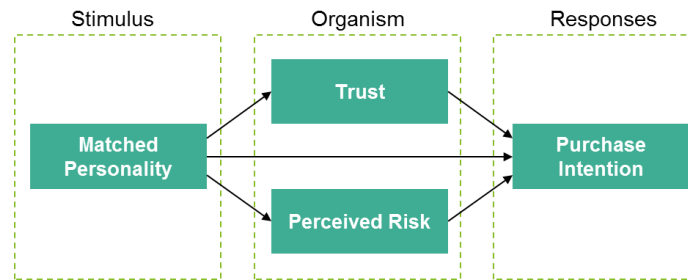
The above research has then been casted into a research framework of stimulus-organism-response (SOR) paradigm (Eroglu et al., 2001) (**Figure 8**). Within the framework, the stimulus is conceptualized as an environmental influence that affects the individual's organismic state. Next, the organism mediates the relationships between the stimulus and the responses and is represented by the cognitive and affective intermediary states (Aboubaker-Ettis, 2017). Donovan and Rossiter (1982) explained how the stimuli would affect the emotional states of consumers in ways they may not be fully aware. Last, the response represents the reaction of the consumers. Although much of the past research has helped us to understand (physical) store environment, the present research has extended it to the more modern context of e-commerce (Richard & Chebat, 2016).

While traditional stimuli may include factors like the store's environment and any visual design factors, the stimulus of interest in the context of this study would be the matched personality which is derived from the similarity attraction theory. Nevertheless, the impact of various botsanality and personality combination has been included in the analysis as well. Furthermore, most studies on the organism have focused on the emotional states of the individual, using the pleasure-arousal-dominance (PAD) dimension, which is defined as three independent axes of a temperament space, initiated by Mehrabian and Russell (1974). However, this approach has been heavily criticized for not capturing much of the stimulus' effects and being too narrow-scoped (Eroglu et al., 2001).

As an alternative, the concept of trust and perceived risk is considered to provide more complete psychological states (Rousseau et al., 1998; Cho and Lee, 2006), which have been identified as crucial mediators in influencing customers' online behavior and decision making (Chau et al., 2007). While such effects have been meticulously researched in more traditional contexts such as in-store behavior, store



search, and interactions with store personnel, in this research we focus on how trust and perceived risks influence consumers' purchase intention in a more modern context of e-commerce (Lim, 2003; Mitchell, 1999). The research's conceptual model is an adaptation of the SOR model and is shown in **Figure 9**.



**Figure 9** Conceptual model based on the SOR framework

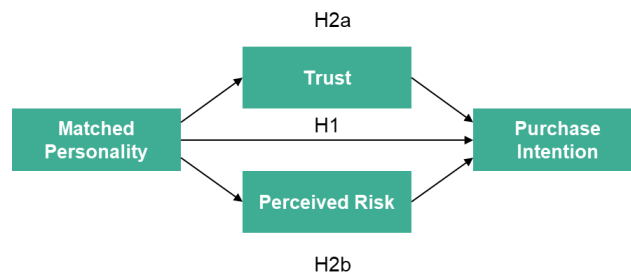
Using similarity attraction theory as the base of this research, a matched personality is expected to result in a more positive interaction in general. When matched, users are hypothesized to like the adjacent chatbot personality that fits to their own liking and therefore feel more attracted. Consequently, the study hypothesized that matching personality would result in higher purchase intention (H1).

*H1: Matched personality directly increases purchase intention.*

At the same time, matched personality is hypothesized to also increase trust (H2a) and lower perceived risk (H2b). Moreover, trust and perceived risk have been shown in earlier research to have direct effects on purchase intention (Chang & Chen, 2008). That study concluded that increasing trust and decreasing perceived risk lead to increased purchase intention. The present study therefore aims to investigate whether the same findings of increase purchase intention mediated by trust and perceived risk apply. The measures for the dependent variable (purchase intention) and the covariates (trust and perceived risk) will be explained in **Section 3.3.3**.

*H2a: Matched personality increases purchase intention and it is mediated by increased trust.*

*H2b: Matched personality increases purchase intention and it is mediated by lowered perceived risk.*



**Figure 10** Conceptual model with hypotheses

### 3. Methodology

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After reviewing the above literature and proposing the conceptual model, the following section describes the research design, its procedures, the sampling and data collection methodology.

#### 3.1. General Research Design and Procedure

All participants received a URL link to the experiment hosted on Qualtrics. On the landing page, participants were welcomed and thanked for joining the experiment. An introduction to the experiment containing rules and instructions on the experiment, as well as chatbots usage for e-commerce applications was then given. First, general questions on internet fluency were presented. These questions acted as the demographics filter to ensure that the participants have at least some affinity to the internet and online shopping. Next, a Big Five questionnaire (explained in later chapters) was presented to gain information about the participants' personalities. Subsequently, a set of questions on the demographics of the participants were given. Next, participants would read the following narrative or 'cover story' (Sekaran & Bougie, 2016) and asked to imagine themselves in that situation.

*"Your best friend, Eric, is turning 30 years old this weekend and he is throwing a big birthday party. It is an important milestone and as his best friend, you would like to give him a special birthday present. You know that Eric really loves gadgets and he lives a very active lifestyle, so you're thinking to buy him a wearable as a present.*

*You decided to go to an electronic online store, Dr. Geek, to look for gift ideas. However, upon arriving on the website, you are overwhelmed with the varieties of options available. Fortunately, Dr. Geek has a new chatbot that can help you find the right present for Greg's 30<sup>th</sup> birthday!"*

The experiment was then presented in the form of movie, which is a form of experiment that presents a hypothetical situation of a real event (Flaskerud, 1979). The subjects were randomly assigned and exposed to a single treatment (one chatbot personality), which is more often called as *between-subjects design* (Greenwald, 1976). The design allowed comparison between the results from the different groups to test the hypothesis and to see the best-performing pair groups.

Meanwhile, the chatbot personalities were designed in such a way so that the different effects of each of the Big Five personalities could be investigated, as seen in **Table 3**. With conscientiousness as a must-have personality in all chatbots, the variations were left with the rest of the personalities. Therefore, this research would see the effect of not just personality matching, but also the direct effect of any chatbot personalities and the dependent variable.

Next, the different personalities of the virtual agents were expressed through the different words that the personalities mostly use, based on various previous research on blogs, vlogs, social media, games and conversations. These words have been well categorized into LIWC categories (Pennebaker et al., 2001), which would then be utilized to form sentences in the conversations. The literature reviewed previously also provided important insights on how the sentences and various emotions should be formed.

For example, extraversion was imagined to be represented by being energetic, chatty, occasionally informal, and the extensive use of emojis and GIFs. Next, agreeableness was imagined to be represented through the affective side in a social interaction. The chatbot would deeply care about its customers' feelings and would do its best to think of their feelings all the time. The conversations would be filled with warm and altruistic questions that guarantee maximum satisfaction of its customers and the feeling of being attended for.

In the context of e-commerce in this experiment, conscientiousness was imagined as an organized chatbot that is highly reliable, responsible, fully aware of the situation that it is in and will get the job done. It is

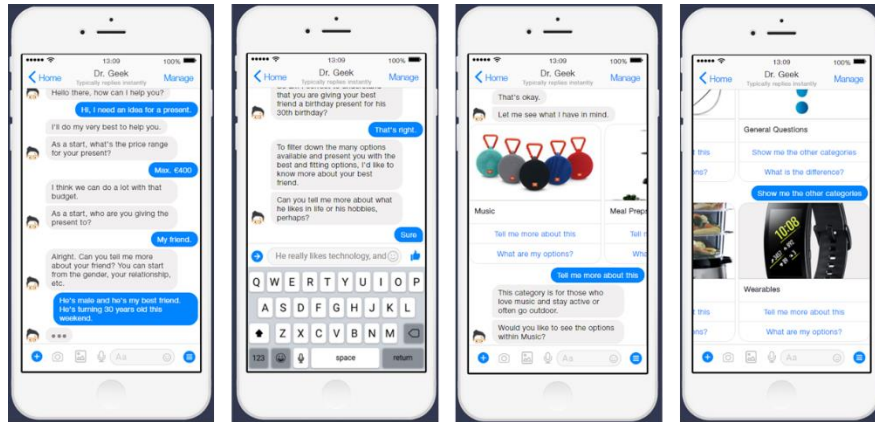
able to fully lead itself from the beginning to the end through all the necessary processes. Due to the nature of a virtual agent whose goal is to assist, conscientiousness is required all the time to make sure that the process is handled from the beginning to the end. Without this trait, the conversations would turn chaotic and disorganized. Therefore, conscientiousness will become the only trait that remains high and unchanged in any chatbots.

Furthermore, openness was projected as a highly creative and authority-challenging chatbot. The chatbot expressed this by occasionally persuade the users to try something new. The chatbot would explain many items during the conversation by taking the customers to imagining themselves using the items in various ways, e.g. with friends and family, at the beach, how you will enjoy the speakers, or how they would look like James Bond. This is contrary with when the chatbot is low on openness, namely the chatbot would stick to the usual and not being able to take the customers to some level of imagination. For example, it would explain things as is, strictly by definition. Last, highly neurotic bot was projected as a nervous, highly insecure and low self-esteem chatbot. When faced with mistakes, it was immediately overwhelmed with negative feelings such as stress, shame and the feeling of being threatened. When emotionally stable (low on neuroticism), the chatbot possessed great control of its emotions, even under pressure, and project strong self-assurance of its abilities. The chatbots had been pretested by 10 participants in three qualitative rounds in the first experiment, and then pretested again to three participants in the second experiment. Sample utterances are shown in **Table 3**. The five final conversation scripts could be found in **Appendix B**.

**Table 3** Examples of the virtual agent's script in different personalities

Agent's Personalities	Sample Utterance	Agent's Personality	Sample Utterance
Responding to customer – OCEAN	Dang it, I'm not so sure.. Maybe when your best friend knows that he's getting this, he'd be the happiest man on earth? I'm still a new technology, don't expect much from me!  In any case, whether it's for work, school, business or just casual sports and spending time with the family, the watch works with any occasions you can think of. The watch will totally fit YOUR active lifestyle and let you be YOURSELF. Isn't that great? 😊	Responding to customer – CE	O yeah, you just have to trust me on this one. My advice is simply the best and if you still don't like it, I simply wouldn't know why..  I personally think it's the best watch out there, so yeah, if I say something, you should just follow whatever I say!
Responding to customer – OCEA	Awesome 😊 Great choice! I would choose the same product if I were you! Get ready with all the wonderful features on this watch! The James Bond dream has finally come true, LOL. AND, it's time to finally try something new!	Responding to customer – C	Thank you for your purchase. Certainly, it would not have been possible without this wonderful and smart chatbot.  See you again in the future.
Responding to customer – CEA	Let me see! If you are not so sure, then maybe we should stick with what you're already comfortable in. Sometimes the latest technology is not for everyone 😊		

Furthermore, looking at how the study aims to understand the true effect of personalities in the setting of e-commerce, the study aimed to eliminate or dampen any unwanted extraneous factors that might influence the outcome and covariances of this research. The first of such factors was the brand of the product. Consumers are known to form certain affiliation and personal preferences (indifferent or even affiliated) towards a particular brand (Laroche, Kim & Zhou, 1996; Hung et al., 2011). Second, price is known to be a major decision of consumers in evaluating purchase intention (Chang & Wildt, 1994; Harlam, Krishna, Lehmann & Mela, 1995). For these particular reasons, the research has taken out the brand and price factor out of the equation.



**Figure 11** Dr. Geek's conversation screenshots

After the video, a post-questionnaire was given to ask how they would perceive the chatbot's personality, their trust and perceived risks towards the chatbot as well as the purchase intention towards the recommended product. The perceived personality questionnaire also acted as a manipulation check to ensure the participants' full attention and to verify that the intended effects are due to the constructs of interest. Last, participants had the opportunity to leave comments about the experiment, as well as their e-mail address, should they be interested in the results of the study.

## 3.2. First Experiment

### 3.2.1. Procedure

The participants watched a 5.5-minute video conversation between the virtual agent and the customer.

### 3.2.2. Participants

Study participants were recruited from Amazon Mechanical Turk (mTurk) and the researcher's personal and non-personal network, from and outside of Deloitte and friends, respectively. mTurk is a crowdsourcing service and marketplace for work that requires human intelligence (Amazon, 2018). Ideally, the sample size would be determined by the desired level of precision (margin of error) and confidence level during the implementation phase of the research (Sekaran & Bougie, 2016). The sample size estimation can also be done with a power analysis calculator available online, although the number of participants predicted is very high (Power and Sample Size, n.d.). Due to time and resource constraints, the rule of thumb of aiming for 30 participants per chatbot personality was used (Sekaran & Bougie, 2016).

The demographic of the chosen target population in this study was defined only by their experience with online shopping due to the e-commerce context of the research and the ability to comprehend the experiment in the English language. Participants were not further bounded by gender, age, or other criteria to include as broad customer's profile as possible. Participation on mTurk was rewarded with USD 40 cents (per task, also called HIT on mTurk) while the participation outside of mTurk was on a voluntary basis.

**Table 4** Nationality sample (1<sup>st</sup> experiment)

Nationality	Frequency
American	78
Indian	49
Dutch	13
Indonesian	10
Others	44
Total	194

The initial sample consisted of 333 participants (195 males and 135 females, with 1 unknown and 2 other genders;  $M_{age} = 19.58$  years,  $SD = 9.54$ ) from both mTurk and non-mTurk. There are 272 mTurk participants collected over a period of one week, while 61 non-mTurk participants had been collected over the period of two weeks. The whole experiment was designed to take a minimum of 9-12 minutes. The participants who performed the experiment under 9 minutes was therefore filtered out. As a result, the final sample consisted of the data of 194 participants (119 males and 72 females;  $M_{age} = 21.72$  years,  $SD = 10.62$ ), which was used for the analyses in this study.

**Table 5** Sample assignment (1<sup>st</sup> experiment)

# Participants Needed	# Participants per Personality	Chatbot's Personality
194 participants	38 participants	OCEAN
	45 participants	OCEA
	35 participants	CEA
	38 participants	CE
	38 participants	C

### 3.2.3. Measures

#### 3.2.3.1. Big Five Personality Scales

Over the course of Big Five development, many measures have been developed to accurately measure the five traits. Early measures – e.g. NEO-FFI (Neo-Five Factor Inventory; Costa & McCrae, 1992), the BFI (Big Five Inventory; John & Srivastava, 1999) – however, contain 50 to 200 questions that inarguably take long to finish. The 20-item Big Five questionnaire (also called as the Mini-IPIP) was developed as the short

form of the 50-item International Personality Item Pool (IPIP) by Goldberg (1999) and has been validated to be consistent and acceptable with other Big Five measures (Donnellan, Oswald, Baird & Lucas, 2006).

Due to the limited available time of the total experiment, the Mini-IPIP was initially chosen as the Big Five tool of measure. The scale consists of 20 statements, with 4 items assessing each of the Big Five factors. Participants were required to read each statement and rate on how well they believed that it described themselves on a five-point Likert scale (1: strongly disagree to 5: strongly agree). The 20-item scale was chosen because shorter scales are likely to produce lower fatigue compared with longer scales (Knapp & Heidingsfelder, 2001). The Mini-IPIP is shown in **Appendices**.

**Table 6** User Personality's PCA Pattern Matrix using Oblimin rotation (1<sup>st</sup> experiment – Mini-IPIP)

Item	Component				
	1	2	3	4	5
Am the life of the party. (E)	-.28	-.02	-.23	<b>-.72</b>	.04
Sympathize with others' feelings. (A)	.09	<b>.81</b>	-.01	.09	-.19
Get chores done right away. (C)	.04	.09	<b>-.69</b>	-.16	-.16
Have frequent mood swings. (N)	<b>-.67</b>	.27	-.10	-.12	.36
Have a vivid imagination. (O)	-.06	<b>.66</b>	.02	-.11	.04
Don't talk a lot. (E/R)	<b>.60</b>	-.01	.18	-.55	.07
Am not interested in other people's problems. (A/R)	<b>.72</b>	.25	.09	.06	.16
Often forget to put things back in their proper place. (C/R)	<b>.73</b>	-.23	-.31	.06	.01
Am relaxed most of the time. (N/R)	-.07	-.24	.21	-.02	<b>.70</b>
Am not interested in abstract ideas. (O/R)	<b>.73</b>	.15	.02	.03	.14
Talk to a lot of different people at parties. (E)	-.18	.16	-.12	<b>-.74</b>	-.13
Feel others' emotions. (A)	.07	<b>.70</b>	-.20	-.07	-.09
Like order. (C)	.05	.07	<b>-.77</b>	.01	.07
Get upset easily. (N)	<b>-.75</b>	.20	.01	.04	.23
Have difficulty understanding abstract ideas. (O/R)	<b>.76</b>	.06	.10	.06	.02
Keep in the background. (E/R)	.46	.00	.30	<b>-.55</b>	-.03
Am not really interested in others. (A/R)	<b>.77</b>	.18	.10	.03	.10
Make a mess of things. (C/R)	<b>.84</b>	-.18	-.26	.00	-.01
Seldom feel blue. (N/R)	.21	-.07	-.10	.07	<b>.77</b>
Do not have a good imagination. (O/R)	<b>.71</b>	.19	.00	.05	.18

E = Extraversion; A = Agreeableness; C = Conscientiousness; N = Neuroticism; O = Openness; R = Reversed.

However, the Mini-IPIP was met with poor and unacceptable reliability (Cronbach's  $\alpha = .58, .62, .54, .42, .68$ ; for extraversion, agreeableness, conscientiousness, neuroticism and openness, respectively) as well as poor scale consistency, as shown in the factor analysis in **Table 6**. For this exact reason, the experiment was deemed unsuitable for further use and declared unusable for the study.



### 3.2.4. Manipulation of User-Chatbot Personality

Upon the completion of five different chatbot personalities, the research aimed to validate that the personalities of the chatbots were indeed accurately designed as intended. Ten participants (two participants per personality) were chosen from the researcher's convenient network to observe a given chatbot conversation and thereafter to assess the personality of the chatbot as perceived, by answering the Mini-IPIP questionnaire. From this first round, the result was not quite as expected, and an investigation was followed up shortly after with one-to-one interviews via WhatsApp, Skype or face-to-face, depending on the convenience of both parties. The interview questions mainly focused on the deviating answers as well as the participants' overall thoughts of the videos.

After the interview, the ideas raised from the interviews were included in the videos. The new videos were then presented once more to the ten participants to re-validate their perceived personalities. The second round showed much better outcome with regards to the intended personality. It is important to note that in the second round, the participants may have already been biased in answering, since they had seen the video earlier and had received a thorough explanation of the questionnaires. The detailed results of the pretest are documented in **Appendix C**.

## 3.3. Second Experiment

### 3.3.1. Procedure

The participants watched a shorter 3.5-minute video conversation between the virtual agent and the customer.

### 3.3.2. Participants

Another round of data collection was undertaken with improved methodology, instructions, as well as better and shorter videos and measures. The new initial sample consisted of 168 participants (80 males and 86 females, with 2 unknown genders;  $M_{age} = 27.40$  years,  $SD = 6.59$ ) that had been collected over the period of one week. The length of the experiment had now become a minimum of 8 minutes, which consisted of 3.5 minutes video as well as (at least) 4 minutes' worth of questions and instructions. The respondents who performed the experiment under 8 minutes were therefore filtered out. As a result, the final sample consisted of the data of 137 participants (68 males and 67 females, with 2 unknown genders;  $M_{age} = 27.92$  years,  $SD = 6.701$ ), which was used for the analyses in this study.

**Table 7** Nationality sample (2<sup>nd</sup> experiment)

Nationality	Frequency
Indonesian	75
Dutch	17
British	10
American	5
Others	30
Total	137

**Table 8** Sample characteristics.  $N = 137$

Characteristic	$N$	Characteristic	$N$
<b>Sex</b>		<b>Employment</b>	
Male	68	Student	59
Female	67	Employed	69
Others	2	Unemployed	5

<b>Education</b>		Retired	0
PhD	5	Others	4
Master's Degree	69	<b>Age range</b>	
Bachelor's Degree	54	15-24	45
High School	7	25-34	74
Elementary School	0	35-44	15
Others	2	45-54	1
		>55	2

**Table 9** The sample's group assignment

# Participants Needed	# Participants per Personality	# Participants based on Matching	Chatbot's Personality
137 participants	28 participants	3 M participants	OCEAN
		25 NM participants	
	28 participants	4 M participants	OCEA
		24 NM participants	
	26 participants	3 M participants	CEA
		23 NM participants	
	21 participants	3 M participants	CE
		18 NM participants	
	34 participants	5 M participants	C
		29 NM participants	

*Note* M: Match; NM = No Match.

### 3.3.3. Measures

#### 3.3.3.1. Big Five Personality Scales

To improve upon the issue of poor reliability and factor structure, the research consequently used a different Big Five measure: the 10-item Personality Inventory (also abbreviated as TIPI), that is shorter, easier to understand and equipped with better instructions. Participants were required to read each statement and rate it on a seven-point Likert scale (1: disagree strongly to 7: agree strongly). However, the goal of the TIPI was to create a very short instrument that optimized validity (including content validity) (Gosling, Rentfrow & Swann, 2003). Consequently, it will most likely result in low alpha coefficients, as well as poor factor structures obtained in factor analyses, with only two items per dimension. For example, the "Extraversion"



scale could be made from items like “Talkative, verbal” and “Untalkative, quiet.”, but this would have only measured just one facet (talkativeness) of Extraversion. The high alphas and impressive structure fit would have to come at the sacrifice of more important concerns e.g. content and criterion validity (Gosling, Rentfrow & Swann, 2003). Criteria like alpha and clean factor structures are only meaningful to the extent they reflect improved validity (Sekaran & Bougie, 2016). Although still proving somewhat inferior relative to other standard multi-item measurements, it has been validated to be consistent and quite acceptable with other Big Five measures (Gosling, Rentfrow & Swann, 2003).

Nevertheless, this research obtained even better than expected results in the new round of experiment. The Cronbach’s alphas for each dimension with the TIPI measure and new sample showed acceptable internal reliabilities for extraversion (.80), agreeableness (.65), conscientiousness (.69), neuroticism (.71), and openness (.65). Principal component analysis using Oblimin rotation and a five-factor solution also confirmed the construct validity of the Big-Five factors, with all scale items showing distinguishing loadings onto the corresponding factor. The TIPI is also shown in **Appendices**.

**Table 10** User Personality’s PCA Pattern Matrix using Oblimin rotation (2<sup>nd</sup> experiment – TIPI)

I see myself as:	Component				
	1	2	3	4	5
Extraverted, enthusiastic. (E)	.01	.07	-.00	.00	<b>.92</b>
Critical, quarrelsome (argumentative) towards others. (A/R)	.05	<b>.86</b>	-.15	-.01	-.15
Dependable, self-disciplined. (C)	-.02	.02	<b>.87</b>	.11	-.04
Anxious, easily upset. (N)	<b>-.88</b>	-.02	.01	-.00	-.03
Open to new experiences, complex. (O)	.26	-.04	-.05	<b>.77</b>	.06
Reserved, quiet. (E/R)	.00	-.07	-.04	.01	<b>.90</b>
Sympathetic, warm. (A)	-.02	<b>.86</b>	.15	.02	.15
Disorganized, careless. (C/R)	.06	-.02	<b>.89</b>	-.11	.00
Calm, emotionally stable. (N/R)	<b>-.88</b>	-.01	-.05	-.01	.02
Conventional, uncreative. (O/R)	-.16	.03	.04	<b>.92</b>	-.02

E = Extraversion; A = Agreeableness; C = Conscientiousness; N = Neuroticism; O = Openness; R = Reversed.

### 3.3.4. Manipulation of User-Chatbot Personality

To improve upon the issues encountered in the first study, shorter chatbot videos of 3.5 minutes were made from the older videos. Since the length of the videos had been changed, a new pretest had to be conducted. Since the earlier videos were already observed to have reasonably great validity, the pretest in the second experiment was rather short and built upon the existing videos. The second pretest used the new TIPI measure and were only given to three participants. The new pretest performed reliably and is also presented in **Appendix C**.

### 3.3.5. Trust Scale

Trust was assessed by the modified nine-item measure from Gefen and Straub (2004). The scale was used and examined by Hwang and Kim (2007), as well as Chang and Chen (2008), who found them to be highly reliable. This has been further proven by the excellent reliability (Cronbach’s  $\alpha = .88$ ) in this research. Moreover, this research has also added the personal attachment measure to provide more thorough measurement of trust. The scale also showed very good reliability (Cronbach’s  $\alpha = .86$ ).

Furthermore, both scale showed very good factor structures and high loadings, with the former confirming the two factors (cognitive and affective trust), as well as the latter with one factor, as seen in

**Table 11.** Both scales were assessed using the original seven-point Likert scale (anchored at 1 = “Strongly disagree” and 7 “Strongly agree”) and shown in **Appendix A**.

**Table 11** Trust’s PCA Pattern Matrix using Oblimin rotation

Item	Component		
	1	2	3
The chatbot is competent. (T/C)	<b>.88</b>	.06	.10
The chatbot knows how to provide excellent service. (T/C)	<b>.86</b>	.06	-.01
Promises made by the chatbot are likely to be reliable. (T/C)	<b>.80</b>	-.00	-.10
I expect that the chatbot will keep the promises they make. (T/C)	<b>.57</b>	-.08	-.47
I expect that the chatbot has good intentions towards me. (T/A)	.02	.03	<b>-.93</b>
I expect that the chatbot’s intentions are benevolent. (T/A)	.02	.10	<b>-.91</b>
I would feel a sense of loss if the chatbot was unavailable and I could no longer use it. (PA)	.04	<b>.75</b>	-.02
I feel a sense of attachment to using the chatbot. (PA)	-.10	<b>.85</b>	.01
I find the chatbot suitable to my style of decision making. (PA)	.15	<b>.78</b>	.02
I like using the chatbot for decision making. (PA)	.08	<b>.84</b>	.09
I have a personal preference for making decisions with the chatbot. (PA)	-.07	<b>.73</b>	-.21

T = Trust; C = Cognitive; A = Affective; PA = Personal Attachment.

### 3.3.6. Perceived Risk Scale

Perceived risk was assessed by the six-item measure with the original seven-point Likert scale (anchored at 1 = “Strongly disagree” and 7 “Strongly agree”) from Corbitt et al. (2003). The scale was reasonably reliable (Cronbach’s  $\alpha = .71$ ). PCA also showed good factor structures, showing two components. The performance and financial risk seemed to be grouped as one factor, as the social, psychological and time are grouped as one. The questions are also shown in **Appendix A**.

**Table 12** Perceived risk’s PCA Pattern Matrix using Oblimin rotation

I believe that online purchases recommended by the chatbot are risky because:	Component	
	1	2
The product may fail to meet my expectations. (P)	<b>.86</b>	-.01
The product may be inferior. (P)	<b>.88</b>	-.04
They may lead to financial loss for me. (F)	<b>.73</b>	.08
They may cause others to think less highly of me. (S)	-.19	<b>.83</b>
They may fail to fit well with my personal image. (P)	.08	<b>.69</b>
They may lead to a time loss for me. (T)	.21	<b>.72</b>

P = Performance risk; F = Financial risk; S = Social risk; P = Psychological risk; T = Time risk.

### 3.3.7. Purchase Intention Scale

Last, purchase intention serves as the dependent variable in this study and was assessed by the three-item measure from Pavlou (2003). The measure was found to have excellent reliability (Cronbach’s  $\alpha = .90$ ) with a solid factor structure of one component. The questions were assessed using the original seven-point Likert scale (1: strongly disagree to 7: strongly agree), as shown in **Table 13**.

**Table 13** Purchase intention’s PCA Component Matrix

Item	Component
	1
I intend to use the chatbot to conduct future purchases.	<b>.92</b>
I expect to purchase with the help of chatbot in the future.	<b>.92</b>
It is likely that I will transact with the chatbot in the near future.	<b>.90</b>

### 3.3.8. Net Promoter Score

The last measure in this experiment is the Net Promoter Score, which simply asks whether the customers would recommend a brand or product to a friend or colleague (Bain & Company, 2018). The score ranges from 0 to 10, categorized into customers giving a 0-6 score as ‘Detractors’, 7-8 as ‘Passives’ and 9-10 as ‘Promoters’. Detractors are customers that are unsatisfied with the associated brand/product. Passives, on the other hand, are indifferent customers that are neither satisfied or dissatisfied, therefore can easily be run after by the competition. Last, promoters are loyal and enthusiastic customers that urge others in their network to do the same. The score is calculated by subtracting the percentage of customers who are promoters with the detractors.

The Net Promoter score can be used to track the performance of each customer segments or geographic units over time. The score is claimed to be measuring the quality of a company’s relationships with its customers, and more importantly, also often linked to growth (Bain & Company, 2018). In the context of the present study, the willingness to promote the chatbot is seen as a way to measure the users’ emotions and general satisfaction towards the chatbot.

## 4. Results

This section presents and discusses the results obtained from the experiment. First, the manipulation check in which how the user perceived the chatbot's personality and relate themselves to the customer in the video is explained. Second, the overall results and hypothesis testing is presented. Third and consequently, some discussions on the results is followed up. Next, both the scientific and practical relevance will be argued. Last, the lessons learned during the research such as limitations and suggestions for future research will also be raised.

### 4.1. Manipulation Check

As shown in **Figure 12**, the green highlights represented a correct match between the participants' average answers and the intended answers. The orange highlight served as a slight mismatch, while the red highlights showed a bold mismatch.

1st attempt	OCEAN (A)	CEA (B)	CEA (C)	CE (D)	C (E)	2nd attempt	OCEAN (A)	CEA (B)	CEA (C)	CE (D)	C (E)
Agree	Agree	Agree	Agree	Disagree	Disagree	Agree	Agree	Agree	Agree	Disagree	Disagree
A/N	N/A	Neutral	N/D	N/D	N/D	Agree	Agree	Agree	Disagree	Disagree	Disagree
Neutral	Agree	Agree	Agree	Agree	Agree	Neutral	Agree	Agree	Agree	Agree	A/N
A/N	Neutral	N/D	N/D	Disagree	Disagree	Agree	Disagree	Disagree	Neutral	Disagree	Disagree
Disagree	Disagree	Disagree	Disagree	Agree	Agree	Agree	Agree	N/D	Disagree	Disagree	Disagree
Disagree	Neutral	Disagree	Neutral	Neutral	Neutral	Disagree	Disagree	Disagree	Disagree	Agree	Agree
Neutral	Disagree	N/D	N/D	Disagree	Disagree	Neutral	Disagree	Disagree	Disagree	Disagree	Disagree
N/A	Agree	Agree	Agree	Agree	Agree	Disagree	Agree	Agree	Agree	Agree	Agree
Neutral	Neutral	Neutral	A/N	Neutral	Neutral	Disagree	Disagree	Disagree	Neutral	Agree	Agree
Agree	Agree	Agree	Agree	Disagree	Disagree	Agree	Agree	Agree	Agree	Disagree	Disagree
A/N	Neutral	Agree	Disagree	Neutral	Neutral	Agree	Agree	Agree	Disagree	Disagree	Disagree
N/A	Agree	Agree	Disagree	Agree	Agree	Agree	Agree	Agree	A/N	Disagree	Disagree
Agree	Disagree	Disagree	A/N	Disagree	Disagree	Agree	Disagree	Disagree	Agree	Agree	Agree
N/D	N/D	Neutral	Neutral	Agree	Agree	Disagree	N/D	Neutral	Agree	Agree	Agree
Disagree	Disagree	Disagree	Disagree	Agree	Agree	Disagree	Disagree	Disagree	Disagree	Agree	Agree
Neutral	N/D	N/D	Neutral	Agree	Agree	Neutral	Disagree	Disagree	Agree	Agree	Agree
Neutral	Disagree	Disagree	Disagree	Disagree	Disagree	Neutral	Disagree	Disagree	Disagree	Disagree	Disagree
A/N	Disagree	Disagree	Neutral	Neutral	Neutral	Disagree	Disagree	Disagree	Disagree	Disagree	Disagree
Disagree	Neutral	Neutral	Neutral	N/A	N/A	Disagree	Disagree	Neutral	A/N	Agree	Agree

**Figure 12** First and second round pretest results

Acting as the manipulation check in this research are the perceived chatbot personality and self-relate questions. Participants were asked to judge the chatbot's personality using the TIPI scale. The measure itself showed good and quite acceptable reliability (Cronbach's  $\alpha = .85, .67, .67, .68, .67$  for extraversion, agreeableness, conscientiousness, neuroticism, openness, respectively), considering the already-weak TIPI measure (Gosling, Rentfrow & Swann, 2003). Meanwhile, PCA showed high loadings and reasonable factor structure with 4 components. Agreeableness and Openness appear to show in one component. This is rather unsurprising seeing how many participants also faced difficulties answering those two traits during the pretest, as explained earlier in **Chapter 3**.

**Table 14** Perceived chatbot personality's PCA Pattern Matrix with Oblimin rotation (2<sup>nd</sup> experiment – TIPI)

	Component			
I see the chatbot as:	1	2	3	4
Extraverted, enthusiastic. (E)	.18	.06	<b>-.86</b>	.12
Critical, quarrelsome (argumentative) towards others. (A/R)	<b>.68</b>	-.14	-.14	-.15
Dependable, self-disciplined. (C)	-.01	<b>.94</b>	-.00	.16
Anxious, easily upset. (N)	-.01	.11	-.09	<b>.89</b>
Open to new experiences, complex. (O)	<b>.74</b>	.02	.09	.15
Reserved, quiet. (E/R)	-.07	-.04	<b>-.97</b>	-.00
Sympathetic, warm. (A)	<b>.73</b>	.10	-.17	-.09
Disorganized, careless. (C/R)	.04	<b>.74</b>	.01	-.32
Calm, emotionally stable. (N/R)	.11	-.22	-.00	<b>.75</b>
Conventional, uncreative. (O/R)	<b>.80</b>	.04	.10	.10

E = Extraversion; A = Agreeableness; C = Conscientiousness; N = Neuroticism; O = Openness; R = Reversed.

Next, participants were asked how they could relate themselves with the customer in the video. This question acts both as manipulation check as well as a validity measure, since the customer was designed subjectively by the researcher and may have been biased. Nevertheless, the customer was designed to be as neutral as possible, showing minimal emotions, so that it can be uniform and suitable in all five videos. Keeping in mind that not all customers would be so ‘emotionless’ such as the one in the video, **Table 15** still shows a reasonable level of self-relation between the participants and the customer in the video.

**Table 15** Self-relate score.  $N = 137$

	Item	$N$ (Total = 137)	Percent (%)
To what extent can you relate yourself to the customer in the video?	Very unrelatable	5	3.6
	Somewhat unrelatable	24	17.5
	Neutral	22	16.1
	Somewhat relatable	64	46.7
	Very relatable	22	16.1

#### 4.2. Sample Characteristics, Correlation and Overall Distribution

**Table 16** shows that majority of participants are internet-fluent, with them spending a substantial portion of time per week using the internet. The other information in the table derives that the participants have conducted online purchases in the past, mostly through websites and shopping applications. Furthermore, a majority of the participants were seen to (may) have had experiences with chatbots in the past. This information on the sample’s characteristics shows that the sample is appropriate for our research.

**Table 16** Sample descriptions.  $N = 137$

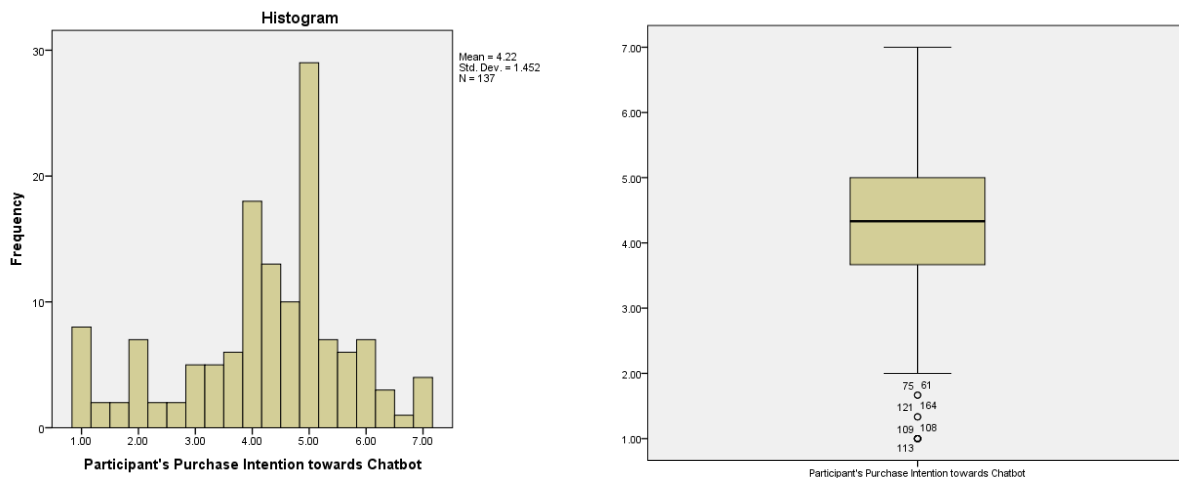
Sample descriptions	Item	$N$ (Total = 137)
How often do you use internet in a week?	Less than 4 hours	2
	4 to 20 hours	48
	More than 20 hours	87
How do you normally conduct an online purchase? (multiple choice possible)	Apps	82
	Websites	130
	Social media	27
	Others	-
Have you ever had any interactions with chatbots in the past?	Yes	53
	Maybe	56
	No	28

**Table 17** shows the descriptive statistics and traditional correlation matrix for the factors in the experimental design, including the arithmetic means and standard deviations for Matched Personality and Chatbot Personality (also called as Condition in SPSS). First, Trust appeared to be significantly and negatively correlated with Perceived Risk as well as positively correlated with Purchase Intention. The same expected relationship was also found for Perceived Risk, which was significantly and negatively correlated with Trust and Purchase Intention. Multicollinearity was absent in all variables, except between Trust and Purchase Intention (.71).

**Table 17** Descriptive statistics and correlations. Note  $N = 137$ ; \*\*  $p < .01$  level; two-tailed

	<i>M</i>	<i>SD</i>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>
<b>1. Matched Personality</b>	.13	.34	-				
<b>2. Chatbot Personality</b>	2.96	1.48	-.37**	-			
<b>3. Trust</b>	4.02	.95	-.04	.08	-		
<b>4. Perceived Risk</b>	4.08	.97	-.06	.04	-.27**	-	
<b>5. Purchase Intention</b>	4.22	1.45	-.02	.07	.71**	-.27**	-

Furthermore, the distribution of Purchase Intention, as seen in **Figure 13** and **Figure 14** (Kolmogorov-Smirnov  $< .05$ ), was found to be non-normal. Despite the attempt to log-transform Purchase Intention's distribution, the distribution of the variable remained non-normal.



**Figure 13** Histogram and box plot for Purchase Intention

### Tests of Normality

	Kolmogorov-Smirnov <sup>a</sup>			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Participant's Purchase Intention towards Chatbot	.154	137	.000	.940	137	.000

a. Lilliefors Significance Correction

**Figure 14** Purchase Intention normality test

## 4.3. Hypotheses Testing – Purchase Intention

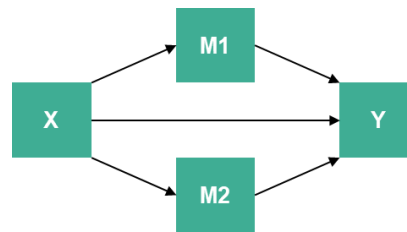
After presenting the sample along with its characteristics and distribution, the hypotheses of this study were tested and analyzed according to the conceptual model, which contains mediation. Alternatively, an analysis in the case of moderation was also included.

### 4.3.1. Mediation Analysis

The mediation in the conceptual model was performed using the popular PROCESS macro for SPSS, which simplifies the implementation of mediation (Hayes, 2013). The macro has become widely used for research especially in business, marketing and other fields (Hayes, Montoya & Rockwood, 2017). **Figure 15** Multiple mediator model shows the model that resembles the conceptual model of this study. The independent



variables (i.e. Matched Personality and Chatbot Personality) are represented by X. The mediators (i.e. Trust and Perceived Risk) are represented by M1 and M2, respectively. While the dependent variable (i.e. Purchase Intention) is represented by Y.



**Figure 15** Multiple mediator model

In the original conceptual model, the experimental factor, Matched Personality(X), failed to have a significant impact on Trust (M1),  $t(137) = -.42$ , ns, CI [-.58, .37] and Perceived Risk (M2),  $t(137) = -.74$ , ns, CI [-.67, .30]. Matched Personality also did not have a direct significant impact on Purchase Intention (Y),  $t(137) = .08$ , ns, CI [-.50, .54]. Perceived Risk (M2) also did not show any significant impact on Purchase Intention (Y),  $t(137) = -1.27$ , ns, CI [-.31, .07]. However, Trust (M1) was found to have a significant positive impact on Purchase Intention (Y),  $t(137) = 10.92$ , s, CI [.87, 1.25]. Nevertheless, the indirect path that Matched Personality has on Purchase Intention via Trust, does not exist, CI [-.56, .27].

Similarly, another experimental factor, Chatbot Personality(X), also failed to have a significant impact on Trust (M1),  $t(137) = .95$ , ns, CI [-.06, .16] and Perceived Risk (M2),  $t(137) = .50$ , ns, CI [-.08, .14]. Chatbot Personality did not show any direct significant impact on Purchase Intention (Y),  $t(137) = .23$ , ns, CI [-.10, .13]. Equally, Perceived Risk (M2) also did not demonstrate any significant impact on Purchase Intention (Y),  $t(137) = -1.29$ , ns, CI [-.31, .06]. However, Trust (M1) was also found to have a significant positive impact on Purchase Intention (Y),  $t(137) = 10.86$ , s, CI [.86, 1.25]. Just like the previous experimental factor, the indirect path that Chatbot Personality has on Purchase Intention via Trust was also found to be nonexistent with CI [-.05, .17].

#### 4.3.2. Moderation Analysis

Alternatively, this study also explored the moderation version of the conceptual model. The General Linear Models (GLMs) module in SPSS was used to evaluate the moderated hypotheses for Purchase Intention. The GLM is a generalization and larger set of linear regression that is specifically developed for the non-parametric analysis of non-normal distribution (Aiken et al., 2015), suitable for the distribution found in this study. Moreover, since Purchase Intention is not a count data but an ordinal data (Likert), the Poisson or Negative Binomial regression would both not be suitable. Consequently, an ordinal logistics regression was used as the most appropriate analysis  $\emptyset = -.10$ , SE = .44, 95% CI [-0.97, 0.77].

Furthermore, the experimental factor, Matched Personality is dummy-coded into 1, 2 (no match versus match). The measures of Trust and Perceived Risk were centered at the grand mean. Next, the cross-products for the interactions between the predictors on Purchase Intention were computed and entered into the equation together with the main effects to test for causality. As a result, seven effects were tested with the ordinal logistics regression model.

The Likelihood Ratio chi-square for the ordinal logistics model was  $\chi^2(7) = 93.97$ ,  $p < .00$ , with a model deviance  $D = .26$ , which showed that the model led was well fitted to the data. This was further supported by the goodness of fit values for the Log Likelihood function = -308.06, Akaike's Information Criterion (AIC) = 666.11, the Bayesian Information Criterion (BIC) = 739.11.

**Table 18** Final model estimates of main and interaction effects of Matched Personality on Purchase Intention

Model effects	B	Std. error	df	Wald $\chi^2$	p
Intercept	1.50	.18	1	72.64	<.000
Matched personality	-.10	.44	1	.05	Ns.
Trust	2.29	.71	1	10.47	<.001
Perceived risk	.03	.51	1	.00	Ns.
Matched personality x Trust	-.51	.71	1	.53	Ns.
Matched personality x Perceived risk	-.34	.54	1	.39	Ns.
Trust x Perceived risk	.52	.82	1	.41	Ns.
Matched personality x Trust x Perceived risk	-.58	.83	1	.50	Ns.

**Table 18** summarizes the results of the ordinal logistics regression analysis. Rejecting Hypothesis 1, 2a and 2b, no significant results were found among those interactions. The only significant result was Trust, which had a significant positive effect on Purchase Intention, Wald  $\chi^2(1) = 10.47$ ,  $p < .001$ . No other significant effects were revealed.

Alternatively, the present study also investigated the effects of chatbot personality itself towards Purchase Intention. The experimental factor, Chatbot Condition is dummy-coded into 1, 2, 3, 4, and 5 (C, CE, CEA, OCEA, and OCEAN, respectively). The measures of Trust and Perceived Risk were also centered at the mean. Next, the cross-products for the interactions between the predictors on Purchase Intention were computed and as a result, 19 effects were tested with the ordinal logistics regression model.

The Likelihood Ratio chi-square for the ordinal logistics model was  $\chi^2(19) = 113.92$ ,  $p < .00$ , with a model deviance  $D = .25$ , which showed the goodness of fit between the model and the data. Furthermore, it was supported by other goodness of fit values for the Log Likelihood function = -300.16, Akaike's Information Criterion (AIC) = 674.32, the Bayesian Information Criterion (BIC) = 782.36.

The results of the ordinal logistics regression analysis are summarized in **Table 19**. Consistent with the previous analysis, Trust was found to have a positive significant effect on Purchase Intention, Wald  $\chi^2(1) = 2.95$ ,  $p < .045$ . The interactions between Chatbot personality 1 (C) and Trust (Wald  $\chi^2(1) = 7.99$ ,  $p < .005$ ), as well as chatbot personality 4 (OCEA) and Trust were also found to be statistically significant (Wald  $\chi^2(1) = 6.68$ ,  $p < .010$ ). No other significant effects were observed.

**Table 19** Alternative model estimates of main and interaction effects of Chatbot Personality on Purchase Intention

Model effects	B	Std. error	df	Wald $\chi^2$	p
Intercept	1.39	.14	1	92.61	<.000
Chatbot personality 1	.24	.48	1	.25	Ns.
Chatbot personality 2	-.10	.52	1	.04	Ns.
Chatbot personality 3	.37	.51	1	.52	Ns.
Chatbot personality 4	.04	.55	1	.01	Ns.
Trust	.74	.43	1	2.95	<.045
Perceived risk	-.19	.30	1	.39	Ns.

Chatbot personality 1 x Trust	1.66	.59	1	7.99	<0.005
Chatbot personality 2 x Trust	.73	.60	1	1.46	Ns.
Chatbot personality 3 x Trust	1.08	.63	1	2.91	Ns.
Chatbot personality 4 x Trust	1.96	.76	1	6.68	<0.010
Chatbot personality 1 x Perceived risk	-.09	.53	1	.03	Ns.
Chatbot personality 2 x Perceived risk	1.75	.72	1	5.85	Ns.
Chatbot personality 3 x Perceived risk	-.40	.48	1	.72	Ns.
Chatbot personality 4 x Perceived risk	-.34	.60	1	.32	Ns.
Trust x Perceived risk	-.00	.42	1	.00	Ns.
Chatbot personality 1 x Trust x Perceived risk	-.03	.61	1	.00	Ns.
Chatbot personality 2 x Trust x Perceived risk	-1.44	.90	1	2.54	Ns.
Chatbot personality 3 x Trust x Perceived risk	-.08	.53	1	.02	Ns.
Chatbot personality 4 x Trust x Perceived risk	.69	.88	1	.62	Ns.

#### 4.4. Net Promoter

Last, the result of the net promoter question is presented as follows. Detractors are those who gave a score between 1 to 6 ( $N = 74$ ; 54%), while Passives 7 to 8 ( $N = 50$ ; 36.5%) and Promoters 9 to 10 ( $N = 13$ ; 9.5%). The Net Promoter score is then calculated by subtracting the percentage of Promoters with Detractors, which results in a score of -44.5.

**Table 20** Net promoter score.  $N = 137$

		Score	$N$ (Total = 137)	Percent (%)	Cumulative Percent (%)
How likely is it that you would recommend the chatbot to a friend? Whereas 1 is 'Not likely at all' and 10 is 'Extremely likely'.	Detractors	1	7	5.1	5.1
		2	6	4.4	9.5
		3	8	5.8	15.3
		4	7	5.1	20.4
		5	21	15.3	35.8
		6	25	18.2	54.0
	Passives	7	36	26.3	80.3
		8	14	10.2	90.5
	Promoters	9	8	5.8	96.4
		10	5	3.6	100.0

## 5. Discussions

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The present study has explored the extent that user's trust, perceived risk and purchase intention would be influenced by the different matching of chatbot's and user's personality. We hypothesized that a matched personality would result in increased trust and purchase intention, as well as decreased perceived risk. Based on the methodology and results that the study has obtained, the discussion is laid out as follows.

### 5.1. The Choice for Movie Experiment

The rationale to use movie as opposed to real simulation is multifold. First, the required time and resources for the development of real conversational chatbot are substantial, something that this study lacked. The development of a real working chatbot is complex, requires certain skill-sets and training, as well as a significant amount of time to make it robust. Most of the resources had been used to develop conversations as the mode to express personalities, which would be one of this research's contributions. In contrast, the process to produce movies is a lot simpler and requires a lot less time. Moreover, the study also lacked the time required to observe all participants in-person during real experiment.

Second, due to the complexity to develop a robust chatbot, the experiment is prone to any deviations that can be made by the participants (e.g. answering with irrelevant replies, testing the chatbots out of fun, or swearing, etc.), simply because it is impossible to develop all possible intents (topics/tasks) within the given timeframe. The lack of participants' interaction in this case is therefore desired, so that a standardized and uniform stimulus can be provided to all participants (Ruzicka, 2013). Last, if done correctly, movies have been shown to still have robust internal validity (Gould, 1996), where it provides the environment in which participants can imagine themselves in the artificially created environment that is not too different from a real e-commerce setting.

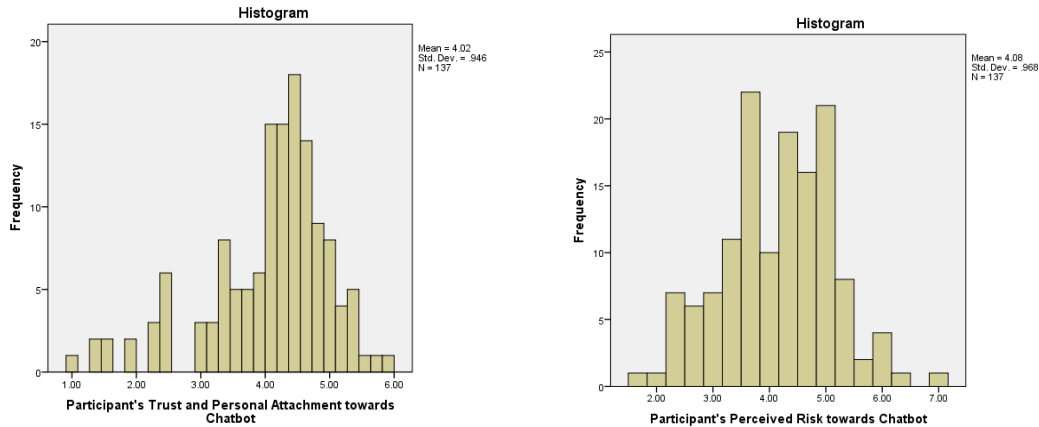
### 5.2. Lessons Learned from the First Experiment

Before that, the study would like to discuss the lessons learned from the first experiment that led to the decision to conduct a second experiment. The present study concluded four things that may have caused issues in the first experiment. First, participants may have had difficulties understanding some of the sentences that may have sounded abstract, e.g. "Am not interested in abstract ideas" or English words that may be uncommon, e.g. "Get chores done right away", since a large majority of the participants were not English native speakers. This is consistent with the author's findings during the pretest, where participants were dominantly confused with what the sentences actually meant and only were able to answer accurately when explanation was provided. Second, the nature of uncontrolled experiment may have caused the participants to inaccurately answer the questions. Third, the already-short questionnaire still seemed to be too long for such voluntary experiment. Participants seemed to want to go through the experiment as quickly as possible, and this can be seen in the short experiment duration. Fourth, it was further amplified with the fact that all 20 questions were put in one page.

In the end, the second experiment attempted to tackle at least item one and four. This resulted in the change of Big-Five measure from Mini-IPIP to TIPI scale, as well as shorter videos and better instructions. Due to the size of the study, the experiment length could not be further reduced.

### 5.3. Trust and Perceived Risk

Overall, the level of trust was found to be left-skewed towards the higher spectrum. The users were observed to be trustful towards chatbots. This finding has the following implications.



**Figure 16** Distribution of Trust (left) and Perceived Risk (right)

This result might be caused by the fact that the chatbots are already very humanlike in the experiment. The chatbots were designed to have different combinations of Big Five personalities. Keeping this mind, the natural consequences of personalities are, to some extent, the projection of humanness into the agents. Moreover, four of the five chatbots are highly extraverted, which trait is claimed to be the most visible social trait (John & Srivastava, 1999). The overall average trust might have then been affected by this asymmetry. In contrast, an experiment by Crone (2017) on emotional versus no-emotional (neutral) chatbot was observed to show discrepancy in the level of trust. It is possible that this was observed when rich-social chatbots are compared with neutral bots (no personality). Furthermore, this is in line with the finding from Dautenhahn, Ogden & Quick (2002), which observed certain clear drop-off in positive evaluations, when a robot becomes extremely humanlike. This suggests that up to some point of displaying human qualities, artificial agents would be perceived positively. However, where that point is and what it entails is currently not known and therefore calls for more work.

Meanwhile, perceived risk was found to be centrally concentrated. In other words, participants were indifferent about the perceived risk towards the chatbot. The present study posited that this might have something to do with a few things. First, it could be that the measure of perceived risk simply is not applicable. Participants might be unsure how they would self-assess the perceived risk. Second, the novelty of chatbot technology might have made it too early to assess such measure. Third, the nature of general online e-commerce perceived risk that is perceived neither risky nor safe. These findings call for future research to confirm these claims.

#### 5.4. Purchase Intention

With regards to the original hypothesis, in which purchase intention is predicted to be affected by matched personality, the present study has shown no statistically significant results in all three hypotheses. From both models of mediation and moderation, the only statistically significant result was the effect between Trust and Purchase Intention. This further supported the study by Chang and Chen (2008). Matching personality did not cause any statistically significant results in purchase intention, nor was it mediated by Trust and Perceived Risk. Therefore, all the hypotheses of the present study are rejected.

Alternatively, the study also investigated the pure effect of chatbot personality towards Purchase Intention, independent from the user's personality. Interestingly, both chatbot personality 1 (C) and 4 (OCEA) together with Trust, were found to give statistically significant results to Purchase Intention. It is logical to see the OCEA chatbot excelling, seeing how the combinations of all those four traits should make up the perfect personality for customer service roles. The chatbot was highly attentive, stable, organized, yet creative. In contrast, the C chatbot was also found to be effective in increasing purchase intention. The

chatbot is most likely seen as the usual chatbots that we see these days, with regard to lean and efficient interaction with customers and simply performed what it was supposed to do, without any unnecessary extras. Users might in fact prefer to chat with such chatbot because it simply did its job within a short period of time.

In any case, the fact that the study failed to achieve statistically significant results in the other variables and interactions has raised some questions for both existing research as well as future research. Perceived risk was found nowhere close to be a reliable predictor for purchase intention. While this might have been caused by the limitations (later explained) of this research, the present study calls for other research to further scrutinize this finding.

Nevertheless, this study attempted to explain the reasons for non-statistical results through five possible arguments. First, trust, perceived risk and purchase intention might not be good measures after all for evaluating the effects of different personality matching. After all, if the chatbots are already very human, other measures might be more suitable in measuring the impact. Second, the participants were exposed with one condition only in the present study. Although this method is considered to be the best in tackling validity errors in bias and fatigue objectively, other methods like within-subject (where participants are exposed to all the conditions) might also be worth considering. This allows participants to compare the different personalities and decide what is best for them themselves.

Third, the results may have been caused by a small and imbalanced sample size. The experiment was designed with five exact personalities. For a matching condition to occur, the chatbots need to be paired with the exact corresponding user personalities. With 32 different combinations ( $2^5$ ), we were faced with imbalanced group size between matched versus non-matched personalities (18 matched versus 119 non-matched). Together with the time constraint to collect samples, the sample size in each condition could not be kept nicely in balance. This imbalance and small sample size might have contributed in the non-statistically significance results, as seen again in **Table 9**.

Fourth, in relation with the argument for ‘efficient’ chatbots, the study’s finding seems to be consistent with various surveys that have been performed on chatbots. When using a chatbot for a specific task, users would most like to get the task done. Chatbots are judged by how well the agent’s actions perform in specified goals. They do not want fluff, funny, smart, but they want it done. 69% of consumers would speak to a chatbot to get instant answers, whereas only 15% would use it for the fun of it (Ubisend, 2017). This goes in line with the general sentiment that the study has received from the participants’ comment box. As one participant stated: *“It’s nice to have a very lively chatbot to assist my shopping. It certainly has made my conversation a lot more fun! It would be nice to use it the first time, however, if I were to use this for the future and expect it that long to find an answer, I’d rather do it myself”*. The message seems to be that performance is more important than fun in the case of e-commerce.



**Figure 17** Gatebox interacting with a user (Gatebox, 2016)



Fifth, it may also be that e-commerce is simply a wrong application for such application. For example, the Poncho bot does a great job holding a conversation with users and has great personalities. However, when imagined using Poncho for a company's HR bot, it would not be appropriate due to its snarky comments or vague diversions. The same might apply for e-commerce chatbots. Rich personality chatbots might simply be most effective for other fun, engaging, communicative and non-task-oriented applications, such as elderly companions and virtual romance like Gatebox in Japan. Nevertheless, we should be cautious to draw conclusions since these claims suffer from burden of proof and therefore call for future research.

### 5.5. Scientific Relevance

To the author's knowledge, the present study is the first ever known academic attempt in the research of botsanality. Most specifically, the researcher did not find any existing systematic methods to project personalities into words. The field of linguistic personality has mainly been dealing with the other side of the coin, i.e. deriving personalities from words. Such reverse-engineering references could not be found, as well as resources like machine learning for such feat has not yet existed and psychologists were also not in our disposal. This research therefore has attempted to do such task without any given reference. In the end, although rather manual and tedious, the methodology of using the LIWC dictionary as well as pretesting it using participants might still be the lowest-hanging fruit for future research in this field. The tiresome and mundane task, however, might still trigger the awareness to other scientists working in artificial intelligence and artificial psychology (as the advanced stage of artificial intelligence) fields to introduce new technology in automation and information science.

In relation to that, the study also provides some insight into an emerging research discipline called "Psychoinformatics". The field of psychoinformatics combines both disciplines of psychology and computer science, by handling very large set of data generated by digital devices or social media, to shed light on a number of psychological traits, such as personality (Montag, Duke & Markowetz, 2016). In the present study, deriving personality proved to be a challenge and highly dependent on the length of such questionnaire, as well as the willingness of participants to rightfully provide answers. Nevertheless, besides personality questionnaires, various literatures have shown how personalities can also be derived by using technologies like the LIWC software and IBM Personality Insight. With such technology, inferring personality from texts (e.g. tweets, blogs, social media) would substantially be a lot less challenging and personality matching (or otherwise) might be even feasible to implement, wherever proven effective. Nevertheless, the limited amount of textual data generated by the general consumers, might call for other technologies to infer personalities from other sources, such as cookies, Instagram posts, and etcetera. The validity of such automatic personality tool also has to be rigorously tested, as the LIWC software and IBM Personality Insight still failed to detect the chatbots' personalities perceived by the consumers.

### 5.6. Practical Relevance

The present study has shown that it is possible to assign personalities into chatbots using linguistic means. As previously observed, the botsanalties are shown to be well perceived by the users. The application prospect of creating such bots with linguistic personality is thought to be extensive as well as providing a much richer experience and engagement with the users. Although the latter may hold true, the former statement needs to be investigated, especially keeping in mind the results that the present study has generated. The effect seems to have originated more from the personality of the users, but less so because of the different botsanality, and let alone the matching between both personalities. As previously stated, customers would like to accomplish their task and would love a bit of an extra help from the chatbot, not to a point where it has become too 'annoying'.

The implication of this finding is of considerable importance. First, this would mean good news for chatbot developers since developing artificial personalities is not an easy feat. This gives them enough time for the

proper technology to catch up, while ultimately being able to focus on maximum performance in the meantime. Second, companies and chatbot developers are going to have to find the right application if they were to assign personalities into their agents someday. While it has been proven inefficient for e-commerce, other goal-oriented applications are also imagined experiencing the same faith. Future research/experiment would be necessary to determine the right applications for such chatbots. The same question would apply for chatbot applications that mainly focus on engagement and entertainment purposes.

Last, the present study has only focused on one aspect of the human factor, i.e. personality. There are still other possible factors that researchers could modify to achieve some level of personalization. Therefore, the study also hopes to open the discussion, promote awareness and progress of personification in the academic and professional world to further investigate such chatbot personalization.

### 5.7. Limitations

The study would also like to acknowledge the limitations. The limitations generally come from the methodology of the experiment. First of all, the samples were collected in a non-probable fashion. In other words, it did not give equal chances of for others in the population for being selected (Sekaran & Bougie, 2016). This is mainly due to convenience sampling, in which the researcher relies on his personal network, as well as snowball sampling, where participants are recruited from the participants' acquaintances. The two pretests were also done by the researchers' acquaintances and were not chosen randomly from the population.

Second, participation (other than from mTurk) to the experiment was on a voluntary basis, with no incentives/reward. The experiment therefore heavily relied on the good faith of the subjects to respond seriously and truthfully. In terms of participants collected from mTurk, even though they were rewarded with a relatively high USD 40 cents, the quality of their data still proved inferior compared with non-mTurkers (Deloitte employees and personal network). While other studies have found mTurkers to be reliable, it certainly was not the case in the present study.

Third, in relation to the previous limitation, the experiment was conducted in an uncontrolled space. Participants had the freedom to conduct the experiment wherever and whenever based on their convenience. Uncontrolled experiment or unsupervised subjects tend to be less attentive than subjects in a lab with an experimenter (Oppenheimer et al., 2009). The results may have been different if performed in a full-fledge laboratory (Sekaran & Bougie, 2016).

Fourth, the TIPI personality scale did not come without limitations. Because of the extensive length of the experiment, a rather short 10-questions measure like TIPI was chosen. However, TIPI was known to have poor reliability as well as factor structure (Gosling, Rentfrow & Swann, 2003). The authors argued that they were aiming for an optimized validity by attempting to go for the full extent of the traits. As an example, by only focusing on talkativeness – which only represents one facet of extraversion – the measure would have been able to achieve higher reliability and factor structure. However, it would have come at a high price of lower content validity. Keeping in mind of the low reliability reference, the present study decided to continue anyway despite a rather low validity. In relation to that, the experiment was conducted in English, which may have not been the first language of many participants. This might have caused some misunderstandings in the instructions and questions, as well as unintended answers.

Fifth, video experiments may yield unexpected effects as opposed to real experiments. Instead of having real interactions with the chatbots, users were asked to only sit and observe. Participants then lacked the freedom to interact like they actually would in real life. Sixth, the videos in the experiment could only be kept for so long. By the second experiment, the length of the videos has been kept at 3.5 minutes, as opposed to 10 minutes and 5.5 minutes in earlier versions. While the benefits of a short video may be clear for the

subjects, it comes at the cost of personality accuracy. Just like the TIPI scale, a short video could only show so much of the personality and may not display the full extent of all facets.

Seventh, the design of the botsanality may as well be biased towards the personality of the designer, which in this case is the researcher of the study. True objectiveness could be better achieved if such personality could be designed by multiple designers, such as a team of writers or psycholinguists.

Last, the present study is the first known and only study in this field. Generalization should not be based on the results of single studies (Driskell & Salas, 1992). Overall, the limitations constitute both weaknesses and opportunities for future research to shed light on these issues.

## 6. Conclusion

With increasing competition and the strive for efficiency, artificial intelligence has become the one of the go-to solutions for many of today's issues. Over the course of time, artificial intelligence has gotten better and shown its capabilities to work alongside and for humans. One of such examples is virtual agents or chatbots, fulfilling the role of agents/assistants in various applications. To further improve the deployed virtual agent's service, this research has proposed the idea to personalize each agents, by giving them unique personalities matched to the user's personality.

Therefore, the main research question of this study is: *"What impacts would a personalized botsanality have on its customer experience?"*. To answer the question, a set of hypotheses overview and result summary of this study are shown in **Table 21**. Two experiments have been conducted for this research, whereby useful data had been collected from the second experiment. The sample was found to be accurate with the desired demographics, i.e. internet-fluent and e-commerce experience. Moreover, the data was shown to have good reliability and factor structure, which gave us the permission to proceed with hypothesis testing. The hypotheses were tested according to the original conceptual model (mediation) and an alternative model (moderation). Moreover, the present study also performed analysis using the chatbot's personality, besides the matched personality, as the independent variables. In the mediation model, no significant results were found, except between Trust and Purchase Intention. In the moderation model, significant results were found only in two of chatbot personalities (C and OCEA) when moderated by Trust, as well as between Trust and Purchase Intention. Thus, in both cases, Trust was consistently found to have a significant impact on Purchase Intention. Consequently, with these results, all the hypotheses were then rejected.

**Table 21** Hypotheses overview

	Hypothesis	Results
<b>H1</b>	Matched personality directly increases purchase intention.	Rejected
<b>H2a</b>	Matched personality increases purchase intention and it is mediated by increased trust.	Rejected
<b>H2b</b>	Matched personality increases purchase intention and it is mediated by lowered perceived risk.	Rejected

In conclusion, the present research has highlighted the need and awareness to account for user personality and chatbot personality in the development of more personalized service in e-commerce. Such idea, however, should be reevaluated after obtaining such results from the present study. The overall results, which led to the rejection of the hypotheses, have failed to find much meaningful findings. It is unfortunately too soon to make statements about the fruits of personality matching, with such results. One thing for sure, this study has certainly raised more questions and homework for future work.

The complexity of personalization through personality has been observed to be much more difficult than initially expected, and therefore calls for more attention and improvements on the methodology design and more importantly, the technology. Whilst improving upon the methodology, researchers in the field of psychology and computer science are invited to collaborate and come up with a structured technological solution for better personality matching. Only until then, can we make conclusions on the precise benefits of such idea and make judgments if the benefits would outperform the required costs. Nevertheless, the

lessons-learned obtained from this study could certainly still be of great contribution and consideration for future research in this topic and field.

### 6.1. Suggestions for Future Research

This subchapter is written as an avenue for raising suggestions and new questions for future researchers in this field. First, the easiest suggestion would be to improve on the sample size. Due to the time constraints, a large sample size could not be collected in the present study, which might have contributed to the non-statistically significant results. Second, the method upon how the sample is collected can be improved as well. Future research should strive for better representation of the population by not relying upon convenience. Despite the popularity and the positive claims over mTurk, the present study could not achieve the same high-quality data as alleged elsewhere. The low-quality data seemed to have originated from the low reward in the first experiment. Future research could build more investigation upon the quality and reliability of mTurk whilst striving for the larger population.

Third, this research has shown how difficult it is to match the user's personality. With only five personalities, we are left with 32 different combinations of personalities. Moreover, the current method treats the traits as a binary (low versus high), while in reality, the different level within such one trait could be made of multiple levels. This calls for future research, possibly in machine learning and psychoinformatics, to systematically design a system that can account for all personality combinations, as well as capable of modifying the level of such traits.

Fourth, it is recommended to approach future work in this field with a bigger team of researcher, preferably a team out of psychologists and computer scientists. This would allow the botsanalties to be better designed through the eyes of many (as opposed to just one creator), therefore reducing the bias and supposedly increasing the quality of such projection. Moreover, instead of static personalities that are designed and set at the beginning of the interaction, more sophisticated approach that allows more real-time personality adjustment with machine learning might be interesting to investigate.

Fifth, as an alternative to designing personalities from scratch, prospects can instead start from a baseline by generalizing a specific personality for a specific application. This can be achieved by using personas. As an example, a persona for the application of HR chatbot might first be designed with a specific Big Five combination and then experimented on. Upon such baseline, incremental tweaks can be followed up afterwards.

Sixth, other methods of experiment are welcomed. Prospective research could pursue doing real experiment, where subjects have the opportunity to interact with the chatbot. It would be fascinating to observe the difference with these types of experiment. Furthermore, the present research only sets the botsanality at the beginning of the conversation, based on the derived users' personality. In the long run, chatbots can adapt real-time to the participants' responses by using a combination of feedback loop or 'Time to frustration', which is the time required for participants to express their frustration.

Seventh, having a look at a different set of variables might also be the next obvious pursuit. While trust, perceived risk and purchase intention might be of interest in measuring e-commerce success, it would be interesting to see how other measures or variables (KPIs) can be observed because of personality differences. One could think of satisfaction, engagement rates, resolution rate/time, customer acquisition cost, customer lifetime value and etcetera.

Eighth, this research calls for other research using other Big Five measures to revalidate the obtained results from this study. Additionally, without a controlled environment, questionnaires remain highly reliant on the good faith of the participants. This is further heightened with no incentives or low reward. Future research should strive for a controlled environment or even possibly better manipulation checks or other

methods of obtaining user's personality. For example, when an amount of textual data is available, services like IBM's Personality Insight would be of great help. Otherwise, other cues like social profiles, demographics, online behavior, cookies or shopping behavior would also be of great interest. With alternative cues, the chatbots would then also need to adapt in a different way other than this research, therefore opening up a whole new approach in this field.

Ninth, future research could also help to validate services like IBM's Personality Insight. The service has shown great promise and use, if proven valid and effective. Thus far, the proofs have only been one sided and come from IBM themselves. This study also failed to validate IBM's results. The researcher therefore invites other researchers to cross-check IBM's claims.

Tenth, forthcoming research could also explore other applications that possess great opportunities for chatbots. Other goal-oriented applications such as customer service can be of great interest, while non-goal-oriented applications are hypothesized to gain more benefits with such rich personality chatbots.

Last, new discussions on the ethical arguments could also be the focus of the psychoinformatics field. Particularly because of amount of data that needs to be collected to gain e.g. users' personality. This might draw some attention into recent data protection (GDPR) debates.



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## 8. Appendices

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### A. Post-Questionnaires

#### a. Purchasing Behavior Demographics

1. How often do you use internet in a week?
  - a. Less than 4 hours
  - b. 4 to 20 hours
  - c. More than 20 hours
2. How do you normally conduct an online purchase (multiple answers are possible)?
  - a. Apps
  - b. Websites
  - c. Social media
  - d. Other, namely:
  - e. Not applicable
3. Have you ever purchased any products or services online?
  - a. Yes
  - b. No
4. Have you ever had any interactions with chatbots in the past?
  - a. Yes
  - b. No

#### b. User's Big Five (Mini-IPIP – Donnellan, 2006)

1. (E) Am the life of the party.
2. (A) Sympathize with others' feelings.
3. (C) Get chores done right away.
4. (N) Have frequent mood swings.
5. (O) Have a vivid imagination.
6. (E) Don't talk a lot. (R)
7. (A) Am not interested in other people's problems. (R)
8. (C) Often forget to put things back in their proper place. (R)
9. (N) Am relaxed most of the time. (R)
10. (O) Am not interested in abstract ideas. (R)
11. (E) Talk to a lot of different people at parties.
12. (A) Feel others' emotions.
13. (C) Like order.
14. (N) Get upset easily.
15. (O) Have difficulty understanding abstract ideas. (R)
16. (E) Keep in the background. (R)
17. (A) Am not really interested in others. (R)
18. (C) Make a mess of things. (R)
19. (N) Seldom feel blue. (R)
20. (O) Do not have a good imagination. (R)

*Note* E = Extraversion; A = Agreeableness; C = Conscientiousness; O = Openness; N = Neuroticism; R = Reverse Scored Item. Five-Likert Scale.

### c. User's Big Five (TIPI – adopted from Gosling et al., 2003)

Here are a number of personality traits that may or may not apply to you. Please write a number next to each statement to indicate the extent to which you agree or disagree with that statement. You should rate the extent to which the pair of traits applies to you, even if one characteristic applies more strongly than the other.

I see myself as:

1. (E) Extraverted, enthusiastic.
2. (A) Critical, quarrelsome. (R)
3. (C) Dependable, self-disciplined.
4. (N) Anxious, easily upset.
5. (O) Open to new experiences, complex.
6. (E) Reserved, quiet. (R)
7. (A) Sympathetic, warm.
8. (C) Disorganized, careless. (R)
9. (N) Calm, emotionally stable. (R)
10. (O) Conventional, uncreative. (R)

*Note* E = Extraversion; A = Agreeableness; C = Conscientiousness; O = Openness; N = Neuroticism; R = Reverse Scored Item. Seven-Likert scale.

### d. Demographic Questions

1. How old are you?
2. What is your gender?
3. What is your nationality?
4. What is your highest level of completed education?
  - a. PhD
  - b. Master
  - c. Bachelor
  - d. High School
  - e. Elementary School
  - f. Other, namely:
5. Which of the following categories best describes your primarily area of employment?
  - a. Student
  - b. Retired
  - c. Unemployed
  - d. Employed
  - e. Other, namely:

### e. Trust (adopted from Gefen and Straub, 2004; Hwang and Kim, 2007; Merritt, 2011)

1. The chatbot is competent. (Cognitive Trust)
2. The chatbot knows how to provide excellent service. (Cognitive Trust)
3. Promises made by the chatbot are likely to be reliable. (Cognitive Trust)
4. I expect that the chatbot will keep the promises they make. (Cognitive Trust)
5. I expect that the chatbot has good intentions towards me. (Faith)
6. I expect that the chatbot's intentions are benevolent (well-meaning and kind). (Faith)

7. I would feel a sense of loss if the Virtual Agent was unavailable and I could no longer use it. (Personal Attachment)
8. I feel a sense of attachment to using the Virtual Agent. (Personal Attachment)
9. I find the Virtual Agent suitable to my style of decision making. (Personal Attachment)
10. I like using the Virtual Agent for decision making. (Personal Attachment)
11. I have a personal preference for making decisions with the Virtual Agent. (Personal Attachment)

*Note* Seven-Likert scale.

#### **f. Perceived Risk (adopted from Corbitt et al., 2003)**

I feel that online purchases recommended by the chatbot are risky because:

1. The product may fail to meet my expectations.
2. The product may be inferior.
3. They may lead to financial loss for me.
4. They may cause others to think less highly of me.
5. They may fail to fit well with my personal image.
6. They may lead to a time loss for me.

*Note* Seven-Likert scale.

#### **g. Purchase Intention (adopted from Pavlou, 2003)**

1. In the scenario, I would have purchased the product with the help of the chatbot.
2. I expect to purchase with the help of chatbot in the future.
3. It is likely that I will use the chatbot for purchase decision making in the near future.

*Note* Seven-Likert scale.

#### **h. Self-projection**

1. To what extent can you relate yourself to the customer in the video?

*Note* Five-Likert scale.

#### **i. Chatbot's Big Five (TIPI – adopted from Gosling et al., 2003)**

Here are a number of personality traits that may or may not apply to the chatbot. Please write a number next to each statement to indicate the extent to which you agree or disagree with that statement. You should rate the extent to which the pair of traits applies to the chatbot, even if one characteristic applies more strongly than the other.

I see the chatbot as:

1. Extraverted, enthusiastic.
2. Critical, quarrelsome.
3. Dependable, self-disciplined.
4. Anxious, easily upset.
5. Open to new experiences, complex.
6. Reserved, quiet.
7. Sympathetic, warm.
8. Disorganized, careless.
9. Calm, emotionally stable.
10. Conventional, uncreative.

*Note* Seven-Likert scale.

### j. Net Promoter (adopted from Pavlou, 2003)

- How likely is it that you would recommend the chatbot to a friend? Whereas 1 is ‘Not likely at all’ and 10 is ‘Extremely likely’.

*Note* Ten-Likert scale.


## B. Chatbot Experiment Conversation Scripts



### a. OCEAN – I

YouTube link: <https://www.youtube.com/watch?v=AMOXWw7KJ3w>



*Note* E = Extraversion; A = Agreeableness; C = Conscientiousness; N = Neuroticism; O = Openness

Personalities	Chatbot	Consumer
E, A, N	Oh, a customer! Umm.. Hi there! 😊 ( <i>Sends flushed emoticon</i> )  My name is Dr. Geek and I’m supposed to know everything about our electronics shop to help you! 😊 ( <i>Sends grinning face with sweat emoticon</i> )	
N	I’m a pretty new technology, so please bear with me.. I hope I can help you.. #nervous	
E, A	So, how are you!! How can I help you today?	
		Hi, I'm looking for wearables.
E, A	Of course!!! Overwhelmed by the options we have, huh?  You deserve the best help you can get and I’ll do everything I can! 😊 ( <i>Sends relaxed emoticon</i> )	
	Do you already have anything in mind?	
		Nah, surprise me.
	Well, first things first, here are the different segments of wearables! <i>Shows Wearables Carousel</i>	
		<i>Chooses “Tell me more about this” on Music</i>
A, N	Errr, yikes.. A tough one to start.. But let me give it a shot..	
E, A, O	Smart watch is like your normal watch, but with SO much more functionalities! From tracking your location and activities to monitoring your health!!  Imagine having James Bond’s watch around your wrist! 🕒 ( <i>Sends spy emoticon and smartwatch picture</i> )	

		
E, A, O	<p>Activity tracker is the perfect way to monitor your activities and health effortlessly, with unmatched accuracy.</p> <p>It's like having a personal doctor following you around! 🕒 (<i>Sends watch emoticon</i>)</p> <p>And you'll always be reminded to walk those extra steps! 🏃 (<i>Sends runner emoticon</i>)</p>	
A, O	<p>I really think you should try something new every now and then! Smart watch might be the one then!</p> <p>Replace the old watch, maybe? 😊 (<i>Sends wink emoticon</i>)</p>	
N	<p>Phew! I hope I got that right.. Any more questions?</p> <p>😓 (<i>Sends anxious face with sweat emoticon</i>)</p>	
		I think I'll go with the smartwatch.
A	Well chosen! 😊 ( <i>Sends blush emoticon</i> )	
	Now, to save you some time, I'll show you the top 3 smart watches according to a filter that you are going to choose, alright?	
	Please choose one of these filters:	
	<i>Shows Quick Replies filters</i>	
		<i>Chooses "Best Seller"</i>
E	Check out our best selling products!!	
	<i>Shows "Best Seller" carousel</i>	
		<i>Chooses "I'd like to ask something else"</i>
A	You could ask me anything! 😊 ( <i>Sends blushed relaxed emoticon</i> )	
		From those 3 best-sellers, which one do you recommend?
E, A, O	<p>Our #1 best seller is the Gear Q3 and it has been rated as the best smartwatch by every top reviewers and I'd figure you don't want to miss that!</p> <p>It'll make your friends jealous! 😏 (<i>Sends smirk emoticon</i>)</p>	
A	You could ask me anything! 😊 ( <i>Sends blushed relaxed emoticon</i> )	

		Can you compare the Gear Q3 and the Gauge?
N	<p>Yikes.. I'm not sure I understand you.. 😓 (Sends weary emoticon and embarrassed GIF)</p> 	
N, A	<p>Oh man, bots are still so dumb in open questions and I am terribly, terribly sorry.. I hate myself for this!!! 😡 (Sends rage emoticon)</p>	
	Do you mind rephrasing your sentence?	
		Comparison between the Gear Q3 and the Gauge.
E	This I understand!!	
	<p>That was so embarrassing.. I hope you don't think low of me.. 😭 (Sends crying emoticon)</p> <p>Anyways..</p>	
E, A, O	<p>The Gear Q3 has a battery that can last up to 4 days, while The Gauge Series 3 can only last for 2 days. No charging every day!! ⚡ (Sends zap emoticon)</p> <p>Moreover, the Gear Q3 has a nice wireless charger that is so easy to use. Extra convenient!!</p>	
E, A, O	<p>AND, we are currently offering a free AJB wireless earphone with the purchase of a Gear Q3 smartwatch.</p> <p>Are you kidding me?? It goes so well with the watch, don't you think? You should not miss this crazy deal!</p> <p>Shows an AJB wireless earphone picture</p> 	
N	<p>Enough reasons? I still haven't convinced you yet?? 😏 (Sends face with rolling eyes emoticon)</p>	
		I think you've convinced me to take the Gear Q3




E, N	Gosh, I've been very scared of not being able to help you, because that didn't go smooth AT ALL! 😞 (Sends pensive emoticon)	
A	Butttt if you're happy, then I'm HAPPY!!! 🍷 (Sends tada emoticon and a thumbs up GIF) 	
	So, here is the final confirmation of the purchase. Shows the purchase confirmation	
		Chooses "Confirm"
E	Thankss! Your order has been processed. (Sends a happy GIF) 	
A	You can track your purchase with this link: <a href="http://drgeek.com/trackorder/apparel/25dTfjVzJ">http://drgeek.com/trackorder/apparel/25dTfjVzJ</a> I understand how nice it is to know where your package exactly is! 😊 (Sends innocent emoticon)	
A	Is there anything else I can help you with? 😊 (Sends blush emoticon)	
		Chooses "No"
N	I still can't believe I just helped a customer.. You sure are one tough customer! 😭 (Sends sob emoticon)	
N	And I apologize once more for all of my mistakes ☹️ (Sends persevere emoticon)	
E, A	We thank you very much for purchasing at our store! I really do hope that you truly enjoy our service and the product!	
		Thank you, bye!




## b. OCEA – II

YouTube link: <https://www.youtube.com/watch?v=tdbfHUFr0bI>

Note E = Extraversion; A = Agreeableness; C = Conscientiousness; O = Openness

Personalities	Chatbot	Consumer
E, A	<p>Hello there! 🙋 (Sends waving emoticon)</p> <p>My name is Dr. Geek and I got you covered with anything related to our electronics shop! 😊 (Sends blush emoticon)</p>	
E, A	So, how are you!! How can I help you today?	
		Hi, I'm looking for wearables.
E, A	<p>Of course!!! Overwhelmed by the options we have, huh?</p> <p>You deserve the best help you can get and I'll do everything I can! 😊 (Sends relaxed emoticon)</p>	
	Do you already have anything in mind?	
		Nah, surprise me.
	Well, first things first, here are the different segments of wearables!	
	Shows Wearables Carousel	
		Chooses "Tell me more about this" on Music
A	Anything to help you! 😊 (Sends wink emoticon)	
E, A, O	<p>Smart watch is like your normal watch, but with SO much more functionalities! From tracking your location and activities to monitoring your health!!</p> <p>Imagine having James Bond's watch around your wrist! 🕒 (Sends spy emoticon and smartwatch picture)</p> 	
E, A, O	<p>Activity tracker is the perfect way to monitor your activities and health effortlessly, with unmatched accuracy.</p> <p>It's like having a personal doctor following you around! 🕒 (Sends watch emoticon)</p> <p>And you'll always be reminded to walk those extra steps! 🏃 (Sends runner emoticon)</p>	
A, O	I really think you should try something new every now and then! Smart watch might be the one then!	

	Replace the old watch, maybe? 😏 (Sends wink emoticon)	
A	Any more questions? 😊 (Sends blushed relaxed emoticon)	
		I think I'll go with the smartwatch.
A	Well chosen! 😊 (Sends blush emoticon)	
	Now, to save you some time, I'll show you the top 3 smart watches according to a filter that you are going to choose, alright?	
	Please choose one of these filters:	
	Shows <u>Quick Replies</u> filters	
		Chooses "Best Seller"
E	Check out our best selling products!!	
	Shows "Best Seller" carousel	
		Chooses "I'd like to ask something else"
A	You could ask me anything! 😊 (Sends blushed relaxed emoticon)	
		From those 3 best-sellers, which one do you recommend?
E, A, O	Our #1 best seller is the Gear Q3 and it has been rated as the best smartwatch by every top reviewers and I'd figure you don't want to miss that!  It'll make your friends jealous! 😏 (Sends smirk emoticon)	
A	You could ask me anything! 😊 (Sends blushed relaxed emoticon)	
		Can you compare the Gear Q3 and the Gauge?
A	Oops! Something went wrong there and I didn't understand you completely. My sincere apologies! 😞 (Sends frowning emoticon)	
	Do you mind rephrasing your sentence?	
		Comparison between the Gear Q3 and the Gauge.
E	This I understand!!	
E, A, O	The Gear Q3 has a battery that can last up to 4 days, while The Gauge Series 3 can only last for 2 days. No charging every day!! ⚡ (Sends zap emoticon)  Moreover, the Gear Q3 has a nice wireless charger that is so easy to use. Extra convenient!!	
E, A, O	AND, we are currently offering a free AJB wireless earphone with the purchase of a Gear Q3 smartwatch.	


	<p>Are you kidding me?? It goes so well with the watch, don't you think? You should not miss this crazy deal!</p> <p><i>Shows an AJB wireless earphone picture</i></p> 	
A	<p>You're welcome to ask me more questions! 😊 (<i>Sends blush emoticon</i>)</p>	
		I think you've convinced me to take the Gear Q3
A	<p>NICE!! This requires a celebration! 🎉 (<i>Sends tada emoticon and a thumbs up GIF</i>)</p> 	
	So, here is the final confirmation of the purchase.	
	<i>Shows the purchase confirmation</i>	
		Chooses "Confirm"
E	<p>Thankss! Your order has been processed. (<i>Sends a happy GIF</i>)</p> 	
A	<p>You can track your purchase with this link:  <a href="http://drgeek.com/trackorder/apparel/25dTfjVzJ">http://drgeek.com/trackorder/apparel/25dTfjVzJ</a></p> <p>I understand how nice it is to know where your package exactly is! 😊 (<i>Sends innocent emoticon</i>)</p>	
A	<p>Is there anything else I can help you with? 😊 (<i>Sends blush emoticon</i>)</p>	

		<i>Chooses “No”</i>
<b>E, A</b>	We thank you very much for purchasing at our store!  I really do hope that you truly enjoy our service and the product!	
		Thank you, bye!

### c. CEA – III



YouTube link: <https://www.youtube.com/watch?v=Hq19luWD80I>

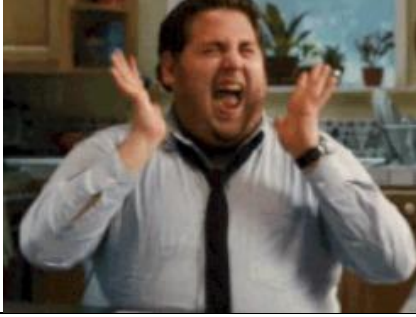
Note E = Extraversion; A = Agreeableness; C = Conscientiousness

Personalities	Chatbot	Consumer
<b>E, A</b>	Hello there! 🙌 ( <i>Sends waving emoticon</i> )  My name is Dr. Geek and I got you covered with anything related to our electronics shop! 😊 ( <i>Sends blush emoticon</i> )	
<b>E, A</b>	So, how are you!! How can I help you today?	
		Hi, I'm looking for wearables.
<b>E, A</b>	Of course!!! Overwhelmed by the options we have, huh?  You deserve the best help you can get and I'll do everything I can! 😊 ( <i>Sends relaxed emoticon</i> )	
	Do you already have anything in mind?	
		Nah, surprise me.
	Well, first things first, here are the different segments of wearables!	
	<i>Shows Wearables Carousel</i>	
		<i>Chooses “Tell me more about this” on Music</i>
<b>A</b>	Anything to help you! 😊 ( <i>Sends wink emoticon</i> )	
<b>E</b>	Smart watch is the ultimate smartphone accessory. It still tells time, but it can also track your location and activities. AND it beams it to your smartphone! 📱 ( <i>Sends mobile emoticon</i> )  And most people also prefer the smart watch! ( <i>Sends smartwatch picture</i> )  	

E	Activity tracker is the perfect way to monitor your activities and health effortlessly, with unmatched accuracy.  If you're a sports enthusiast, then this might be it! 🏃 (Sends runner emoticon)	
A	But, I really think you should have what other people already like! Smart watch is the safe option then! 😊 (Sends wink emoticon)	
A	Any more questions? 😊 (Sends blushed relaxed emoticon)	
		I think I'll go with the smartwatch.
A	Well chosen! 😊 (Sends blush emoticon)	
	Now, to save you some time, I'll show you the top 3 smart watches according to a filter that you are going to choose, alright?	
	Please choose one of these filters:	
	Shows Quick Replies filters	
		Chooses "Best Seller"
E	Check out our best selling products!!	
	Shows "Best Seller" carousel	
		Chooses "I'd like to ask something else"
A	You could ask me anything! 😊 (Sends blushed relaxed emoticon)	
		From those 3 best-sellers, which one do you recommend?
E, A	Our #1 best seller is the Gear Q3 and it has been rated as the best smartwatch by every top reviewers and I'm sure you don't want to miss that!  It simply offers the greatest value to other products! 😊 (Sends smirk emoticon)	
A	You could ask me anything! 😊 (Sends blushed relaxed emoticon)	
		Can you compare the Gear Q3 and the Gauge?
A	Oops! Something went wrong there and I didn't understand you completely. My sincere apologies! 😞 (Sends frowning emoticon)	
	Do you mind rephrasing your sentence?	
		Comparison between the Gear Q3 and the Gauge.
E	This I understand!!	



E	<p>The Gear Q3 has a battery that can last up to 4 days, while The Gauge Series 3 can only last for 2 days. Clear winner, right!! ⚡ (Sends zap emoticon)</p> <p>Moreover, the Gear Q3 has a nice wireless charger. You'll love it!!</p>	
E	<p>AND, we are currently offering a free AJB wireless earphone with the purchase of a Gear Q3 smartwatch.</p> <p>Are you kidding me?? You should not miss this crazy deal, right!</p> <p>Shows an AJB wireless earphone picture</p> 	
A	<p>You're welcome to ask me more questions! 😊 (Sends blush emoticon)</p>	
		I think you've convinced me to take the Gear Q3
A	<p>NICE!! This requires a celebration! 🎉 (Sends tada emoticon and a thumbs up GIF)</p> 	
	So, here is the final confirmation of the purchase.	
	Shows the purchase confirmation	
		Chooses "Confirm"
E	<p>Thankss! Your order has been processed. (Sends a happy GIF)</p>	


		
A	You can track your purchase with this link: <a href="http://drgeek.com/trackorder/apparel/25dTfjVzJ">http://drgeek.com/trackorder/apparel/25dTfjVzJ</a>  I understand how nice it is to know where your package exactly is! 😊 (Sends innocent emoticon)	
A	Is there anything else I can help you with? 😊 (Sends blush emoticon)	
		Chooses "No"
E, A	We thank you very much for purchasing at our store!  I really do hope that you truly enjoy our service and the product!	
		Thank you, bye!



#### d. CE – IV



YouTube link: <https://www.youtube.com/watch?v=QwboS56MHAg>

Note E = Extraversion; C = Conscientiousness

Personalities	Chatbot	Consumer
E	Yo yo yo! 🙌 (Sends waving emoticon)  My name is Dr. Geek and I am the almighty bot that knows anything about our electronics shop! 😎 (Sends smiling face with sunglasses emoticon)  Pretty sick right?	
E	So, what brings you here today? Is it me you're looking for?	
		Hi, I'm looking for wearables.
E	Overwhelmed by the options we have, huh?  Lucky for you, I'm the very best bot to do that! This will be a piece of cake!! 💪 (Sends muscle emoticon)	
	Do you already have anything in mind?	
		Nah, surprise me.
	Well, first things first, here are the different segments of wearables!	
	Shows Wearables Carousel	

		<i>Chooses “Tell me more about this” on Music</i>
E	You don’t know the differences yourself? Easy peasy! (Sends smirk emoticon)	
E	Smart watch is the ultimate smartphone accessory. It still tells time, but it can also track your location and activities. AND it beams it to your smartphone! 📱 (Sends mobile emoticon)  And most people also prefer the smart watch! (Sends smartwatch picture) 	
E	Activity tracker is the perfect way to monitor your activities and health effortlessly, with unmatched accuracy.  If you’re a sports enthusiast, then this might be it! 🏃 (Sends runner emoticon)	
E	I really think you should have what other people already like! Smart watch is the safe option then! OK?? 🤔 (Sends thinking face emoticon)	
		I think I'll go with the smartwatch.
E	My advice is always the best, trust me! 😎 (Sends smiling face with sunglasses emoticon)	
	Now, to save you some time, I'll show you the top 3 smart watches according to a filter that you are going to choose, alright?	
	Please choose one of these filters:	
	Shows Quick Replies filters	
		<i>Chooses “Best Seller”</i>
E	Check out our best selling products!!	
	Shows “Best Seller” carousel	
		<i>Chooses “I’d like to ask something else”</i>
E	Ask away! 🤔 (Sends thinking face emoticon)	
		From those 3 best-sellers, which one do you recommend?
E	Our #1 best seller is the Gear Q3 and it has been rated as the best smartwatch by every top reviewers!  Just follow my advice! 😏 (Sends smirk emoticon)	

E	Anything else! 🤔 (Sends thinking face emoticon)	
		Can you compare the Gear Q3 and the Gauge?
E	Dang it! Something went wrong there and I didn't understand you completely. 😡 (Sends face with steam from nose emoticon)	
	Do you mind rephrasing your sentence?	
		Comparison between the Gear Q3 and the Gauge.
E	This I understand!!	
E	The Gear Q3 has a battery that can last up to 4 days, while The Gauge Series 3 can only last for 2 days. Clear winner, right!! ⚡ (Sends zap emoticon)  Moreover, the Gear Q3 has a nice wireless charger. You'll love it!!	
E	AND, we are currently offering a free AJB wireless earphone with the purchase of a Gear Q3 smartwatch.  Are you kidding me?? You should not miss this crazy deal!  Shows an AJB wireless earphone picture 	
E	Anything else? 🤔 (Sends thinking face emoticon)	
		I think you've convinced me to take the Gear Q3
E	FINALLY!! You sure took a while! 🎉 (Sends tada emoticon and a thumbs up GIF) 	
	So, here is the final confirmation of the purchase.	
	Shows the purchase confirmation	
		Chooses "Confirm"


E	<p>Thankss! Your order has been processed. (<i>Sends a happy GIF</i>)</p> 	
	<p>You can track your purchase with this link:  <a href="http://drgeek.com/trackorder/apparel/25dTfjVzJ">http://drgeek.com/trackorder/apparel/25dTfjVzJ</a></p>	
	<p>Is there anything else this bad boy can help you with?   (<i>Sends face with steam from nose emoticon</i>)</p>	
		<i>Chooses "No"</i>
E	<p>Thank you for purchasing!</p> <p>With my awesome recommendation, there's no way you won't enjoy the product!</p>	
		Thank you, bye!

#### e. C – V


YouTube link: <https://www.youtube.com/watch?v=mh1nYSCHLIg>

Note C = Conscientiousness

Personalities	Chatbot	Consumer
	Hi, my name is Dr. Geek and I am the almighty bot that knows anything about our electronics shop.	
	So, why are you here today?	
		Hi, I'm looking for wearables.
	Overwhelmed by the options we have, huh?	
	Lucky for you, I can do that easily.	
	Do you already have anything in mind?	
		Nah, surprise me.
	Well, first things first, here are the different segments of wearables!	
	<i>Shows Wearables Carousel</i>	
		<i>Chooses "Tell me more about this" on Music</i>
	Easy peasy..	
	Smart watch is the ultimate smartphone accessory. It still tells time, but it can also track your location and activities, as well as beaming it to your smartphone!	
	And most people also prefer the smart watch.. ( <i>Sends smartwatch picture</i> )	

		
	Activity tracker is the perfect way to monitor your activities and health effortlessly, with unmatched accuracy.  If you're a sports enthusiast, then this might be it..	
	But to be honest, I really think you should just stick to what other people already like..  Smart watch is the safe option then! OK??	
		I think I'll go with the smartwatch.
	Good.	
	Now, to save you some time, I'll show you the top 3 smart watches according to a filter that you are going to choose, alright?	
	Please choose one of these filters:	
	<i>Shows Quick Replies filters</i>	
		<i>Chooses "Best Seller"</i>
	Check out our best-selling products.	
	<i>Shows "Best Seller" carousel</i>	
		<i>Chooses "I'd like to ask something else"</i>
	Ask away.	
		From those 3 best-sellers, which one do you recommend?
	Our #1 best seller is the Gear Q3 and it has been rated as the best smartwatch by every top reviewers..  There's really no reason why you should not follow my advice..  Anything else?	
		Can you compare the Gear Q3 and the Gauge?
	Hmm.. Something went wrong there and I didn't understand you completely.	
	Do you mind rephrasing your sentence?	
		Comparison between the Gear Q3 and the Gauge.
	Ah.	
	The Gear Q3 has a battery that can last up to 4 days, while The Gauge Series 3 can only last for 2 days.	



	Moreover, the Gear Q3 has a nice wireless charger.	
	<p>AND, we are currently offering a free AJB wireless earphone with the purchase of a Gear Q3 smartwatch.</p> <p>Only I can get special deals like this.</p> <p><i>Shows an AJB wireless earphone picture</i></p> 	
	Anything else?	
		I think you've convinced me to take the Gear Q3
	Congrats, well chosen. You sure took a while.	
	So, here is the final confirmation of the purchase.	
	<i>Shows the purchase confirmation</i>	
		<i>Chooses "Confirm"</i>
	<p>You can track your purchase with this link:</p> <p><a href="http://drgeek.com/trackorder/apparel/25dTfjVzJ">http://drgeek.com/trackorder/apparel/25dTfjVzJ</a></p>	
	Is there anything else this bad boy can help you with?	
		<i>Chooses "No"</i>
	<p>Thank you for purchasing!</p> <p>With my awesome recommendation, there's no way you won't enjoy the product.</p>	
	See ya.	
		Thank you, bye!

### C. Pretest Survey

#### a. Answer Sheet (First Experiment) – Mini-IPIP

	OCEAN (A)	OCEA (B)	CEA (C)	CE (D)	C (E)
1. (E) The chatbot could be the life of the party.	Agree	Agree	Agree	Agree	Disagree
2. (A) The chatbot could sympathize with others' feelings.	Agree	Agree	Agree	Disagree	Disagree
3. (C) The chatbot seems to get chores done right away.	Agree	Agree	Agree	Agree	Agree
4. (N) The chatbot seems to have frequent mood swings.	Agree	Disagree	Disagree	Disagree	Disagree
5. (O) The chatbot seems to have a vivid imagination.	Agree	Agree	Disagree	Disagree	Disagree
6. (E/R) The chatbot doesn't talk a lot.	Disagree	Disagree	Disagree	Disagree	Agree
7. (A/R) The chatbot seems to not be interested in other people's problems.	Disagree	Disagree	Disagree	Agree	Agree
8. (C/R) The chatbot seems to be sloppy and careless.	Disagree	Disagree	Disagree	Disagree	Disagree

9. (N/R) The chatbot seems relaxed.	Disagree	Agree	Agree	Agree	Agree
10. (O/R) The chatbot seems to not be interested in abstract ideas.	Disagree	Disagree	Agree	Agree	Agree
11. (E) The chatbot will most likely talk to a lot of different people at parties.	Agree	Agree	Agree	Agree	Disagree
12. (A) The chatbot feels others' emotions.	Agree	Agree	Agree	Disagree	Disagree
13. (C) The chatbot likes order.	Agree	Agree	Agree	Agree	Agree
14. (N) The chatbot gets upset easily.	Agree	Disagree	Disagree	Disagree	Disagree
15. (O/R) The chatbot is not creative.	Disagree	Disagree	Agree	Agree	Agree
16. (E/R) The chatbot seems to like being in the background.	Disagree	Disagree	Disagree	Disagree	Agree
17. (A/R) The chatbot is not really interested in others.	Disagree	Disagree	Disagree	Agree	Agree
18. (C/R) The chatbot is a mess.	Disagree	Disagree	Disagree	Disagree	Disagree
19. (N/R) The chatbot seems to feel blue seldom.	Agree	Disagree	Disagree	Disagree	Disagree
20. (O/R) The chatbot seems to not have a good imagination.	Disagree	Disagree	Agree	Agree	Agree

OCEAN: Tim and Ivo

OCEA: Efrain and Daniel

CEA: Yohandi and Hasan

CE: Bram and Stella

C: Edward and Al

#### b. First Round Survey Results (First Experiment) – Mini-IPIP

	OCEAN (A)	OCEA (B)	CEA (C)	CE (D)	C (E)
1	Agree	Agree	Agree	Agree	Disagree
2	A/N	N/D	Neutral	N/D	N/D
3	Neutral	Agree	Agree	Agree	Agree
4	A/N	Neutral	N/D	N/D	Disagree
5	Agree	Agree	Neutral	A/D	N/D
6	Disagree	Disagree	Disagree	Disagree	Agree
7	Disagree	Neutral	Disagree	Neutral	Neutral
8	Neutral	Disagree	N/D	N/D	Disagree
9	A/D	Agree	Agree	Agree	Agree
10	Neutral	Neutral	Neutral	A/N	Neutral
11	Agree	Agree	Agree	Agree	Disagree
12	A/N	Neutral	Agree	Disagree	Neutral
13	A/D	Agree	Agree	Disagree	Agree
14	Agree	Disagree	Disagree	A/N	Disagree
15	N/D	N/D	Neutral	Neutral	Agree
16	Disagree	Disagree	Disagree	Disagree	Agree
17	Neutral	N/D	N/D	Neutral	Agree
18	Neutral	Disagree	Disagree	Disagree	Disagree
19	A/N	Disagree	Disagree	Neutral	Neutral
20	Disagree	Neutral	Neutral	Neutral	N/D

**c. Second Round Survey Results (First Experiment) – Mini-IPIP**

	OCEAN (A)	OCEA (B)	CEA (C)	CE (D)	C (E)
1	Agree	Agree	Agree	Agree	Disagree
2	Agree	Agree	Agree	Disagree	Disagree
3	Neutral	Agree	Agree	Agree	A/N
4	Agree	Disagree	Disagree	Neutral	Disagree
5	Agree	Agree	N/D	Disagree	Disagree
6	Disagree	Disagree	Disagree	Disagree	Agree
7	Disagree	Disagree	Disagree	Agree	Agree
8	Neutral	Disagree	Disagree	Disagree	Disagree
9	Disagree	Agree	Agree	Agree	Agree
10	Disagree	Disagree	Neutral	Agree	Agree
11	Agree	Agree	Agree	Agree	Disagree
12	Agree	Agree	Agree	Disagree	Disagree
13	Agree	Agree	Agree	A/N	Agree
14	Agree	Disagree	Disagree	Disagree	N/D
15	Disagree	N/D	Neutral	Agree	Agree
16	Disagree	Disagree	Disagree	Disagree	Agree
17	N/D	Disagree	Disagree	Agree	Agree
18	Neutral	Disagree	Disagree	Disagree	Disagree
19	Agree	Disagree	Disagree	Disagree	Disagree
20	Disagree	Disagree	Neutral	A/N	Agree

**d. Answer Sheet (Second Experiment) – TIPI**

	OCEAN (A)	OCEA (B)	CEA (C)	CE (D)	C (E)
1. (E) Extraverted, enthusiastic.	Agree	Agree	Agree	Agree	Disagree
2. (A/R) Critical, quarrelsome.	Disagree	Disagree	Disagree	Agree	Agree
3. (C) Dependable, self-disciplined.	Agree	Agree	Agree	Agree	Agree
4. (N) Anxious, easily upset.	Agree	Disagree	Disagree	Disagree	Disagree
5. (O) Open to new experiences, complex.	Agree	Agree	Disagree	Disagree	Disagree
6. (E/R) Reserved, quiet.	Disagree	Disagree	Disagree	Disagree	Agree
7. (A) Sympathetic, warm.	Agree	Agree	Agree	Disagree	Disagree
8. (C/R) Disorganized, careless.	Disagree	Disagree	Disagree	Disagree	Disagree
9. (N/R) Calm, emotionally stable.	Disagree	Agree	Agree	Agree	Agree
10. (O/R) Conventional, uncreative.	Disagree	Disagree	Agree	Agree	Agree

### e. Survey Results (Second Experiment) - TIPI

	OCEAN (A)	OCEA (B)	CEA (C)	CE (D)	C (E)
1	Agree	Agree	Agree	Agree	Disagree
2	Disagree	Disagree	Disagree	Agree	Agree
3	Agree	Agree	Agree	Agree	Agree
4	Agree	Disagree	Disagree	Disagree	Disagree
5	Agree	Agree	Neutral	Disagree	Disagree
6	Disagree	Disagree	Disagree	Disagree	Agree
7	Agree	Agree	Agree	Disagree	Disagree
8	Disagree	Disagree	Disagree	Disagree	Disagree
9	Disagree	Agree	Agree	Agree	Agree
10	Disagree	Disagree	Neutral	Agree	Agree

OCEAN: Ivo

OCEA: Edward

CEA: Hasan

CE: Edward

C: Ivo

## D. Pretest Interview Transcript

### I. Transcript 1 (Ivo Bahar Nugroho) - OCEAN

**Interviewer:** Hey man, so thank you again for taking the time to do the experiment.

**Interviewee:** Yo, you're welcome, bro.

**Interviewer:** Alright, I'll just start right away, okay. So, I've collected the answers from your questionnaire that you filled not so long ago, and I have a few questions on your answers on those questions. Generally, I'm curious to know, er, why some of your answers do not match with what I was expecting. For example, you answered some questions with neutral. Why is that? Did you truly think it was neutral, or were you just not sure with what you want to answer?

**Interviewee:** Yeah, I answered neutral because I wasn't sure if it should be a yes or a no.

**Interviewer:** But if you'd watch it again and think about it, what would it be?

**Interviewee:** I'm pretty sure it'd still be a neutral. I've already thought about it.

**Interviewer:** Alright, that's fine. So, I'm just going to go through the questions one by one if you don't mind. If you could think about the question of sympathizing, why did you think it was neutral? Did the chatbot not always ask or say something about your feeling?

**Interviewee:** But that's minimum information.

**Interviewer:** What do you mean?

**Interviewee:** If you don't have that, the chatbot wouldn't be able to give a recommendation.

**Interviewer:** Hmm, actually it still would be able to give a recommendation, despite it not sympathizing. But then I would know, because I knew the differences. Otherwise, maybe yeah, I would agree with you. So, how do you think the bot should be made to show its sympathy?

**Interviewee:** I think [the] definition of sympathy must be explained in the questionnaire. Like, what do you mean by sympathy here? Is just asking the customer things considered as sympathy? I would argue that if you only ask for information, that is not sympathy.

**Interviewer:** Right. So what's your definition of sympathy? Is it not caring for other people's feelings? Like, also making sure that they like what you give to them. Whatever it suggests, it wants to make sure that the customers really like it.

**Interviewee:** Ahh, that's what you meant.

**Interviewer:** So, I guess the questions are not that clear, huh?

**Interviewee:** If that's what you meant, then I'd agree, yeah. So yeah, again, maybe you could try explaining this sympathy part clearer in your questionnaire.

**Interviewer:** I see, I see, gotcha. So, what do you think of mood swings? Did the bot not show how it got annoyed, and then happy again, then back to sad and other emotions?

**Interviewee:** Hmm I don't know. I think it's also neutral since I perceive the mood to be like that.

**Interviewer:** Okay, let me take one example. The bot said: "Finally. you sure asked a lot of questions"

**Interviewee:** "Damn."?

**Interviewer:** Yeah! Those kinds of sentences.

**Interviewee:** I think that's okay and not mood swings. but I think everybody's perception is different, right. maybe I also show mood swings [that] I don't recognize myself. [laughter]

**Interviewer:** Yeah, it's fine man, I want to know YOUR perspective this time.

**Interviewee:** Yeah bro, you have to state the definition in every question.

**Interviewer:** So... how do you understand mood swings?

**Interviewee:** Yeah just like you said. From sad to happy and back.

**Interviewer:** I thought wasn't it like that? It was happy because you're looking for a present, but sad 'cause now it also wants a present for itself. Erm, alright, here's the deal. I'll show you this Big Five diagram. What do you think the scores are?

**Interviewee:** Hmm, I really can't think if you don't ask me the question. I thought it was just being chatty, that's all. It was only one line after all.

**Interviewer:** I see. Okay, next one. Alright, erm. Even you also disagreed on "gets upset easily".

**Interviewee:** Can't you only focus on 3 personalities? Don't do all of them. Unless you can give more defined scope on the questions.

**Interviewer:** No can do. the framework that We've already agreed on together with the supervisors is as it is.

**Interviewee:** Alright. Then maybe you just have to clarify the questions even more. If you've done it, I'll do it again.

**Interviewer:** Thanks man, will do so. My intention was also to do the first round like a discussion, and then ask you guys to do it again.

**Interviewee:** Alright. Good luck bro!

## II. Transcript 2 (Tim Crone) - OCEAN

**Interviewer:** Alright, Tim. So, tell me what you think of the bot.

**Interviewee:** Okay. First things first. Why did you say 'bro'? What if participant is a woman?

**Interviewer:** Yeah. Bro is just like a slang that I thought should work on everybody. But. On a second thought, you're right. I should change that. I'll do that. Good point.

**Interviewee:** Cool. Next one. Why did you have so much categories to show? It made the conversation unbearably long. I thought the key of this experiment is about the personality of the chatbot, right. But this way, I think it has come to a point where it is redundant.

**Interviewer:** Yeah, I completely see your point. I agree, I guess you're right and I definitely could cut down so much more. I was thinking to show what the bots can do as well, but I agree that there are still some redundant things that I can throw away. Erm, the video is now around 11 minutes, I guess I can still cut it down to 5 to 6 minutes, hopefully. But not too short, since I need some space to show so many personalities.

**Interviewee:** Right. Okay, it's good if you also agree. Um, next one. Why don't you use a hypothetical situation stating [that] "you are looking for a sports watch for your 30-year-old friend but don't know what to choose, you determine to ask the shop assistant chatbot". It could save you a lot of time in the conversation I guess. For example, comparing two watches? Or picking one of two Gear 3s?

**Interviewer:** Yeah, yeah, you're absolutely right. That's some really good advice, thanks.

**Interviewee:** Um, yeah, that's it, I guess. The rest looks good!

**Interviewer:** Alright, thanks a lot, Tim!



**Interviewee:** Yo!

### **III. Transcript 3 (Efrain Soza Cisneros) - OCEA**

**Interviewer:** Efra, my man! How's it going? Thanks for filling my questionnaire the other day!

**Interviewee:** Yo, my pleasure, man! Hope it was helpful.

**Interviewer:** Yeah it certainly is! Erm, by the way, can I ask you some questions regarding the answers you gave me in the questionnaire? Surprisingly, your answers resembled what I was expecting really well! Erm, so I only have a few questions.

**Interviewee:** [Laughter] Really? Yeah man, just ask away.

**Interviewer:** Yeah, the other participants seem to have answered with lots of variations with what I was expecting, but you did really great. Anyway, I just need to know why you have answered neutral on a few things. So, first, you answered neutral on the chatbot not being so [sympathetic] to others or not interested in other people's problems. Can you shed some light on that?

**Interviewee:** Um. Let me remember what it was again. Sympathizing. Yeah, I just feel like I can't agree nor disagree with either options.

**Interviewer:** Okay, that's fine. So, can I ask you why that is? What's, like, your definition of sympathizing?

**Interviewee:** Uh, I, I mean, it would be caring for other people and uh, their feelings, maybe?

**Interviewer:** Alright. That's exactly my definition of sympathizing too and that was how I made my chatbot to be! So where did it miss? Why did you think it was not sympathetic enough?

**Interviewee:** [Laughter] Now I'm not sure and it's hard to remember now. I have to watch the video again to answer your question.

**Interviewer:** Yeah, I thought so too. Um, so this is the chatbot that you got back then. Do you mind having another look at it?

**Interviewee:** Yeah man, sure.

**Interviewer:** Oh yeah, before looking into that, I have another question too. Might as well squeeze it in there before you watch it the video [laughter]. Um. Yeah, abstract ideas. Does it seem to be interested in abstract ideas? Or just think about whether the chatbot is creative. Okay?

**Interviewee:** Okay, okay, gotcha. Give me a minute, man.

**Interviewer:** So! How was it?

**Interviewee:** Yeah, okay, err. I remember again now [laughter]. Sorry about that. So, what was the question again?

**Interviewer:** [Laughter] Yeah, it's okay. Um, did you think the chatbot was creative?

**Interviewee:** Hmm, yeah this I'm not so sure. But I guess it was kinda creative.

**Interviewer:** Kinda? So why did you answer neutral on this question?

**Interviewee:** Huh, did I? Let me see. Ah, you wrote abstract ideas there. I wasn't really sure what that meant by then. Now you told me it's about creativity, then I guess I'd agree that it's kind of creative.

**Interviewer:** Ah, good to know. Yeah, I've had similar comments on how the questions not being so clear. Alright, last, we're back to sympathy. What about that?

**Interviewee:** Hmm. I'm still not so sure about that. But now that you told me what you meant by caring for other people, I really paid attention to the video and I guess I kinda agree now. But before, I wasn't paying attention to much to it, and just thought, like, it was normal for the bot to ask that to me.

**Interviewer:** I see. Wow, I guess after some clarifications and guidance, you actually came to agree with me on all answers. But only, after some guidance, huh. Otherwise, you wouldn't have noticed or paid too much attention?

**Interviewee:** Yeah, that's right.

**Interviewer:** Alright, Efra. Thanks a lot for your time. I have some more thinking to do on my own, but I'll let you know how it goes with the other participants, okay? Thanks again!

**Interviewee:** Yeah, no worries, man.

#### **IV. Transcript 4 (Daniel Tjhin) - OCEA**

**Interviewer:** Yo my man! Can I ask you some questions on the questionnaire that you filled the other day? Some of your answers differed from what I was expecting, so I wanted to get some insights on why you answered them like that.

**Interviewee:** Oy. Yeah, sure.

**Interviewer:** Alright, cool. So, you answered neutral on some questions, and disagree on one question. First, I was wondering why you answered neutral on mood swings. Were you not sure what to answer, or you truly think that It was neutral?

**Interviewee:** Phew. Let me remember. Um, mood swings as in happy and sad? Nah, I think it actually was not that bad. I think it was pretty stable. I guess it was really neutral. I just didn't feel anything about it having mood swings.

**Interviewer:** Huh, so you should've answered disagree then. Does the chatbot go through a series of mood swings

**Interviewee:** Hmmm. What was the question on the questionnaire again?

**Interviewer:** The chatbot seems to have frequent mood swings.

**Interviewee:** Yeah, you're right. I should've answered disagree on that. Sorry.

**Interviewer:** [Laughter] Yeah, no worries, man. Good to hear the answer I was expecting. Um, next, you answered disagree on sympathizing. Why was it?

**Interviewee:** Did I? [Laughter] Man, I forgot, um, all the details about the video. Oh yeah, speaking of that. Your video was too freaking long, dude. I got bored after a while since I already know what the video is all about, but you kept it 'til so long. By the time the video ended, I couldn't remember all the little details about it.

**Interviewer:** [Big laughter] Yeah, you're not alone in that regard. That is totally my bad, and hey, hearing this multiple times from you guys confirmed it even further that the video was indeed too long.

**Interviewee:** Even now if you ask me to watch it again, I'd politely decline bro [Big laughter].

**Interviewer:** Dang it, man, I was about to ask that, LOL. Well, your scores aren't that deviating anyway from what I was expecting. But if you don't mind, what's your definition of sympathy in a chatbot?

**Interviewee:** Understanding?

**Interviewer:** Was it not understanding?!

**Interviewee:** Huh. Yeah, I guess it was cooperative and all, trying to really be careful in making sure I'm satisfied? Now that you made me think about it, I guess it had some sense of sympathy.

**Interviewer:** Alright, alright, that's all I need man [laughter]. I've been doing this a couple of times, the problem seems to be that no one seems to be paying attention to it, unless I ask it to them explicitly and make them think about it.

**Interviewee:** Well, what's the intention of it anyway? Is this the experiment?

**Interviewer:** No, no, this is what we call the pretest. So, in the main experiment, I want to randomly give 5 different chatbot personalities to different people. But before I can safely say, that uh, chatbot 1 has this so and so personality, I need to check or test it with you guys, whether that's true, what I'm claiming. Gotcha?

**Interviewee:** Right. How's it looking so far?

**Interviewer:** It's looking pretty okay. Um, most complaints come around the length of the videos, sympathy, and creativity. Some of them about mood swings. Those are the things that aren't very clear from the questions itself, and possibly the personalities aren't that obvious too from the chatbot, I guess.

**Interviewee:** Okay. Still need anything else from me?

**Interviewer:** Nah bro, that's it. Thanks for helping me out!

**Interviewee:** Yo man. Good luck.

#### **V. Transcript 5 (Yohandi Wijaya) - CEA**

**Interviewer:** Yo! Want to ask you some questions regarding the questionnaire that you filled last time, okay?

**Interviewee:** Okay. What about it?

**Interviewer:** Yeah, you gave some really good answers, but some of them aren't what I was expecting. So, I want to ask why you answered them the way you did.

**Interviewee:** Bro, the video was really long. To be honest, I fast forwarded some part of the video.

**Interviewer:** Damn man, you shouldn't have done that [laughter]. But alright, I understand completely, and I agree with you that it was too long.

**Interviewee:** Can't blame me [laughter].

**Interviewer:** But can I still ask why you answered neutral on the chatbot not having a good imagination? If you still remember, of course [laughter].

**Interviewee:** Dude, come on, it was like a few days ago. I think the neutral answers were because I was not sure what it should be.

**Interviewer:** Right. So, what's your definition of a creative chatbot then?

**Interviewee:** In the case of this product recommendation thing? Hmm.

**Interviewer:** Yeah. So now the chatbot seems to be very algorithmic, sticking to routine and all that, don't you think?

**Interviewee:** I, I guess if it was creative, then it would've not done that. Maybe think of something completely unthinkable? Something unconventional?

**Interviewer:** Right. So, I was thinking, if the chatbot would ask the user to think along to find something creative, would something like that work, you think?

**Interviewee:** Yeah, could be, could be. Like brainstorming, possibly.

**Interviewer:** Sure, sure, that works too. I mean, in this experiment, the bot is not going to do any actual brainstorm, but maybe it can act as if it's brainstorming. Yeah, great idea. Umm, also, you answered neutral on the chatbot being sloppy and careless. Why was that?

**Interviewee:** Uhm, I don't know. What I remember was that the chatbot was pretty chatty. It certainly gave me the impression that it is somewhat sloppy. But on the other hand, it knew what it had to do after one another, so it was also organized in that regard. I guess that's why I answered neutral.

**Interviewer:** Right. Okay, I think if I would make the entire conversation a lot shorter, people would then perceive it as being less chatty and hopefully the organized aspect might pop up much more than the chattiness. I really want to make the chattiness to be perceived as something positive to the user.

**Interviewee:** So how many participants did your experiment?

**Interviewer:** Uh, I've got around 10 that I want to ask, but this isn't the real experiment by the way. It's what we call the pretest. In the main experiment, I'd like to assign 5 different chatbots, but to be really sure that the personalities are really the personalities that are desired, I have to test them first, and ask what the users would perceive them. That's exactly what, uh, I'm doing now.

**Interviewee:** Ahh I see.

**Interviewer:** Alright man, that's it. I've got everything from you, I think. Thanks for the info! Appreciate your help.

**Interviewee:** [You're] welcome.

## **VI. Transcript 6 (Hasan Abdullah) - CEA**

**Interviewer:** San, can I ask you a couple of questions on the questionnaire that you did yesterday?

**Interviewee:** Oy, Stephen. Yeah, ask [me] anything.

**Interviewer:** You answered some questions differently from what I was expecting, so I want to ask you why. Okay?

**Interviewee:** Oh, okay. I might be replying a bit slow [though], by the way. I'm helping Rika with cooking.

**Interviewer:** Yeah, it's okay. So, why did you answer neutral on the chatbot's mood swing?

**Interviewee:** Eh, I'm not sure what mood swing is. Is it like, eh, happy to sad?

**Interviewer:** Yeah, something like that. Did you see the bot becoming happy and then sad, or maybe angry for some trivial reasons?

**Interviewee:** As far as I can remember, no [laughter].

**Interviewer:** Huh, alright. Then why did you answer neutral?

**Interviewee:** Really? Then maybe I should disagree then. The only thing that really sticks to me is how talkative the bot is. Really annoying in my opinion. Too much.

**Interviewer:** Yeah, I agree with you and you're not the first one to say that [laughter]. Maybe the personality just doesn't suit you, but I agree that the video is way too long.

**Interviewee:** Yeah. I think, like, I got the whole idea of the video after a few minutes already. So, it was just too long.

**Interviewer:** Gotcha. What about the creativity? Did you think the bot was creative?

**Interviewee:** Um. I really can't say. I think I remember when answering the questions about abstract thinking and imagination, um, I wasn't sure what to answer.

**Interviewer:** Right. Yeah, can be. Then the bot isn't that creative, don't you think? I mean, if you even didn't notice much about creativity, right.

**Interviewee:** I remember the bot, talking about some algorithm that it uses based on the user's data and history, etcetera. And I think that's great isn't it? That's what every technology nowadays are doing, which is using data.

**Interviewer:** So, do you think using data is creative? Let's say, we compare it with if the bot would not use the data and think along, or possibly think of something new for the user?

**Interviewee:** I think, right, then that would be more creative. If the bot would somehow not use some algorithm, but to be able to think creatively just like humans. But can it do that? I would not want to sacrifice, um, the quality of the recommendation just for the sake of creativity.

**Interviewer:** Fair point. But is it okay if we act as if the chatbot is really creative, while in fact it isn't? So, we would tell them that we would brainstorm with them, but in fact, what [really] happens really at the backend, is same old, same old.

**Interviewee:** Um. But then what's the difference in result? Only the 'packaging' is different? [laughter]

**Interviewer:** Yea, at least for now. Only until we get to a point where AI could really, truly be creative, you know.

**Interviewee:** Sure. Then I agree.

**Interviewer:** Well, I guess that's it for your part. I already get the other parts from the others. Thanks, san!

**Interviewee:** You're welcome. Hope it helps.

## **VII. Transcript 7 (Bram Dees) - CE**

**Interviewer:** Hey Bram! How's it going?

**Interviewee:** Good, Stephen. How are you? Everything good with your thesis?

**Interviewer:** Yeah, it's going pretty well. Like everybody else, it's not going that fast as planned, but it's going. In fact, that's the reason I'm calling you [laughter]. How's yours?



**Interviewee:** [Laughter] Yeah, I was talking about our thesis with Vimal and the others. We all suffer to some sort of delay. From not bad to not so good delay [laughter]. But, go ahead, what do you want to ask?

**Interviewer:** So basically, you answered some questions about the chatbot's personality after you watch the video, right. Some of your answers deviated from what I was expecting. One of them, was why you answered that the chatbot seems to have a good imagination.

**Interviewee:** Umm, I think, if I think of the way the bot explains um, music, or the smartwatch, he actually explained it in a pretty imaginative way, I thought. He was talking about how it would look great, what it can do. When I read about it, I actually imagined along.

**Interviewer:** Wow, I didn't look at it that way, but you're completely right. I guess the way you explain the products can also be imaginative, huh.

**Interviewee:** Yeah. I remember him talking about the smartwatch can do this feature or that feature. Also when he talked about the music, he said that it's perfect for people who love music and outdoor activities, I think he actually understands abstract ideas, you know.

**Interviewer:** Yeah, yeah, you're absolutely right. I didn't think of it that way. Now I know how to make it less creative and more creative on some of the chatbots. I think this is actually a very solid feedback.

**Interviewee:** Good that you agree [laughter].

**Interviewer:** Yeah absolutely. Um, I guess that's it. The rest of the items are known, but I was just curious why you said agree on imagination. Thanks a lot, Bram! Really good input, thank you!

**Interviewee:** No problem, Stephen. Let me know if I can help again with anything.

## VIII. Transcript 8 (Stella Wanda) - CE

**Interviewer:** Alright, I need to ask you about the questionnaire that you filled yesterday. Some of the answers are not what I was expecting. Some examples, okay. The chatbot could be the life of the party and you answered neutral. Why?

**Interviewee:** Um, yeah, I think it can be yes, can also be a no. For some people who already know what they're going to buy, um, they're just going to be more confused if the bot talks too much.

**Interviewer:** I get it. But the bot was very chatty right?

**Interviewee:** Yes. Too much. Way over.

**Interviewer:** Then you should have answered agree.

**Interviewee:** OK. But please. With all the emoji and how the bot acted rude and all bossy, I didn't like the bot at all.

**Interviewer:** Well, that's his personality right. And maybe, it's just not your style, I guess. But anyway, next. The chatbot could sympathize with others' feelings, and you answered agree. Why?

**Interviewee:** Huh, I forgot. Let me watch the video again. Do you still have the link?

**Interviewer:** Yeah. Hang on. Here you go.

**Interviewee:** On a second thought, I disagree. When the customer didn't choose music in the end, the bot seemed to not be so happy to accept that. With it being so bossy and all, yeah, it's not so sympathizing.

**Interviewer:** Alright good. Next, vivid imagination, you said agree.

**Interviewee:** I think this is, um, when the bot was talking about music. He really talked a lot then. About how the music is all about, and why you might like it.

**Interviewee:** Ah, yeah, I think I get what you mean. Another guy also talked about this. Alright, move on. The chatbot likes order and you disagreed. Why is that?

**Interviewer:** I think [it's] neutral, maybe. I feel like it doesn't have any further willingness to tell the customer to order? When the customer did order, that's it, seems like nothing much is happening.

**Interviewer:** [Laughter] I think you got it wrong. The order here is order as in being organized. Not order, as in to order something, you know.

**Interviewee:** Ahh, okay. Then, I guess it's agree then.

**Interviewer:** Cool. And, the chatbot gets upset easily, this is also neutral.

**Interviewee:** It wasn't that upset, I think.

**Interviewer:** Yeah, then you should've answered disagree.

**Interviewee:** Okay. By the way, speaking of imagination, maybe it can do better by explaining more about the product.

**Interviewer:** Sure. But the bot that you got was not supposed to be creative.

**Interviewee:** Ah, okay.

**Interviewer:** Last one, last one. the chatbot is not really interested in others, and you answered neutral.

**Interviewee:** I just feel nothing. The bot simply answers whatever is asked. I don't really understand what you meant by 'others' here.

**Interviewer:** Don't you think feeling others' emotions is like caring about your opinion, wanting the customers to be satisfied, etcetera? Or what's your definition?

**Interviewee:** Feeling others' emotion meaning caring about how your customer feel. Um, he should be happy or disappointed or confused or angry whatever.

**Interviewer:** Okay, fair point. So, was it already doing that?

**Interviewee:** Well, it certainly showed a lot of emotions. Especially reacting to what the customers said or chose. But the bot focused too much on himself, as if it didn't want to help the customer.

**Interviewer:** And that's exactly how the bot should be perceived for this personality. Alright, that's it! I've got tons of information, thanks yeah!

**Interviewee:** Okay, okay, anytime.

### **IX. Transcript 9 (Al Kautsar Sugiharto) - C**

**Interviewer:** Al, my man! Thanks for filling in the questionnaire the other day. I just need to ask a few things on your answers, yeah?

**Interviewee:** Hey, Phen. Yeah, helping fellow friends is my motto [laughter].

**Interviewer:** Well. I don't think so [big laughter]. but you certainly hold up to your motto this time!

**Interviewee:** What do you want to ask, bro?

**Interviewer:** So, you answered that the chatbot is neutral in being interested in abstract ideas. Why?

**Interviewee:** What do you mean by abstract ideas?

**Interviewer:** Ah. so, you weren't sure about it, and you answered disagree, huh.

**Interviewee:** Oh. was it one of the questions? Then yeah, I sure was not sure about it then [laughter].

**Interviewer:** Alright, that's okay. So, basically, was the chatbot creative?

**Interviewee:** No, not at all. It was um, very basic, very boring, bland, whatever you want to call it.

**Interviewer:** No emotions whatsoever, very robotic, right?

**Interviewee:** Yeah, yeah, that's it.

**Interviewer:** Alright. Let me see what else. Sympathy. So, feeling others' emotions and interested in other people's problems.

**Interviewee:** Again. Not at all. The bot was just very cold.

**Interviewer:** Right, so you disagree on that, right?

**Interviewee:** Yes, yes.

**Interviewer:** Okay, that's it! This is a short one. I've already collected the other answers from the others. Thanks, Al! I'll see you on July 1 at our gathering, okay.

#### **X. Transcript 10 (Edward Kurniawan) - C**

**Interviewer:** Hi Do. Thanks again for taking the time to do the experiment. So, I've collected the answers from your questionnaire that you filled not so long ago, and I have a few questions on your answers on those questions.

**Interviewee:** No worries, buddy. Shoot.

**Interviewer:** So, generally, I'm curious to know why some of your answers do not match with what I was expecting. Just an example, you answered some questions with neutral. Why is that? Did you truly think it was neutral, or were you just not sure with what you want to answer?

**Interviewee:** Yeah, I would say that there's not enough information for me to determine or to make up my mind about that.

**Interviewer:** Don't you think feeling others' emotions is like caring about your opinion, wanting the customers to be satisfied, etcetera? Or what's your definition?

**Interviewee:** Yeah, I think that is an apt description.

**Interviewer:** So why did you still think otherwise?

**Interviewee:** Wait, I said neutral, right?

**Interviewer:** Yeah. You got a very cold chatbot, so. the answer should've been "disagree".

**Interviewee:** Am I answering these questions as if I'm the buyer in the scenario or as a witness to it?

**Interviewer:** As the buyer. Would there be any difference?

**Interviewee:** Well, as a witness, the buyer himself in this scenario doesn't seem to show much emotions. It's very different than the very first one you showed to me back then. That's why I'm "Neutral" on the aforementioned question.

As a buyer, I think there's a lot of subjectivity at play here. Like what I've what told you before, I have a certain preference on my interaction with bots. That's why even if this one is supposedly cold (all relative by the way), I personally do not feel that it doesn't care about my emotions. Or at least I do not see any evidence of it.

But, if the statement of your question is "this chatbot seems to be cold towards others", then I'd probably agree. You get what I mean?

**Interviewer:** Instead of feeling others' emotions, I'd say cold towards others?

**Interviewee:** Yeah, ‘cause the latter wording invokes a more emotional/impressionable judgment. While the first one invokes a more rational argument. At least for me.

**Interviewer:** I see. The questions that I picked were standardized questions from earlier proven research and they were used to find out the personality of a person. They’re really used to assess your own personality. Maybe it’s not suitable for observation after all.

**Interviewee:** There’s a few scenarios there, right, mate. Does the buyer show different behaviors as well?

**Interviewer:** No, I can’t vary the buyer’s responses. It has to stay uniform across all different chatbots, ‘cause the chatbots’ personalities would be the main focus of the research, and not the buyer.

**Interviewee:** OK. So, by the way, I don’t have to do the very first chatbot that you shared with us back then anymore?

**Interviewer:** Ah. Forget about that one. That one was like the first version and it was 11 minutes.

**Interviewee:** Hmm, ‘cause both the buyer and the chatbot were very much ‘active’ (or what I say wish washy) in that convo.

**Interviewer:** Huh, really? I guess that’s true. I’ve revised it again multiple times and cut down a lot from 11 minutes to just 5,5 minutes. And along the way, I must’ve realized that the I have to ‘neutralize’ the user so that it’s more fitting and suitable across all different chatbots.

**Interviewee:** Right. So, enlighten me again if I’m wrong, but to reach the objective of your research, shouldn’t you run all these different scenarios to the same person (and repeat with the others)?

**Interviewer:** Yeah, what you just mentioned is called “within subjects” method in research methodology. But the thing is, with that, you’ll run into fatigue, especially if for example, you have multiple chatbots you have to go through. Also, after a while, you’ll also forget which is which, and the results are then not valid anymore.

In my case, I’ve chosen the method to randomly assign one chatbot to a person, and then later subtract the different results from my sample. Only by then do you get a pure experimental result.

**Interviewee:** Right. How many people is in your sample size?

**Interviewer:** I need 150 people. Nett, yeah. Most likely I’ll need 200-300 people gross.

**Interviewee:** Right. Okay, anything else?

**Interviewer:** Yeah, so can I conclude that your bottom line is, the perceived personalities will differ subjectively, but to get better objective answers, I’d have to clarify the questions even more?

**Interviewee:** Yeah, that’s it.

**Interviewer:** Alright, thanks buddy.

## E. Raw SPSS Statistical Outputs

### CORRELATIONS

Correlations						
		Matched_Personality	Chatbot Condition	MeanCentered_T	MeanCentered_PR	Participant's Purchase Intention towards Chatbot
Matched_Personality	Pearson Correlation	1	-.372**	-.036	-.064	-.015
	Sig. (2-tailed)		.000	.673	.460	.858
	N	137	137	137	137	137
Chatbot Condition	Pearson Correlation	-.372**	1	.081	.043	.067
	Sig. (2-tailed)	.000		.344	.616	.439
	N	137	137	137	137	137
MeanCentered_T	Pearson Correlation	-.036	.081	1	-.269**	.710**
	Sig. (2-tailed)	.673	.344		.001	.000
	N	137	137	137	137	137
MeanCentered_PR	Pearson Correlation	-.064	.043	-.269**	1	-.266**
	Sig. (2-tailed)	.460	.616	.001		.002
	N	137	137	137	137	137
Participant's Purchase Intention towards Chatbot	Pearson Correlation	-.015	.067	.710**	-.266**	1
	Sig. (2-tailed)	.858	.439	.000	.002	
	N	137	137	137	137	137

\*\* . Correlation is significant at the 0.01 level (2-tailed).

### RELIABILITY

- TIPI
  - Extraversion

#### Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.803	.803	2

#### Item Statistics

	Mean	Std. Deviation	N
I see myself as: Extraverted, enthusiastic.	4.57	1.644	137
I see myself as: Reserved, quiet. (R)	3.91	1.649	137

#### Inter-Item Correlation Matrix



	I see myself as: Extraverted, enthusiastic.	I see myself as: Reserved, quiet. (R)
I see myself as: Extraverted, enthusiastic.	1.000	.671
I see myself as: Reserved, quiet. (R)	.671	1.000

○ **Agreeableness**

**Reliability Statistics**

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.651	.654	2

**Item Statistics**

	Mean	Std. Deviation	N
I see myself as: Critical, quarrelsome (argumentative) towards others. (R)	4.48	1.373	137
I see myself as: Sympathetic, warm.	5.57	1.230	137

**Inter-Item Correlation Matrix**

	I see myself as: Critical, quarrelsome (argumentative) towards others. (R)	I see myself as: Sympathetic, warm.
I see myself as: Critical, quarrelsome (argumentative) towards others. (R)	1.000	.485
I see myself as: Sympathetic, warm.	.485	1.000

○ **Conscientiousness**

### Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.689	.700	2

### Item Statistics

	Mean	Std. Deviation	N
I see myself as: Dependable, self-disciplined.	5.47	1.243	168
I see myself as: Disorganized, careless. (R)	4.83	1.558	168

### Inter-Item Correlation Matrix

	I see myself as: Dependable, self-disciplined.	I see myself as: Disorganized, careless. (R)
I see myself as: Dependable, self-disciplined.	1.000	.539
I see myself as: Disorganized, careless. (R)	.539	1.000

#### ○ Neuroticism

### Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.713	.714	2

### Item Statistics

	Mean	Std. Deviation	N
I see myself as: Anxious, easily upset.	3.76	1.729	168
I see myself as: Calm, emotionally stable. (R)	3.14	1.653	168

### Inter-Item Correlation Matrix

	I see myself as: Anxious, easily upset.	I see myself as: Calm, emotionally stable. (R)
I see myself as: Anxious, easily upset.	1.000	.555
I see myself as: Calm, emotionally stable. (R)	.555	1.000

#### ○ Openness

### Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.651	.655	2

### Item Statistics

	Mean	Std. Deviation	N
I see myself as: Open to new experiences (ideas), complex (imaginative).	5.88	.903	137
I see myself as: Conventional, uncreative. (R)	5.43	1.042	137

### Inter-Item Correlation Matrix

	I see myself as: Open to new experiences (ideas), complex (imaginative).	I see myself as: Conventional, uncreative. (R)
I see myself as: Open to new experiences (ideas), complex (imaginative).	1.000	.487

I see myself as: Conventional, uncreative. (R)	.487	1.000
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- Trust

### Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.883	.883	6

### Item Statistics

	Mean	Std. Deviation	N
(T) The chatbot is competent.	5.36	1.265	137
(T) The chatbot knows how to provide excellent service.	5.09	1.387	137
(T) Promises made by the chatbot are likely to be reliable.	4.67	1.510	137
(T) I expect that the chatbot will keep the promises they make.	4.97	1.604	137
(T) I expect that the chatbot has good intentions towards me.	4.94	1.617	137
(T) I expect that the chatbot's intentions are benevolent (well-meaning and kind).	5.12	1.462	137

### Inter-Item Correlation Matrix

	(T) The chatbot is competent.	(T) The chatbot knows how to provide excellent service.	(T) Promises made by the chatbot are likely to be reliable.	(T) I expect that the chatbot will keep the promises they make.	(T) I expect that the chatbot has good intentions towards me.	(T) I expect that the chatbot's intentions are benevolent (well-meaning and kind).
(T) The chatbot is competent.	1.000	.717	.583	.534	.338	.393

(T) The chatbot knows how to provide excellent service.	.717	1.000	.633	.606	.442	.454
(T) Promises made by the chatbot are likely to be reliable.	.583	.633	1.000	.700	.423	.405
(T) I expect that the chatbot will keep the promises they make.	.534	.606	.700	1.000	.620	.641
(T) I expect that the chatbot has good intentions towards me.	.338	.442	.423	.620	1.000	.877
(T) I expect that the chatbot's intentions are benevolent (well-meaning and kind).	.393	.454	.405	.641	.877	1.000

- Personal Attachment

#### Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.856	.856	5

#### Item Statistics

	Mean	Std. Deviation	N
(PA) I would feel a sense of loss if the chatbot was unavailable and I could no longer use it.	2.59	1.108	137
(PA) I feel a sense of attachment to using the chatbot.	2.48	1.189	137
(PA) I find the chatbot suitable to my style of decision making.	2.93	1.235	137
(PA) I like using the chatbot for decision making.	2.96	1.194	137

(PA) I have a personal preference for making decisions with the chatbot.	3.12	1.215	137
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### Inter-Item Correlation Matrix

	(PA) I would feel a sense of loss if the chatbot was unavailable and I could no longer use it.	(PA) I feel a sense of attachment to using the chatbot.	(PA) I find the chatbot suitable to my style of decision making.	(PA) I like using the chatbot for decision making.	(PA) I have a personal preference for making decisions with the chatbot.
(PA) I would feel a sense of loss if the chatbot was unavailable and I could no longer use it.	1.000	.625	.472	.525	.442
(PA) I feel a sense of attachment to using the chatbot.	.625	1.000	.495	.502	.472
(PA) I find the chatbot suitable to my style of decision making.	.472	.495	1.000	.736	.604
(PA) I like using the chatbot for decision making.	.525	.502	.736	1.000	.561
(PA) I have a personal preference for making decisions with the chatbot.	.442	.472	.604	.561	1.000

- **Perceived Risk**

### Reliability Statistics

Cronbach's Alpha Based on Standardized Items		
Cronbach's Alpha	Items	N of Items
.709	.714	6

### Item Statistics

Mean	Std. Deviation	N
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(PR) I feel that online purchases recommended by the chatbot are risky because: - The product may fail to meet my expectations.	4.86	1.301	137
(PR) I feel that online purchases recommended by the chatbot are risky because: - The product may be inferior.	4.37	1.361	137
(PR) I feel that online purchases recommended by the chatbot are risky because: - They may lead to financial loss for me.	4.55	1.599	137
(PR) I feel that online purchases recommended by the chatbot are risky because: - They may cause others to think less highly of me.	2.97	1.475	137
(PR) I feel that online purchases recommended by the chatbot are risky because: - They may fail to fit well with my personal image.	3.81	1.607	137
(PR) I feel that online purchases recommended by the chatbot are risky because: - They may lead to a time loss for me.	3.93	1.716	137

## Inter-Item Correlation Matrix

	(PR) I feel that online purchases recommended by the chatbot are risky because: - The product may fail to meet my expectations.	(PR) I feel that online purchases recommended by the chatbot are risky because: - The product may be inferior.	(PR) I feel that online purchases recommended by the chatbot are risky because: - They may lead to financial loss for me.	(PR) I feel that online purchases recommended by the chatbot are risky because: - They may cause others to think less highly of me.	(PR) I feel that online purchases recommended by the chatbot are risky because: - They may fail to fit well with my personal image.	(PR) I feel that online purchases recommended by the chatbot are risky because: - They may lead to a time loss for me.
(PR) I feel that online purchases recommended by the chatbot are risky because: - The product may fail to meet my expectations.	1.000	.639	.475	.032	.258	.302
(PR) I feel that online purchases recommended by the chatbot are risky because: - The product may be inferior.	.639	1.000	.496	.071	.130	.316
(PR) I feel that online purchases recommended by the chatbot are risky because: - They may lead to financial loss for me.	.475	.496	1.000	.138	.210	.260
(PR) I feel that online purchases recommended by the chatbot are risky because: - They may cause others to think less highly of me.	.032	.071	.138	1.000	.280	.394
(PR) I feel that online purchases recommended by the chatbot are risky because: - They may fail to fit well with my personal image.	.258	.130	.210	.280	1.000	.398

(PR) I feel that online purchases recommended by the chatbot are risky because: - They may lead to a time loss for me.	.302	.316	.260	.394	.398	1.000
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- **Purchase Intention**

### Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.903	.903	3

### Item Statistics

	Mean	Std. Deviation	N
(PI) I intend to use the chatbot to conduct future purchases.	4.15	1.593	137
(PI) I expect to purchase with the help of chatbot in the future.	4.31	1.585	137
(PI) It is likely that I will transact with the chatbot in the near future.	4.21	1.583	137

### Inter-Item Correlation Matrix

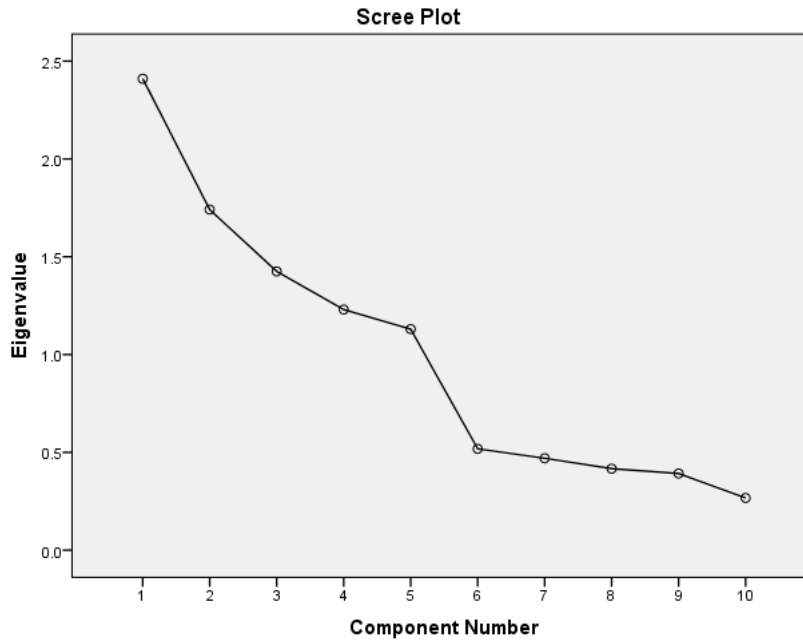
	(PI) I intend to use the chatbot to conduct future purchases.	(PI) I expect to purchase with the help of chatbot in the future.	(PI) It is likely that I will transact with the chatbot in the near future.
(PI) I intend to use the chatbot to conduct future purchases.	1.000	.786	.734

(PI) I expect to purchase with the help of chatbot in the future.	.786	1.000	.747
(PI) It is likely that I will transact with the chatbot in the near future.	.734	.747	1.000

## FACTOR ANALYSIS

- TIPI Big Five

Correlation Matrix											
		I see myself as: Extraverted, enthusiastic.	I see myself as: Critical, quarrelsome (argumentative) towards others. (R)	I see myself as: Dependable, self-disciplined.	I see myself as: Anxious, easily upset.	I see myself as: Open to new experiences (ideas), complex (imaginative).	I see myself as: Reserved, quiet. (R)	I see myself as: Sympathetic, warm.	I see myself as: Disorganized, careless. (R)	I see myself as: Calm, emotionally stable. (R)	I see myself as: Conventional, uncreative. (R)
Correlation	I see myself as: Extraverted, enthusiastic.	1.000	-.132	.050	-.231	.251	.671	.122	.008	-.168	.152
	I see myself as: Critical, quarrelsome (argumentative) towards others. (R)	-.132	1.000	.023	-.065	-.034	-.162	.485	-.073	-.070	.003
	I see myself as: Dependable, self-disciplined.	.050	.023	1.000	-.070	.078	-.005	.141	.559	-.105	.085
	I see myself as: Anxious, easily upset.	-.231	-.065	-.070	1.000	-.301	-.167	-.111	-.106	.577	-.031
	I see myself as: Open to new experiences (ideas), complex (imaginative).	.251	-.034	.078	-.301	1.000	.264	.064	-.055	-.267	.487
	I see myself as: Reserved, quiet. (R)	.671	-.162	-.005	-.167	.264	1.000	-.031	.015	-.171	.140
	I see myself as: Sympathetic, warm.	.122	.485	.141	-.111	.064	-.031	1.000	.182	-.105	.077
	I see myself as: Disorganized, careless. (R)	.008	-.073	.559	-.106	-.055	.015	.182	1.000	-.134	-.018
	I see myself as: Calm, emotionally stable. (R)	-.168	-.070	-.105	.577	-.267	-.171	-.105	-.134	1.000	-.046
	I see myself as: Conventional, uncreative. (R)	.152	.003	.085	-.031	.487	.140	.077	-.018	-.046	1.000
Sig. (1-tailed)	I see myself as: Extraverted, enthusiastic.		.062	.281	.003	.002	.000	.077	.462	.025	.038
	I see myself as: Critical, quarrelsome (argumentative) towards others. (R)	.062		.394	.224	.345	.030	.000	.199	.209	.486
	I see myself as: Dependable, self-disciplined.	.281	.394		.209	.183	.478	.050	.000	.111	.160
	I see myself as: Anxious, easily upset.	.003	.224	.209		.000	.026	.097	.108	.000	.361
	I see myself as: Open to new experiences (ideas), complex (imaginative).	.002	.345	.183	.000		.001	.228	.262	.001	.000
	I see myself as: Reserved, quiet. (R)	.000	.030	.478	.026	.001		.359	.430	.023	.052
	I see myself as: Sympathetic, warm.	.077	.000	.050	.097	.228	.359		.016	.111	.186
	I see myself as: Disorganized, careless. (R)	.462	.199	.000	.108	.262	.430	.016		.060	.419
	I see myself as: Calm, emotionally stable. (R)	.025	.209	.111	.000	.001	.023	.111	.060		.295
	I see myself as: Conventional, uncreative. (R)	.038	.486	.160	.361	.000	.052	.186	.419	.295	



**Component Matrix<sup>a</sup>**

	Component				
	1	2	3	4	5
I see myself as: Extraverted, enthusiastic.	.671	-.332	.100	.036	.524
I see myself as: Critical, quarrelsome (argumentative) towards others. (R)	-.014	.551	-.644	.091	.238
I see myself as: Dependable, self-disciplined.	.274	.566	.557	.239	-.063
I see myself as: Anxious, easily upset.	-.633	-.163	.157	.529	.226
I see myself as: Open to new experiences (ideas), complex (imaginative).	.651	-.165	-.205	.315	-.407
I see myself as: Reserved, quiet. (R)	.630	-.436	.156	.013	.458
I see myself as: Sympathetic, warm.	.244	.603	-.391	.218	.406
I see myself as: Disorganized, careless. (R)	.227	.584	.637	.052	.020

I see myself as: Calm, emotionally stable. (R)	-.612	-.206	.122	.521	.263
I see myself as: Conventional, uncreative. (R)	.421	-.123	-.162	.681	-.367

Extraction Method: Principal Component Analysis.

a. 5 components extracted.

#### Pattern Matrix<sup>a</sup>

	Component				
	1	2	3	4	5
I see myself as: Extraverted, enthusiastic.	.007	.068	-.004	.001	.920
I see myself as: Critical, quarrelsome (argumentative) towards others. (R)	.052	.857	-.145	-.013	-.148
I see myself as: Dependable, self-disciplined.	-.016	.022	.867	.110	-.038
I see myself as: Anxious, easily upset.	-.875	-.021	.005	-.001	-.033
I see myself as: Open to new experiences (ideas), complex (imaginative).	.257	-.044	-.051	.777	.062
I see myself as: Reserved, quiet. (R)	.001	-.068	-.035	.009	.898
I see myself as: Sympathetic, warm.	-.024	.861	.149	.015	.146
I see myself as: Disorganized, careless. (R)	.058	-.021	.888	-.111	.001
I see myself as: Calm, emotionally stable. (R)	-.875	-.006	-.047	-.006	.019
I see myself as: Conventional, uncreative. (R)	-.155	.033	.039	.915	-.021

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 7 iterations.

### Structure Matrix

	Component				
	1	2	3	4	5
I see myself as: Extraverted, enthusiastic.	.214	.008	.049	.208	.917
I see myself as: Critical, quarrelsome (argumentative) towards others. (R)	.079	.859	-.078	-.013	-.204
I see myself as: Dependable, self-disciplined.	.077	.098	.869	.127	.026
I see myself as: Anxious, easily upset.	-.884	-.095	-.082	-.142	-.223
I see myself as: Open to new experiences (ideas), complex (imaginative).	.380	-.003	-.002	.827	.290
I see myself as: Reserved, quiet. (R)	.189	-.130	.006	.204	.902
I see myself as: Sympathetic, warm.	.099	.862	.225	.078	.095
I see myself as: Disorganized, careless. (R)	.124	.052	.888	-.074	.036
I see myself as: Calm, emotionally stable. (R)	-.877	-.087	-.130	-.137	-.176
I see myself as: Conventional, uncreative. (R)	-.014	.056	.055	.889	.147

Extraction Method: Principal Component Analysis.

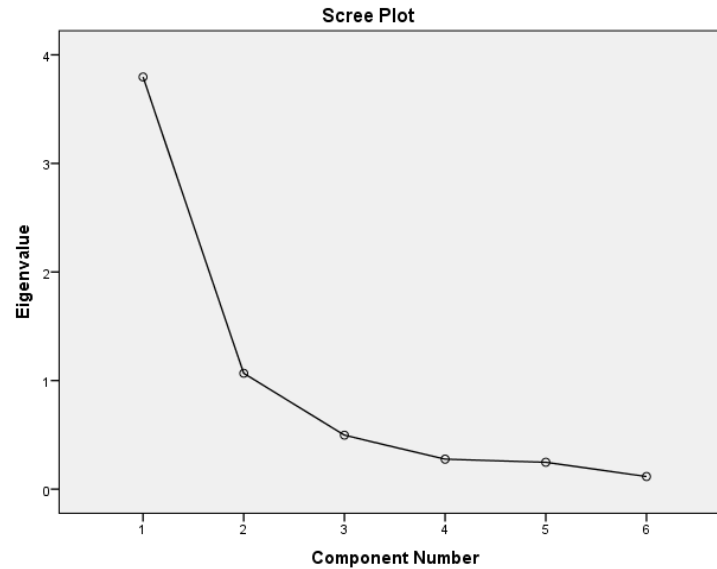
Rotation Method: Oblimin with Kaiser Normalization.



- Trust

Correlation Matrix

		(T) The chatbot is competent.	(T) The chatbot knows how to provide excellent service.	(T) Promises made by the chatbot are likely to be reliable.	(T) I expect that the chatbot will keep the promises they make.	(T) I expect that the chatbot has good intentions towards me.	(T) I expect that the chatbot's intentions are benevolent (well-meaning and kind).
Correlation	(T) The chatbot is competent.	1.000	.717	.583	.534	.338	.393
	(T) The chatbot knows how to provide excellent service.	.717	1.000	.633	.606	.442	.454
	(T) Promises made by the chatbot are likely to be reliable.	.583	.633	1.000	.700	.423	.405
	(T) I expect that the chatbot will keep the promises they make.	.534	.606	.700	1.000	.620	.641
	(T) I expect that the chatbot has good intentions towards me.	.338	.442	.423	.620	1.000	.877
	(T) I expect that the chatbot's intentions are benevolent (well-meaning and kind).	.393	.454	.405	.641	.877	1.000
Sig. (1-tailed)	(T) The chatbot is competent.		.000	.000	.000	.000	.000
	(T) The chatbot knows how to provide excellent service.	.000		.000	.000	.000	.000
	(T) Promises made by the chatbot are likely to be reliable.	.000	.000		.000	.000	.000
	(T) I expect that the chatbot will keep the promises they make.	.000	.000	.000		.000	.000
	(T) I expect that the chatbot has good intentions towards me.	.000	.000	.000	.000		.000
	(T) I expect that the chatbot has good intentions towards me.	.000	.000	.000	.000		.000
	(T) I expect that the chatbot's intentions are benevolent (well-meaning and kind).	.000	.000	.000	.000	.000	



**Component Matrix<sup>a</sup>**

	Component	
	1	2
(T) The chatbot is competent.	.741	.464
(T) The chatbot knows how to provide excellent service.	.807	.364
(T) Promises made by the chatbot are likely to be reliable.	.786	.325
(T) I expect that the chatbot will keep the promises they make.	.867	-.030
(T) I expect that the chatbot has good intentions towards me.	.776	-.566
(T) I expect that the chatbot's intentions are benevolent (well-meaning and kind).	.791	-.541

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

### Pattern Matrix<sup>a</sup>

	Component	
	1	2
(T) The chatbot is competent.	.924	.111
(T) The chatbot knows how to provide excellent service.	.872	-.026
(T) Promises made by the chatbot are likely to be reliable.	.821	-.056
(T) I expect that the chatbot will keep the promises they make.	.538	-.464
(T) I expect that the chatbot has good intentions towards me.	-.029	-.974
(T) I expect that the chatbot's intentions are benevolent (well-meaning and kind).	.005	-.956

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 5 iterations.

### Structure Matrix

	Component	
	1	2
(T) The chatbot is competent.	.869	-.346
(T) The chatbot knows how to provide excellent service.	.885	-.457
(T) Promises made by the chatbot are likely to be reliable.	.849	-.462
(T) I expect that the chatbot will keep the promises they make.	.768	-.730
(T) I expect that the chatbot has good intentions towards me.	.453	-.960

(T) I expect that the chatbot's intentions are benevolent (well-meaning and kind).	.477	-.958
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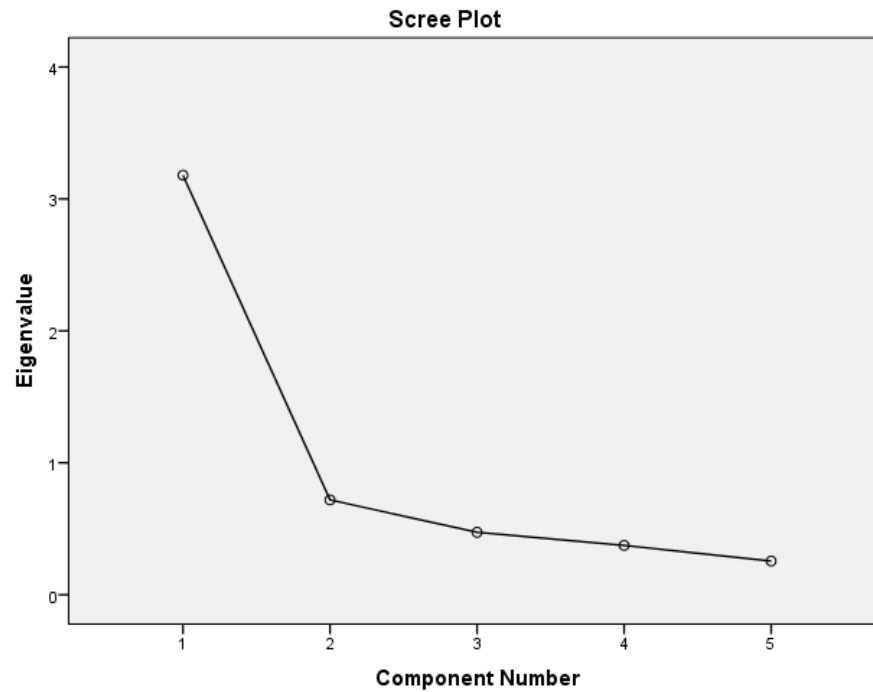
Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

- Personal Attachment

#### Correlation Matrix

		(PA) I would feel a sense of loss if the chatbot was unavailable and I could no longer use it.	(PA) I feel a sense of attachment to using the chatbot.	(PA) I find the chatbot suitable to my style of decision making.	(PA) I like using the chatbot for decision making.	(PA) I have a personal preference for making decisions with the chatbot.
Correlation	(PA) I would feel a sense of loss if the chatbot was unavailable and I could no longer use it.	1.000	.625	.472	.525	.442
	(PA) I feel a sense of attachment to using the chatbot.	.625	1.000	.495	.502	.472
	(PA) I find the chatbot suitable to my style of decision making.	.472	.495	1.000	.736	.604
	(PA) I like using the chatbot for decision making.	.525	.502	.736	1.000	.561
	(PA) I have a personal preference for making decisions with the chatbot.	.442	.472	.604	.561	1.000
Sig. (1-tailed)	(PA) I would feel a sense of loss if the chatbot was unavailable and I could no longer use it.		.000	.000	.000	.000
	(PA) I feel a sense of attachment to using the chatbot.	.000		.000	.000	.000
	(PA) I find the chatbot suitable to my style of decision making.	.000	.000		.000	.000
	(PA) I like using the chatbot for decision making.	.000	.000	.000		.000
	(PA) I have a personal preference for making decisions with the chatbot.	.000	.000	.000	.000	



**Component Matrix<sup>a</sup>**

	Component 1
(PA) I would feel a sense of loss if the chatbot was unavailable and I could no longer use it.	.762
(PA) I feel a sense of attachment to using the chatbot.	.770
(PA) I find the chatbot suitable to my style of decision making.	.838
(PA) I like using the chatbot for decision making.	.843
(PA) I have a personal preference for making decisions with the chatbot.	.771

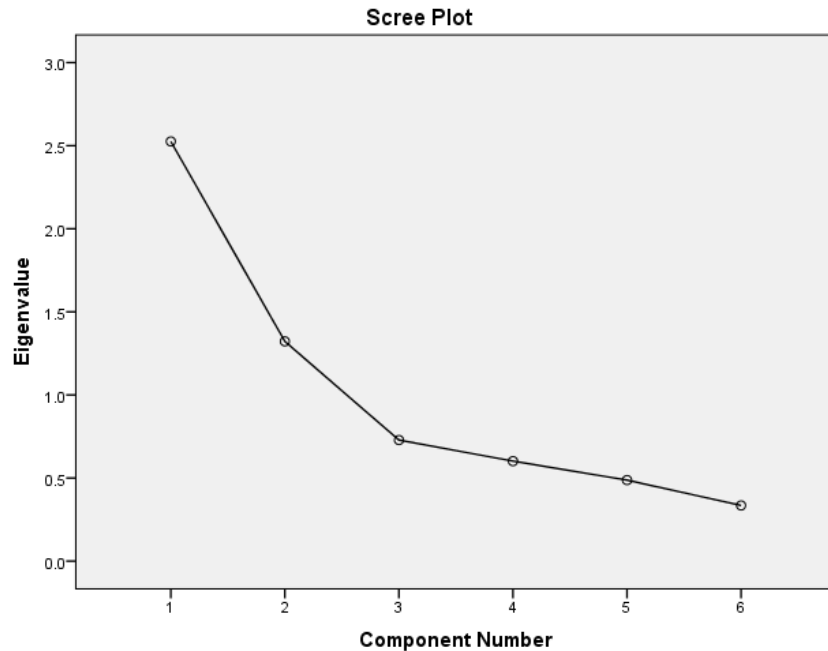
Extraction Method: Principal Component Analysis.

a. 1 components extracted.

- Perceived Risk

Correlation Matrix

		(PR) I feel that online purchases recommended by the chatbot are risky because: - The product may fail to meet my expectations.	(PR) I feel that online purchases recommended by the chatbot are risky because: - The product may be inferior.	(PR) I feel that online purchases recommended by the chatbot are risky because: - They may lead to financial loss for me.	(PR) I feel that online purchases recommended by the chatbot are risky because: - They may cause others to think less highly of me.	(PR) I feel that online purchases recommended by the chatbot are risky because: - They may fail to fit well with my personal image.	(PR) I feel that online purchases recommended by the chatbot are risky because: - They may lead to a time loss for me.
Correlation	(PR) I feel that online purchases recommended by the chatbot are risky because: - The product may fail to meet my expectations.	1.000	.639	.475	.032	.258	.302
	(PR) I feel that online purchases recommended by the chatbot are risky because: - The product may be inferior.	.639	1.000	.496	.071	.130	.316
	(PR) I feel that online purchases recommended by the chatbot are risky because: - They may lead to financial loss for me.	.475	.496	1.000	.138	.210	.260
	(PR) I feel that online purchases recommended by the chatbot are risky because: - They may cause others to think less highly of me.	.032	.071	.138	1.000	.280	.394
	(PR) I feel that online purchases recommended by the chatbot are risky because: - They may fail to fit well with my personal image.	.258	.130	.210	.280	1.000	.398
	(PR) I feel that online purchases recommended by the chatbot are risky because: - They may lead to a time loss for me.	.302	.316	.260	.394	.398	1.000
Sig. (1-tailed)	(PR) I feel that online purchases recommended by the chatbot are risky because: - The product may fail to meet my expectations.		.000	.000	.354	.001	.000
	(PR) I feel that online purchases recommended by the chatbot are risky because: - The product may be inferior.	.000		.000	.204	.065	.000
	(PR) I feel that online purchases recommended by the chatbot are risky because: - They may lead to financial loss for me.	.000	.000		.054	.007	.001
	(PR) I feel that online purchases recommended by the chatbot are risky because: - They may cause others to think less highly of me.	.354	.204	.054		.000	.000
	(PR) I feel that online purchases recommended by the chatbot are risky because: - They may fail to fit well with my personal image.	.001	.065	.007	.000		.000
	(PR) I feel that online purchases recommended by the chatbot are risky because: - They may lead to a time loss for me.	.000	.000	.001	.000	.000	



**Component Matrix<sup>a</sup>**

	Component	
	1	2
(PR) I feel that online purchases recommended by the chatbot are risky because: - The product may fail to meet my expectations.	.765	-.393
(PR) I feel that online purchases recommended by the chatbot are risky because: - The product may be inferior.	.751	-.428
(PR) I feel that online purchases recommended by the chatbot are risky because: - They may lead to financial loss for me.	.705	-.275



(PR) I feel that online purchases recommended by the chatbot are risky because: - They may cause others to think less highly of me.	.386	.699
(PR) I feel that online purchases recommended by the chatbot are risky because: - They may fail to fit well with my personal image.	.535	.479
(PR) I feel that online purchases recommended by the chatbot are risky because: - They may lead to a time loss for me.	.667	.436

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

#### Pattern Matrix<sup>a</sup>

	Component	
	1	2
(PR) I feel that online purchases recommended by the chatbot are risky because: - The product may fail to meet my expectations.	.862	-.006
(PR) I feel that online purchases recommended by the chatbot are risky because: - The product may be inferior.	.875	-.044
(PR) I feel that online purchases recommended by the chatbot are risky because: - They may lead to financial loss for me.	.734	.075

(PR) I feel that online purchases recommended by the chatbot are risky because: - They may cause others to think less highly of me.	-.186	.826
(PR) I feel that online purchases recommended by the chatbot are risky because: - They may fail to fit well with my personal image.	.081	.693
(PR) I feel that online purchases recommended by the chatbot are risky because: - They may lead to a time loss for me.	.212	.715

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 4 iterations.

### Structure Matrix

	Component	
	1	2
(PR) I feel that online purchases recommended by the chatbot are risky because: - The product may fail to meet my expectations.	.860	.218
(PR) I feel that online purchases recommended by the chatbot are risky because: - The product may be inferior.	.864	.183
(PR) I feel that online purchases recommended by the chatbot are risky because: - They may lead to financial loss for me.	.753	.265

(PR) I feel that online purchases recommended by the chatbot are risky because: - They may cause others to think less highly of me.	.029	.777
(PR) I feel that online purchases recommended by the chatbot are risky because: - They may fail to fit well with my personal image.	.261	.714
(PR) I feel that online purchases recommended by the chatbot are risky because: - They may lead to a time loss for me.	.398	.770

Extraction Method: Principal Component Analysis.

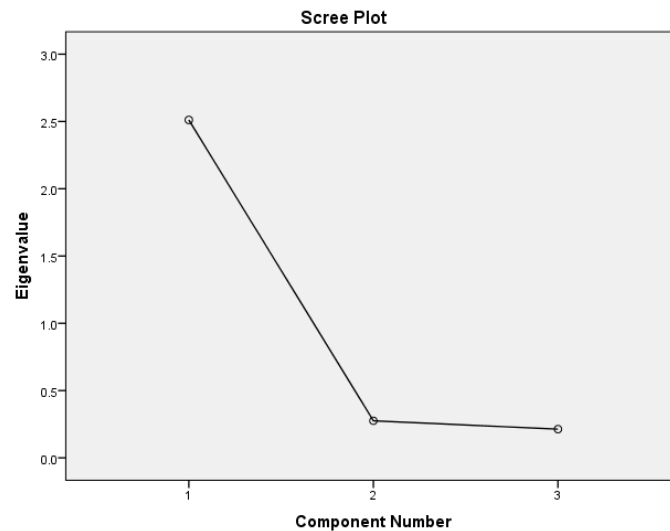
Rotation Method: Oblimin with Kaiser Normalization.

- **Purchase Intention**

### Correlation Matrix

		(PI) I intend to use the chatbot to conduct future purchases.	(PI) I expect to purchase with the help of chatbot in the future.	(PI) It is likely that I will transact with the chatbot in the near future.
Correlation	(PI) I intend to use the chatbot to conduct future purchases.	1.000	.786	.734
	(PI) I expect to purchase with the help of chatbot in the future.	.786	1.000	.747
	(PI) It is likely that I will transact with the chatbot in the near future.	.734	.747	1.000
Sig. (1-tailed)	(PI) I intend to use the chatbot to conduct future purchases.		.000	.000

(PI) I expect to purchase with the help of chatbot in the future.	.000		.000
(PI) It is likely that I will transact with the chatbot in the near future.	.000	.000	



### Component Matrix<sup>a</sup>

	Component 1
(PI) I intend to use the chatbot to conduct future purchases.	.919
(PI) I expect to purchase with the help of chatbot in the future.	.924
(PI) It is likely that I will transact with the chatbot in the near future.	.903

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

## MEDIATION

- **Matched Personality**

Run MATRIX procedure:

\*\*\*\*\* PROCESS Procedure for SPSS Version 3.00 \*\*\*\*\*

Written by Andrew F. Hayes, Ph.D. [www.afhayes.com](http://www.afhayes.com)

Documentation available in Hayes (2018). [www.guilford.com/p/hayes3](http://www.guilford.com/p/hayes3)

\*\*\*\*\*

Model : 4

Y : Purchase (Purchase Intention)

X : Matched\_ (Matched\_Personality)

M1 : MeanCent (MeanCentered\_Trust)

M2 : MeanCe\_1 (MeanCentered\_PerceivedRisk)

Sample

Size: 137

\*\*\*\*\*

OUTCOME VARIABLE:

MeanCent

Model Summary

R	R-sq	MSE	F	df1	df2	p
.0364	.0013	.9008	.1790	1.0000	135.0000	.6729

Model

	coeff	se	t	p	LLCI	ULCI
constant	.0159	.0870	.1828	.8552	-.1562	.1880
Matched_	-.1016	.2400	-.4231	.6729	-.5763	.3731

\*\*\*\*\*

OUTCOME VARIABLE:

MeanCe\_1

Model Summary

R	R-sq	MSE	F	df1	df2	p
.0637	.0041	.9411	.5498	1.0000	135.0000	.4597

Model

	coeff	se	t	p	LLCI	ULCI
constant	.0278	.0889	.3131	.7547	-.1480	.2037
Matched_	-.1819	.2453	-.7415	.4597	-.6671	.3033

\*\*\*\*\*

#### OUTCOME VARIABLE:

Purchase

#### Model Summary

R	R-sq	MSE	F	df1	df2	p
.7145	.5105	1.0551	46.2364	3.0000	133.0000	.0000

#### Model

	coeff	se	t	p	LLCI	ULCI
constant	4.2190	.0942	44.7764	.0000	4.0327	4.4054
Matched_	.0196	.2607	.0753	.9401	-.4961	.5353
MeanCent	1.0569	.0968	10.9184	.0000	.8655	1.2484
MeanCe_1	-.1204	.0947	-1.2710	.2059	-.3077	.0670

\*\*\*\*\* DIRECT AND INDIRECT EFFECTS OF X ON Y \*\*\*\*\*

#### Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
.0196	.2607	.0753	.9401	-.4961	.5353

#### Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
TOTAL	-.0854	.2255	-.5745	.3188
MeanCent	-.1073	.2118	-.5611	.2727
MeanCe_1	.0219	.0411	-.0424	.1256

\*\*\*\*\* ANALYSIS NOTES AND ERRORS \*\*\*\*\*

Level of confidence for all confidence intervals in output:

95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:

5000

NOTE: Variables names longer than eight characters can produce incorrect output.

Shorter variable names are recommended.

----- END MATRIX -----

- Chatbot Personality

Run MATRIX procedure:

\*\*\*\*\* PROCESS Procedure for SPSS Version 3.00 \*\*\*\*\*

Written by Andrew F. Hayes, Ph.D. [www.afhayes.com](http://www.afhayes.com)

Documentation available in Hayes (2018). [www.guilford.com/p/hayes3](http://www.guilford.com/p/hayes3)

\*\*\*\*\*

Model : 4

Y : Purchase (Purchase Intention)

X : Matched\_ (Matched\_Personality)

M1 : MeanCent (MeanCentered\_Trust)

M2 : MeanCe\_1 (MeanCentered\_PerceivedRisk)

Sample

Size: 137

\*\*\*\*\*

OUTCOME VARIABLE:

MeanCent

Model Summary

R	R-sq	MSE	F	df1	df2	p
.0814	.0066	.8960	.9006	1.0000	135.0000	.3443

Model

	coeff	se	t	p	LLCI	ULCI
constant	-.1520	.1818	-.8359	.4047	-.5115	.2076
Conditio	.0521	.0549	.9490	.3443	-.0565	.1608

\*\*\*\*\*

OUTCOME VARIABLE:

MeanCe\_1

Model Summary

R	R-sq	MSE	F	df1	df2	p
.0433	.0019	.9431	.2532	1.0000	135.0000	.6156

Model

	coeff	se	t	p	LLCI	ULCI
--	-------	----	---	---	------	------



constant	-.0801	.1865	-.4296	.6682	-.4490	.2888
Conditio	.0284	.0564	.5032	.6156	-.0831	.1398

\*\*\*\*\*

OUTCOME VARIABLE:

Purchase

Model Summary

R	R-sq	MSE	F	df1	df2	p
.7146	.5107	1.0547	46.2699	3.0000	133.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	4.1800	.1981	21.1006	.0000	3.7882	4.5719
Conditio	.0140	.0599	.2341	.8152	-.1045	.1326
MeanCent	1.0543	.0971	10.8593	.0000	.8623	1.2464
MeanCe_1	-.1224	.0946	-1.2937	.1980	-.3096	.0648

\*\*\*\*\* DIRECT AND INDIRECT EFFECTS OF X ON Y \*\*\*\*\*

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
.0140	.0599	.2341	.8152	-.1045	.1326

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
TOTAL	.0515	.0588	-.0610	.1712
MeanCent	.0550	.0566	-.0537	.1695
MeanCe_1	-.0035	.0086	-.0237	.0129

\*\*\*\*\* ANALYSIS NOTES AND ERRORS \*\*\*\*\*

Level of confidence for all confidence intervals in output:

95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:

5000

NOTE: Variables names longer than eight characters can produce incorrect output.

Shorter variable names are recommended.

----- END MATRIX -----