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Factors influencing the adoption of welcoming service-robots in bank

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Abstract

In this paper, we aimed to discover and quantify the importance of some factors on the welcoming service-robot acceptance. In that goal, we first developed the recent advances in the field of AI and service-robots technologies before examining in detail the different theories about technology acceptance. More specifically, we first presented the advances in AI around the levels of intelligence and the four intelligences.

We then presented the advances in the service-robots technologies and developed the models of technology acceptance of TAM, TRA, UTAUT, IDT, SST's acceptance model and sRAM. On that basis, we compared the two models TAM and UTAUT with both mediation and moderation analyses to fully assess their explanatory power.

We obtained some key results such as the confirmation of the high relevance of the mediator Usefulness and the relative relevance of the mediator Ease of use as mediators of the Usage intention. The study also puts in light that both models have similar explanatory power with a slight advantage in favor of TAM model.

Moreover, this study pointed out some interesting relationships between variables that could be explored in further studies such as the prominence of the mediator and predictor Usefulness that tends to overshadow other variables

The results obtained also allowed to have a better view of hypothetic criteria of welcoming service-robots adoption as well as hypothetic non-criteria such as the variables Result demonstrability and Subjective norm that seems to play only a minor role in the technology adoption mechanism of such a technology.

Our results then provide useful insights for practitioners as well as for researchers by expanding the existent theory and increasing the field of research.

Foreword

First of all, I would like to thank every people who make this Master Thesis possible. I would like to express my sincere gratitude to my master thesis supervisor, Hammedi Wafa for her teaching and guidance.

I would also thank my parents, my brother and my sisters, my family, and my friends for their support during the realization of this thesis.

Finally, I would like to thank every single people that took the time to participate in my master thesis by answering to the survey. It is not exaggerating to say that without them, this master thesis would have never come to an end.

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1. Introduction

A. Context

Today, technology keeps on going to quickly change the nature of service, the service experiences, and the relationships that customers can have with the service providers (Ostrom, Parasuraman, Bowen, Patricio, & Voss, 2015; Rust & Huang, 2014). Artificial Intelligence (AI) has continued to gain in interest over the years, proving itself capable of solving more and more concerns faced by managers and business owners in a large number of contexts, both in healthcare and in retailing (Mende, Scott, van Doorn, Grewal, & Shanks, 2019). A survey conducted by Salesforce shows that the technology that will be the most adopted in the coming years by managers is AI (Columbus, 2019).

It is therefore unsurprising that we can observe in all sectors (e.g., healthcare, financial, retailing, manufacturing) companies investing heavily in new technologies in order to achieve their objectives. Many companies are therefore purchasing robots to mechanize parts of their production chain and thus reduce their costs.

Within the retailing industry, firms are investing more and more in online tools to build and retain community. As such, social media platforms such as Facebook and Twitter can play a key role in achieving these goals. To go further, the economic results of the firms are examined by these social networks users that are sometimes highly critical on those results (Oscar Lemaire, Twitter).

Social networks thus transform customers into fully-fledged stakeholders and tend to increase their power over companies. It therefore appears essential for organizations to develop an effective online communication strategy.

While the impact of new information and communication technologies (ICT) on firms and their customers is well known, the impact of AI and service robots tends to be highlighted. The last few years have seen the development of a number of initiatives in this area. AI in driverless car is a good example. Cars are becoming more and more sophisticated and now have many driving aids. The future of the automobile seems to turn resolutely towards AI, in particular with the advances in the field made by Tesla under the leadership of its leader Elon Musk.

Many other technological advances can be cited such as the Rock'em and Sock'em service robots, two bartending robots operating on a Disney ferry, the Pepper service robot now used throughout the world, but also the Watson software from IBM as well as Erica, a Bank of America chatbot providing financial advice (Davenport, Guha, Grewal, & Bressgott, 2020).

Service-robots, thanks to the advancements of artificial intelligence (A.I.), are becoming widely used. The Robotics Industries Association (R.I.A.) shows that customer service-robots are increasingly popular with 53% more sales in 2018 compared to 2017, which means more

than 8,000 robots were sold in 2018. The R.I.A. is even more enthusiastic for the future as it predicts sales over 40,000 for the period 2019-2021.

The impact of robots on our societies seem then to be huge. Some experts speak of a possible automatization of 50% of today's work by 2055 (McKinsey Global Institute, 2017). They even highlight an increase of the service-robots adoption rates in every industry which could then lead to the replacement of more than 170 million jobs by 2022 (World Economic Forum, 2018).

The robotics and AI both can provide a lot of benefits to organizations such as an improved reliability, productivity gains, cost reduction but also a better security and compliance (Wirtz & Zeithaml, 2018). We can also notice some other gains such as an improved customer retention and creativity of managers (Kumar, Rajan, Venkatesan, & Lecinski, 2019).

Recent technological advances show that robots can now be used in many cases such as offering wealth management advice (Avery, 2019) or detecting dementia (Lay, 2019) or even assisting surgeons through mechanical arms controlled by voice (Barrett, Oborn, Orlikowski, & Yates, 2012). Researchers have also shown that service robots will be able to perform tasks of any difficulty but also any task requiring little emotion (Paluch, Wirtz, & Kunz, 2020; Wirtz et al, 2018). Those requiring a greater range of emotions will, however, be inaccessible to service robots and will therefore be entrusted to frontline employees.

However, if the future seems bright, companies should be aware of the risks that come with A.I. and service-robots. Data privacy, algorithm biases and ethics (Larson, 2019) are ones of the challenges' firms will face with the introduction of these new technologies. It is also important to underline that before implementing such technologies, firms need to have evidence of the benefits they will grant to them, otherwise it could lead to failure. Recent studies show that 61% of people are still reluctant to interact with service-robots (West, 2018).

An example of an implementation failure is the Henn-na Hotel in Japan that "fired" more than 120 service-robots because of rants from their guests. The reason behind this exceptional step back is that in-room robotics assistants misinterpreted snoring sounds as vocal commands and thus woke up guests. As employees have to fix these problems, productivity gains are sometimes limited or inexistent (Gale & Mochizuki, 2019).

The situation in the banking sector is a bit different. With the new trends among customers (i.e., the desire to check their account in their home or on their smartphone for instance), banks need to develop new infrastructures and rethink their business strategies in order to survive in an environment of low interest rates. Banks then multiply innovative solutions such as e-banking, banking on smartphone, in-real-time notification, chatbots, and many others.

And such innovations are meeting the customers in Belgium. E-banking and mobile banking are rising in Belgium with more than 12.9 million subscriptions for internet banking and 7.0 million subscriptions for mobile banking (European Banking Federation, Belgium's banking sector, 2019). The challenges met by banks are huge: they have to stay profitable, and even

more profitable for their shareholders, in an environment of low interest rates. To reach their operational goals, many banks are restructuring their retail distribution network.

This is the case of BNP Paribas Fortis that closed 1 in 10 of its Belgium branches, which represents 62 closing, in 2019 (The Bulletin, 2018). Agencies will be merge with some others as the trend is now e-banking which means that less customers go in branch. With the Covid-19 pandemic, we expect more people to use E-banking than before.

Another answer to these challenges is the service-robots and more specifically those used to welcome customers. Introduced a few years ago in Japan, welcoming service-robots are on the rise in banks. They promise queuing reduction and accurate service. Welcoming service-robots gain interest, especially with the pandemic. They allow employees to focus on operations with more added value while they do the low added value tasks. Pepper and Nao are examples of such service-robots.

If they promise to make banks more profitable, banking institutions should nonetheless implement welcoming service-robots after having carefully check they suit to their business.

B. Research Motivation

With the fast development of AI and robot technologies, firms and their managers need to have a deep comprehension of those technologies to be able to use them at their full potential in their work environment. The image we depicted above of the current environment is an evidence of this need. Yet marketing literature related to AI and service robots is quite limited. Marketers and managers plan to use AI in areas like segmentation and analytics (linked to the marketing strategy) but also in personalization, messaging and predictive behaviors (related to customer behaviors) (Columbus, 2019).

Service-robots are able to provide massive benefits to organizations. We listed them above. The organizations face huge competition nowadays which means they have to reduce their costs increasingly to be able to keep doing business.

The cost-chasing is even more pregnant in the banking sector where it represents a significant part of the strategy of the banks. Banks have a lot of tools to their disposal to reach their goals in terms of cost savings. Among them, we can list the chatbots, such as Erica from Bank of America that can give financial advices and thus can help banks to keep in touch with their clients anytime and anywhere, a lot of banks also invest in bots to mechanize some operations in order to avoid human error in processing, this is particularly interesting in the case of big data that human cannot process as fast as robots would and finally banks now also use these technologies to welcome their clients in branches with welcoming service-robots.

In the latter case, we can name Bank of America, HSBC bank and Bank of Tokyo as banks that currently use welcoming service-robots. If a few ones already use welcoming service-robots, the vast majority still does not. They are waiting to see if this technology is able to give them more benefits than costs.

Managers then are in a position where they have to wait before using new technologies because they do not have insights about these new technologies. Moreover, if their competitors successfully implement these new technologies, it does not mean they should implement them too. Indeed, each business has its own specificities and characteristics, managers should thus aim to first see whether or not these new technologies apply to their business before making a move.

To be able to check the applicability of these technologies in their business, managers thus need to fully understand the technologies themselves and the adoption mechanism of such innovations by their client if they want to be able to get the most of those technologies. The first step is currently well-addressed by the scientific literature; however, the second step is only at its beginning.

This master thesis will then help managers to have a better view of the adoption mechanism by highlighting the underlying determinants of the welcoming service-robots adoption.

C. Academic Motivation

From now a few years, researchers are massively exploring these subjects of AI and service-robots, however until now the vast majority of them were exploratory. There is still a lot to do in order to have a better understanding of these new technologies and of the horizons they broaden. As service-robots make use of AI technology, the learning process is thus largely focusing on the comprehension and the implications (social, economic, political, ethical) of this technology first before moving on the service-robots technology.

If the studies led on this field allowed researchers to have a better understanding of what those technologies were capable of, we do not know how the adoption mechanism function in their case.

Some studies tried to make some advances in regard to that goal (Paluch et al, 2020; Wirtz et al, 2018), however we are still far away from having operational understanding of the phenomenon. This master thesis will then provide some results on that specific question. The advance of technology should lead to a wider service sector (Rust & Huang, 2014), a better productivity (Rust & Huang, 2012) and should increase the adoption of technologies such as Self-service technologies (Meuter, Ostrom, Roundtree, & Bitner, 2000).

In particular, this master thesis aims to go deeper in the question of the consumer adoption of welcoming service robots. Recent studies have made some advances in the subject by defining the main axes of the consumer adoption, such as the Service-robot acceptance model (Wirtz et al, 2018) that makes link between the functional determinants from the Theory of acceptance model (TAM) (Davis, 1986) and new concepts that arise in the recent years regrouped into the Social-emotional determinants (Perceived Humanness, Perceived Social interactivity and Perceived Social Presence) and the relational elements (Trust and rapport). However, this theoretical model has not yet been widely tested.

The scarcity of the literature on the subject of service-robot adoption make harder the establishment of a clear framework to understand this mechanism. The model developed by Wirtz et al. (2018) is a first step, but must still be tested. The recent advancements in the field unveiled some interesting concepts that could play some role in the adoption process, such as the Automated Social Presence (van Doorn et al, 2017) and the humanness (Wirtz et al, 2018), however these concepts must still be theorized. In particular, the humanness could lead to a feeling named the "uncanny valley" that makes humanization a lot more ambivalent that we might believe (Mori, Mac-Dorman, & Kageki, 2012).

This thesis will then focus on the determinants well-theorized from the technology acceptance models to get some clues about how customers feel to adopt such a technology as welcoming service-robots in regard to these specific determinants. As the results could potentially vary depending on the sector, we chose to focus on the banking sector. We aim to contribute to the understanding of the adoption mechanism by testing these specific determinants which would thus lead to a classification of the determinants in regard to their relevance.

In this master thesis, we will then examine the following research question:

- **RQ**: What are the factors influencing the adoption of welcoming service-robots in bank?

By answering this question, this paper will then allow scholars to have a better understanding of the current evolution of welcoming service-robots in the banking sector. We expect to propose an insightful comparison of the most-known existing models that will allow researchers to have a more accurate view of this innovation.

D. Approach

In this master thesis, we will first make a review of literature about the topic of Artificial Intelligence in the service field and more specifically the case of service-robots. A review of the main theories of technology adoption will be also presented.

The literature review will focus on the main theories that have emerged regarding to AI and service-robots the last couple of years in which this research is anchored.

To answer our research question, we will compare two existing models of technology acceptance on the basis of a survey administered to Walloons.

2. Literature Review

This literature review will cover the most recent advances in the field of AI and more specifically the field of service-robot. In the past few years, a number of concepts and theories emerged to better understand these technologies. We will discuss in the following sections the different dimensions of AI, the intelligence typology of AI, before focusing on service-robots advancements.

The service-robot literature is developing and a lot of new theories are published every year. We will focus on the latest advancements such as the Automated social presence (van Doorn et al, 2017), the Service-robot acceptance model (Wirtz et al, 2018) and its new arising concepts of Humanness and Social interactivity.

A. Artificial intelligence

a. Definitions

According to Shankar (2018, p. 6), AI is referring "to programs, algorithms, systems and machines that demonstrate intelligence". We can go further by adding that AI is "manifested by machines that exhibit aspects of human intelligence" (Huang & Rust, 2018).

AI is based on several technologies, namely the machine learning, the rule-based expert systems, the deep learning, the physical robots, the robotic process automation (Davenport, 2018). By using them, AI is then able to give a mean to "interpret external data correctly, learn from such data, and exhibit flexible adaptation" (Kaplan & Haenlein, 2019).

b. Levels of intelligence

We will speak of two differentiate levels of intelligence: task automation and context awareness. Davenport and Kirby (2016) highlighted the differences between both concepts. The former involves standardized AI applications with the imposition of a logic (Huang & Rust, 2018). An example of such an AI is IBM's Deep Blue. This AI makes use of standardized rules to beat chess players. The AI is then not evolving, it only applies the rules we set. Some other examples include the two robots officing on the Symphony of the Seas, a cruise ship of Disney, or the service-robot Pepper that is used to welcome customers. In every case, the rules are clearly defined, and the AI simply follows them.

The context awareness, on the other hand, involves an evolution of the AI. The studies are still ongoing to conceive AI with a context awareness (Ghahramani, 2015; Mnih et al, 2015). Context awareness is an intelligence form that requires machines to "learn to learn" and constantly improving their capabilities by the constant collection and analysis of data. It allows AI to make complex tasks by using context-specific responses (Huang & Rust, 2018). We will still wait years before such a revolution appears, a survey of 2016 stating that the

probability to achieve context awareness was only 50% by 2050 (Müller & Bostrom, 2016). Context awareness is then defined as the goal of every AI.

The difference between task automation and context awareness can also be illustrated with the concepts of narrow and general AI (Baum, Goertzel, & Goertzel, 2011; Kaplan & Haenlein, 2019; Reese, 2018). Narrow and general AI both have the ability to exceed human performance. The difference lies in the spectrum of areas in which they can do so. A narrow AI will be focused on a specific area and is unable to reach new areas, as it cannot learn, whereas general AI has the ability to learn and thus can reach new areas (Kaplan & Haenlein, 2019).

If we take the assumption of boundaries between these two intelligences, the best model will be one that makes those two intelligences as a continuum. The AI Replika and Libratus both lies between these two concepts; they are capable to learn but still have not reached the context awareness.

c. Type of tasks

The task type can be defined as the type of data that the AI application analyzes. Those data can be divided into two main groups: numeric and non-numeric (for instance: images, text, voice) Despite being both useful for companies, they are not analyzed in the same way. It is much more complex to analyze non-numerical data than numeric ones. For instance, if we take the voice, there are a lot of criteria such as the tone, the way of speaking, the synonyms, and the antonyms.

All of these criteria must be taken into consideration before making an analysis. Analyze numbers is in comparison much easier. As most of the data are non-numeric ones, it is critical to develop AI applications that can analyze these types of data. Those data types are often then translated into numeric data such as pixelization for an image.

Even though the AI's abilities to understand and also analyze non-numeric data are still limited, developing this ability is essential to take the most from AI. Computer scientists are currently working on it (for instance: Le Cun, Bengio, & Hinton, 2015; You, Jin, Wang, Fang, & Luo, 2016).

d. AI in robots

The vast majority of AI are virtual, such as Erika, the chatbot of Bank of America or Replika that is available on smartphones. AI can however also be embedded in a robot, humanoid or non-humanoid. Milgram, Takemura, Utsumi, and Kishino (1995) developed a framework on that specific subject: the virtuality-reality continuum. We should thus view virtuality and reality as boundaries rather than categories. An AI like Erika is entirely virtual, we cannot chat with her without an internet browser, whereas an AI like the two robots Sock'em and Rock'em

from the Symphony of the Seas lies between the two boundaries of virtuality and reality. They possess a physical body but cannot do something else than making a drink. Companion robots would be for their part near reality as they will be able to operate in many contexts such as travelling with individuals or sharing physical proximity.

In the specific case of AI, prior works indicate that customers feel better with an AI embedded in a robot than with a purely virtual AI. They thus prefer interacting with robots than with an application on their phones. Kwak, Kim, Kim, Shin, and Cho (2013) also showed that individuals empathized more with physically robots than a robot simulation in a replication of the Milgram's experiment. Individuals also tends to interact more with robots than with virtual forms of AI in the case of a diet coach (Kidd & Breaze, 2008).

e. Intelligences typology

We considered above the two levels of intelligence: task automation and context awareness. These two levels apply to AI. We will now discuss of the four intelligences that apply to humans and that AI tends to replicate. The literature of human intelligence defines intelligence as "the ability to learn from experience and adapt to the environment" (Gardner, 1983, 1999; Sternberg, 1984, 2005). The nature of service influences the need of one intelligence. The literature on Human Intelligence and Artificial Intelligence distinguish four types of intelligences: mechanical, analytical, intuitive and empathetic. Those four types coexist, and no hierarchy exists between them in human, however an order exist in the case of AI. We listed them in the order that makes the first one the easiest to replicate for AI and the last one the most difficult to emulate.

AI is excellent on the side of mechanical intelligence, exceeding human capabilities, however AI cannot yet emulate the empathetic intelligence, whereas human uses this intelligence form quite easily.

We will develop each intelligence in a separate category and put in light their characteristics as well as their applications and relevance for machines and humans. Figure 1 shows the relation between the intelligence type and the time needed to reach it for AI.

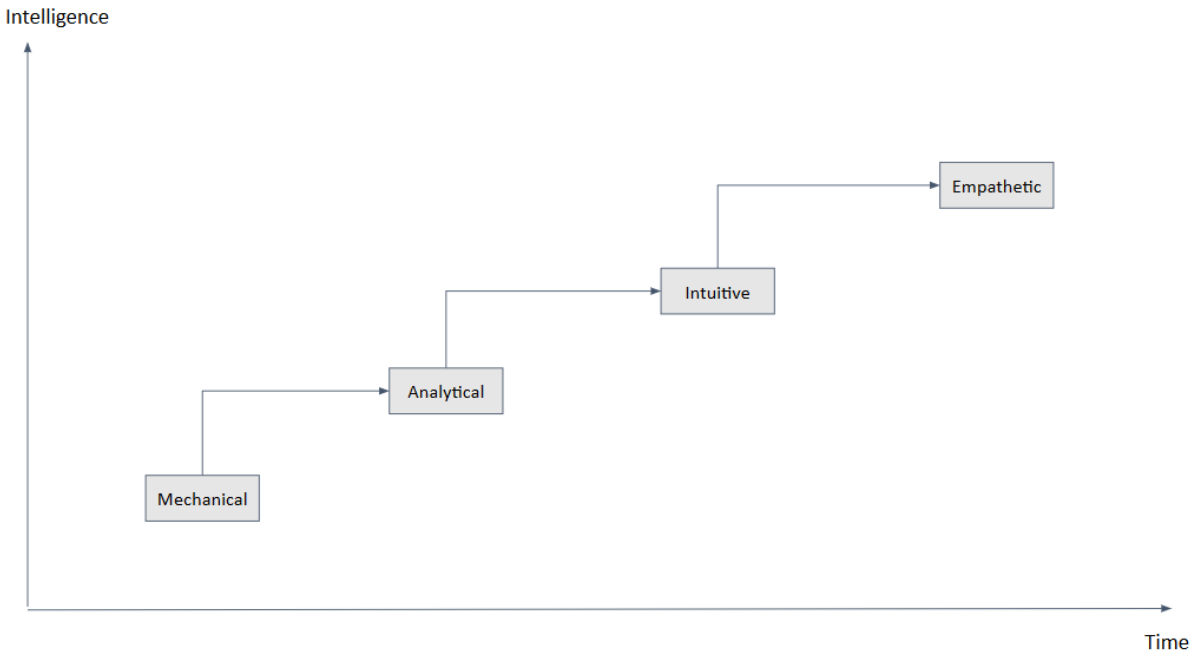


Figure 1: The four intelligences.

1. Mechanical Intelligence

Mechanical intelligence can be defined as the ability to perform a task automatically as routine. This type of intelligence does not require any particular form of creativity and tends to be viewed as degrading for humans, even though it is essential for many tasks. A human does not need to be qualified to use this type of intelligence. Some examples of jobs that use mainly mechanical skills can be given such as call center agents, taxi drivers or waiters.

In the case of AI, the mechanical intelligence can be referred to the task automation. Such AI is designed to perform routinized tasks. An example of such AI can be found into robots or into search engines like Google. In the latter case, the search is purely mechanical, the search engines do not understand what they process, they use keywords to assess the relevance of the pages (Del Prado, 2015).

In contrast to humans, AI can perform with an extreme consistency mechanical tasks whereas humans often fail due to factors such as fatigue or stress. The usefulness of learning in such a context is then limited as the task will not evolve by time.

2. Analytical Intelligence

Analytical intelligence can be defined as "the ability to process information for problem-solving and learn from it" (Sternberg, 1984, 2005). It involves mathematical skills, some logical reasoning and information processing (Sternberg, 1999). Human acquires those skills via training and expertise. We can give some jobs examples such as Data scientists, mathematicians, physicists.

In the case of AI, the applications include machine learning and data analytics. An example of such AI is the IBM AI Deep Blue, a chess computer using rule-based learning to beat chess players. If the rules are wrongly set, the AI will then make the same mistakes again and again, until the rules are rewriting. Bots in videogames and arcade games are of that type. They follow the rules the developers wrote to beat human opponent.

The AI literature categorizes this AI type as "weak AI" due to their inability to predict human behaviors nor make use of intuition. This intelligence is thus useful for complex but consistent tasks such as data mining to create collective intelligence.

3. Intuitive intelligence

Intuitive intelligence can be defined as "the ability to think creatively and adjust effectively to new situations" (Sternberg, 1984, 1999, 2005). This intelligence form involves professional skills that require creative problem-solving. Some jobs examples requiring this intelligence are for instance marketing managers, lawyers, or sales managers.

The understanding is the key concept of this intelligence form in the chief of AI. It is the element that distinguish Intuitive AI from analytical AI. The literature calls these forms of AI as "strong AI" due to their resemblance with the human brain. In its best form, this AI intelligence can provide answers to complex problems and could be the future of search engines. Instead of giving us websites that fit our query, they could process the content and give the answer to the question we are asking.

Such features still remain dreams but could become reality one day. The google search engine can for instance give us the real-time temperature for a specific region when we ask the temperature of that specific region, however its ability to answer questions does not go further for the moment.

Intuitive AI will thus rarely make the same mistake twice as it learns from experience. For instance, Google's DeepMind AlphaGo can simulate instinct (BBC News, 2016) whereas the AI poker player Libratus can elaborate strategies with incomplete information, a behavior similar to the one of human poker players (The Wall Street Journal, 2017). IBM is advanced in that field with its AI Watson that can reason, understand, and learn. Such AI can be employed to improve the customer relationship with the clients of a specific brands by getting to know the customers' needs better over time in sector such as luxury goods and sports.

4. Empathetic Intelligence

Empathetic intelligence can be defined as "the ability to recognize and understand other peoples' emotions, respond appropriately emotion-ally, and influence others' emotions" (Goleman, 1996). It involves social, interpersonal and people skills. These skills are the ones that make human able to feel and work with others (Gardner, 1983; Johnson, 2014). More

specific skills are communication, negotiating, Human Resources managing . This intelligence type can be found in human in jobs such as politician HR manager, Team manager, psychologists. This intelligence type does not systematically require formation and relies more on the personal attitudes.

In the case of AI, an Empathetic AI would be one able to emulate the human feelings and emotions and that could feel the sadness of individuals it would interact with. Picard (1995) postulates that affective computing is a computing form that relates to or influences emotions. The keyword of such an AI is then "experience". Empathetic AI should be able to experience things and evolve by experiencing. A debate is thus raised to know whether or not AI's can feel like humans. The philosophy and psychology literatures postulate that feelings are biological reactions and thus cannot be emulated. Alternatively, the AI literature sees emotions just as it sees cognition, they could then be emulated.

The applications of Empathetic AI, the most advanced generation of AI, in service are rare. Sophia, a human-like AI from Hanson Robotics (Campanella, 2016), is designed to act like humans would do. This AI embedded was awarded by Saudi government for her citizenship (Maza, 2017). Empathetic AI thus requires a high level of social presence (Giebelhausen, Robinson, Sirianni, & Brady 2014).

Empathetic-related jobs will be the last ones to be replaced by AI (Huang et al, 2018). The theory of job replacement developed by Huang et al (2018), postulates that replacements will occur with the advancements in AI technology and in the order of which AI integrate the different intelligences, which means the following order: Mechanical, Analytical, Intuitive and Empathetic.

B. Service-robots

Service-robots are "technology that can perform physical tasks, operate autonomously without needing instruction, and are directed by computers without help from people" (Colby, Mithas, & Parasuraman, 2016). Another definition is given by Wirtz et al (2018), they would be "system-based autonomous and adaptable interfaces that interact, communicate and deliver service to an organization's customers." The latter is a definition more operational than the former one.

In a service environment, the service-robots can be viewed by humans as social robot as it is possible to interact with them. The robot can therefore create a sort of Automated Social Presence (ASP) during the service. This concept refers to the ability to create a feeling in the customer that is in presence of another social entity (van Doorn et al, 2017). Moreover, a service-robot can have a humanoid shape. This specific type of service-robots is therefore named as Humanoid Social Robots (HSR). It will be further discussed in detail.

Recent years have seen some great advances in the field with some emerging concepts as the Humanness (Tinwell, Grimshaw, & Williams, 2011) and the Social interactivity (van Doorn et

al, 2017). Both concepts are well summarized with Automated Social Presence as Social-emotional dimensions (Stock & Merkle, 2018).

If we look at the future, it seems that it will be constituted of huge cloud-based AI's, cumulated with voice and facial recognition and databases from enterprises, service-robots could then be able to recognize clients and then provide customized services to them (Wirtz et al, 2018).

a. Humanoid service-robots (HSR)

Humanoid service-robots have seen some huge advances in the recent years and could lead to a human replacement in many industries (Harris, Kimson, & Schwedel, 2018). Welcoming service-robots are such service-robots.

As an example, we can mention the service-robot Sophia that was awarded by the Saudi government or more service-focused, the service-robot Pepper that have been sold worldwide at more than 10,000 units (Tobe, 2016). This service-robot revolutionized some business, by selling coffee machines in Nescafe stores in Japan (Nestlé, 2014), by working as a waiter in Pizza hut restaurant in Asia (Curtis, 2016) or even by helping customers in bank agencies of HSBC bank in the U.S (Finovate, 2019).

In the following sections, we will first compare the humanoid service-robots and the self-service technologies, before presenting some concepts related to humanoid service-robots that arise in the recent years and that are essential to grasp the essence of this new technology. These concepts are the Automated Social Presence, the Humanness and the Social interactivity.

1. Humanoid service-robots and Self-service technologies

Humanoid service-robots should not be confounded with Self-service technologies (SST's). The humanoid service-robots contrast with self-service technologies as they can engage customers more deeply than self-service technologies (Van Doorn et al, 2017). Moreover, Wirtz et al (2018) use three dimensions to assess the differences between the two technologies: service scripts and roles, customer error tolerance and service recovery.

One major difference between HSR and SST lies in the service script that must be read and understood by the consumer in the case of an SST while the HSR can help the customer to get through this. A second difference is the customer error tolerance that is often low in the case of an SST as a mistake often leads to a dysfunction of the machine while a HSR is able to fix the mistakes of the customer. Finally, a third difference is the service recovery that is mostly made unable in the case of an SST while a HSR should be able to "deal with" the failure and offer you another way to get what you desire as a real employee would.

These three differences often lead to a long adoption period for SST's (Meuter, Bitner, Ostrom, and Brown, 2005) which could thus be shortened in the case of an HSR.

2. Automated social presence

The Automated Social Presence can be defined in the context of service-robots as "the extent to which customers feel that they are with another social being" (Van Doorn et al, 2017). It refers to the extent to which one believe that someone is "really present" (Heerink, Kröse, Evers, & Wielinga, 2008).

Social presence has been shown to affect trust building since individuals are more likely to develop trust in another person when they meet personally. It can be assumed that social presence, or the feeling that "someone is taking care," affect the acceptance and has consequently an influence on customer behaviors.

3. Humanness

The concept of humanness refers to the ability of some service-robots to blur the frontier between humans and robots by becoming almost indiscernible from humans (Wirtz et al, 2018). This effect is mostly seen on call and on chat with specific bots. A study conducted by Wünderlich and Paluch (2017) found that 38% of participants could not say whether they interacted with a human or a robot on chat while 18% made the wrong assumption.

Humanness is however not limited to virtual service-robots, it is also a major component of the emerging physical service-robots. Welcoming service-robots tend to be human-like, just as other service-robots, in order to allow significant social interactions with humans (Duffy, 2003). The humanness can both appear in shape and in behavior.

The literature showed that service-robots were designed with the desire to be perceived as sociable, inspiring trust and allowing to create bonds (Broad-bent et al., 2008; Li, Rau, & Li, 2010). However, some studies highlighted the possibility that customers will be reluctant to interact with humanoid service (Moosa & Ud-Dean, 2010). This probability is even bigger in case of a humanoid robot that cannot reach humanness. In this specific case, people tend to feel some discomfort due to the non-perfect matching between the service-robot appearance and the way it behaves. Uncanny valley is related to this sensation (Mori, Mac-Dorman, & Kageki, 2012).

A study of Mathur and Reichling (2016) showed that individuals tends to feel more likeable the faces of robots when they look more human. However, the same study also pointed out that this trend was unchanged until a specific point. More specifically, the individuals felt less likeable robots faces if they look too human.

On that subject, some studies pointed out that humanoid reluctance was coming from evolution (Gray & Wegner, 2012). Some other studies posited that robots were associated

with a threat to human identity for humans. Some examples of threats are the loss of control, the dysfunctional robot or the slavery of mankind by humans (Ray, Mondada, & Siegwart, 2008), as the movies trilogy Matrix showed it. Eeriness is then seen as an instinct protecting people from danger (Mori, MacDorman, & Kageki, 2012).

However, as the "uncanny valley" theory suggests, perfect humanness should not be aimed for service-robots. In order to avoid such disengagement, service-robots should be conceived as close to human while being still different (Mori, 1970). Duffy (2003) argues that people tends to have overly optimistic expectations about a service-robot when it possesses many anthropomorphic qualities, leading to disappointment in case of failure.

4. Social interactivity

The social interactivity concept refers to the ability for a service-robot to engage with humans in a way that is seen credible (Breazeal, 2003). In that sense, a service-robot shape does not matter to assess its social competences. Bates (1994) argues that what matters is the possession of social intelligence. If current service-robots do not yet possess empathetic intelligence as defined above, they do possess some sort of social intelligence algorithms-based. The robot Sophia is an example of such a robot (Campanella, 2016).

C. Theories of technology adoption

The challenge is now to know if customers are ready to make use of these new technologies. A technology could promise the moon, however if it does not match customers' needs, such a technology will remain a failure for every B2C firm that would implement it in its business model to deepen the customer experience. In that context, we may have a look on the main models that are used in the literature to assess the potential of a technology to be adopted by customers. The two main approaches are the technology acceptance model (Davis, Bagozzi, & Warshaw, 1989), TAM, and the unified theory of acceptance and use of technology (Venkatesh, Morris, Davis, & Davis, 2003), UTAUT. We will also have a look at four other models: Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975; Ajzen & Fishbein, 1980), Innovation Diffusion Theory (IDT) (Rogers, 1995), the SST's acceptance model (Blut et al, 2016) and the Service Robot Adoption model (Wirtz et al, 2018).

a. Theory of Acceptance Model (TAM)

The Theory of Acceptance Model, conceived by Davis (1986), is an adaptation of the Theory of Reasoned Action (TRA) that is coming from social psychology. The social psychology is concerned with the consciously intended behaviors factors (Fishbein & Ajzen, 1975; Ajzen and Fishbein, 1980). The postulate of the TRA is that the behavioral intention (BI) of a person to perform a behavior determine his or her actual performance of the behavior. This theory then

features that BI is jointly determined by the person's attitude (A) and the subjective norm (SN) concerning the studied behavior (Figure 2).

$$BI = A + SN$$

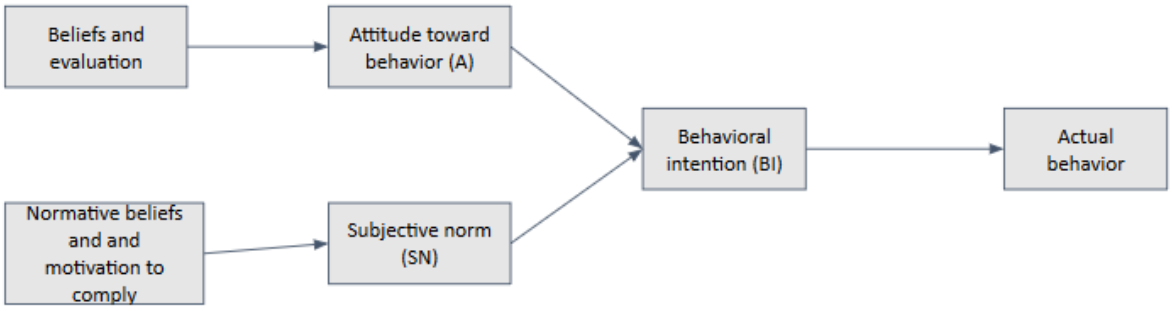


Figure 2: Theory of Reasoned Action (TRA).

The Theory of Acceptance Model (TAM) has been widely used to explain the acceptance of various technologies, including service-robots technologies (Wirtz et al, 2018). The theory postulates that perceived usefulness and ease of use determine adoption and use of technology. The other factors would thus influence technology adoption through these two determinants (Venkatesh & Bala, 2008).

A key purpose of TAM is therefore to provide a basis for tracing the impact of external factors on internal beliefs, attitudes, and intentions. TAM was formulated in an attempt to achieve these goals by identifying a small number of fundamental variables suggested by previous studies.

TAM posits that two particular beliefs, perceived usefulness and perceived ease of use, are of primary relevance for computer acceptance behaviors (Figure 3). Perceived usefulness (U) is defined as subjective probability that using a specific application system will increase a user's job performance within an organizational context. Perceived ease of use (EOU) refers to the degree to which the user expects the technology is used without any effort. Additionally, factor analyses suggest that U and EOU are statistically distinct dimensions (Hauser & Shugan, 1980; Larcker & Lessig, 1980; Swanson, 1987).

The model was refined in 1996 with the withdrawal of the attitude component from the model. The authors made this choice because it was not a meaningful component.

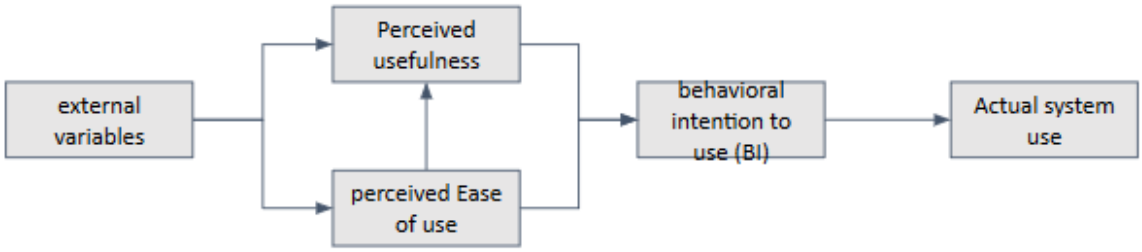


Figure 3: Technology Acceptance Model (TAM), 1996.

This model thus implies that the other variables (i.e., "External Variables") only affects the Behavioral Intention to use a new technology only through the prism of the Perceived Usefulness and the Perceived Ease of Use.

b. Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) is another major technology acceptance theory. Created by examining eight different existing models, UTAUT proposes a different set of determinants of technology acceptance (Venkatesh et al., 2003). UTAUT makes the postulate that individual differences (e.g., age, gender) also influence technology acceptance (Figure 4). In practice, individual differences are both used as moderators (Weijters, Rangarajan, Falk, & Schillewaert, 2007) and as determinants (Meuter et al, 2005).

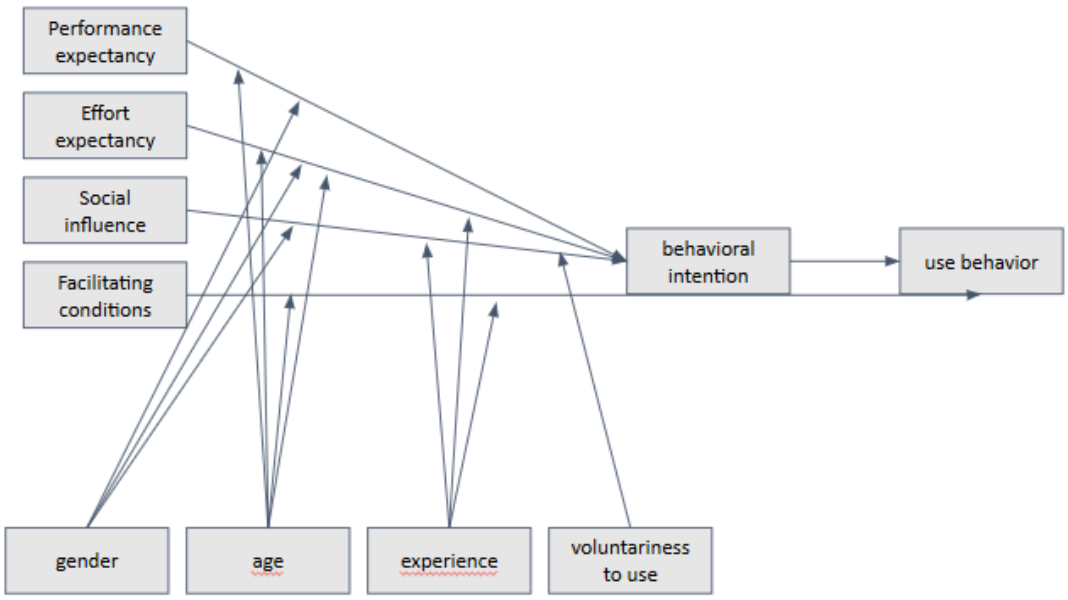


Figure 4: UTAUT model

Four constructs play a significant role as direct determinants of user acceptance and usage behavior: performance expectancy, effort expectancy, social influence, and facilitating conditions. Attitude toward using technology, self-efficacy, and anxiety are not considered as direct determinants of intention. There are four key moderators in this model: Gender, Age, Experience and Voluntariness of Use.

c. Innovation diffusion theory (IDT)

Another technology adoption theory is the Innovation diffusion theory (IDT). That theory assumes that an individual's decision to adopt or reject an innovation is determined by five major innovation characteristics: relative advantage, complexity, observability, compatibility, and trialability (Rogers, 1995).

d. Self-service technologies acceptance model

A fourth model is also to consider. Developed by Blut et al (2016), this model aims to better explain the factors influencing social acceptance of Self-Service Technologies (SST's) (Figure 5). Obtained by fusing the first two models: TAM and UTAUT models, and with some refining, it establishes a bigger importance to factors that were neglected before such as Anxiety.

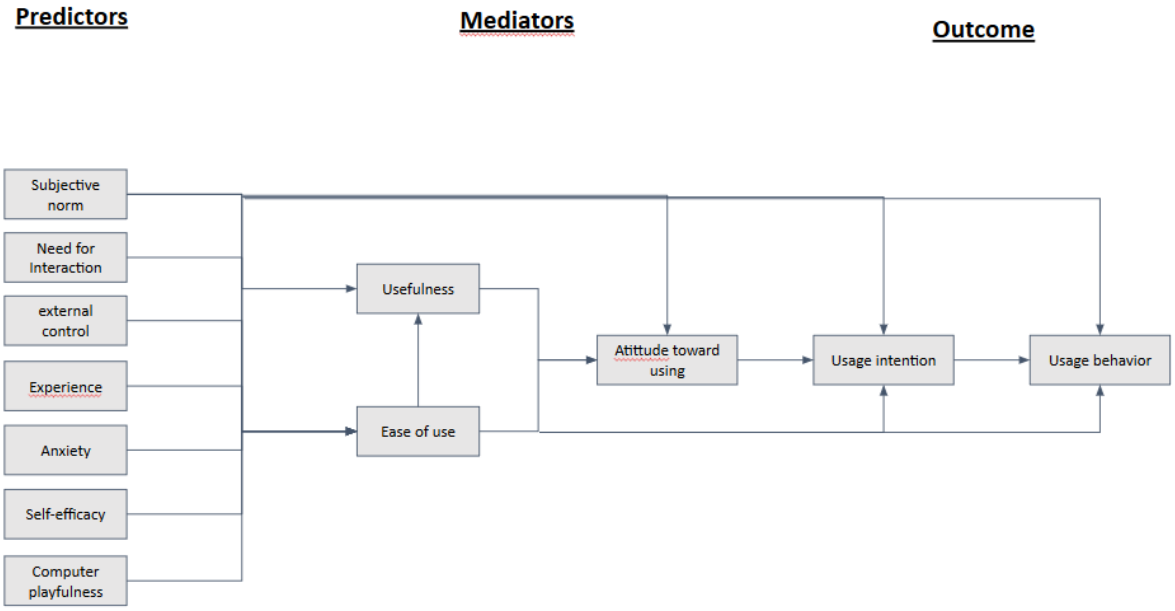


Figure 5: SST's acceptance model

This study shows that usefulness, ease of use, subjective norm, enjoyment, self-efficacy, compatibility, trialability, and technology readiness are the most influential predictors for Self-service technologies.

e. Service robot acceptance model (sRAM)

This model postulates that the service robot acceptance can be measured with three different types of elements. The functional elements from the TAM (perceived usefulness, perceived ease of use and subjective norm), the Social emotional elements (Perceived humanness, perceived social presence and perceived social interactivity) and the Trust and rapport (Wirtz et al, 2017).

D. Models used

For this study, we decided to compare the models of TAM and UTAUT in order to be able to examine in depth the relationships between the new technology of welcoming service-robots and the main determinants used in technology adoption. We believe it is important to first have a better understanding of how the traditional determinants can explain the technology acceptance by customers before including the latest advancements (i.e., social-emotional elements and the relational elements highlighted in the sRAM) in order to avoid potential crossover effects.

In this section, the different determinants used in this study will be defined as well as the hypotheses made on them. We will first have a look on the determinants present in both TAM and UTAUT model, then to those present in only one of them.

a. TAM/UTAUT determinants

- Usefulness: It can be defined as the sum of utility an individual can get by using a technology. To specify the causality between the perception of usefulness and usage intention, TAM refers to the theory of reasoned action (Venkatesh, 2000). In the TAM, we make the assumption that individuals who think a technology will be useful are more likely to use this specific technology.
- Ease of use: Referring to the theory of reasoned action, TAM proposes that when customers perceive a technology as simple to use, they are more likely to use it (Gelbrich and Sattler, 2014). The model also posits that Ease of use is a direct determinant of usefulness (Davis, Bagozzi, and Warshaw, 1989) as an individual is more likely to find a technology useful if it is easily used.
- Subjective norm: TAM suggests that the subjective norm has a direct effect on usage intention. Indeed, people could perform a behavior even if they are not favorable of doing it if a referent individual approve this behavior. Furthermore, TAM argues that

when important referents communicate a belief in SST usefulness, people can change their beliefs.

Hence, we can make the following assumptions:

- Hypothesis 1a: Usefulness has a positive impact on usage intention.
- Hypothesis 1b: Ease of use has a positive impact on usefulness and usage intention.
- Hypothesis 1c: Subjective norm has a positive impact on usefulness and usage intention.

b. TAM determinants

- Self-efficacy: TAM shows that self-efficacy relates to the perceived ease of use (Venkatesh and Davis, 1996). When people experienced a technology, their general confidence in the technology knowledge is used to judge whether or not it is easy to use it. The SST literature also proposes a direct effect of self-efficacy on usage intention. Meuter et al (2005) show that in technology-mediated environments, the perceived confidence in ability to do a task influences the likelihood of technology use.
- Anxiety: TAM shows that computer anxiety negatively influences the perceived ease of use (Venkatesh, 2000). We thus make the underlying assumption that individuals with a high technology anxiety will be less likely to adopt a specific technology, in this case a welcoming service-robot.
- Result demonstrability: TAM shows that when the gains in performances are not directly attributed to the use of the technology, users are less likely to adopt this technology. We then make the assumption that the result demonstrability positively influences the usefulness perception. SST studies also propose that result demonstrability directly influences usage intention and behavior (Meuter et al, 2005).

Hence, we can make the following assumptions:

- Hypothesis 2a: Self-efficacy has a positive impact on ease of use, usage intention.
- Hypothesis 2b: Anxiety has a negative impact on ease of use, usage intention.
- Hypothesis 2c: Result demonstrability has a positive impact on usefulness, usage intention.

c. UTAUT determinants

- Age: The demographics characteristics were examined in previous studies on the adoption of technologies (Rogers, 1995). The causal link seem that older people are less likely to adopt a specific technology due to the fact they face more problems when using this specific technology. We then make the assumption that young people are more likely to use welcoming service-robot. However, the study conducted by Blut et al (2016) tends to relativize the age effect as they concluded on an insignificant impact on the SST's adoption.
- Gender: According to Meuter et al (2005), men would be more interested in technology than women which would then lead to an increased rate of technology adoption among men than women. Some prior SST studies also provide evidence for a significant direct relationship between customer gender and SST acceptance (Ding, Verma, and Iqbal, 2007) whereas one more recent does not (Blut et al, 2016).
- Experience: Heavy users of technologies are more confident in their ability to use the technology and are therefore more likely to try new technologies such as welcoming service-robots (Meuter et al, 2005). The literature also shows that the more a user is experienced in using a specific technology the more he will find it useful.
- Banking habit: As showed in UTAUT, the habits can influence the likelihood an individual will use a technology, we then infer that individuals will have a different likelihood to use welcoming service-robot depending on their banking habit (i.e., if they use more e-banking or not).

Hence, we can make the following assumptions:

- Hypothesis 3a: Age has an impact on usage intention, in a way that younger people are more likely to use robot technology than older people.
- Hypothesis 3b: Gender has an impact on usage intention, in such a way that men are more likely to use robot technology than women.
- Hypothesis 3c: Experience has a positive impact on ease of use, usefulness, and usage intention.
- Hypothesis 3d: Banking habit has an impact on usage intention, in such a way that people managing their bank account exclusively online are more likely to use welcoming service-robots.

Summary of dimensions		TAM	UTAUT
	Variables		
	Usage intention	X	X
	Usefulness	X	X
	Ease of Use	X	X
	Subjective norm	X	X
	Self-efficacy	X	
	Anxiety	X	
	Result demonstrability	X	
	Age		X
	Gender		X
	Experience		X
	Banking habit		X

3. Research Design

A. Methodology

a. Target population and sampling base

In this study, the target population can be defined as every citizen from Wallonia possessing a bank account. As our goal is to be able to find out what are the most relevant aspects to focus on to allow service-robots to come into banks, we needed to ask to people who have experience with banks. The obligation to possess a bank account to be hired assured that people employed or who were employed would have an account, however younger people such as students do not necessarily possess one for the moment, even though they will in the future.

Add this segment (i.e.: people having no bank account) to the study could have led to potential biases as people from this segment did not necessarily have an accurate view of the services offered by a bank. The choice was then made to not integrate them in the analysis, in order to avoid erroneous conclusions. For this purpose, a filter question was used to separate this segment from our reference population.

With regard to our survey method, we decided to use the quota sampling. We justify this choice by the complexity to get a representative survey base to make good use of probabilistic sampling methods and the relative reliability of the quota sampling in terms of representativeness of the population. The questionnaire was therefore distributed both online and in paper, the latter one being used for population segments hard to reach via internet (i.e., older people).

Before distributing the questionnaire, we first made a pretest on 26 that meet our criteria: they were all Walloons, aged from 15 to 72 with a banking account and presenting different professions as well as banking purpose. This pretest allowed to make some adjustments to the questionnaire. In particular, some people could not figure out what was a welcoming service robot and did not know what the words “technology” and “service robots” referred to in the questionnaire.

The choice was then made to include a picture of the service-robot Pepper in the introduction and to explicit the two terms in the explanation part. Finally, a last remark was made on the formulation of one item. A few individuals made the remark that the item “I test a technology before adopting it” was subject to interpretation as the answer was depending on the frequency of the behavior. The item was thus modified in the following way: “I always test a technology before adopting it”.

We thus administered the questionnaire online within communities of people whom we made sure that they met the conditions mentioned above as the Facebook student pages of the Wallonia universities. However, while this method may have been useful for collecting data from certain categories of people (i.e., mostly young subjects), it was not enough to collect data from subjects of other age categories.

In order to ensure a certain representativity of the sample, the distribution of the online questionnaire was accompanied by the distribution of the questionnaire in paper format among groups of people that we were unable to reach with the online survey (i.e., older people). In order to reach these people, we administered the survey to employees of firms based in Wallonia and to the residents of a rest house in Arlon. By making use of these two methods of data collection, we were able to get more data from the part of the population that was difficult to reach via internet, namely older people. In both cases, the questionnaires were self-administered, the interviewees completed the questionnaire themselves. For the responses obtained in paper format, they were encoded in the Excel database directly. The data collection was realized between July 10 and July 27.

The sample, as constituted, comprises 283 individuals. It is made up of people with a bank account. The sample is also made up of men and women. Finally, it is made up of people of all ages and of people with different banking purpose and profession. Table 1 gives the relative frequencies of our sample for each of the methods described.

Table 1: Structure of the sample

Variables	Modalities	Percentages
Gender	Male	48.8%
	Female	51.2%
Age	<18	5.3%
	18-23	9.5%
	24-29	14.1%
	30-39	16.3%
	40-49	15.9%
	50-59	15.9%
	60-69	11.7%
	>69	11.3%
Profession	Student	30.7%
	Employed	40.3%
	Retired	21.6%
	Independent	5.3%
	Unemployed	2.1%
	To receive my salary	67.14%

Purpose of possessing a bank account	To put money in safety	70.32%
	To spare money	72.44%
	To invest money	33.92%
	To have access to online payments and payments by card	72.44%
	My parents created it for me	15.90%

We can say that our sample is representative of the target population in terms of gender and age. Indeed, the sample is very close to the Walloon population figures given by Statbel for the year 2019, namely 48.9% and 51.1%, respectively of men and women (Structure of the population, Statbel, 2019).

The representativity of the sample with regard to the age is also quite good. The percentages of the extreme age categories (i.e.: <18 and> 69) are similar in terms of frequency while the age categories located between these two extremes constitute the bulk of the sample. The profession representativeness is also quite good despite percentages of the Unemployed and Independent a bit lower than it was expected. Despite the big differences between the groups, the groups of students, employed and retired are relatively representative of the population studied with the employed representing the bulk of the population.

Finally, we also wanted to be convinced that we not asked to people with the same purposes to possess a bank account as it could have led to potential biases in the analysis. In that sense, we can see our sample benefit from a good diversity of purposes with only two low percentages that can be explained by the rarity they can be observed in a population.

The fact that the sample is well balanced is important because it allows us to be convinced that we have collected data from sufficiently people with different characteristics, it therefore allows us to draw conclusions for the population on the basis of the tests carried out on the sample.

B. Measures

a. Variables and scales

To answer the research questions, we used different variables and scales. In total, 10 independent variables were used to predict the dependent variable (i.e., "Usage Intention"). Among those 10 independent variables, 7 were based on a Likert scale of 7 modalities from 1 (Totally disagree) to 7 (Totally agree). Due to the nature of the concepts we tried to evaluate, Likert scales were the "go-to" option. These ones are Usefulness, Ease of use, Experience, Self-Efficacy, Anxiety, Subjective norm and Result demonstrability.

To evaluate each dimension, multi-items Likert scales were used. Each dimension was then composed of 3 to 4 items to capture the dimension. The 3 remaining independent variables are based on a nominal scale, due to their nature. These variables are Banking habit, Gender and Age. More specifically, the choice was made to create age categories to make the interpretation of results easier.

We coded our variables on the software SPSS. To do so, we first reversed items to be sure that every single item of each question went in the same direction. We then translated every modality into a number comprised between 1 and 7 for our Likert variables. For our 3 non-metric independent variables, we used a slightly different code. The gender variable was coded with the following rule: woman= 0 and man=1. The age category variable was coded from 1 (<18) to 8 (>69). Finally, the variable Banking habit was coded with two dummy variables as follows: 00 (I always go online to manage my bank account), 10 (I use every option depending on the situation) and 01 (I always go into an agency when I want to manage my bank account). Table 2 summarizes each dependent and independent variable used in this study and their code.

Table 2: Variables summary

	Variable denomination	**Type of variable**	**Question formulation (and items formulation)**	**Measurement scale**	**Type of scale**	**Source**
Dependent variable	Usage intention	Metric	« In what extent do you agree with these statements? » - I will never use service-robots, human interactions prevail - I don't think service-robots are great for me - I will recommend my relatives to not use service-robots - I'm opposed to the introduction of service-robots	1 Totally disagree 2 Disagree 3 Rather Disagree 4 Neutral 5 Rather agree 6 Agree 7 Totally agree	Ordinal scale	TAM and UTAUT

Independent variable n°1	Usefulness	Metric	« In what extent do you agree with these statements? » - Use service-robots would allow me to save time - The service-robots would increase the overall service-quality - Service-robots would be a great addition - I don't think service-robots make sense in bank agencies	1 Totally disagree 2 Disagree 3 Rather Disagree 4 Neutral 5 Rather agree 6 Agree 7 Totally agree	Ordinal scale	TAM and UTAUT
Independent variable n°2	Ease of Use	Metric	« In what extent do you agree with these statements? » - Learning to use a service-robot would be easy for me - It would be easy to use a service-robot for me - I wouldn't make a good use of service-robots	1 Totally disagree 2 Disagree 3 Rather Disagree 4 Neutral 5 Rather agree 6 Agree 7 Totally agree	Ordinal scale	TAM and UTAUT
Independent variable n°3	Experience	Metric	« In what extent do you agree with these statements? » - I already use service-robots in a different context - I'm not accustomed with service-robots at all - I regularly use service-robots in some context	1 Totally disagree 2 Disagree 3 Rather Disagree 4 Neutral 5 Rather agree 6 Agree 7 Totally agree	Ordinal scale	UTAUT
Independent variable n°4	Self-Efficacy	Metric	« In what extent do you agree with these statements? » - I know how to make a good use of service-robots - I'm not sure how to use service-robots - The process seems clear to me	1 Totally disagree 2 Disagree 3 Rather Disagree 4 Neutral 5 Rather agree 6 Agree 7 Totally agree	Ordinal scale	Theory of Acceptance Model (TAM)
Independent variable n°5	Anxiety	Metric	« In what extent do you agree with these statements? » - I don't feel at ease when I use technology - If possible, I prefer not using technology because it is not reliable - Using technology is intuitive for me	1 Totally disagree 2 Disagree 3 Rather Disagree 4 Neutral 5 Rather agree 6 Agree 7 Totally agree	Ordinal scale	Theory of Acceptance Model (TAM)
Independent variable n°6	Subjective norm	Metric	« In what extent do you agree with these statements? » - Seeing that everyone in my relatives use a technology except me makes me feel bad - I don't like using the same technology as everyone	1 Totally disagree 2 Disagree 3 Rather Disagree 4 Neutral 5 Rather agree 6 Agree 7 Totally agree	Ordinal scale	TAM and UTAUT

			- I use the technology that a relative recommends me			
Independent variable n°7	Result demonstrability	Metric	« In what extent do you agree with these statements? » - The advantages of using a specific technology must be clearly shown before I consider using it - I don't pay much attention to the advantages of a technology - Disadvantages are important in a technology adoption	1 Totally disagree 2 Disagree 3 Rather Disagree 4 Neutral 5 Rather agree 6 Agree 7 Totally agree	Ordinal scale	Theory of Acceptance Model (TAM)
Independent variable n°8	Banking habit	Non-metric	- Please tick the one that fits the best your habit	0 0 I always go online to manage my bank account 1 0 I use every option depending on the situation 0 1 I always go into an agency when I want to manage my bank account	Nominal scale	Personal elaboration based on UTAUT
Independent variable n°9	Gender	Non-metric	- What is your gender?	0 Female 1 Male	Nominal scale	UTAUT
Independent variable n°10	Age	Non-metric	- In which age category are you?	1 <18 2 18-23 3 24-29 4 30-39 5 40-49 6 50-59 7 60-69 8 >69	Ordinal scale	Personal elaboration based on UTAUT
Filter question		Non-metric	- Do you have a bank account?	- Yes - No	Nominal scale	Personal elaboration
Checking question n°1		Non-metric	- Do you manage your bank account by yourself or is it managed by someone else (for instance your family)?	- I manage it myself - Someone else manage it for me	Nominal scale	Personal elaboration

Checking question n°2		Non-metric	- For what purpose(s) do you possess a bank account?	- To receive my salary - To put money in safety - To spare money - To invest money - To have access to online payments and payments by card - My parents created it for me - Other	Nominal scale	Personal elaboration

4. Results

A. Data reduction, checking of the scale reliability and coherence

Before making the analyses, we tested the reliability of the scales used and proceeded to a data reduction. To that goal, we first made a factor analysis and more specifically an Exploratory Factor Analysis (EFA). The goal of factor analysis is to examine the relationships among a large number of items and replace that large number of items with a smaller number of factors or dimensions, the EFA allows then to check if the items can be summarized into one or more factors. The results of the EFA confirmed that every multi-items Likert scale we used to capture the dimensions actually captured one dimension only each one.

Bartlett's sphericity test allowed us to verify the relevance of the factor analysis. It makes it possible to prove that certain basic variables are correlated with each other. If they were not, factor analysis would not make sense because if the variables are not correlated, there cannot be a latent variable capable of describing all of these items. The null hypothesis of this test is that there is no correlation between the items, the alternative hypothesis being that the correlation between the items is different from 0, and therefore that the items are correlated. With a test significance level equal to 0 in all the analyzes carried out, it is necessarily lower than the significance level chosen (except 0). We can therefore reject the null hypothesis according to which the items of the analyzes are not correlated. According to Bartlett’s test, factor analysis is therefore relevant.

Considering the Kaiser-Meyer-Olkin fit index of the analyses, we notice that every single variable reaches the minimum threshold of 0.6, which is the preferable minimum value for this parameter. We can they say that the analysis is reliable.

Finally, we tested the internal consistency of the different Likert-type scales used in the questionnaire. To do this, we used the Cronbach's alpha method. This method consists of estimating the degree of internal consistency in the form of an index between 0 and 1 inclusive. In this regard, it can be noted that the more elements a scale contains, the more the Cronbach's alpha index is likely to increase. Likewise, a low inter-item correlation will decrease alpha, while a high inter-item correlation will increase it. Cronbach's alpha method thus gives a relatively precise idea of the degree of inter-item correlation and, coupled with a principal component analysis, allows us to isolate faulty items that do not measure the same construct.

We therefore calculated Cronbach's alpha for each variable measured on a Likert-type scale. At the end of these calculations, we obtained satisfactory or even excellent indices. The values taken by Cronbach's alpha for the variables are all located above the threshold of 0.7. We can therefore say that the different variables now all benefit from a satisfactory internal consistency. Table 3 summarizes the analyses carried out on the variables in this first part and returns for each the values of the three tests carried out. More specifically, with regard to Cronbach's alpha, the first column returns the value taken by default by the index in the absence of changes while the second takes the maximum value taken by the index in the case where an item would be omitted.

It is possible to make some improvements at the margin of internal consistency, however, examination of the intermediate columns of the Items-Total Statistics table (appendix 3) shows that this is not practically feasible due to sufficiently high inter-item correlations to justify retaining the items (i.e.: the threshold of 0.3 is generally retained as the minimum threshold for retaining an item. Below this threshold, the item must be withdrawn. See appendix 3).

Table 3: EFA and Cronbach results after data reduction

		KMO	**Bartlett's sphericity test**	**Cronbach's alpha**
	Variables	Index	Approx. Chi-Square	Alpha
	Usage intention	.788	689.184	.888
	Usefulness	.802	604.558	.864
	Ease of Use	.740	672.256	.923
	Experience	.657	182.816	.720
	Self-Efficacy	.723	428.974	.869

	Anxiety	.676	268.496	.793
	Subjective Norm	.683	223.851	.764
	Result Demonstrability	.670	154.799	.704

On this basis, we group the different items under the same variable by averaging the items measuring the same dimension. We thus obtain for each observation the mean of the items for the eight variables mentioned above and visible in the table.

B. Correlation analysis: Pearson coefficient

We will continue by analyzing the potential correlations existing between our variables. It is important to check the value of the Pearson coefficient to be reassured about the correlations between our variables. To do this, we first perform an inter-variable correlation analysis using the Pearson coefficient. Our independent variables of Likert type being metric as well as our dependent variable and our mediator variables (i.e., Usefulness and Ease of Use), we can use this method. We add our demographic independent variables (gender, age category and banking habit) to the analysis too, in order to test their relationship with the other variables.

The purpose of this test is to measure the importance of the linear relationship between two metric-type variables by the mean of a coefficient, between -1 and 1: the Pearson coefficient. To observe a relationship between the variables, this coefficient must be different from 0, otherwise the variables are said to be uncorrelated. The sign, for its part, defines whether the variables are positively or negatively correlated. However, the Pearson coefficient does not define any meaning in the relationship between variables, it only specifies the existence or absence of a linear relationship between the variables. In order to test our hypotheses, we perform the correlation analysis on three specific variables, namely our dependent variable and our two potential mediator variables. Table 4 illustrates the results of this analysis.

Cohen's (1988) tags allow us to know the size of the effect. Around 0.10 it is a weak correlation, around 0.30 it is a medium correlation and above 0.5 it is called a strong correlation. We will interpret the values of the coefficients according to these tags, widely accepted by the scientific community.

a. TAM/UTAUT determinants

We can see that the effect sizes are significant for two of the three variables. Only the subjective norm is not significant, Usefulness and Ease of use for their part show a very high correlation (.840) and a moderate correlation (.425) respectively. These correlations are both positive, as it was suggested. In addition to being insignificant, subjective norm had only a weak correlation with our dependent variable, Usage intention.

b. TAM determinants

We can see that the effect sizes are significant for two of the three predictors. More specifically, the correlation of the variable Result demonstrability is not significant (sig = .136), unlike the coefficients of Self-efficacy and Anxiety. The effect of Result demonstrability is also very weak and negative (-.089). The other two predictors have a medium (.389) and high (-542) correlation, respectively. Their signs corroborate with our predictions.

c. UTAUT determinants

We can see that the effect sizes are significant for the four predictors. More specifically, the Gender coefficient is significant at 5% while those of the other three predictors are significant at 1%. The size of their effect varies, however. If the effect of the Gender variable remains marginal (.142), the other three predictors show an average correlation with our dependent variable. The signs of the four coefficients corroborate with our hypotheses, the coefficients of the Age and Banking habit variables are both negative, as our coding suggested, while those of Experience and Gender are positive.

d. Correlations with mediators

Regarding the correlations of the two mediators, we can observe coefficients relatively similar to those observed for our dependent variable. The Subjective norm and Result demonstrability predictors remain insignificant for the Usefulness variable as well as for the Ease of use mediator. However, in the case of Ease of use, the predictor Result Demonstrability is for its part just insignificant with a significance of .050. We can also observe that the variable Gender is insignificant in both cases.

We also observe the same signs of the relations for the mediators as those observed for the dependent variable. Finally, we note some differences in the size-effect of correlations according to the mediator compared to those observed for our dependent variable. More specifically, the Age category and Banking Habit predictors seem to have little correlation with Usefulness but seem to be strongly correlated with Ease of use.

Table 4: Pearson coefficient

Pearson coefficient		Usage Intention	Usefulness	Ease of Use	Experience	Self-efficacy	Anxiety
	Variables	Corr.	Corr.	Corr.	Corr.	Corr.	Corr.
	Usage intention	1.000**					
	Usefulness	.840**	1.000**				
	Ease of Use	.425**	.412**	1.000**			
	Experience	.372**	.385**	.377**	1.000**		
	Self-Efficacy	.358**	.347**	.638**	.567**	1.000**	
	Anxiety	-.542**	-.452**	-.541**	-.264**	-.428**	1.000**
	Subjective Norm	.013	.073	.078	.006	.055	-.107
	Result Demonstrability	-.089	-.077	-.118*	-.233**	-.236**	.087
	Gender	.142*	.133	.054	.093	.180*	-.113
	Age Category	-.330**	-.245**	-.436**	-.140*	-.358**	.518**
	Banking Habit	-.385**	-.220**	-.467**	-.250**	-.364**	.519**
		Subjective norm	**Result Demonstrability**	**Gender**	**Age Category**	**Banking habit**	
	Variables	Corr.	Corr.	Corr.	Corr.	Corr.	
	Subjective Norm	1.000**					
	Result Demonstrability	.131*	1.000**				
	Gender	-.064	.003	1.000**			
	Age Category	.072	.247**	.027	1.000**		
	Banking Habit	-.099	.131*	-.036	.420**	1.000**	

** : significant at 0.01, * : significant at 0.05

C. Comparison of TAM and UTAUT models

We will now compare the two models. We will therefore first make specific tests for each model (i.e., mediation analysis for the TAM model and moderator analysis for the UTAUT model) before comparing their explanatory power with regressions.

a. TAM model: mediator analysis

As stated above, TAM model introduces the concept of mediators with two key mediators: Usefulness and Ease of use. We will then test in this section whether or not mediation effect occurs in this specific study. To test the mediation between the two presumed mediators, Usefulness and Ease of use, with the variables from the TAM model, Self-efficacy, Anxiety and Result demonstrability, we will use the procedure developed by Baron and Kenny (Baron and Kenny, 1986). They developed a 4-steps procedure to determine whether or not there is a mediation effect between the variables and if the mediation is partial or full.

The four steps are as follows:

- Step 1: Regressing the independent variable (IV) on the dependent variable (DV)
- Step 2: Regressing IV on the mediator (M)
- Step 3: Regressing IV and M on DV
- Step 4: Based on the results of the 3 previous steps, we assess the mediation effect.

To perform these analyses, the add-on for SPSS, PROCESS developed by Andrew F. Hayes, was used. As the sample we used was only comprised of 283 individuals, we used the bootstrap technique (bootstrap of 1000) to ensure the results of the analyses are robust. The null hypothesis of bootstrapping is that the results are valid if 0 is not part of the confidence interval the bootstrap technique generates. Otherwise, the results are subsequently rejected.

The results of these analyses show that some mediation effect does occur between the mediator Usefulness and the variables Self-efficacy, Anxiety and Ease of use but also between the mediator Ease of use and the variables Self-efficacy, Anxiety. The results have also shown that subjective norm and Result demonstrability variables were not mediated by any of the mediators, Usefulness and Ease of use, at a significative level of 5%. The bootstrapping confidence interval does include 0 for the variables Subjective norm and Result demonstrability, which is a proof that we cannot consider some mediating effect in their case.

More precisely, the analyses conducted put in light that Usefulness was a strong mediator of the variables Ease of use (indirect effect = 77.62%), Self-efficacy (indirect effect = 78.86%) and Anxiety (indirect effect = 62.31%), while Ease of use is a weaker mediator of the variables Self-efficacy (indirect effect = 59.11%) and Anxiety (indirect effect = 18.63%).

Regarding the robustness of the analyses conducted, we can say the analyses are valid as the bootstrap confidence interval never includes 0 for the significant mediations. The results

obtained can therefore be trusted. Table 5 shows the results of the mediation analyses performed.

Table 5: Mediation analyses

Mediation			**Usefulness**	**Ease of use**
	Variables	Relationships	Beta	Beta
	Ease of Use	Step 1: X → Y	.4071**	/
		Step 2: X → M	.3597**	
		Step 3: X M → Y	.0912** (X) .8784** (M)	
		Step 4: Assessment	Partial mediation (indirect effect = 77.62%)	
	Self-Efficacy	Step 1: X → Y	.3333**	.3333**
		Step 2: X → M	.2945**	.6203**
		Step 3: X M → Y	.0705* (X) .8926** (M)	.1363* (X) .3176** (M)
		Step 4: Assessment	Partial mediation (indirect effect = 78.86%)	Partial mediation (indirect effect = 59.11%)
	Anxiety	Step 1: X → Y	-.5658**	-.5658**
		Step 2: X → M	-.4299**	-, 5893**
		Step 3: X M → Y	-,2133** (X) .8202** (M)	-.4605** (X) .1788** (M)
		Step 4: Assessment	Partial mediation (indirect effect = 62.31%)	Partial mediation (indirect effect = 18.63%)
	Subjective Norm	Step 1: X → Y	.0133	.0133
		Step 2: X → M	.0698	.0855
		Step 3: X M → Y	-.0512 (X) .9254** (M)	-.0216 (X) .4087** (M)
		Step 4: Assessment	No mediation	No mediation

	Result Demonstrability	Step 1: X → Y	-.1286	-.1286
		Step 2: X → M	-.1028	-.1760
		Step 3: X M → Y	-.0341 (X) .9195** (M)	-.0577 (X) .4027** (M)
		Step 4: Assessment	No mediation	No mediation

** : significant at 0.01, * : significant at 0.05

b. UTAUT model: moderator analysis

The UTAUT model postulates the existence of moderating variables: Age, gender, experience and habits (here: Banking habits). The following section will thus explore the possibility of moderation with the three predictors: Usefulness, Ease of use and Subjective norm. The goal of the mediation analysis is to check if a tierce variable does interfere between the independent variable and the dependent variable. If a tierce variable is at play, then omit it would lead to erroneous conclusions. Moderation analysis comes thus as a way to discover every tierce variable that influence the predictors. To perform these moderation analyses, we will re-use the add-on PROCESS. The analysis will feature three different value types coming from the predictor (X), the hypothetic moderator (Z) and the interaction effect of both (X*Z). Table 6 summarizes the results of the analyses.

As the results show it, most of the moderations tested were not significant, which thus lead to only a few of moderating effects for the three predictors tested. To go further, the moderating effect of the variable gender was observed significant for the predictors Ease of use and Subjective norm, while it failed to be significant in the case of Usefulness (prob. simple effect: .43 and prob. Interaction: .50) despite Usefulness being significant. In the case of Ease of use, every single effect is significant at 5%, unlike in the case of Subjective norm which is insignificant (prob. main effect: .68) despite the moderator being significant (prob. Simple effect: .02). Therefore, the gender variable is only retained as moderator of the variable Ease of use.

The moderation analyses conducted for the possible moderator Experience revealed also only one moderation for the variable Usefulness, the interaction effect being insignificant for the variable Ease of use and exception of the moderator itself, everything else was non-significant in the case of Subjective norm.

The banking habits were also shown as a moderator for the variable Usefulness at 5% with exception of the second interaction effect being insignificant at this threshold. However, the moderator is insignificant in the case of Ease of use while the effect of the predictor Subjective norm is insignificant in this moderation analysis, despite the moderation being significant.

Finally, the moderation analysis with the moderator age were not conclusive. Despite the three effect of the predictors being significant, most of the simple effects and interaction effects are insignificant. No overall tendency can be found. We therefore conclude that the moderator age is not a relevant moderator of the variables Usefulness, Ease of use and Subjective norm.

Table 6: Moderation analyses

Moderation			**Gender**	**Experience**	**Banking Habits**	**Age**
	Variables		Beta	Beta	Beta	Beta
	Usefulness	Predictor	.9171**	.8800**	.8753**	.9667**
		Moderator	.0668	.0644*	.4933** (Z1) .9641** (Z2)	-.1294 (Z1) -.3160 (Z2) .0234 (Z3) -.5827** (Z4) .0034 (Z5) -.3438 (Z6) -.9832** (Z7)
		Interaction effect	.0437	-.0699**	.2114* (X Z1) .0900 (X Z2)	-.2255 (X*Z1) .0323 (X*Z2) -.3392 (X*Z3) .0655 (X*Z4) -.1447 (X*Z5) .1413 (X*Z6) -.0900 (X*Z7)
	Ease of use	Predictor	.3871**	.2791**	.2817**	.6579**
		Moderator	.3132*	.2598**	.9120 (Z1) 1.2105 (Z2)	-.0338 (Z1) -.3721 (Z2) .2879 (Z3) .1008 (Z4)

						-.0879 (Z5) -.7410* (Z6) -.3503 (Z7)
		Interaction effect	.3067**	-.0713	.0636 (X Z1) -.1907 (X Z2)	-.1187 (X*Z1) -.2562 (X*Z2) -.5493* (X*Z3) -.4215 (X*Z4) -.6573** (X*Z5) -.3183 (X*Z6) -.0114 (X*Z7)
	Subjective Norm	Predictor	.0303	.0204	-.0166	.5697**
		Moderator	.3759*	.3678**	1.5878** (Z1) 2.0099** (Z2)	.5834 (Z1) .1086 (Z2) .5407 (Z3) .3739 (Z4) .1491 (Z5) -.8445* (Z6) -1.3030** (Z7)
		Interaction effect	-.2793	.0847	-.3230*(X Z1) -.3602**(X Z2)	-.5746* (X*Z1) -.3780 (X*Z2) -.7890** (X*Z3) -.7103* (X*Z4) -.5775 (X*Z5) -.3151 (X*Z6) -.1088 (X*Z7)

** : significant at 0.01, * : significant at 0.05

c. Regressions of TAM and UTAUT

We then tested the two models by performing the regressions on our dependent variable, Usage intention. We have used the Step-by-step method for this purpose. This method differs from more traditional methods such as Enter and Remove in that it considers the partial inter-variable correlations, making it possible to arrive at a model in which the selected variables have necessarily significant effect. Table 7 summarizes the results of the two regressions.

As the results highlight it, the TAM model predicts slightly better the dependent variable, Usage Intention, with a R-squared of .843 in contrast to .815 for the UTAUT model.

If we take each model separately, we can see that in the case of the TAM model, the regression shows four non-significant effect of variables at the significative level of 5% (Ease of use, Self-efficacy, Subjective norm and Result demonstrability) and also two significant effects for the variables Usefulness and Anxiety.

In particular, the mediator Usefulness is prevalent with a beta value of .811 whereas the variable Anxiety have a beta value of -.249. According to these results, we can then say the mediator Usefulness is a key component of the model as every variation of one unit of its value is translated with a variation of .811 in the value of the dependent variable. The Anxiety is less important but still interesting as a variation in its value results in a variation of .249 in the value of the dependent variable. The signs of Usefulness and Anxiety are also coherent with the hypotheses that were made on them as we expected them to be positive.

The four variables with non-significant effect sizes are for their part consistent with the results of mediation analysis. As the mediation analysis shows it, Usefulness highly mediates the Ease of use (indirect effect = 77.62%) and the Self-efficacy (indirect effect = 78.86%) which thus explain why their effects are not significant in a regression with Usefulness, as most of their effect is channeled by the mediator itself. However, it does not go the same for the two last variables Result demonstrability and Subjective norm which also feature insignificant effect despite being not mediated by the Usefulness. Such a result is more likely to be explained by the relative unimportance of the variables as predictors of the Usage intention in the case of welcoming service-robots.

Table 7: Structural Equation Models (SEM)

Structural Equation Model		**TAM**		**UTAUT**	
	Variables	Beta	R-squared	Beta	R-squared
	Usage intention	1.839**	**.843**	4.457**	**.815**
	Usefulness	.811**		.906**	

	Anxiety	-.249**		/	
	Subjective norm	-.004		-.030	
	Ease of use	.008		.036	
	Self-efficacy	.045		/	
	Result demonstrability	.045		/	
	Experience	/		.036	
	Gender	/		.037	
	Age Category	/		-.043	
	Banking Habit	/		(a) .004 (b) .502**	

** : significant at 0.01, * : significant at 0.05

As stated above, the UTAUT model seems to be slightly less predictive than the TAM model. The final model shows six significant variables among the ones tested. They are Usefulness, Banking habits (only the second dummy variable: BHb) and eventually four interaction variables (CBHbEase, CExpSubj, CExpUsef, CBHbSubj). If we take the variables that each model has in common (i.e. : Usefulness, Ease of use and Subjective norm), the results of each variable are close to TAM results. Once more, the Usefulness, here predictor, is prevalent with a beta value of .906 and a high significance. The effect of the other two variables, similarly to TAM model, are non-significant at the 5% threshold. We can also notice that the beta-value of Usefulness is a bit superior in UTAUT than in the TAM model. It is mainly due to the mean-centering of every variable tested in UTAUT. We made this choice to ensure a low level of multicollinearity, as the regression both features variables and interaction effects.

The effect size of the variable Banking habit is also significant for the second dummy variable: BHb. The effect size can be interpreted as follows: people who goes exclusively in branch to manage their bank account are more likely to use welcoming service-robots than people managing their bank account online exclusively. In terms of standard deviation, it means that people going into branch are .192 standard deviation more likely to use welcoming service-robots than people who never goes into branch. As the other dummy variable: BHa does not possess a significant effect size, we however cannot say if there is a difference in adoption of welcoming service-robots between people going both online and in branch to manage their bank account and people managing their bank account online exclusively.

5. Discussions

This master's thesis aims to provide a comprehensive understanding of welcoming service-robots potential in banks by using the latest advancements in technology acceptation research. We thus developed a comprehensive theoretical framework of welcoming service-robots by integrating theories, constructs and relationships from prior studies in the field. We then compared the two main models of technology acceptance, namely the TAM and UTAUT models. The results support that the TAM model has more explanatory power. However, the difference in explanatory power is quite low (.843 for TAM and .815 for UTAUT) which thus means that UTAUT model could still fit in some cases.

We first found that a substantial part of the determinants used in prior studies (TAM and UTAUT acceptance model) drive welcoming service-robot adoption. More specifically, out of the 10 determinants tested, 8 were significantly correlated to our dependent variable and 3 were eventually significant when we regressed the determinants. If the correlation analysis gave us some clues that the effect of the variables Subjective norm and Result demonstrability could be non-significant, we did not expect that the effect of the variables Self-efficacy, Experience, Ease of use, Gender and Age category would also be insignificant. In this regard, we hypothesize a particularism of the study subject in relation to some of these predictors such as experience.

If Experience proves to be relevant in some cases, it seems to be different in the case welcoming service-robots. Experimenting, as showed by Paluch et al (2020), is less necessary in the case of service robots, as they are able to overcome the problems caused by the lack of experience of the user by their own. Thus, it gives credit to the non-significance of its effect in our regression.

It should also be noted that some of the variables with insignificant effect are highly mediated by the mediator Usefulness which is a potential explanation to the non-significance effect. It is the case of the variables Ease of use and Self-efficacy (respectively mediated at 77.62% and 78.86%). Despite being itself a mediator as the analysis proved it, the Ease of use variable was overshadowed by the mediator Usefulness that is seen as a more powerful one. The same goes for Self-efficacy that has only a moderate effect on the usage intention, making its effect non-significant when Usefulness is present.

The non-significant effect of the variable Result Demonstrability is however less intuitive. It would be interesting to deepen this specific case to understand what the roots of this non-significance are. It indeed seems counter-intuitive that one could not favorize a technology if it does show good results. There could be here some confounding variables at play that would hamper its effect.

Our results also allow to relativize the use of mediation and moderation analysis to better explain the likelihood of one customer to make use of a welcoming service-robot. In particular, the mediation analysis stated the high relevance of the variable Usefulness as a mediator, but they also revealed a weaker effect of the variable Ease of use as mediator. The

mediator Ease of use seems indeed to only moderately mediate two variables, namely Self-efficacy and Anxiety (respectively, 59.11% and 18.63% of indirect effects). The two variables, Result demonstrability and Subjective norm, also revealed to be not mediated even by the mediator Usefulness. One explanation would be their relative uselessness in the model in the case of such a technology which is supported by the non-significance of their effect in the regression.

Another point to notice is the relative relevance of the mediator Ease of use. As the regressions showed it, the effect of the mediator Ease of use tends to be non-significant when the mediator Usefulness is part of the regression which is mainly due to the high indirect effect that results of the mediation by the variable Usefulness.

The moderation analyses mostly concluded of no moderation between variables as the results highlighted it. Out of the four variables tested as hypothetic moderators (i.e., Gender, Experience, Banking habits and Age category), three revealed to moderate at least one variable among the ones tested (i.e., Usefulness, Ease of use and Subjective norm): Gender, Experience and Banking habit. Gender seems to moderate the Ease of use whereas Experience and Banking habit moderate the Usefulness variable. These are however the only actual moderations out of the twelve tested.

The variable Age category failed to moderate any variable. One explanation could be the nature of the variable itself, composed of eight age groups, and the fact that behaviors do not necessarily evolve linearly. It could then be interesting to test whether or not a moderation effect occurs with less age groups.

The results of the moderation analyses, more than the ones of the mediation analyses, raise the question of the relevance of the concept in the case of welcoming service-robots. As the regressions illustrated it, the difference is quite low between the explanatory power of the TAM and UTAUT models, despite the higher complexity of the UTAUT model. It therefore seems interesting to test in what extent does the moderation analysis help to understand the underlying mechanism of customer usage intention.

In terms of hypotheses, our results can be translated as follows. Table 7 summarizes our assumptions and their assessment in the models. Relatively to the hypotheses related to the two models, the regressions confirmed the hypothesis 1a. The variable Usefulness does seem to have a positive influence on the dependent variable as our results emphasized it. However, hypotheses 1b and 1c are respectively partially and completely disconfirmed.

The variable Ease of use does have a positive impact on the Usefulness, however its impact on the dependent variable is non-significant, as the results highlighted it. Subsequently, the hypothesis 1b, made on the Ease of use, is partially supported.

We postulated in the hypothesis 1c that the variable Subjective norm would have a positive impact on the Usefulness and the Usage Intention. However, none of these assumptions could be verified in this study. We advocate that the non-significant effect of this predictor is more

likely to be explained by the study subject which makes the feeling of social pressure less prevalent than for other technologies. As such, hypothesis 1c is rejected.

In the hypotheses 2, related to TAM-exclusive variables, we posited that Self-efficacy would be positively linked to Ease of use and Usage intention (hypothesis 2a), we also stated that Anxiety would negatively impact Ease of use and Usage intention (hypothesis 2b) while we expected Result demonstrability to be positively related to Usefulness and Usage Intention (hypothesis 2c).

As our results show it, the variable Self-efficacy does seem to be linked to the Ease of use. The mediation analysis revealed a mediation effect between the two variables. However, its impact on the dependent variable could not be verified. We hypothesize that its relationship with the mediator Usefulness could explain these results. The variable Self-efficacy is highly mediated by Usefulness (indirect effect: 78.86%) which thus hamper the likelihood to have a significant effect in a regression featuring the mediator. We also did not expect such a mediation would occur. We may hypothesize that some confounding variable could be at play. It would be interesting to deepen this relationship in further research. As such, hypothesis 2a, is partially supported.

We expected the predictor Anxiety would be related to Ease of use and Usage intention, both negatively. The mediation analysis shows that the predictor Anxiety is mediated by both Ease of use and Usefulness, which was not predicted. We indeed only predicted the variable to be mediated by Ease of use. The variables also possess a significant effect in the TAM regression. The sign is also coherent with our hypothesis. As a result, the hypothesis 2b is supported.

The hypothesis 2c must however be rejected. As our results show it, we were not able to verify the significance of the effect of the variable Result demonstrability in the TAM regression. Moreover, the mediation analysis did not reveal any mediation between the predictor and the mediators, making impossible to consider the mediation results as an explanation for the non-significant effect of the predictor in the TAM regression. As explained above, it seems that the result demonstrability is not a key criterion to adopt a welcoming service-robot.

In the hypotheses 3, related to the UTAUT-exclusive determinants, we posited that age influences the intent to use welcoming service-robots in the sense that younger people would use it more than older people (hypothesis 3a), we also hypothesized that a similar impact would be observed between men and women (hypothesis 3b). The hypothesis 3c linked Experience with Usefulness, Ease of use and the dependent variable while the hypothesis 3d stated that people going into agency exclusively would be less inclined to use welcoming service-robots than people managing their bank account online exclusively.

As our results show it, the variable Age category does not seem to be related to our dependent variable. Despite a significant moderate Pearson's coefficient (-.330), the variable failed to have a significant effect in the regression model. The variable does not seem to have any moderating effect too. We evoked above that such a result could be caused by the

number of groups the variable possesses. The variable thus lacks effect on the dependent variable. As a result, the hypothesis 3a is rejected.

The variable Gender was expected to have an impact on the Usage Intention, the dependent variable. We found evidence that gender is positively correlated to the dependent variable at the 5% threshold (.142) even though the correlation is weak. The moderation analysis gave it some importance with a significant moderating effect on the variable Ease of use. We were however unable to prove this hypothesis. The effect size of the variable Gender was ultimately non-significant which makes us unable to confirm this hypothesis. The effect of the variable Gender was however shown non-significant in the final regression, with a positive beta-value of .037. As a result, the hypothesis 3b is rejected.

In the hypothesis 3c, we postulated the existence of an impact of the variable Experience on Usefulness, Ease of use and on the dependent variable. Our results confirmed that Experience has an impact on the variable Usefulness via moderation analysis, however the variable Experience did not have a significant effect in the final regression and did not have any moderating effect on the variable Ease of use. As a result, the hypothesis 3c is partially supported.

Our last hypothesis was about the banking habits variable. To assess this dimension, we used two dummy variables named BHa and BHb as described in the coding. The moderation analysis showed a significant moderating effect for the variable Usefulness but not for any other variable. However, only one of the two dummy variables effect size was revealed significant in the final regression: BHb with beta-value of .502 while BHa had a non-significant effect size with a beta value of .004. We believe that the difference between people going both in branch and online to manage their bank account and people managing exclusively their bank account online was not systematic, leading ultimately to the non-significant effect size. Our results thus show an opposite relationship than the one predicted. As such, hypothesis 3d is rejected.

Table 7: Hypotheses summary

Summary of hypotheses	**Hypotheses**	**Prediction**	**Finding**	**Explanation**
	Hypothesis 1a	Usefulness has a positive impact on usage intention.	Supported	
	Hypothesis 1b	Ease of use has a positive impact on usefulness and usage intention.	Partially supported	Ease of use was not significantly related to Usage intention.
	Hypothesis 1c	Subjective norm has a positive impact on	Rejected	The predictor has shown no significant effect with

		usefulness and usage intention.		Usefulness and Usage intention.
	Hypothesis 2a	Self-efficacy has a positive impact on ease of use, usage intention.	Partially supported	The predictor was not significantly related to Usage intention and was instead significantly related to Usefulness.
	Hypothesis 2b	Anxiety has a negative impact on ease of use, usage intention.	Supported	The predictor was also significantly related to Usefulness.
	Hypothesis 2c	Result demonstrability has a positive impact on usefulness, usage intention.	Rejected	The predictor has shown no significant effect with Usefulness and Usage intention.
	Hypothesis 3a	Age has an impact on usage intention, such that younger people are more likely to use robot technology than older people.	Rejected	The predictor has shown no significant relationship with Usage intention.
	Hypothesis 3b	Gender has an impact on usage intention, such that men are more likely to use robot technology than women.	Rejected	The predictor has shown no significant relationship with Usage intention.
	Hypothesis 3c	Experience has a positive impact on ease of use, usefulness, and usage intention.	Partially supported	Experience was not significantly related to Ease of use and Usage intention.
	Hypothesis 3d	Banking habit has an impact on usage intention, such that people managing their bank account exclusively online are more likely to use welcoming service-robots.	Rejected	The predictor has shown an opposite relationship with Usage intention.

Finally, the comparison between the two models pointed out that some variables are key to assess the Usage intention of a specific technology. Both models feature a high beta-value for the variable Usefulness. We can only highly encourage researchers to examine in depth this variable in future studies. The comparison also showed some misconceptions we had such as the prevalence of the variable Ease of use that eventually had a non-significant effect in both

regressions and the importance of the variable subjective norm as a predictor that we overestimated.

We can also see that, despite different approaches, the two models come to similar explanator power (.843 and .815 for TAM and UTAUT respectively) which puts in light that more complexity does not necessarily mean higher explanatory power as the UTAUT model performs slightly less good than TAM. We would thus advocate to rather use TAM model for future research on the subject than the UTAUT model. The simplicity of the TAM model makes it intuitive and easy to interpret which is not the case of the UTAUT.

6. Conclusion

A. Summary

This paper aims to study the adoption of service robots in the banking sector. Two important adoption models have been considered, namely TAM and UTAUT, which were empirically tested and compared. In that goal, we first developed the recent advances in the field of AI and service-robots technologies before examining in detail the different theories about technology acceptance. More specifically, we first presented the advances in AI around the levels of intelligence and the four intelligences.

We then presented the advances in the service-robots technologies and developed the models of technology acceptance of TAM, TRA and UTAUT acceptance model. On that basis we developed the hypotheses made on the different determinants of the TAM and UTAUT models.

We then tested the explanatory power of the two models by first doing correlation analysis then by doing mediation and moderation analysis as well as regressions. In particular, we tested mediation for the variables Usefulness and Ease of use, and we tested moderation for the variables Gender, Age, Experience and Banking habits.

First, our results showed that the Usage intention is predicted by only a few variables in both models. The final regression of the TAM model features only two significant variables (Usefulness and Anxiety), among the 6 variables tested, whereas the UTAUT model features 6 significant variables among the ones tested. They are Usefulness, Banking habits (only the second dummy variable: BHb) and eventually four interaction variables (CBHbEase, CExpSubj, CExpUsef, CBHbSubj).

Moreover, the regression showed that Usefulness was by far the most important factor to Usage intention and that Ease of use was a minor factor. These results are coherent with the idea that banking services must be useful for customers.

The regressions also excluded some variables that we thought related to Usage intention such as the Experience, the Gender, the Self-efficacy and the Ease of use. We then infer that these criteria are not important in the technology adoption of welcoming service-robots.

Our results showed an influence of one categorical variable (Banking Habit) on the intention to use welcoming service-robot. However, it seems to impact the usage intention in a different way than the one we expected. The results show people going into branch to manage their bank account are more likely to use welcoming service-robots.

We also analyzed our two mediators to examine deeper the relations they have with the predictors. The mediation analysis of Usefulness indicated that three variables were significantly mediated by usefulness, namely Ease of use, Self-efficacy and Anxiety. Despite the TAM assumes mediation for the variables Result demonstrability and Subjective norm too, we were not able to demonstrate it in the case of this study, the variables being non-significant in the analyses we ran.

The mediation analysis ran with the Ease of use as mediator indicated two mediated variables: Self-efficacy and Anxiety. The Result demonstrability and Subjective norm being non-significant. However, the effects were weaker than in the case of Usefulness as mediator which is understandable as the Ease of use is also highly mediated by the Usefulness.

We finally analyzed the moderation that could exist between the variables of the UTAUT model. The moderation analyses did however only reveal a few of moderating effects for the variables Usefulness and Ease of use by the moderators Gender, Experience and Banking habits. The Age category did not seem to have any moderating effect in our analyses.

B. Managerial implications

We expressed our wish to give insights on what factors explain the welcoming service-robots acceptance to managers by testing the two most-recognized models of technology acceptance. This analytical framework provided a lot of insights to managers.

First, our results showed that one categorical variable was related to the usage intention, namely Banking habit, while the Age category and the Gender seem to not influence the acceptance of welcoming service-robots. We therefore suggest managers and marketers to use this variable as segmentation variable for the further studies on the acceptance of welcoming service-robots. These results also show that practitioners must think the service-robots to make people going in branches more likely to use them or, alternatively, give incentives to e-bankers to go in branches.

Second, our results emphasized the importance of the Usefulness as determinant of Usage Intention. Managers should thus focus on this specific mediator to effectively reach their target and make successful the introduction of welcoming service-robots. More specifically, the regression of TAM showed that Anxiety was a key determinant of usage intention. We then suggest marketers and managers to build their strategic plan with this relationship in mind. To do so, they should determine what could come from anxiety to use welcoming service-robots then work on solutions to reduce as much as possible their negative effects.

In the case of the Ease of use, our study highlighted its relative impact. However, we would advocate to nonetheless pay attention to that specific factor. Indeed, the TAM mediation analyses having shown a high mediating effect between Usefulness and Ease of use, it does seem interesting to build on it. The Ease of use should thus not be completed neglecting. Indeed, if younger generations find Easy to use nearly any technology, older people can sometimes experience trouble using technology.

C. Theoretical implications

This study showed some interesting results for researchers and expanded the research possibilities in this field by giving some clues of potential relations that could be further explored.

First, our study showed that both TAM and UTAUT models seem to have similar explanatory power which thus suggests that any model could potentially fit the need of research. However, it also proves that adding more variables does not lead to better explanatory power as shown with UTAUT. As such, the research should thus rather focus on using the TAM model which is much simpler than the UTAUT model as the difference in explanatory power (.843 for TAM and .815 for UTAUT) gives the edge to TAM.

The results emphasize the prevalence of Usefulness as determinant of welcoming service-robots adoption in both TAM and UTAUT regressions. Future studies on the subject should thus try to focus on this specific variable to assess the relevance of a model. Despite different variables in the two models, the effect of Usefulness was nonetheless by far the most powerful one.

Our results also showed that the effects of the variables result demonstrability, subjective norm, Self-efficacy, Gender, Experience and Ease of use were not significant in the regressions which could then raise the question of their relevance to assess the likelihood of adopting welcoming service-robot. We therefore suggest to researchers that are interesting in this topic to consider these variables as potentially inapplicable in this case. We should notice that some of these variables are overshadowed by the variable Usefulness. It could then be interesting to test more in depth in what extent these different variables are potential predictors of Usage intention in case of absence of Usefulness in the regression.

The comparison we made between the two well-known models of technology acceptance, TAM and UTAUT, is then a first step to have a perfect comprehension of the mechanism of acceptance in the case of welcoming service-robots. The regressions feature high explanatory power with .843 and .815 in TAM and UTAUT regressions, respectively. The TAM is then a good starting point for researchers that aim to unveil the underlying mechanism of customer technology acceptance. Its simplicity makes easy to add concepts on it and makes it easily understandable.

D. Limitations and suggestions for further research

The findings of this study can effectively guide future research. We first recommend that researchers interested into this subject use different acceptance theories whose the TAM and the UTAUT. Our results indeed showed that both are relevant to explore the acceptance determinants. The perceived humanness and the perceived automated social presence are both interesting factors to explore and could help to better understand the acceptance mechanism as suggesting by Wirtz et al. in their Service-robot acceptance model (2018).

Second, as discussed above, the focus should be put on the Usefulness as key mediator of the welcoming service-robot acceptance. We encourage researchers to explore this specific mediator. In particular, its relationship with the ease of use should be examined carefully. Our results did show that the Usefulness highly mediates the Ease of use mediator which raises questions about its relevance in the case of welcoming service-robots. The introduction of new variables such as the ones suggested above should allow researchers to deepen the understand of the usefulness.

Third, we led this study on a restricted population (i.e., Walloons). Future studies should then increase the scope and even test different populations to see whether or not cultural differences can be meaningful in such a topic. Indeed, the population Wallonia perhaps shares some characteristics that could therefore alter the results of the analyses we run. It would be interesting to see if that is the case. For instance, by testing both the Flemish's and Walloons to explore the potential cultural difference that could exist between both.

Fourth, the sampling method choice we made could potentially lead to some selection bias that are difficult to avoid. Indeed, people with some characteristics could have been more interesting in answering to our survey, making them more numerous in the dataset. We then encourage future researchers to try to get a solid survey base in order to use probabilistic sampling method such as the simple random sampling. It would be interesting to compare results on that base. They could lead to some other results that were not possible to discover in this study due to the potential biases.

Fifth, as we mentioned it in the pretest part. We added a picture of a welcoming service-robots as a visual example for people that answered to the survey. By doing so, however, we potentially created an anchoring bias as people had then in mind this specific representation of a welcoming service-robots which could potentially alter in some way the validity of the data we collected. Future studies on the subject should thus try to avoid that bias by using more pictures, presenting different welcoming service-robots, to reduce the occurrence of this bias.

Finally, our study made in contrast the two mediators. The relative importance of each one seems considerably different with a low importance for the Ease of use. It could be interesting for future researchers to see in what extent does it apply to every population. Some cultural differences may be at play which would therefore be a good source of knowledge if we were able to figure them out.

7. Appendices

A. Survey

Service-robots in banks

Hello !

My name is Julien Rossion. I am finishing my master at UNamur. For my master thesis, I am studying service-robot in the banking sector. In that goal, I collect insights from bank customers.

This survey only takes a few minutes to be completed, but it would be a great help for me if you could spend that time to complete it.

Please note that every information will be treated as confidential and will be use exclusively for this master thesis.

*Obligatoire

1. Do you have a bank account? *

Une seule réponse possible.

- Yes *Passer à la question 2*
- No *Passer à la question 18*

Banking habits

2. Do you manage your bank account by yourself or is it managed by someone else (for instance: your family)? *

Une seule réponse possible.

- I manage it by myself
- Someone else manage it for me

3. For what purpose(s) do you possess a bank account? *

Plusieurs réponses possibles.

- [ ] To receive my salary
- [ ] To put money in safety
- [ ] To spare money
- [ ] To invest money
- [ ] To have access to online payments and payments by card
- [ ] My parents created it for me

Autre : [ ] _____

4. Please tick the one that fits the best your habit *

Une seule réponse possible.

- I always go into an agency when I want to manage my bank account
- I always go online to manage my bank account
- I use every option depending on the situation

Passer à la question 5

Service-robots

Please let's now focus on service-robots. In the banking sector, service-robots can be used to welcome the customer and answer to his main concerns (physical "welcoming" robots and online chatbots) or to give him advices for his investments and even manage his portfolio (online robo-advisors).

In the following questions, please consider only the appearance of "welcoming" robots.

To avoid any misunderstanding, please note that "technology" refers to any kind of technology whereas "service-robots" relates to "welcoming" robots.

Example of a "welcoming" Service-robot: Pepper robot

5. In what extent do you agree with these statements? *

Une seule réponse possible par ligne.

	Totally disagree	Disagree	Rather disagree	Neutral	Rather agree	Agree	Totally agree
I already used service-robots in a different context							
I'm not accustomed with service-robots at all							
I regularly use service-robots in some context							

6. In what extent do you agree with these statements? *

Une seule réponse possible par ligne.

	Totally disagree	Disagree	Rather disagree	Neutral	Rather agree	Agree	Totally agree
I know how to make a good use of service-robots							
I'm not sure how to use service-robots							
The process seems clear for me							

7. In what extent do you agree with these statements? *

Une seule réponse possible par ligne.

	Totally disagree	Disagree	Rather disagree	Neutral	Rather agree	Agree	Totally agree
Service-robots are not compatible with my needs							
It doesn't suit me to use service-robots							
The use of service-robots is totally compatible with my lifestyle							

8. In what extent do you agree with these statements? *

Une seule réponse possible par ligne.

	Totally disagree	Disagree	Rather disagree	Neutral	Rather agree	Agree	Totally agree
Human contact in a bank is something I appreciate							
To talk with an employee is important for me							
I don't like to be observed by employees							

9. In what extent do you agree with these statements? *

Une seule réponse possible par ligne.

	Totally disagree	Disagree	Rather disagree	Neutral	Rather agree	Agree	Totally agree
I always think before giving any personal data via technology							
Technology performance is very unreliable							
I don't think the online systems are completely secured							
I doubt service-robots can improve banking services							

10. In what extent do you agree with these statements? *

Une seule réponse possible par ligne.

	Totally disagree	Disagree	Rather disagree	Neutral	Rather agree	Agree	Totally agree
I always test a technology before adopting it							
I don't need to test a technology to know whether or not it suits me							
To see someone use the technology is enough to make my opinion on this technology							

11. In what extent do you agree with these statements? *

Une seule réponse possible par ligne.

	Totally disagree	Disagree	Rather disagree	Neutral	Rather agree	Agree	Totally agree
I always use the latest technology available							
I am always skeptical about new technologies							
I don't change of technology before the one I use is completely obsolete							

12. In what extent do you agree with these statements? *

Une seule réponse possible par ligne.

	Totally disagree	Disagree	Rather disagree	Neutral	Rather agree	Agree	Totally agree
I don't feel at ease when I use technology							
If possible, I prefer not using technology because it is not reliable							
Using technology is intuitive, for me							

13. In what extent do you agree with these statements? *

Une seule réponse possible par ligne.

	Totally disagree	Disagree	Rather disagree	Neutral	Rather agree	Agree	Totally agree
Use service-robots would allow me to save time							
The service-robots would increase the overall service-quality							
Service-robots would be a great addition							
I don't think service-robots make sense in bank agencies							

14. In what extent do you agree with these statements? *

Une seule réponse possible par ligne.

	Totally disagree	Disagree	Rather disagree	Neutral	Rather agree	Agree	Totally agree
Seeing that everyone in my relatives use a technology except me makes me feel bad							
I don't like using the same technology as everyone							
I use the technology that a relative recommends me							

15. In what extent do you agree with these statements? *

Une seule réponse possible par ligne.

	Totally disagree	Disagree	Rather disagree	Neutral	Rather agree	Agree	Totally agree
The advantages of using a specific technology must be clearly shown before I consider using it							
I don't pay much attention to the advantages of a technology							
Disadvantages are important in a technology adoption							

16. In what extent do you agree with these statements? *

Une seule réponse possible par ligne.

	Totally disagree	Disagree	Rather disagree	Neutral	Rather agree	Agree	Totally agree
Learning to use a service-robot is easy for me							
It would be easy to use a service-robot for me							
I wouldn't make a good use of service-robots							

17. In what extent do you agree with these statements? *

Une seule réponse possible par ligne.

	Totally disagree	Disagree	Rather disagree	Neutral	Rather agree	Agree	Totally agree
I will never use service-robots, human interactions prevail							
I don't think service-robots are great for me							
I will recommend my relatives to not use service-robots							
I'm opposed to the introduction of service-robots							

Passer à la question 19

Demographics

Before leaving you, I just need some pieces of information about yourself.

19. What is your gender? *

Une seule réponse possible.

- Male
- Female

20. In which age category are you? *

Une seule réponse possible.

- <18
- 18-23
- 24-29
- 30-39
- 40-49
- 50-59
- 60-69
- >69

21. What correspond to your current situation? *

Une seule réponse possible.

- Student
- Employed
- Independent
- Unemployed
- Retired

B. Variable description

Frequencies

Statistics

		Age	Gender	What correspond to your current situation?	Do you have a bank account?	Do you manage your bank account by yourself or is it managed by someone else (for instance: your family)?
N	Valid	283	283	283	283	283
	Missing	0	0	0	0	0

Frequency Table

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	<18	15	5,3	5,3	5,3
	>69	27	9,5	9,5	14,8
	18-23	40	14,1	14,1	29,0
	24-29	46	16,3	16,3	45,2
	30-39	45	15,9	15,9	61,1
	40-49	45	15,9	15,9	77,0
	50-59	33	11,7	11,7	88,7
	60-69	32	11,3	11,3	100,0
	Total	283	100,0	100,0	

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	145	51,2	51,2	51,2
	Male	138	48,8	48,8	100,0
	Total	283	100,0	100,0	

What correspond to your current situation?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Employed	114	40,3	40,3	40,3
	Independent	15	5,3	5,3	45,6
	Retired	61	21,6	21,6	67,1
	Student	87	30,7	30,7	97,9
	Unemployed	6	2,1	2,1	100,0
	Total	283	100,0	100,0	

Do you have a bank account?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	283	100,0	100,0	100,0

Do you manage your bank account by yourself or is it managed by someone else (for instance: your family)?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	I manage it by myself	259	91,5	91,5	91,5
	Someone else manage it for me	24	8,5	8,5	100,0

Total	283	100,0	100,0	

C. EFA analysis

a. Experience

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,657
Bartlett's Test of Sphericity	Approx. Chi-Square	182,816
	df	3
	Sig.	,000

Correlation Matrix

		I already used service-robots in a different context	I'm not accustomed with service-robots at all	I regularly use service-robots in some context
Sig. (1-tailed)	I already used service-robots in a different context		,000	,000
	I'm not accustomed with service-robots at all	,000		,000
	I regularly use service-robots in some context	,000	,000	

Communalities

	Initial	Extraction
I already used service-robots in a different context	,379	,610
I'm not accustomed with service-robots at all	,217	,295
I regularly use service-robots in some context	,364	,549

Extraction Method: Principal Axis Factoring.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1,941	64,714	64,714	1,454	48,455	48,455
2	,639	21,284	85,998			

3	,420	14,002	100,000			

Extraction Method: Principal Axis Factoring.

Factor Matrix[a]

	Factor 1
I already used service-robots in a different context	,781
I'm not accustomed with service-robots at all	,543
I regularly use service-robots in some context	,741

Extraction Method: Principal Axis Factoring.[a]

a. 1 factors extracted. 11 iterations required.

b. Self-efficacy

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,723
Bartlett's Test of Sphericity	Approx. Chi-Square	428,974
	df	3
	Sig.	,000

Correlation Matrix

		I know how to make a good use of service-robots	I'm not sure how to use service-robots	The process seems clear for me
Sig. (1-tailed)	I know how to make a good use of service-robots		,000	,000
	I'm not sure how to use service-robots	,000		,000
	The process seems clear for me	,000	,000	

Communalities

	Initial	Extraction
I know how to make a good use of service-robots	,644	,834
I'm not sure how to use service-robots	,556	,640
The process seems clear for me	,536	,614

Extraction Method: Principal Axis Factoring.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,383	79,440	79,440	2,088	69,606	69,606
2	,374	12,479	91,919			
3	,242	8,081	100,000			

Extraction Method: Principal Axis Factoring.

Factor Matrix[a]

	Factor 1
I know how to make a good use of service-robots	,913
I'm not sure how to use service-robots	,800
The process seems clear for me	,784

Extraction Method: Principal Axis Factoring.[a]

a. 1 factors extracted. 12 iterations required.

c. Anxiety

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,676
Bartlett's Test of Sphericity	Approx. Chi-Square	268,496
	df	3

Sig.	,000

Correlation Matrix

		I don't feel at ease when I use technology	If possible, I prefer not using technology because it is not reliable	Using technology is intuitive, for me
Sig. (1-tailed)	I don't feel at ease when I use technology		,000	,000
	If possible, I prefer not using technology because it is not reliable	,000		,000
	Using technology is intuitive, for me	,000	,000	

Communalities

	Initial	Extraction
I don't feel at ease when I use technology	,512	,791
If possible, I prefer not using technology because it is not reliable	,435	,532
Using technology is intuitive, for me	,337	,405

Extraction Method: Principal Axis Factoring.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,123	70,768	70,768	1,728	57,613	57,613
2	,546	18,209	88,977			
3	,331	11,023	100,000			

Extraction Method: Principal Axis Factoring.

Factor Matrix[a]

Factor
1

I don't feel at ease when I use technology	,889
If possible, I prefer not using technology because it is not reliable	,729
Using technology is intuitive, for me	,637

Extraction Method: Principal Axis Factoring.[a]

a. 1 factors extracted. 16 iterations required.

d. Usefulness

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,812
Bartlett's Test of Sphericity	Approx. Chi-Square	613,825
	df	6
	Sig.	,000

Correlation Matrix

		Use service-robots would allow me to save time	The service-robots would increase the overall service-quality	Service-robots would be a great addition
Sig. (1-tailed)	Use service-robots would allow me to save time		,000	,000
	The service-robots would increase the overall service-quality	,000		,000
	Service-robots would be a great addition	,000	,000	
	I don't think service-robots make sense in bank agencies	,000	,000	,000

Correlation Matrix

	I don't think service-robots make sense in bank agencies

Sig. (1-tailed)	Use service-robots would allow me to save time	,000
	The service-robots would increase the overall service-quality	,000
	Service-robots would be a great addition	,000
	I don't think service-robots make sense in bank agencies	

Communalities

	Initial	Extraction
Use service-robots would allow me to save time	,534	,592
The service-robots would increase the overall service-quality	,654	,765
Service-robots would be a great addition	,671	,781
I don't think service-robots make sense in bank agencies	,421	,462

Extraction Method: Principal Axis Factoring.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,930	73,251	73,251	2,600	65,009	65,009
2	,510	12,739	85,990			
3	,342	8,550	94,540			
4	,218	5,460	100,000			

Extraction Method: Principal Axis Factoring.

Factor Matrix[a]

	Factor 1
Use service-robots would allow me to save time	,769
The service-robots would increase the overall service-quality	,875

Service-robots would be a great addition	,884
I don't think service-robots make sense in bank agencies	,680

Extraction Method: Principal Axis Factoring.[a]

a. 1 factors extracted. 6 iterations required.

e. Subjective norm

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,682
Bartlett's Test of Sphericity	Approx. Chi-Square	223,272
	df	3
	Sig.	,000

Correlation Matrix

		Seeing that everyone in my relatives use a technology except me makes me feel bad	I don't like using the same technology as everyone	I use the technology that a relative recommends me
Sig. (1-tailed)	Seeing that everyone in my relatives use a technology except me makes me feel bad		,000	,000
	I don't like using the same technology as everyone	,000		,000
	I use the technology that a relative recommends me	,000	,000	

Communalities

	Initial	Extraction
Seeing that everyone in my relatives use a technology except me makes me feel bad	,317	,417

I don't like using the same technology as everyone	,367	,493
I use the technology that a relative recommends me	,433	,689

Extraction Method: Principal Axis Factoring.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,050	68,320	68,320	1,598	53,278	53,278
2	,552	18,402	86,722			
3	,398	13,278	100,000			

Extraction Method: Principal Axis Factoring.

Factor Matrix[a]

	Factor 1
Seeing that everyone in my relatives use a technology except me makes me feel bad	,645
I don't like using the same technology as everyone	,702
I use the technology that a relative recommends me	,830

Extraction Method: Principal Axis Factoring.[a]

a. 1 factors extracted. 14 iterations required.

f. Result demonstrability

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,672
Bartlett's Test of Sphericity	Approx. Chi-Square	157,353
	df	3
	Sig.	,000

Correlation Matrix

		The advantages of using a specific technology must be clearly shown before I consider using it	I don't pay much attention to the advantages of a technology	Disadvantages are important in a technology adoption
Sig. (1-tailed)	The advantages of using a specific technology must be clearly shown before I consider using it		,000	,000
	I don't pay much attention to the advantages of a technology	,000		,000
	Disadvantages are important in a technology adoption	,000	,000	

Communalities

	Initial	Extraction
The advantages of using a specific technology must be clearly shown before I consider using it	,318	,549
I don't pay much attention to the advantages of a technology	,264	,402
Disadvantages are important in a technology adoption	,268	,410

Extraction Method: Principal Axis Factoring.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1,901	63,357	63,357	1,361	45,355	45,355
2	,595	19,843	83,200			
3	,504	16,800	100,000			

Extraction Method: Principal Axis Factoring.

Factor Matrix[a]

	Factor 1
The advantages of using a specific technology must be clearly shown before I consider using it	,741
I don't pay much attention to the advantages of a technology	,634
Disadvantages are important in a technology adoption	,640

Extraction Method: Principal Axis Factoring.[a]

a. 1 factors extracted. 11 iterations required.

g. Ease of use

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,739
Bartlett's Test of Sphericity	Approx. Chi-Square	655,953
	df	3
	Sig.	,000

Correlation Matrix

		Learning to use a service-robot is easy for me	It would be easy to use a service-robot for me	I wouldn't make a good use of service-robots
Sig. (1-tailed)	Learning to use a service-robot is easy for me		,000	,000
	It would be easy to use a service-robot for me	,000		,000
	I wouldn't make a good use of service-robots	,000	,000	

Communalities

	Initial	Extraction

Learning to use a service-robot is easy for me	,753	,819
It would be easy to use a service-robot for me	,785	,903
I wouldn't make a good use of service-robots	,630	,675

Extraction Method: Principal Axis Factoring.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,591	86,359	86,359	2,397	79,908	79,908
2	,273	9,114	95,473			
3	,136	4,527	100,000			

Extraction Method: Principal Axis Factoring.

Factor Matrix[a]

	Factor 1
Learning to use a service-robot is easy for me	,905
It would be easy to use a service-robot for me	,950
I wouldn't make a good use of service-robots	,822

Extraction Method: Principal Axis Factoring.[a]

a. 1 factors extracted. 9 iterations required.

h. Usage intention

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,781
Bartlett's Test of Sphericity	Approx. Chi-Square	663,583
	df	6
	Sig.	,000

Correlation Matrix

		I will never use service-robots, human interactions prevail	I don't think service-robots are great for me	I will recommend my relatives to not use service-robots
Sig. (1-tailed)	I will never use service-robots, human interactions prevail		,000	,000
	I don't think service-robots are great for me	,000		,000
	I will recommend my relatives to not use service-robots	,000	,000	
	I'm opposed to the introduction of service-robots	,000	,000	,000

Correlation Matrix

		I'm opposed to the introduction of service-robots
Sig. (1-tailed)	I will never use service-robots, human interactions prevail	,000
	I don't think service-robots are great for me	,000
	I will recommend my relatives to not use service-robots	,000
	I'm opposed to the introduction of service-robots	

Communalities

	Initial	Extraction
I will never use service-robots, human interactions prevail	,685	,769
I don't think service-robots are great for me	,658	,679
I will recommend my relatives to not use service-robots	,475	,477
I'm opposed to the introduction of service-robots	,620	,715

Extraction Method: Principal Axis Factoring.

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,966	74,138	74,138	2,640	65,996	65,996
2	,547	13,681	87,819			
3	,286	7,158	94,977			
4	,201	5,023	100,000			

Extraction Method: Principal Axis Factoring.

Factor Matrix[a]

	Factor 1
I will never use service-robots, human interactions prevail	,877
I don't think service-robots are great for me	,824
I will recommend my relatives to not use service-robots	,691
I'm opposed to the introduction of service-robots	,846

Extraction Method: Principal Axis Factoring.[a]

a. 1 factors extracted. 6 iterations required.

D. Cronbach analysis

a. Experience

Reliability

Case Processing Summary

		N	%
Cases	Valid	283	100,0
	Excluded[a]	0	,0
	Total	283	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,720	,725	3

Item Statistics

	Mean	Std. Deviation	N
I already used service-robots in a different context	3,07	1,736	283
I'm not accustomed with service-robots at all	3,48	1,850	283
I regularly use service-robots in some context	2,57	1,557	283

Inter-Item Correlation Matrix

	I already used service-robots in a different context	I'm not accustomed with service-robots at all	I regularly use service-robots in some context
I already used service-robots in a different context	1,000	,425	,579
I'm not accustomed with service-robots at all	,425	1,000	,401
I regularly use service-robots in some context	,579	,401	1,000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation
I already used service-robots in a different context	6,06	8,153	,591	,379
I'm not accustomed with service-robots at all	5,64	8,565	,465	,217

I regularly use service-robots in some context	6,55	9,163	,577	,364

Item-Total Statistics

	Cronbach's Alpha if Item Deleted
I already used service-robots in a different context	,566
I'm not accustomed with service-robots at all	,731
I regularly use service-robots in some context	,596

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
9,12	17,024	4,126	3

b. Self-efficacy

Reliability

Case Processing Summary

		N	%
Cases	Valid	283	100,0
	Excluded[a]	0	,0
	Total	283	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,869	,870	3

Item Statistics

	Mean	Std. Deviation	N
I know how to make a good use of service-robots	3,65	1,537	283
I'm not sure how to use service-robots	3,88	1,607	283

The process seems clear for me	3,82	1,618	283

Inter-Item Correlation Matrix

	I know how to make a good use of service-robots	I'm not sure how to use service-robots	The process seems clear for me
I know how to make a good use of service-robots	1,000	,731	,716
I'm not sure how to use service-robots	,731	1,000	,626
The process seems clear for me	,716	,626	1,000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation
I know how to make a good use of service-robots	7,70	8,452	,802	,644
I'm not sure how to use service-robots	7,47	8,541	,731	,556
The process seems clear for me	7,53	8,555	,720	,536

Item-Total Statistics

	Cronbach's Alpha if Item Deleted
I know how to make a good use of service-robots	,770
I'm not sure how to use service-robots	,834
The process seems clear for me	,844

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
11,35	17,987	4,241	3

c. Anxiety

Reliability

Case Processing Summary

		N	%
Cases	Valid	283	100,0
	Excluded[a]	0	,0
	Total	283	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,793	,792	3

Item Statistics

	Mean	Std. Deviation	N
I don't feel at ease when I use technology	3,07	1,538	283
If possible, I prefer not using technology because it is not reliable	3,22	1,560	283
Using technology is intuitive, for me	3,28	1,391	283

Inter-Item Correlation Matrix

	I don't feel at ease when I use technology	If possible, I prefer not using technology because it is not reliable	Using technology is intuitive, for me
I don't feel at ease when I use technology	1,000	,649	,567
If possible, I prefer not using technology because it is not reliable	,649	1,000	,463
Using technology is intuitive, for me	,567	,463	1,000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation
I don't feel at ease when I use technology	6,50	6,379	,713	,512
If possible, I prefer not using technology because it is not reliable	6,36	6,727	,633	,435
Using technology is intuitive, for me	6,29	7,917	,567	,337

Item-Total Statistics

	Cronbach's Alpha if Item Deleted
I don't feel at ease when I use technology	,630
If possible, I prefer not using technology because it is not reliable	,721
Using technology is intuitive, for me	,787

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
9,58	14,288	3,780	3

d. Usefulness

Reliability

Case Processing Summary

		N	%
Cases	Valid	283	100,0
	Excluded[a]	0	,0
	Total	283	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,870	,877	4

Item Statistics

	Mean	Std. Deviation	N
Use service-robots would allow me to save time	4,13	1,375	283
The service-robots would increase the overall service-quality	3,93	1,359	283
Service-robots would be a great addition	4,10	1,268	283
I don't think service-robots make sense in bank agencies	4,13	1,627	283

Inter-Item Correlation Matrix

	Use service-robots would allow me to save time	The service-robots would increase the overall service-quality	Service-robots would be a great addition	I don't think service-robots make sense in bank agencies
Use service-robots would allow me to save time	1,000	,651	,707	,517
The service-robots would increase the overall service-quality	,651	1,000	,770	,625
Service-robots would be a great addition	,707	,770	1,000	,576
I don't think service-robots make sense in bank agencies	,517	,625	,576	1,000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation
Use service-robots would allow me to save time	12,16	13,895	,703	,534
The service-robots would increase the overall service-quality	12,37	13,297	,792	,654
Service-robots would be a great addition	12,20	13,890	,793	,671

I don't think service-robots make sense in bank agencies	12,16	12,888	,638	,421

Item-Total Statistics

	Cronbach's Alpha if Item Deleted
Use service-robots would allow me to save time	,841
The service-robots would increase the overall service-quality	,807
Service-robots would be a great addition	,811
I don't think service-robots make sense in bank agencies	,878

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
16,30	22,990	4,795	4

e. Subjective norm

Reliability

Case Processing Summary

		N	%
Cases	Valid	283	100,0
	Excluded[a]	0	,0
	Total	283	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,764	,768	3

Item Statistics

	Mean	Std. Deviation	N

Seeing that everyone in my relatives use a technology except me makes me feel bad	3,52	1,627	283
I don't like using the same technology as everyone	4,27	1,495	283
I use the technology that a relative recommends me	4,39	1,425	283

Inter-Item Correlation Matrix

	Seeing that everyone in my relatives use a technology except me makes me feel bad	I don't like using the same technology as everyone	I use the technology that a relative recommends me
Seeing that everyone in my relatives use a technology except me makes me feel bad	1,000	,452	,536
I don't like using the same technology as everyone	,452	1,000	,583
I use the technology that a relative recommends me	,536	,583	1,000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation
Seeing that everyone in my relatives use a technology except me makes me feel bad	8,66	6,751	,554	,317
I don't like using the same technology as everyone	7,90	7,167	,585	,367
I use the technology that a relative recommends me	7,79	7,083	,655	,433

Item-Total Statistics

	Cronbach's Alpha if Item Deleted
Seeing that everyone in my relatives use a technology except me makes me feel bad	,736

I don't like using the same technology as everyone	,694
I use the technology that a relative recommends me	,621

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
12,17	14,087	3,753	3

f. Result demonstrability

Reliability

Case Processing Summary

		N	%
Cases	Valid	283	100,0
	Excluded[a]	0	,0
	Total	283	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,707	,711	3

Item Statistics

	Mean	Std. Deviation	N
The advantages of using a specific technology must be clearly shown before I consider using it	5,38	1,086	283
I don't pay much attention to the advantages of a technology	5,18	1,255	283
Disadvantages are important in a technology adoption	5,01	1,100	283

Inter-Item Correlation Matrix

	The advantages of using a specific technology must be clearly shown before I consider using it	I don't pay much attention to the advantages of a technology	Disadvantages are important in a technology adoption
The advantages of using a specific technology must be clearly shown before I consider using it	1,000	,470	,475
I don't pay much attention to the advantages of a technology	,470	1,000	,405
Disadvantages are important in a technology adoption	,475	,405	1,000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation
The advantages of using a specific technology must be clearly shown before I consider using it	10,19	3,900	,563	,318
I don't pay much attention to the advantages of a technology	10,39	3,522	,509	,264
Disadvantages are important in a technology adoption	10,56	4,035	,509	,268

Item-Total Statistics

	Cronbach's Alpha if Item Deleted
The advantages of using a specific technology must be clearly shown before I consider using it	,573
I don't pay much attention to the advantages of a technology	,644
Disadvantages are important in a technology adoption	,635

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
15,57	7,494	2,738	3

g. Ease of use

Reliability

Case Processing Summary

		N	%
Cases	Valid	283	100,0
	Excluded[a]	0	,0
	Total	283	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,921	,921	3

Item Statistics

	Mean	Std. Deviation	N
Learning to use a service-robot is easy for me	4,57	1,499	283
It would be easy to use a service-robot for me	4,49	1,540	283
I wouldn't make a good use of service-robots	4,42	1,393	283

Inter-Item Correlation Matrix

	Learning to use a service-robot is easy for me	It would be easy to use a service-robot for me	I wouldn't make a good use of service-robots
Learning to use a service-robot is easy for me	1,000	,860	,743
It would be easy to use a service-robot for me	,860	1,000	,781
I wouldn't make a good use of service-robots	,743	,781	1,000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation
Learning to use a service-robot is easy for me	8,91	7,662	,852	,753
It would be easy to use a service-robot for me	8,99	7,287	,881	,785
I wouldn't make a good use of service-robots	9,06	8,589	,791	,630

Item-Total Statistics

	Cronbach's Alpha if Item Deleted
Learning to use a service-robot is easy for me	,875
It would be easy to use a service-robot for me	,851
I wouldn't make a good use of service-robots	,925

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
13,48	16,981	4,121	3

h. Usage intention

Reliability

Case Processing Summary

		N	%
Cases	Valid	283	100,0
	Excluded[a]	0	,0
	Total	283	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,882	,883	4

Item Statistics

	Mean	Std. Deviation	N
I will never use service-robots, human interactions prevail	4,13	1,583	283
I don't think service-robots are great for me	4,02	1,684	283
I will recommend my relatives to not use service-robots	4,75	1,276	283
I'm opposed to the introduction of service-robots	4,74	1,549	283

Inter-Item Correlation Matrix

	I will never use service-robots, human interactions prevail	I don't think service-robots are great for me	I will recommend my relatives to not use service-robots	I'm opposed to the introduction of service-robots
I will never use service-robots, human interactions prevail	1,000	,790	,584	,694
I don't think service-robots are great for me	,790	1,000	,506	,678
I will recommend my relatives to not use service-robots	,584	,506	1,000	,668
I'm opposed to the introduction of service-robots	,694	,678	,668	1,000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation
I will never use service-robots, human interactions prevail	13,51	15,215	,808	,685
I don't think service-robots are great for me	13,62	14,938	,762	,658
I will recommend my relatives to not use service-robots	12,89	18,897	,647	,475

I'm opposed to the introduction of service-robots	12,90	15,718	,780	,620

Item-Total Statistics

	Cronbach's Alpha if Item Deleted
I will never use service-robots, human interactions prevail	,823
I don't think service-robots are great for me	,844
I will recommend my relatives to not use service-robots	,885
I'm opposed to the introduction of service-robots	,835

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
17,64	27,698	5,263	4

E. Correlation analysis

Correlations

Descriptive Statistics

	Mean	Std. Deviation	N
Usage Intention	4,4108	1,31573	283
Usefulness	4,0742	1,19869	283
Ease of Use	4,4935	1,37360	283
Experience	3,0412	1,37532	283
Self-Efficacy	3,7833	1,41371	283
Anxiety	3,1920	1,25997	283
Subjective Norm	4,0577	1,25109	283
Result Demonstrability	5,1908	,90860	283
Gender	,49	,501	283
Age Category	4,51	2,032	283
Banking Habit	1,60	,657	283

Correlations

		Usage Intention	Usefulness	Ease of Use	Experience	Self-Efficacy
Usage Intention	Pearson Correlation	--				
	N	283				
Usefulness	Pearson Correlation	,840**	--			
	Sig. (2-tailed)	,000				
	N	283	283			
Ease of Use	Pearson Correlation	,425**	,412**	--		
	Sig. (2-tailed)	,000	,000			
	N	283	283	283		
Experience	Pearson Correlation	,372**	,385**	,377**	--	
	Sig. (2-tailed)	,000	,000	,000		
	N	283	283	283	283	
Self-Efficacy	Pearson Correlation	,358**	,347**	,638**	,567**	--
	Sig. (2-tailed)	,000	,000	,000	,000	
	N	283	283	283	283	283
Anxiety	Pearson Correlation	-,542**	-,452**	-,541**	-,264**	-,428**
	Sig. (2-tailed)	,000	,000	,000	,000	,000
	N	283	283	283	283	283
Subjective Norm	Pearson Correlation	,013	,073	,078	,006	,055
	Sig. (2-tailed)	,832	,222	,192	,924	,357
	N	283	283	283	283	283

Result Demonstrability	Pearson Correlation	-,089	-,078	-,116	-,233**	-,236**
	Sig. (2-tailed)	,136	,191	,050	,000	,000
	N	283	283	283	283	283
Gender	Pearson Correlation	,142*	,139*	,054	,093	,180**
	Sig. (2-tailed)	,017	,019	,361	,120	,002
	N	283	283	283	283	283
Age Category	Pearson Correlation	-,330**	-,245**	-,436**	-,140*	-,358**
	Sig. (2-tailed)	,000	,000	,000	,019	,000
	N	283	283	283	283	283
Banking Habit	Pearson Correlation	-,385**	-,220**	-,467**	-,250**	-,364**
	Sig. (2-tailed)	,000	,000	,000	,000	,000
	N	283	283	283	283	283

Correlations

		Anxiety	Subjective Norm	Result Demonstrability	Gender
Usage Intention	Pearson Correlation				
	N				
Usefulness	Pearson Correlation				
	Sig. (2-tailed)				
	N				
Ease of Use	Pearson Correlation				

	Sig. (2-tailed)				
	N				
Experience	Pearson Correlation				
	Sig. (2-tailed)				
	N				
Self-Efficacy	Pearson Correlation				
	Sig. (2-tailed)				
	N				
Anxiety	Pearson Correlation	--			
	Sig. (2-tailed)				
	N	283			
Subjective Norm	Pearson Correlation	-,107	--		
	Sig. (2-tailed)	,072			
	N	283	283		
Result Demonstrability	Pearson Correlation	,087	,131*	--	
	Sig. (2-tailed)	,143	,028		
	N	283	283	283	
Gender	Pearson Correlation	-,113	-,064	,003	--
	Sig. (2-tailed)	,057	,284	,965	
	N	283	283	283	283
Age Category	Pearson Correlation	,518**	,072	,247**	,027
	Sig. (2-tailed)	,000	,230	,000	,650

	N	283	283	283	283
Banking Habit	Pearson Correlation	,519**	-,099	,131*	-,036
	Sig. (2-tailed)	,000	,098	,028	,541
	N	283	283	283	283

Correlations

		Age Category	Banking Habit
Usage Intention	Pearson Correlation		
	N		
Usefulness	Pearson Correlation		
	Sig. (2-tailed)		
	N		
Ease of Use	Pearson Correlation		
	Sig. (2-tailed)		
	N		
Experience	Pearson Correlation		
	Sig. (2-tailed)		
	N		
Self-Efficacy	Pearson Correlation		
	Sig. (2-tailed)		
	N		
Anxiety	Pearson Correlation		
	Sig. (2-tailed)		
	N		
Subjective Norm	Pearson Correlation		
	Sig. (2-tailed)		

	N		
Result Demonstrability	Pearson Correlation		
	Sig. (2-tailed)		
	N		
Gender	Pearson Correlation		
	Sig. (2-tailed)		
	N		
Age Category	Pearson Correlation	--	
	Sig. (2-tailed)		
	N	283	
Banking Habit	Pearson Correlation	,420**	--
	Sig. (2-tailed)	,000	
	N	283	283

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

*. Correlation is significant at the 0.05 level (2-tailed).

F. Mediator analysis

a. Usefulness

1. Subjective norm

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : UsageInt
    X  : SubjNorm
    M  : Usefulne

Sample
Size:  283
```

```
**************************************************************************
OUTCOME VARIABLE:
 Usefulne

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,0728      ,0053     1,4343     1,4972     1,0000   281,0000      ,2221

Model
              coeff         se          t          p       LLCI       ULCI
constant     3,7912      ,2420    15,6649      ,0000     3,3148     4,2676
SubjNorm      ,0698      ,0570     1,2236      ,2221     -,0425      ,1820

Standardized coefficients
              coeff
SubjNorm      ,0728

**************************************************************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,8409      ,7071      ,5106   338,0173     2,0000   280,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,8486      ,1976     4,2934      ,0000      ,4595     1,2376
SubjNorm     -,0512      ,0341    -1,5024      ,1341     -,1184      ,0159
Usefulne      ,9254      ,0356    25,9977      ,0000      ,8553      ,9954

Standardized coefficients
              coeff
SubjNorm     -,0487
Usefulne      ,8430

************************** TOTAL EFFECT MODEL ****************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,0127      ,0002     1,7370      ,0450     1,0000   281,0000      ,8322

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,3568      ,2663    16,3583      ,0000     3,8325     4,8810
SubjNorm      ,0133      ,0627      ,2121      ,8322     -,1102      ,1368

Standardized coefficients
              coeff
SubjNorm      ,0127

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI       c_ps
c_cs
      ,0133      ,0627      ,2121      ,8322
-,1102      ,1368      ,0101      ,0127

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI      c'_ps
c'_cs
     -,0512      ,0341    -1,5024      ,1341     -,1184      ,0159     -,0389
-,0487
```

```
Indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
Usefulne      ,0645      ,0644     -,0597      ,1869

Partially standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
Usefulne      ,0491      ,0489     -,0439      ,1418

Completely standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
Usefulne      ,0614      ,0609     -,0535      ,1790

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

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  1000

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

2. Self-efficacy

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : UsageInt
    X  : SelfEffi
    M  : Usefulne

Sample
Size:  283

**************************************************************************
OUTCOME VARIABLE:
 Usefulne

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3473      ,1206     1,2680    38,5433     1,0000   281,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,9601      ,1915    15,4550      ,0000     2,5831     3,3371
SelfEffi      ,2945      ,0474     6,2083      ,0000      ,2011      ,3878

Standardized coefficients
              coeff
SelfEffi      ,3473
```

```
**************************************************************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,8425      ,7098      ,5060   342,4326     2,0000   280,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,5075      ,1646     3,0840      ,0022      ,1836      ,8314
SelfEffi      ,0705      ,0320     2,2055      ,0282      ,0076      ,1334
Usefulne      ,8926      ,0377    23,6876      ,0000      ,8184      ,9668

Standardized coefficients
              coeff
SelfEffi      ,0757
Usefulne      ,8132

************************** TOTAL EFFECT MODEL ****************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3581      ,1283     1,5145    41,3471     1,0000   281,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3,1497      ,2093    15,0477      ,0000     2,7377     3,5617
SelfEffi      ,3333      ,0518     6,4302      ,0000      ,2313      ,4354

Standardized coefficients
              coeff
SelfEffi      ,3581

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI       c_ps
c_cs
      ,3333      ,0518
6,4302      ,0000      ,2313      ,4354      ,2533      ,3581

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI      c'_ps
c'_cs
      ,0705      ,0320
2,2055      ,0282      ,0076      ,1334      ,0536      ,0757

Indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
Usefulne      ,2629      ,0450      ,1742      ,3500

Partially standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
Usefulne      ,1998      ,0328      ,1339      ,2598

Completely standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
Usefulne      ,2824      ,0457      ,1884      ,3674

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

Level of confidence for all confidence intervals in output:
  95,0000
```

```
Number of bootstrap samples for percentile bootstrap confidence intervals:
  1000

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

3. Anxiety

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : UsageInt
    X  : Anxiety
    M  : Usefulne

Sample
Size:  283

**************************************************************************
OUTCOME VARIABLE:
 Usefulne

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,4519      ,2042     1,1476    72,0924     1,0000   281,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     5,4464      ,1737    31,3548      ,0000     5,1045     5,7883
Anxiety      -,4299      ,0506    -8,4907      ,0000     -,5295     -,3302

Standardized coefficients
             coeff
Anxiety     -,4519

**************************************************************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,8590      ,7380      ,4569   394,2622     2,0000   280,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1,7499      ,2325     7,5278      ,0000     1,2923     2,2076
Anxiety      -,2133      ,0358    -5,9555      ,0000     -,2838     -,1428
Usefulne      ,8202      ,0376    21,7896      ,0000      ,7461      ,8943

Standardized coefficients
              coeff
Anxiety      -,2042
```

```
Usefulne      ,7472

************************* TOTAL EFFECT MODEL ***************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5419      ,2936     1,2272   116,8022     1,0000   281,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     6,2170      ,1796    34,6100      ,0000     5,8634     6,5706
Anxiety      -,5658      ,0524   -10,8075      ,0000     -,6689     -,4628

Standardized coefficients
             coeff
Anxiety     -,5419

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI       c_ps
c_cs
     -,5658      ,0524   -10,8075      ,0000     -,6689     -,4628     -,4301
-,5419

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI      c'_ps
c'_cs
     -,2133      ,0358    -5,9555      ,0000     -,2838     -,1428     -,1621
-,2042

Indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
Usefulne     -,3526      ,0419     -,4320     -,2711

Partially standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
Usefulne     -,2680      ,0291     -,3227     -,2123

Completely standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
Usefulne     -,3376      ,0390     -,4102     -,2578

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

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  1000

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

4. Result demonstrability

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : UsageInt
    X  : ResultDe
    M  : Usefulne

Sample
Size:  283

**************************************************************************
OUTCOME VARIABLE:
 Usefulne

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,0779      ,0061     1,4332     1,7153     1,0000   281,0000      ,1914

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,6076      ,4135    11,1443      ,0000     3,7938     5,4215
ResultDe     -,1028      ,0785    -1,3097      ,1914     -,2572      ,0517

Standardized coefficients
              coeff
ResultDe     -,0779

**************************************************************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,8398      ,7053      ,5138   335,0805     2,0000   280,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,8416      ,2973     2,8313      ,0050      ,2565     1,4268
ResultDe     -,0341      ,0471     -,7233      ,4701     -,1268      ,0587
Usefulne      ,9195      ,0357    25,7424      ,0000      ,8492      ,9898

Standardized coefficients
              coeff
ResultDe     -,0235
Usefulne      ,8377

************************** TOTAL EFFECT MODEL ****************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,0888      ,0079     1,7236     2,2327     1,0000   281,0000      ,1362

Model
              coeff         se          t          p       LLCI       ULCI
```

```
constant     5,0782      ,4534    11,2000      ,0000     4,1857     5,9707
ResultDe     -,1286      ,0860    -1,4942      ,1362     -,2979      ,0408

Standardized coefficients
              coeff
ResultDe     -,0888

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI       c_ps
c_cs
     -,1286      ,0860    -1,4942      ,1362     -,2979      ,0408     -,0977
-,0888

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI      c'_ps
c'_cs
     -,0341      ,0471     -,7233      ,4701     -,1268      ,0587     -,0259
-,0235

Indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
Usefulne     -,0945      ,0671     -,2357      ,0379

Partially standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
Usefulne     -,0718      ,0511     -,1793      ,0278

Completely standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
Usefulne     -,0652      ,0456     -,1602      ,0250

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

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  1000

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

5. Ease of use

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : UsageInt
    X  : EaseofUs
    M  : Usefulne
```

```
Sample
Size:  283

**************************************************************************
OUTCOME VARIABLE:
 Usefulne

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,4122      ,1699     1,1970    57,5129     1,0000   281,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,4579      ,2228    11,0302      ,0000     2,0193     2,8965
EaseofUs      ,3597      ,0474     7,5837      ,0000      ,2663      ,4531

Standardized coefficients
              coeff
EaseofUs      ,4122

**************************************************************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,8440      ,7123      ,5016   346,5906     2,0000   280,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,4223      ,1727     2,4453      ,0151      ,0823      ,7622
EaseofUs      ,0912      ,0337     2,7055      ,0072      ,0248      ,1575
Usefulne      ,8784      ,0386    22,7456      ,0000      ,8024      ,9544

Standardized coefficients
              coeff
EaseofUs      ,0952
Usefulne      ,8003

************************* TOTAL EFFECT MODEL ***************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,4250      ,1807     1,4234    61,9613     1,0000   281,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,5813      ,2430    10,6226      ,0000     2,1030     3,0596
EaseofUs      ,4071      ,0517     7,8716      ,0000      ,3053      ,5090

Standardized coefficients
              coeff
EaseofUs      ,4250

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI       c_ps
c_cs
      ,4071      ,0517
7,8716      ,0000      ,3053      ,5090      ,3094      ,4250

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI      c'_ps
```

```
c'_cs
      ,0912      ,0337
2,7055      ,0072      ,0248      ,1575      ,0693      ,0952

Indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
Usefulne      ,3160      ,0412      ,2338      ,3999

Partially standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
Usefulne      ,2401      ,0304      ,1793      ,3018

Completely standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
Usefulne      ,3299      ,0433      ,2453      ,4169

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

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  1000

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

b. Ease of use

1. Subjective norm

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : UsageInt
    X  : SubjNorm
    M  : EaseofUs

Sample
Size:  283

**************************************************************************
OUTCOME VARIABLE:
 EaseofUs

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,0778      ,0061     1,8820     1,7125     1,0000   281,0000      ,1917

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,1468      ,2772    14,9581      ,0000     3,6011     4,6925
SubjNorm      ,0855      ,0653     1,3086      ,1917     -,0431      ,2140
```

```
Standardized coefficients
              coeff
SubjNorm      ,0778

**************************************************************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,4255      ,1811     1,4278    30,9580     2,0000   280,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,6621      ,3236     8,2259      ,0000     2,0251     3,2991
SubjNorm     -,0216      ,0570     -,3789      ,7051     -,1339      ,0907
EaseofUs      ,4087      ,0520     7,8652      ,0000      ,3064      ,5110

Standardized coefficients
              coeff
SubjNorm     -,0206
EaseofUs      ,4266

************************** TOTAL EFFECT MODEL ***************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,0127      ,0002     1,7370      ,0450     1,0000   281,0000      ,8322

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,3568      ,2663    16,3583      ,0000     3,8325     4,8810
SubjNorm      ,0133      ,0627      ,2121      ,8322     -,1102      ,1368

Standardized coefficients
              coeff
SubjNorm      ,0127

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI       c_ps
c_cs
      ,0133      ,0627      ,2121      ,8322
-,1102      ,1368      ,0101      ,0127

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI      c'_ps
c'_cs
     -,0216      ,0570     -,3789      ,7051     -,1339      ,0907     -,0164
-,0206

Indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
EaseofUs      ,0349      ,0295     -,0224      ,0961

Partially standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
EaseofUs      ,0265      ,0225     -,0166      ,0725

Completely standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
EaseofUs      ,0332      ,0280     -,0201      ,0923
```

```
********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  1000

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

2. Self-efficacy

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : UsageInt
    X  : SelfEffi
    M  : EaseofUs

Sample
Size:  283

**************************************************************************
OUTCOME VARIABLE:
 EaseofUs

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,6384      ,4076     1,1217   193,3245     1,0000   281,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,1467      ,1801    11,9168      ,0000     1,7921     2,5013
SelfEffi      ,6203      ,0446    13,9041      ,0000      ,5325      ,7081

Standardized coefficients
              coeff
SelfEffi      ,6384

**************************************************************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,4397      ,1934     1,4064    33,5637     2,0000   280,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,4680      ,2475     9,9725      ,0000     1,9809     2,9552
SelfEffi      ,1363      ,0649     2,1008      ,0366      ,0086      ,2641
EaseofUs      ,3176      ,0668     4,7541      ,0000      ,1861      ,4490
```

```
Standardized coefficients
              coeff
SelfEffi      ,1465
EaseofUs      ,3315

************************** TOTAL EFFECT MODEL ***************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3581      ,1283     1,5145    41,3471     1,0000   281,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3,1497      ,2093    15,0477      ,0000     2,7377     3,5617
SelfEffi      ,3333      ,0518     6,4302      ,0000      ,2313      ,4354

Standardized coefficients
              coeff
SelfEffi      ,3581

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI       c_ps
c_cs
      ,3333      ,0518
6,4302      ,0000      ,2313      ,4354      ,2533      ,3581

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI      c'_ps
c'_cs
      ,1363      ,0649
2,1008      ,0366      ,0086      ,2641      ,1036      ,1465

Indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
EaseofUs      ,1970      ,0518      ,0966      ,3105

Partially standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
EaseofUs      ,1497      ,0400      ,0728      ,2360

Completely standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
EaseofUs      ,2116      ,0575      ,0991      ,3343

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

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  1000

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

3. Anxiety

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : UsageInt
    X  : Anxiety
    M  : EaseofUs

Sample
Size:  283

**************************************************************************
OUTCOME VARIABLE:
 EaseofUs

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5405      ,2922     1,3402   115,9974     1,0000   281,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     6,3745      ,1877    33,9578      ,0000     6,0050     6,7441
Anxiety      -,5893      ,0547   -10,7702      ,0000     -,6970     -,4816

Standardized coefficients
             coeff
Anxiety     -,5405

**************************************************************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5642      ,3183     1,1886    65,3659     2,0000   280,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     5,0770      ,3994    12,7126      ,0000     4,2909     5,8631
Anxiety      -,4605      ,0612    -7,5184      ,0000     -,5810     -,3399
EaseofUs      ,1788      ,0562     3,1833      ,0016      ,0682      ,2894

Standardized coefficients
              coeff
Anxiety      -,4409
EaseofUs      ,1867

************************* TOTAL EFFECT MODEL ***************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5419      ,2936     1,2272   116,8022     1,0000   281,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
```

```
constant     6,2170      ,1796    34,6100      ,0000     5,8634     6,5706
Anxiety      -,5658      ,0524   -10,8075      ,0000     -,6689     -,4628

Standardized coefficients
             coeff
Anxiety     -,5419

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI       c_ps
c_cs
     -,5658      ,0524   -10,8075      ,0000     -,6689     -,4628     -,4301
-,5419

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI      c'_ps
c'_cs
     -,4605      ,0612    -7,5184      ,0000     -,5810     -,3399     -,3500
-,4409

Indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
EaseofUs     -,1054      ,0431     -,1951     -,0296

Partially standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
EaseofUs     -,0801      ,0334     -,1534     -,0231

Completely standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
EaseofUs     -,1009      ,0420     -,1904     -,0281

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

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  1000

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

4. Result demonstrability

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : UsageInt
    X  : ResultDe
    M  : EaseofUs
```

```
Sample
Size:  283

**************************************************************************
OUTCOME VARIABLE:
 EaseofUs

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,1164      ,0136     1,8678     3,8627     1,0000   281,0000      ,0504

Model
              coeff         se          t          p       LLCI       ULCI
constant     5,4073      ,4720    11,4564      ,0000     4,4782     6,3364
ResultDe     -,1760      ,0896    -1,9654      ,0504     -,3524      ,0003

Standardized coefficients
              coeff
ResultDe     -,1164

**************************************************************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,4269      ,1822     1,4258    31,1974     2,0000   280,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,9006      ,4995     5,8073      ,0000     1,9174     3,8839
ResultDe     -,0577      ,0788     -,7320      ,4648     -,2128      ,0974
EaseofUs      ,4027      ,0521     7,7263      ,0000      ,3001      ,5053

Standardized coefficients
              coeff
ResultDe     -,0398
EaseofUs      ,4204

************************** TOTAL EFFECT MODEL ***************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,0888      ,0079     1,7236     2,2327     1,0000   281,0000      ,1362

Model
              coeff         se          t          p       LLCI       ULCI
constant     5,0782      ,4534    11,2000      ,0000     4,1857     5,9707
ResultDe     -,1286      ,0860    -1,4942      ,1362     -,2979      ,0408

Standardized coefficients
              coeff
ResultDe     -,0888

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y
     Effect         se          t          p       LLCI       ULCI       c_ps
c_cs
     -,1286      ,0860    -1,4942      ,1362     -,2979      ,0408     -,0977
-,0888

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI      c'_ps
```

```
c'_cs
     -,0577      ,0788     -,7320      ,4648     -,2128      ,0974     -,0438
-,0398

Indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
EaseofUs     -,0709      ,0488     -,1800      ,0114

Partially standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
EaseofUs     -,0539      ,0372     -,1385      ,0082

Completely standardized indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
EaseofUs     -,0490      ,0328     -,1207      ,0077

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

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  1000

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

G. Moderator analysis

a. Gender

1. Usefulness

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : UsageInt
    X  : Usefulne
    W  : Gender

Sample
Size:  283

**************************************************************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE     F(HC3)        df1        df2          p
      ,8401      ,7058      ,5148   268,1801     3,0000   279,0000      ,0000
```

```
Model
              coeff    se(HC3)          t          p       LLCI       ULCI
constant     4,4071      ,0425   103,8044      ,0000     4,3236     4,4907
Usefulne      ,9171      ,0324    28,3181      ,0000      ,8534      ,9809
Gender        ,0668      ,0851      ,7855      ,4328     -,1007      ,2344
Int_1         ,0437      ,0648      ,6748      ,5004     -,0838      ,1712

Product terms key:
 Int_1    :        Usefulne x        Gender

Test(s) of highest order unconditional interaction(s):
       R2-chng     F(HC3)        df1        df2          p
X*W      ,0004      ,4553     1,0000   279,0000      ,5004
----------
    Focal predict: Usefulne (X)
          Mod var: Gender   (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   Usefulne   Gender     UsageInt   .
BEGIN DATA.
    -1,0742     -,4876     3,4123
      ,1758     -,4876     4,5320
     1,1758     -,4876     5,4278
    -1,0742      ,5124     3,4322
      ,1758      ,5124     4,6066
     1,1758      ,5124     5,5461
END DATA.
GRAPH/SCATTERPLOT=
 Usefulne WITH     UsageInt BY       Gender   .

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

Level of confidence for all confidence intervals in output:
  95,0000

NOTE: A heteroscedasticity consistent standard error and covariance matrix
estimator was used.

NOTE: The following variables were mean centered prior to analysis:
          Gender   Usefulne

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

2. Ease of use

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : UsageInt
```

```
    X  : EaseofUs
    W  : Gender

Sample
Size:  283

**************************************************************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE     F(HC3)        df1        df2          p
      ,4692      ,2202     1,3645    27,0317     3,0000   279,0000      ,0000

Model
              coeff    se(HC3)          t          p       LLCI       ULCI
constant     4,3993      ,0707    62,2018      ,0000     4,2601     4,5386
EaseofUs      ,3871      ,0580     6,6775      ,0000      ,2730      ,5012
Gender        ,3132      ,1409     2,2226      ,0270      ,0358      ,5906
Int_1         ,3067      ,1150     2,6681      ,0081      ,0804      ,5330

Product terms key:
 Int_1    :        EaseofUs x        Gender

Test(s) of highest order unconditional interaction(s):
       R2-chng     F(HC3)        df1        df2          p
X*W      ,0254     7,1187     1,0000   279,0000      ,0081
----------
    Focal predict: EaseofUs (X)
          Mod var: Gender   (W)

Conditional effects of the focal predictor at values of the moderator(s):

     Gender     Effect    se(HC3)          t          p       LLCI       ULCI
     -,4876      ,2375      ,0938     2,5331      ,0119      ,0529      ,4220
      ,5124      ,5442      ,0665     8,1804      ,0000      ,4132      ,6752

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   EaseofUs   Gender     UsageInt   .
BEGIN DATA.
    -1,8269     -,4876     3,8128
      ,5065     -,4876     4,3669
     1,1731     -,4876     4,5252
    -1,8269      ,5124     3,5656
      ,5065      ,5124     4,8354
     1,1731      ,5124     5,1982
END DATA.
GRAPH/SCATTERPLOT=
 EaseofUs WITH     UsageInt BY       Gender   .

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

Level of confidence for all confidence intervals in output:
  95,0000

NOTE: A heteroscedasticity consistent standard error and covariance matrix
estimator was used.

NOTE: The following variables were mean centered prior to analysis:
          Gender   EaseofUs

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
```

```
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

3. Subjective norm

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : UsageInt
    X  : SubjNorm
    W  : Gender

Sample
Size:  283

**************************************************************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE     F(HC3)        df1        df2          p
      ,1952      ,0381     1,6831     2,6716     3,0000   279,0000      ,0478

Model
              coeff    se(HC3)          t          p       LLCI       ULCI
constant     4,3996      ,0777    56,6348      ,0000     4,2467     4,5525
SubjNorm      ,0303      ,0727      ,4167      ,6772     -,1127      ,1733
Gender        ,3759      ,1555     2,4179      ,0163      ,0699      ,6819
Int_1        -,2793      ,1448    -1,9295      ,0547     -,5643      ,0056

Product terms key:
 Int_1    :        SubjNorm x        Gender

Test(s) of highest order unconditional interaction(s):
       R2-chng     F(HC3)        df1        df2          p
X*W      ,0176     3,7231     1,0000   279,0000      ,0547
----------
    Focal predict: SubjNorm (X)
          Mod var: Gender   (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   SubjNorm   Gender     UsageInt   .
BEGIN DATA.
    -1,5777     -,4876     3,9537
      ,2756     -,4876     4,2622
     1,2756     -,4876     4,4287
    -1,5777      ,5124     4,7703
      ,2756      ,5124     4,5611
     1,2756      ,5124     4,4483
END DATA.
GRAPH/SCATTERPLOT=
 SubjNorm WITH     UsageInt BY       Gender   .
```

```
********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

NOTE: A heteroscedasticity consistent standard error and covariance matrix
estimator was used.

NOTE: The following variables were mean centered prior to analysis:
          Gender   SubjNorm

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

b. Banking habit

1. Subjective norm

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 2
    Y  : UsageInt
    X  : SubjNorm
    W  : BHa
    Z  : BHb

Sample
Size:  283

**************************************************************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE     F(HC3)        df1        df2          p
      ,4429      ,1962     1,4166    35,7591     5,0000   277,0000      ,0000

Model
              coeff    se(HC3)          t          p       LLCI       ULCI
constant     4,4130      ,0715    61,7011      ,0000     4,2722     4,5538
SubjNorm     -,0166      ,0661     -,2512      ,8018     -,1468      ,1136
BHa          1,5878      ,1928     8,2362      ,0000     1,2083     1,9673
Int_1        -,3230      ,1515    -2,1317      ,0339     -,6213     -,0247
BHb          2,0099      ,1876    10,7144      ,0000     1,6406     2,3792
Int_2        -,3602      ,1365    -2,6379      ,0088     -,6289     -,0914

Product terms key:
 Int_1    :        SubjNorm x        BHa
 Int_2    :        SubjNorm x        BHb

Test(s) of highest order unconditional interaction(s):
        R2-chng     F(HC3)        df1        df2          p
```

```
X*W       ,0089     4,5443     1,0000   277,0000      ,0339
X*Z       ,0115     6,9587     1,0000   277,0000      ,0088
BOTH      ,0118     3,9528     2,0000   277,0000      ,0203
----------
    Focal predict: SubjNorm (X)
          Mod var: BHa      (W)
          Mod var: BHb      (Z)

Conditional effects of the focal predictor at values of the moderator(s):

        BHa        BHb     Effect    se(HC3)          t          p       LLCI
ULCI
     -,4134     -,4912      ,2938      ,1002
2,9314      ,0037      ,0965      ,4912
     -,4134      ,5088     -,0663      ,0927     -,7155      ,4749
-,2488      ,1162
      ,5866     -,4912     -,0292      ,1136     -,2569      ,7975
-,2529      ,1945
      ,5866      ,5088     -,3894      ,1776    -2,1918      ,0292     -,7390
-,0397

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   SubjNorm   BHa        BHb        UsageInt   .
BEGIN DATA.
    -1,5777     -,4134     -,4912     2,3058
      ,2756     -,4134     -,4912     2,8503
     1,2756     -,4134     -,4912     3,1442
    -1,5777     -,4134      ,5088     4,8839
      ,2756     -,4134      ,5088     4,7610
     1,2756     -,4134      ,5088     4,6947
    -1,5777      ,5866     -,4912     4,4032
      ,2756      ,5866     -,4912     4,3491
     1,2756      ,5866     -,4912     4,3199
    -1,5777      ,5866      ,5088     6,9814
      ,2756      ,5866      ,5088     6,2598
     1,2756      ,5866      ,5088     5,8704
END DATA.
GRAPH/SCATTERPLOT=
 SubjNorm WITH     UsageInt BY       BHa      /PANEL   ROWVAR=  BHb      .

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

Level of confidence for all confidence intervals in output:
  95,0000

NOTE: A heteroscedasticity consistent standard error and covariance matrix
estimator was used.

NOTE: The following variables were mean centered prior to analysis:
          BHa      BHb      SubjNorm

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

2. Ease of use

```
Run MATRIX procedure:
```

```
***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 2
    Y  : UsageInt
    X  : EaseofUs
    W  : BHa
    Z  : BHb

Sample
Size:  283

**************************************************************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE     F(HC3)        df1        df2          p
      ,5031      ,2531     1,3163    41,0855     5,0000   277,0000      ,0000

Model
              coeff    se(HC3)          t          p       LLCI       ULCI
constant     4,4561      ,1061    41,9897      ,0000     4,2472     4,6650
EaseofUs      ,2817      ,0697     4,0426      ,0001      ,1445      ,4189
BHa           ,9120      ,8794     1,0371      ,3006     -,8191     2,6431
Int_1         ,0636      ,3738      ,1701      ,8650     -,6722      ,7994
BHb          1,2105      ,8777     1,3791      ,1690     -,5174     2,9384
Int_2        -,1907      ,3694     -,5162      ,6061     -,9179      ,5365

Product terms key:
 Int_1    :        EaseofUs x        BHa
 Int_2    :        EaseofUs x        BHb

Test(s) of highest order unconditional interaction(s):
        R2-chng     F(HC3)        df1        df2          p
X*W      ,0002      ,0289     1,0000   277,0000      ,8650
X*Z      ,0016      ,2665     1,0000   277,0000      ,6061
BOTH     ,0120     1,7827     2,0000   277,0000      ,1701
----------
    Focal predict: EaseofUs (X)
          Mod var: BHa      (W)
          Mod var: BHb      (Z)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   EaseofUs   BHa        BHb        UsageInt   .
BEGIN DATA.
    -1,8269     -,4134     -,4912     2,8467
      ,5065     -,4134     -,4912     3,6613
     1,1731     -,4134     -,4912     3,8940
    -1,8269     -,4134      ,5088     4,4056
      ,5065     -,4134      ,5088     4,7752
     1,1731     -,4134      ,5088     4,8808
    -1,8269      ,5866     -,4912     3,6425
      ,5065      ,5866     -,4912     4,6054
     1,1731      ,5866     -,4912     4,8806
    -1,8269      ,5866      ,5088     5,2015
      ,5065      ,5866      ,5088     5,7194
     1,1731      ,5866      ,5088     5,8674
END DATA.
```

```
GRAPH/SCATTERPLOT=
 EaseofUs WITH     UsageInt BY       BHa      /PANEL   ROWVAR=  BHb      .

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

Level of confidence for all confidence intervals in output:
  95,0000

NOTE: A heteroscedasticity consistent standard error and covariance matrix
estimator was used.

NOTE: The following variables were mean centered prior to analysis:
          BHa      BHb      EaseofUs

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

3. Usefulness

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 2
    Y  : UsageInt
    X  : Usefulne
    W  : BHa
    Z  : BHb

Sample
Size:  283

**************************************************************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE     F(HC3)        df1        df2          p
      ,8664      ,7506      ,4395   336,8864     5,0000   277,0000      ,0000

Model
              coeff    se(HC3)          t          p       LLCI       ULCI
constant     4,3918      ,0431   101,8941      ,0000     4,3069     4,4766
Usefulne      ,8753      ,0349    25,1097      ,0000      ,8067      ,9439
BHa           ,4933      ,1335     3,6939      ,0003      ,2304      ,7561
Int_1         ,2114      ,0860     2,4582      ,0146      ,0421      ,3807
BHb           ,9641      ,1356     7,1072      ,0000      ,6970     1,2311
Int_2         ,0900      ,0922      ,9762      ,3298     -,0915      ,2716

Product terms key:
 Int_1    :        Usefulne x        BHa
 Int_2    :        Usefulne x        BHb

Test(s) of highest order unconditional interaction(s):
        R2-chng     F(HC3)        df1        df2          p
X*W       ,0024     6,0427     1,0000   277,0000      ,0146
```

```
X*Z       ,0004      ,9529     1,0000   277,0000      ,3298
BOTH      ,0037     3,3817     2,0000   277,0000      ,0354
----------
    Focal predict: Usefulne (X)
          Mod var: BHa      (W)
          Mod var: BHb      (Z)

Conditional effects of the focal predictor at values of the moderator(s):

        BHa        BHb     Effect    se(HC3)          t          p       LLCI
ULCI
     -,4134     -,4912      ,7437      ,0722
10,2982      ,0000      ,6015      ,8858
     -,4134      ,5088      ,8337      ,0574
14,5234      ,0000      ,7207      ,9467
      ,5866     -,4912      ,9550      ,0467    20,4532      ,0000      ,8631
1,0470
      ,5866      ,5088     1,0451      ,1034    10,1079      ,0000      ,8416
1,2486

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   Usefulne   BHa        BHb        UsageInt   .
BEGIN DATA.
    -1,0742     -,4134     -,4912     2,9155
      ,1758     -,4134     -,4912     3,8451
     1,1758     -,4134     -,4912     4,5887
    -1,0742     -,4134      ,5088     3,7828
      ,1758     -,4134      ,5088     4,8250
     1,1758     -,4134      ,5088     5,6587
    -1,0742      ,5866     -,4912     3,1817
      ,1758      ,5866     -,4912     4,3755
     1,1758      ,5866     -,4912     5,3305
    -1,0742      ,5866      ,5088     4,0490
      ,1758      ,5866      ,5088     5,3554
     1,1758      ,5866      ,5088     6,4005
END DATA.
GRAPH/SCATTERPLOT=
 Usefulne WITH     UsageInt BY       BHa      /PANEL   ROWVAR=  BHb      .

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

Level of confidence for all confidence intervals in output:
  95,0000

NOTE: A heteroscedasticity consistent standard error and covariance matrix
estimator was used.

NOTE: The following variables were mean centered prior to analysis:
          BHa      BHb      Usefulne

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

c. Experience

1. Usefulness

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : UsageInt
    X  : Usefulne
    W  : Experien

Sample
Size:  283

**************************************************************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE     F(HC3)        df1        df2          p
      ,8449      ,7139      ,5006   264,4625     3,0000   279,0000      ,0000

Model
              coeff    se(HC3)          t          p       LLCI       ULCI
constant     4,4549      ,0456    97,7045      ,0000     4,3652     4,5447
Usefulne      ,8800      ,0356    24,7016      ,0000      ,8098      ,9501
Experien      ,0644      ,0315     2,0457      ,0417      ,0024      ,1263
Int_1        -,0699      ,0234    -2,9833      ,0031     -,1160     -,0238

Product terms key:
 Int_1    :        Usefulne x        Experien

Test(s) of highest order unconditional interaction(s):
       R2-chng     F(HC3)        df1        df2          p
X*W      ,0063     8,9002     1,0000   279,0000      ,0031
----------
    Focal predict: Usefulne (X)
          Mod var: Experien (W)

Conditional effects of the focal predictor at values of the moderator(s):

   Experien     Effect    se(HC3)          t          p       LLCI       ULCI
    -1,3746      ,9761      ,0416    23,4844      ,0000      ,8942     1,0579
     -,0412      ,8828      ,0354    24,9445      ,0000      ,8132      ,9525
     1,6254      ,7663      ,0583    13,1340      ,0000      ,6515      ,8812

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   Usefulne   Experien   UsageInt   .
BEGIN DATA.
    -1,0742    -1,3746     3,3180
      ,1758    -1,3746     4,5380
     1,1758    -1,3746     5,5141
    -1,0742     -,0412     3,5039
      ,1758     -,0412     4,6075
     1,1758     -,0412     5,4903
    -1,0742     1,6254     3,7364
      ,1758     1,6254     4,6943
     1,1758     1,6254     5,4606
END DATA.
GRAPH/SCATTERPLOT=
```

```
 Usefulne WITH     UsageInt BY       Experien .

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

Level of confidence for all confidence intervals in output:
  95,0000

W values in conditional tables are the 16th, 50th, and 84th percentiles.

NOTE: A heteroscedasticity consistent standard error and covariance matrix
estimator was used.

NOTE: The following variables were mean centered prior to analysis:
          Experien Usefulne

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

2. Ease of use

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : UsageInt
    X  : EaseofUs
    W  : Experien

Sample
Size:  283

**************************************************************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE     F(HC3)        df1        df2          p
      ,4904      ,2405     1,3289    48,5150     3,0000   279,0000      ,0000

Model
              coeff    se(HC3)          t          p       LLCI       ULCI
constant     4,4614      ,0789    56,5494      ,0000     4,3061     4,6167
EaseofUs      ,2791      ,0671     4,1600      ,0000      ,1470      ,4111
Experien      ,2598      ,0554     4,6864      ,0000      ,1507      ,3689
Int_1        -,0713      ,0404    -1,7647      ,0787     -,1508      ,0082

Product terms key:
 Int_1    :        EaseofUs x        Experien

Test(s) of highest order unconditional interaction(s):
       R2-chng     F(HC3)        df1        df2          p
X*W      ,0077     3,1142     1,0000   279,0000      ,0787
----------
    Focal predict: EaseofUs (X)
          Mod var: Experien (W)
```

```
Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   EaseofUs   Experien   UsageInt   .
BEGIN DATA.
    -1,8269    -1,3746     3,4155
      ,5065    -1,3746     4,2952
     1,1731    -1,3746     4,5466
    -1,8269     -,0412     3,9355
      ,5065     -,0412     4,5935
     1,1731     -,0412     4,7815
    -1,8269     1,6254     4,5855
      ,5065     1,6254     4,9663
     1,1731     1,6254     5,0751
END DATA.
GRAPH/SCATTERPLOT=
 EaseofUs WITH     UsageInt BY       Experien .

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

Level of confidence for all confidence intervals in output:
  95,0000

NOTE: A heteroscedasticity consistent standard error and covariance matrix
estimator was used.

NOTE: The following variables were mean centered prior to analysis:
          Experien EaseofUs

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

3. Subjective norm

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : UsageInt
    X  : SubjNorm
    W  : Experien

Sample
Size:  283

**************************************************************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE     F(HC3)        df1        df2          p
      ,3862      ,1492     1,4888    20,8423     3,0000   279,0000      ,0000
```

```
Model
              coeff    se(HC3)          t          p       LLCI       ULCI
constant     4,4099      ,0732    60,2685      ,0000     4,2659     4,5540
SubjNorm      ,0204      ,0674      ,3019      ,7630     -,1124      ,1531
Experien      ,3678      ,0505     7,2767      ,0000      ,2683      ,4673
Int_1         ,0847      ,0499     1,6980      ,0906     -,0135      ,1828

Product terms key:
 Int_1    :        SubjNorm x        Experien

Test(s) of highest order unconditional interaction(s):
       R2-chng     F(HC3)        df1        df2          p
X*W      ,0109     2,8832     1,0000   279,0000      ,0906
----------
    Focal predict: SubjNorm (X)
          Mod var: Experien (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   SubjNorm   Experien   UsageInt   .
BEGIN DATA.
    -1,5777    -1,3746     4,0559
      ,2756    -1,3746     3,8780
     1,2756    -1,3746     3,7820
    -1,5777     -,0412     4,3682
      ,2756     -,0412     4,3994
     1,2756     -,0412     4,4163
    -1,5777     1,6254     4,7585
      ,2756     1,6254     5,0513
     1,2756     1,6254     5,2092
END DATA.
GRAPH/SCATTERPLOT=
 SubjNorm WITH     UsageInt BY       Experien .

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

Level of confidence for all confidence intervals in output:
  95,0000

NOTE: A heteroscedasticity consistent standard error and covariance matrix
estimator was used.

NOTE: The following variables were mean centered prior to analysis:
          Experien SubjNorm

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

d. Age category

1. Subjective norm

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3
```

```
**************************************************************************
Model  : 1
    Y  : UsageInt
    X  : SubjNorm
    W  : AgeCat

Sample
Size:  283

Coding of categorical W variable for analysis:
 AgeCat     W1     W2     W3     W4     W5     W6     W7
  1,000   ,000   ,000   ,000   ,000   ,000   ,000   ,000
  2,000  1,000   ,000   ,000   ,000   ,000   ,000   ,000
  3,000   ,000  1,000   ,000   ,000   ,000   ,000   ,000
  4,000   ,000   ,000  1,000   ,000   ,000   ,000   ,000
  5,000   ,000   ,000   ,000  1,000   ,000   ,000   ,000
  6,000   ,000   ,000   ,000   ,000  1,000   ,000   ,000
  7,000   ,000   ,000   ,000   ,000   ,000  1,000   ,000
  8,000   ,000   ,000   ,000   ,000   ,000   ,000  1,000

**************************************************************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE     F(HC3)        df1        df2          p
      ,4802      ,2306     1,4068    10,3678    15,0000   267,0000      ,0000

Model
              coeff    se(HC3)          t          p       LLCI       ULCI
constant     4,3284      ,2681    16,1436      ,0000     3,8005     4,8563
SubjNorm      ,5697      ,2176     2,6176      ,0094      ,1412      ,9982
W1            ,5834      ,3455     1,6886      ,0925     -,0968     1,2636
W2            ,1086      ,3324      ,3267      ,7442     -,5459      ,7631
W3            ,5407      ,2990     1,8079      ,0717     -,0481     1,1294
W4            ,3739      ,3314     1,1281      ,2603     -,2787     1,0265
W5            ,1491      ,3486      ,4278      ,6692     -,5373      ,8355
W6           -,8445      ,3722    -2,2691      ,0241    -1,5772     -,1117
W7          -1,3030      ,3131    -4,1621      ,0000    -1,9194     -,6866
Int_1        -,5746      ,2540    -2,2625      ,0245    -1,0746     -,0746
Int_2        -,3780      ,2884    -1,3103      ,1912     -,9459      ,1900
Int_3        -,7890      ,2861    -2,7575      ,0062    -1,3523     -,2256
Int_4        -,7103      ,2890    -2,4574      ,0146    -1,2794     -,1412
Int_5        -,5775      ,3064    -1,8845      ,0606    -1,1809      ,0259
Int_6        -,3151      ,2763    -1,1402      ,2552     -,8591      ,2290
Int_7        -,1088      ,2489     -,4373      ,6622     -,5989      ,3812

Product terms key:
 Int_1    :        SubjNorm x        W1
 Int_2    :        SubjNorm x        W2
 Int_3    :        SubjNorm x        W3
 Int_4    :        SubjNorm x        W4
 Int_5    :        SubjNorm x        W5
 Int_6    :        SubjNorm x        W6
 Int_7    :        SubjNorm x        W7

Test(s) of highest order unconditional interaction(s):
       R2-chng     F(HC3)        df1        df2          p
X*W      ,0381     2,7064     7,0000   267,0000      ,0100
----------
    Focal predict: SubjNorm (X)
          Mod var: AgeCat   (W)

Conditional effects of the focal predictor at values of the moderator(s):
```

```
     AgeCat     Effect    se(HC3)          t          p       LLCI       ULCI
     1,0000      ,5697      ,2176     2,6176      ,0094      ,1412      ,9982
     2,0000     -,0049      ,1309     -,0373      ,9703     -,2626      ,2528
     3,0000      ,1917      ,1893     1,0129      ,3120     -,1810      ,5645
     4,0000     -,2193      ,1857    -1,1806      ,2388     -,5850      ,1464
     5,0000     -,1406      ,1902     -,7391      ,4605     -,5151      ,2339
     6,0000     -,0078      ,2157     -,0361      ,9712     -,4326      ,4170
     7,0000      ,2546      ,1702     1,4959      ,1359     -,0805      ,5898
     8,0000      ,4609      ,1208     3,8165      ,0002      ,2231      ,6986

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   SubjNorm   AgeCat     UsageInt   .
BEGIN DATA.
    -1,5777     1,0000     3,4296
      ,2756     1,0000     4,4854
     1,2756     1,0000     5,0551
    -1,5777     2,0000     4,9195
      ,2756     2,0000     4,9104
     1,2756     2,0000     4,9055
    -1,5777     3,0000     4,1345
      ,2756     3,0000     4,4898
     1,2756     3,0000     4,6816
    -1,5777     4,0000     5,2150
      ,2756     4,0000     4,8086
     1,2756     4,0000     4,5893
    -1,5777     5,0000     4,9241
      ,2756     5,0000     4,6636
     1,2756     5,0000     4,5230
    -1,5777     6,0000     4,4898
      ,2756     6,0000     4,4754
     1,2756     6,0000     4,4676
    -1,5777     7,0000     3,0822
      ,2756     7,0000     3,5541
     1,2756     7,0000     3,8088
    -1,5777     8,0000     2,2983
      ,2756     8,0000     3,1524
     1,2756     8,0000     3,6132
END DATA.
GRAPH/SCATTERPLOT=
 SubjNorm WITH     UsageInt BY       AgeCat   .

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

Level of confidence for all confidence intervals in output:
  95,0000

NOTE: A heteroscedasticity consistent standard error and covariance matrix
estimator was used.

NOTE: The following variables were mean centered prior to analysis:
          SubjNorm

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

2. Ease of use

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : UsageInt
    X  : EaseofUs
    W  : AgeCat

Sample
Size:  283

Coding of categorical W variable for analysis:
 AgeCat     W1     W2     W3     W4     W5     W6     W7
  1,000   ,000   ,000   ,000   ,000   ,000   ,000   ,000
  2,000  1,000   ,000   ,000   ,000   ,000   ,000   ,000
  3,000   ,000  1,000   ,000   ,000   ,000   ,000   ,000
  4,000   ,000   ,000  1,000   ,000   ,000   ,000   ,000
  5,000   ,000   ,000   ,000  1,000   ,000   ,000   ,000
  6,000   ,000   ,000   ,000   ,000  1,000   ,000   ,000
  7,000   ,000   ,000   ,000   ,000   ,000  1,000   ,000
  8,000   ,000   ,000   ,000   ,000   ,000   ,000  1,000

**************************************************************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE     F(HC3)        df1        df2          p
      ,5413      ,2930     1,2926    18,1603    15,0000   267,0000      ,0000

Model
              coeff    se(HC3)          t          p       LLCI       ULCI
constant     4,5653      ,1246    36,6362      ,0000     4,3200     4,8107
EaseofUs      ,6579      ,1103     5,9638      ,0000      ,4407      ,8752
W1           -,0338      ,2203     -,1533      ,8783     -,4675      ,4000
W2           -,3721      ,2062    -1,8047      ,0723     -,7780      ,0339
W3            ,2879      ,2124     1,3556      ,1764     -,1303      ,7061
W4            ,1008      ,2261      ,4458      ,6561     -,3444      ,5460
W5           -,0879      ,2822     -,3113      ,7558     -,6435      ,4678
W6           -,7410      ,3572    -2,0745      ,0390    -1,4442     -,0377
W7           -,3503      ,3562     -,9836      ,3262    -1,0516      ,3509
Int_1        -,1187      ,1849     -,6422      ,5213     -,4827      ,2453
Int_2        -,2562      ,2214    -1,1572      ,2482     -,6920      ,1797
Int_3        -,5493      ,2371    -2,3168      ,0213    -1,0161     -,0825
Int_4        -,4215      ,2157    -1,9545      ,0517     -,8462      ,0031
Int_5        -,6573      ,1935    -3,3967      ,0008    -1,0384     -,2763
Int_6        -,3183      ,1952    -1,6306      ,1042     -,7025      ,0660
Int_7        -,0114      ,1852     -,0616      ,9509     -,3760      ,3532

Product terms key:
 Int_1    :        EaseofUs x        W1
 Int_2    :        EaseofUs x        W2
 Int_3    :        EaseofUs x        W3
 Int_4    :        EaseofUs x        W4
 Int_5    :        EaseofUs x        W5
 Int_6    :        EaseofUs x        W6
 Int_7    :        EaseofUs x        W7

Test(s) of highest order unconditional interaction(s):
       R2-chng     F(HC3)        df1        df2          p
X*W      ,0349     2,5707     7,0000   267,0000      ,0140
```

```
----------
    Focal predict: EaseofUs (X)
          Mod var: AgeCat   (W)

Conditional effects of the focal predictor at values of the moderator(s):

     AgeCat     Effect    se(HC3)          t          p       LLCI       ULCI
     1,0000      ,6579      ,1103     5,9638      ,0000      ,4407      ,8752
     2,0000      ,5392      ,1483     3,6351      ,0003      ,2472      ,8313
     3,0000      ,4018      ,1919     2,0936      ,0372      ,0239      ,7796
     4,0000      ,1087      ,2099      ,5178      ,6050     -,3045      ,5218
     5,0000      ,2364      ,1853     1,2757      ,2032     -,1285      ,6013
     6,0000      ,0006      ,1590      ,0038      ,9970     -,3124      ,3136
     7,0000      ,3397      ,1610     2,1097      ,0358      ,0227      ,6567
     8,0000      ,6465      ,1487     4,3469      ,0000      ,3537      ,9394

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   EaseofUs   AgeCat     UsageInt   .
BEGIN DATA.
    -1,8269     1,0000     3,3634
      ,5065     1,0000     4,8986
     1,1731     1,0000     5,3372
    -1,8269     2,0000     3,5465
      ,5065     2,0000     4,8047
     1,1731     2,0000     5,1641
    -1,8269     3,0000     3,4592
      ,5065     3,0000     4,3967
     1,1731     3,0000     4,6646
    -1,8269     4,0000     4,6547
      ,5065     4,0000     4,9083
     1,1731     4,0000     4,9807
    -1,8269     5,0000     4,2342
      ,5065     5,0000     4,7859
     1,1731     5,0000     4,9435
    -1,8269     6,0000     4,4764
      ,5065     6,0000     4,4778
     1,1731     6,0000     4,4782
    -1,8269     7,0000     3,2038
      ,5065     7,0000     3,9964
     1,1731     7,0000     4,2229
    -1,8269     8,0000     3,0338
      ,5065     8,0000     4,5424
     1,1731     8,0000     4,9735
END DATA.
GRAPH/SCATTERPLOT=
 EaseofUs WITH     UsageInt BY       AgeCat   .

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

Level of confidence for all confidence intervals in output:
  95,0000

NOTE: A heteroscedasticity consistent standard error and covariance matrix
estimator was used.

NOTE: The following variables were mean centered prior to analysis:
          EaseofUs

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.
```

```
------ END MATRIX -----
```

3. Usefulness

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : UsageInt
    X  : Usefulne
    W  : AgeCat

Sample
Size:  283

Coding of categorical W variable for analysis:
 AgeCat     W1     W2     W3     W4     W5     W6     W7
  1,000   ,000   ,000   ,000   ,000   ,000   ,000   ,000
  2,000  1,000   ,000   ,000   ,000   ,000   ,000   ,000
  3,000   ,000  1,000   ,000   ,000   ,000   ,000   ,000
  4,000   ,000   ,000  1,000   ,000   ,000   ,000   ,000
  5,000   ,000   ,000   ,000  1,000   ,000   ,000   ,000
  6,000   ,000   ,000   ,000   ,000  1,000   ,000   ,000
  7,000   ,000   ,000   ,000   ,000   ,000  1,000   ,000
  8,000   ,000   ,000   ,000   ,000   ,000   ,000  1,000

**************************************************************************
OUTCOME VARIABLE:
 UsageInt

Model Summary
          R       R-sq        MSE     F(HC3)        df1        df2          p
      ,8770      ,7692      ,4220   118,1475    15,0000   267,0000      ,0000

Model
              coeff    se(HC3)          t          p       LLCI       ULCI
constant     4,7217      ,1651    28,5928      ,0000     4,3966     5,0469
Usefulne      ,9667      ,2144     4,5077      ,0000      ,5444     1,3889
W1           -,1294      ,2252     -,5747      ,5660     -,5729      ,3140
W2           -,3160      ,2091    -1,5115      ,1319     -,7277      ,0956
W3            ,0234      ,2082      ,1124      ,9106     -,3865      ,4333
W4           -,5827      ,1801    -3,2363      ,0014     -,9372     -,2282
W5            ,0034      ,2069      ,0162      ,9871     -,4040      ,4107
W6           -,3438      ,1836    -1,8726      ,0622     -,7053      ,0177
W7           -,9832      ,1801    -5,4602      ,0000    -1,3377     -,6287
Int_1        -,2255      ,2326     -,9693      ,3333     -,6836      ,2325
Int_2         ,0323      ,2336      ,1381      ,8903     -,4276      ,4921
Int_3        -,3392      ,2445    -1,3871      ,1666     -,8206      ,1423
Int_4         ,0655      ,2255      ,2904      ,7717     -,3785      ,5095
Int_5        -,1447      ,2572     -,5625      ,5743     -,6511      ,3618
Int_6         ,1413      ,2224      ,6352      ,5258     -,2966      ,5792
Int_7        -,0900      ,2245     -,4010      ,6887     -,5320      ,3519

Product terms key:
 Int_1    :        Usefulne x        W1
 Int_2    :        Usefulne x        W2
 Int_3    :        Usefulne x        W3
 Int_4    :        Usefulne x        W4
 Int_5    :        Usefulne x        W5
```

```
 Int_6    :        Usefulne x        W6
 Int_7    :        Usefulne x        W7

Test(s) of highest order unconditional interaction(s):
       R2-chng     F(HC3)        df1        df2          p
X*W      ,0167     3,3941     7,0000   267,0000      ,0017
----------
    Focal predict: Usefulne (X)
          Mod var: AgeCat   (W)

Conditional effects of the focal predictor at values of the moderator(s):

     AgeCat     Effect    se(HC3)          t          p       LLCI       ULCI
     1,0000      ,9667      ,2144     4,5077      ,0000      ,5444     1,3889
     2,0000      ,7412      ,0902     8,2167      ,0000      ,5636      ,9188
     3,0000      ,9989      ,0926    10,7912      ,0000      ,8167     1,1812
     4,0000      ,6275      ,1175     5,3402      ,0000      ,3961      ,8588
     5,0000     1,0322      ,0697    14,8050      ,0000      ,8949     1,1694
     6,0000      ,8220      ,1420     5,7869      ,0000      ,5423     1,1016
     7,0000     1,1079      ,0590    18,7775      ,0000      ,9918     1,2241
     8,0000      ,8766      ,0663    13,2248      ,0000      ,7461     1,0072

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   Usefulne   AgeCat     UsageInt   .
BEGIN DATA.
    -1,0742     1,0000     3,6833
      ,1758     1,0000     4,8917
     1,1758     1,0000     5,8583
    -1,0742     2,0000     3,7961
      ,1758     2,0000     4,7226
     1,1758     2,0000     5,4637
    -1,0742     3,0000     3,3327
      ,1758     3,0000     4,5813
     1,1758     3,0000     5,5802
    -1,0742     4,0000     4,0711
      ,1758     4,0000     4,8554
     1,1758     4,0000     5,4829
    -1,0742     5,0000     3,0303
      ,1758     5,0000     4,3205
     1,1758     5,0000     5,3526
    -1,0742     6,0000     3,8421
      ,1758     6,0000     4,8696
     1,1758     6,0000     5,6916
    -1,0742     7,0000     3,1878
      ,1758     7,0000     4,5727
     1,1758     7,0000     5,6807
    -1,0742     8,0000     2,7968
      ,1758     8,0000     3,8926
     1,1758     8,0000     4,7693
END DATA.
GRAPH/SCATTERPLOT=
 Usefulne WITH     UsageInt BY       AgeCat   .

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

Level of confidence for all confidence intervals in output:
  95,0000

NOTE: A heteroscedasticity consistent standard error and covariance matrix
estimator was used.

NOTE: The following variables were mean centered prior to analysis:
          Usefulne
```

```
WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

H. Regression analysis

a. TAM regression

1. First regression

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Usefulness	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
2	Anxiety	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
3	Subjective Norm	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Usage Intention

Model Summary[d]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,840[a]	,705	,704	,71618	
2	,859[b]	,738	,736	,67593	
3	,861[c]	,742	,739	,67182	1,856

a. Predictors: (Constant), Usefulness

b. Predictors: (Constant), Usefulness, Anxiety

c. Predictors: (Constant), Usefulness, Anxiety, Subjective Norm

d. Dependent Variable: Usage Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	344,054	1	344,054	670,776	,000[b]
	Residual	144,130	281	,513		
	Total	488,185	282			
2	Regression	360,259	2	180,129	394,262	,000[c]
	Residual	127,926	280	,457		
	Total	488,185	282			
3	Regression	362,258	3	120,753	267,538	,000[d]
	Residual	125,926	279	,451		
	Total	488,185	282			

a. Dependent Variable: Usage Intention

b. Predictors: (Constant), Usefulness

c. Predictors: (Constant), Usefulness, Anxiety

d. Predictors: (Constant), Usefulness, Anxiety, Subjective Norm

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	,657	,151		4,345	,000
	Usefulness	,921	,036	,840	25,899	,000
2	(Constant)	1,750	,232		7,528	,000
	Usefulness	,820	,038	,747	21,790	,000
	Anxiety	-,213	,036	-,204	-5,956	,000
3	(Constant)	2,036	,268		7,596	,000
	Usefulness	,822	,037	,749	21,972	,000
	Anxiety	-,220	,036	-,210	-6,146	,000
	Subjective Norm	-,068	,032	-,064	-2,105	,036

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF

1	(Constant)		
	Usefulness	1,000	1,000
2	(Constant)		
	Usefulness	,796	1,257
	Anxiety	,796	1,257
3	(Constant)		
	Usefulness	,795	1,258
	Anxiety	,790	1,265
	Subjective Norm	,988	1,012

a. Dependent Variable: Usage Intention

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Ease of Use	,095[b]	2,705	,007	,160	,830
	Subjective Norm	-,049[b]	-1,502	,134	-,089	,995
	Self-Efficacy	,076[b]	2,206	,028	,131	,879
	Anxiety	-,204[b]	-5,956	,000	-,335	,796
	Result Demonstrability	-,024[b]	-,723	,470	-,043	,994
2	Ease of Use	,010[c]	,265	,791	,016	,672
	Subjective Norm	-,064[c]	-2,105	,036	-,125	,988
	Self-Efficacy	,014[c]	,414	,679	,025	,787
	Result Demonstrability	-,013[c]	-,418	,676	-,025	,991
3	Ease of Use	,011[d]	,305	,761	,018	,672
	Self-Efficacy	,015[d]	,428	,669	,026	,787
	Result Demonstrability	-,004[d]	-,121	,904	-,007	,970

Excluded Variables[a]

Model		Collinearity Statistics VIF	Minimum Tolerance
1	Ease of Use	1,205	,830
	Subjective Norm	1,005	,995
	Self-Efficacy	1,137	,879
	Anxiety	1,257	,796
	Result Demonstrability	1,006	,994
2	Ease of Use	1,487	,645
	Subjective Norm	1,012	,790
	Self-Efficacy	1,270	,712

	Result Demonstrability	1,010	,793
3	Ease of Use	1,488	,642
	Self-Efficacy	1,270	,708
	Result Demonstrability	1,031	,786

a. Dependent Variable: Usage Intention

b. Predictors in the Model: (Constant), Usefulness

c. Predictors in the Model: (Constant), Usefulness, Anxiety

d. Predictors in the Model: (Constant), Usefulness, Anxiety, Subjective Norm

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions		
				(Constant)	Usefulness	Anxiety
1	1	1,959	1,000	,02	,02	
	2	,041	6,954	,98	,98	
2	1	2,825	1,000	,00	,01	,01
	2	,156	4,255	,00	,17	,39
	3	,019	12,106	,99	,82	,60
3	1	3,747	1,000	,00	,00	,01
	2	,162	4,803	,00	,11	,43
	3	,074	7,115	,00	,26	,03
	4	,016	15,251	,99	,62	,53

Collinearity Diagnostics[a]

Model	Dimension	Variance Proportions
		Subjective Norm
1	1	
	2	
2	1	
	2	
	3	
3	1	,01
	2	,03
	3	,76
	4	,21

a. Dependent Variable: Usage Intention

Casewise Diagnostics[a]

Case Number	Std. Residual	Usage Intention	Predicted Value	Residual
12	3,222	5,75	3,5853	2,16475

18	3,017	6,75	4,9650	1,78503
26	3,585	6,25	3,8413	2,40869
52	-3,158	1,50	3,6216	-2,12163
105	4,173	6,00	3,1967	2,80335
119	3,390	6,00	3,9940	2,00605
146	-3,065	1,75	3,5635	-1,81346
200	3,698	5,25	2,7653	2,48466

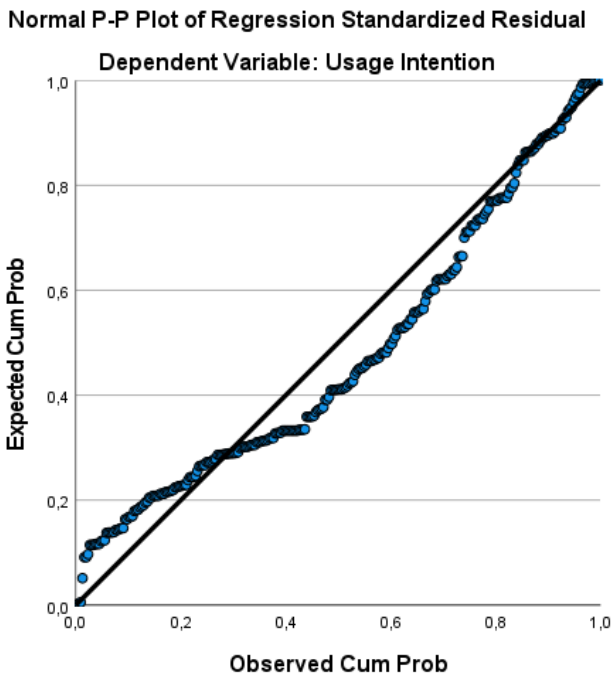
a. Dependent Variable: Usage Intention

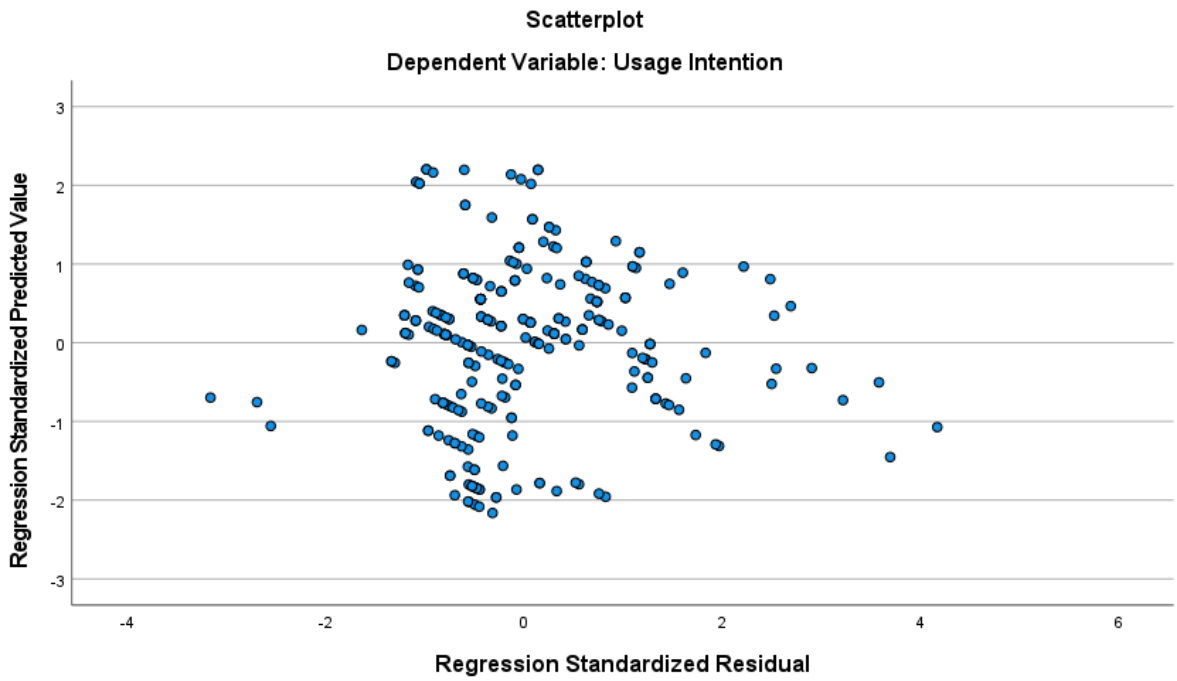
Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1,9601	6,9079	4,4108	1,13340	283
Residual	-2,12163	2,80335	,00000	,66824	283
Std. Predicted Value	-2,162	2,203	,000	1,000	283
Std. Residual	-3,158	4,173	,000	,995	283

a. Dependent Variable: Usage Intention

Charts





2. Second regression

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Usefulness	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
2	Anxiety	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Usage Intention

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,874[a]	,764	,763	,62800	
2	,901[b]	,812	,810	,56190	1,903

a. Predictors: (Constant), Usefulness

b. Predictors: (Constant), Usefulness, Anxiety

c. Dependent Variable: Usage Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	348,505	1	348,505	883,675	,000[b]
	Residual	107,666	273	,394		
	Total	456,171	274			
2	Regression	370,292	2	185,146	586,398	,000[c]
	Residual	85,880	272	,316		
	Total	456,171	274			

a. Dependent Variable: Usage Intention

b. Predictors: (Constant), Usefulness

c. Predictors: (Constant), Usefulness, Anxiety

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	,561	,134		4,170	,000
	Usefulness	,936	,031	,874	29,727	,000
2	(Constant)	1,846	,196		9,418	,000
	Usefulness	,818	,032	,764	25,904	,000
	Anxiety	-,252	,030	-,245	-8,307	,000

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	(Constant)		
	Usefulness	1,000	1,000
2	(Constant)		
	Usefulness	,797	1,255
	Anxiety	,797	1,255

a. Dependent Variable: Usage Intention

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Ease of Use	,113[b]	3,535	,000	,210	,819
	Subjective Norm	-,018[b]	-,612	,541	-,037	,996
	Self-Efficacy	,111[b]	3,604	,000	,213	,880
	Anxiety	-,245[b]	-8,307	,000	-,450	,797
	Result Demonstrability	,004[b]	,140	,888	,009	,992
2	Ease of Use	,000[c]	,014	,989	,001	,642
	Subjective Norm	-,037[c]	-1,399	,163	-,085	,989
	Self-Efficacy	,045[c]	1,518	,130	,092	,801
	Result Demonstrability	,011[c]	,417	,677	,025	,991

Excluded Variables[a]

Model		Collinearity Statistics VIF	Minimum Tolerance
1	Ease of Use	1,222	,819
	Subjective Norm	1,004	,996
	Self-Efficacy	1,136	,880
	Anxiety	1,255	,797
	Result Demonstrability	1,008	,992
2	Ease of Use	1,558	,625
	Subjective Norm	1,011	,791
	Self-Efficacy	1,249	,724
	Result Demonstrability	1,009	,793

a. Dependent Variable: Usage Intention

b. Predictors in the Model: (Constant), Usefulness

c. Predictors in the Model: (Constant), Usefulness, Anxiety

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	Usefulness	Anxiety
1	1	1,960	1,000	,02	,02	
	2	,040	6,958	,98	,98	
2	1	2,825	1,000	,00	,01	,01
	2	,156	4,257	,00	,17	,39

3	,019	12,103	,99	,82	,60

a. Dependent Variable: Usage Intention

Casewise Diagnostics[a]

Case Number	Std. Residual	Usage Intention	Predicted Value	Residual
38	3,028	7,00	5,2988	1,70123
111	3,209	6,50	4,6966	1,80342
127	3,265	5,75	3,9154	1,83462
214	3,268	5,50	3,6634	1,83655
226	3,028	7,00	5,2988	1,70123
241	-3,058	1,50	3,2182	-1,71816

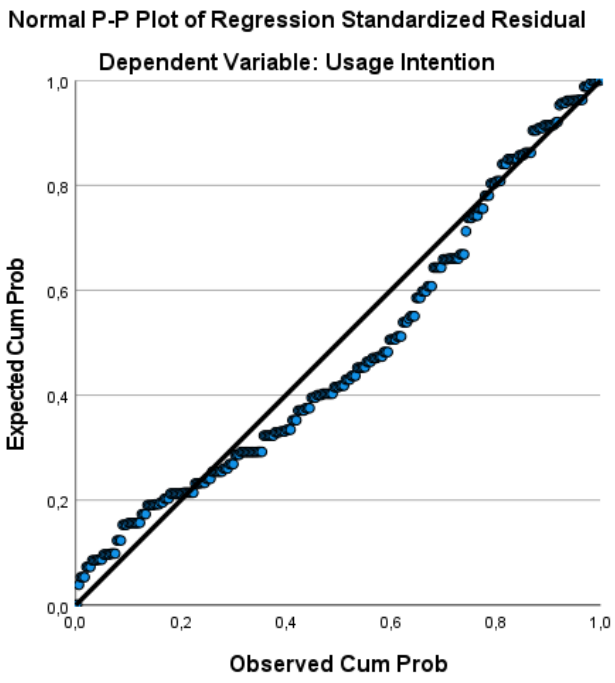
a. Dependent Variable: Usage Intention

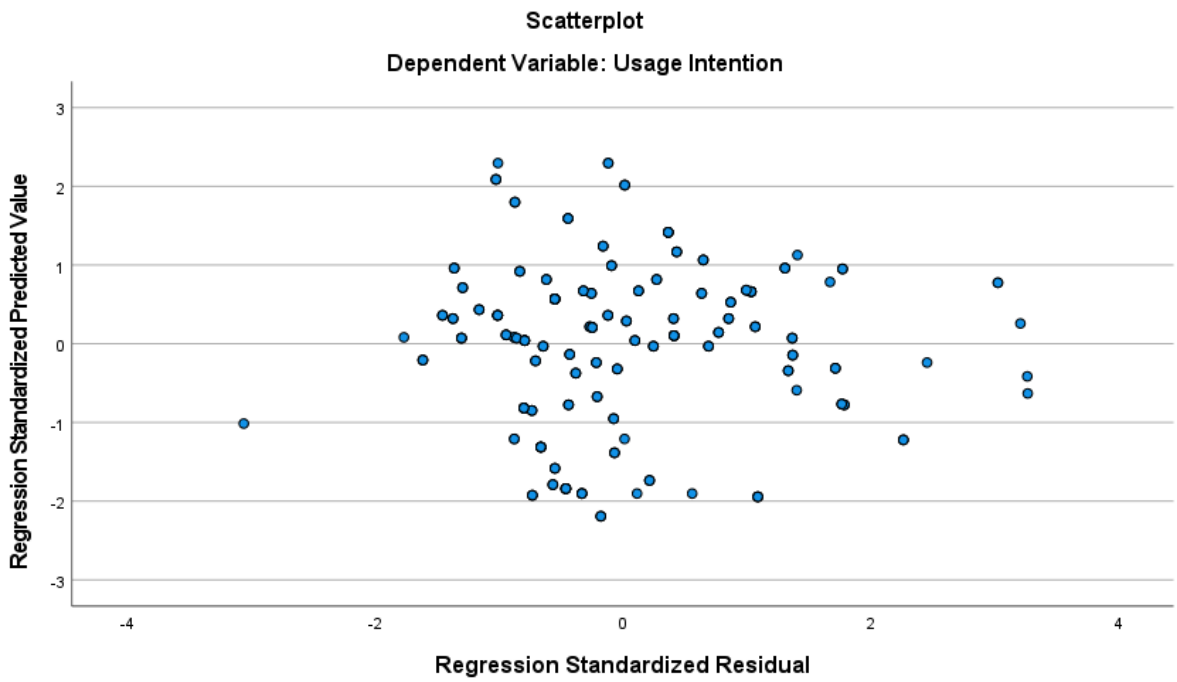
Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1,8491	7,0656	4,3964	1,16251	275
Residual	-1,71816	1,83655	,00000	,55985	275
Std. Predicted Value	-2,191	2,296	,000	1,000	275
Std. Residual	-3,058	3,268	,000	,996	275

a. Dependent Variable: Usage Intention

Charts





3. <u>Third regression</u>

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method

1	Usefulness	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
2	Anxiety	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Usage Intention

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,891[a]	,794	,793	,57336	
2	,918[b]	,843	,842	,50160	1,933

a. Predictors: (Constant), Usefulness

b. Predictors: (Constant), Usefulness, Anxiety

c. Dependent Variable: Usage Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	338,799	1	338,799	1030,585	,000[b]
	Residual	87,775	267	,329		
	Total	426,573	268			
2	Regression	359,648	2	179,824	714,719	,000[c]
	Residual	66,926	266	,252		
	Total	426,573	268			

a. Dependent Variable: Usage Intention

b. Predictors: (Constant), Usefulness

c. Predictors: (Constant), Usefulness, Anxiety

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	,553	,124		4,463	,000
	Usefulness	,931	,029	,891	32,103	,000
2	(Constant)	1,839	,178		10,327	,000
	Usefulness	,811	,029	,776	28,357	,000
	Anxiety	-,249	,027	-,249	-9,103	,000

Coefficients[a]

Model		Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)		
	Usefulness	1,000	1,000
2	(Constant)		
	Usefulness	,787	1,270
	Anxiety	,787	1,270

a. Dependent Variable: Usage Intention

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Ease of Use	,119[b]	3,984	,000	,237	,815
	Subjective Norm	,017[b]	,625	,532	,038	,996
	Self-Efficacy	,110[b]	3,811	,000	,228	,877
	Anxiety	-,249[b]	-9,103	,000	-,487	,787
	Result Demonstrability	,043[b]	1,551	,122	,095	,987
2	Ease of Use	,008[c]	,259	,796	,016	,641
	Subjective Norm	-,004[c]	-,165	,869	-,010	,987
	Self-Efficacy	,045[c]	1,673	,096	,102	,802
	Result Demonstrability	,045[c]	1,842	,067	,112	,987

Excluded Variables[a]

Model		Collinearity Statistics VIF	Collinearity Statistics Minimum Tolerance
1	Ease of Use	1,227	,815
	Subjective Norm	1,004	,996
	Self-Efficacy	1,140	,877
	Anxiety	1,270	,787

	Result Demonstrability	1,013	,987
2	Ease of Use	1,559	,619
	Subjective Norm	1,013	,780
	Self-Efficacy	1,246	,720
	Result Demonstrability	1,013	,780

a. Dependent Variable: Usage Intention

b. Predictors in the Model: (Constant), Usefulness

c. Predictors in the Model: (Constant), Usefulness, Anxiety

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions		
				(Constant)	Usefulness	Anxiety
1	1	1,959	1,000	,02	,02	
	2	,041	6,947	,98	,98	
2	1	2,823	1,000	,00	,01	,01
	2	,158	4,230	,00	,17	,39
	3	,019	12,181	,99	,83	,60

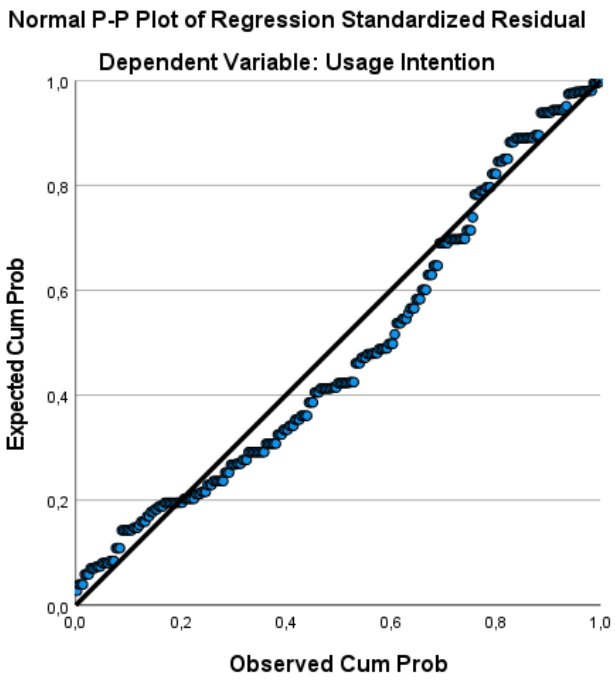
a. Dependent Variable: Usage Intention

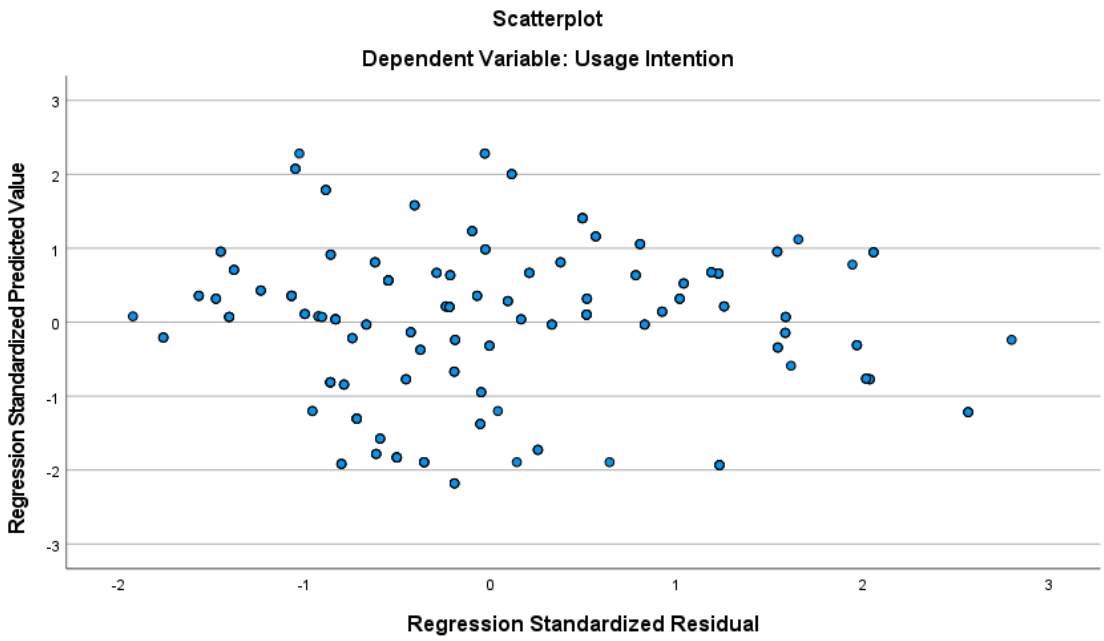
Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1,8467	7,0148	4,3708	1,15843	269
Residual	-,96342	1,40515	,00000	,49972	269
Std. Predicted Value	-2,179	2,282	,000	1,000	269
Std. Residual	-1,921	2,801	,000	,996	269

a. Dependent Variable: Usage Intention

Charts





b. UTAUT regression

1. First regression

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method

1	CentUseful	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
2	CentBHb	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
3	CBHbEase	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
4	CExpSubj	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
5	CBHbSubj	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

6	CentAge	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Usage Intention

Model Summary[g]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,840[a]	,705	,704	,71618	
2	,862[b]	,742	,741	,67022	
3	,871[c]	,759	,756	,64972	
4	,874[d]	,763	,760	,64465	
5	,876[e]	,767	,763	,64050	
6	,879[f]	,773	,768	,63400	1,735

a. Predictors: (Constant), CentUseful

b. Predictors: (Constant), CentUseful, CentBHb

c. Predictors: (Constant), CentUseful, CentBHb, CBHbEase

d. Predictors: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj

e. Predictors: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj, CBHbSubj

f. Predictors: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj, CBHbSubj, CentAge

g. Dependent Variable: Usage Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	344,054	1	344,054	670,776	,000[b]
	Residual	144,130	281	,513		
	Total	488,185	282			
2	Regression	362,408	2	181,204	403,392	,000[c]
	Residual	125,776	280	,449		
	Total	488,185	282			
3	Regression	370,408	3	123,469	292,486	,000[d]
	Residual	117,777	279	,422		
	Total	488,185	282			
4	Regression	372,655	4	93,164	224,182	,000[e]

	Residual	115,529	278	,416		
	Total	488,185	282			
5	Regression	374,548	5	74,910	182,599	,000[f]
	Residual	113,637	277	,410		
	Total	488,185	282			
6	Regression	377,245	6	62,874	156,420	,000[g]
	Residual	110,940	276	,402		
	Total	488,185	282			

a. Dependent Variable: Usage Intention

b. Predictors: (Constant), CentUseful

c. Predictors: (Constant), CentUseful, CentBHb

d. Predictors: (Constant), CentUseful, CentBHb, CBHbEase

e. Predictors: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj

f. Predictors: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj, CBHbSubj

g. Predictors: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj, CBHbSubj, CentAge

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	4,411	,043		103,606	,000
	CentUseful	,921	,036	,840	25,899	,000
2	(Constant)	4,411	,040		110,710	,000
	CentUseful	,903	,033	,822	27,003	,000
	CentBHb	,511	,080	,195	6,392	,000
3	(Constant)	4,470	,041		109,174	,000
	CentUseful	,889	,033	,810	27,308	,000
	CentBHb	,518	,078	,197	6,683	,000
	CBHbEase	-,261	,060	-,129	-4,353	,000
4	(Constant)	4,471	,041		110,048	,000
	CentUseful	,888	,032	,809	27,494	,000
	CentBHb	,527	,077	,201	6,837	,000
	CBHbEase	-,267	,060	-,131	-4,478	,000
	CExpSubj	,055	,023	,068	2,325	,021
5	(Constant)	4,481	,041		110,190	,000
	CentUseful	,889	,032	,810	27,689	,000
	CentBHb	,530	,077	,202	6,921	,000
	CBHbEase	-,263	,059	-,130	-4,445	,000
	CExpSubj	,072	,025	,089	2,905	,004

	CBHbSubj	-,140	,065	-,066	-2,148	,033
6	(Constant)	4,476	,040		111,067	,000
	CentUseful	,870	,033	,793	26,725	,000
	CentBHb	,478	,078	,182	6,097	,000
	CBHbEase	-,229	,060	-,113	-3,813	,000
	CExpSubj	,079	,025	,098	3,214	,001
	CBHbSubj	-,173	,066	-,081	-2,635	,009
	CentAge	-,054	,021	-,083	-2,590	,010

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	(Constant)		
	CentUseful	1,000	1,000
2	(Constant)		
	CentUseful	,992	1,008
	CentBHb	,992	1,008
3	(Constant)		
	CentUseful	,983	1,017
	CentBHb	,992	1,008
	CBHbEase	,991	1,009
4	(Constant)		
	CentUseful	,983	1,017
	CentBHb	,990	1,010
	CBHbEase	,989	1,011
	CExpSubj	,996	1,004
5	(Constant)		
	CentUseful	,983	1,017
	CentBHb	,989	1,011
	CBHbEase	,988	1,012
	CExpSubj	,894	1,119
	CBHbSubj	,896	1,116
6	(Constant)		
	CentUseful	,936	1,069
	CentBHb	,925	1,082
	CBHbEase	,941	1,063
	CExpSubj	,882	1,134
	CBHbSubj	,861	1,161
	CentAge	,808	1,238

a. Dependent Variable: Usage Intention

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance	VIF	Minimum Tolerance
1	CentAge	-,132[b]	-4,062	,000	-,236	,940	1,064	,940
	CAgeUsef	,092[b]	2,859	,005	,168	,993	1,007	,993
	CAgeEase	,078[b]	2,394	,017	,142	,970	1,030	,970
	CAgeSubj	,003[b]	,087	,931	,005	1,000	1,000	1,000
	CentExperience	,057[b]	1,639	,102	,097	,852	1,174	,852
	CentSubjNorm	-,049[b]	-1,502	,134	-,089	,995	1,005	,995
	CentEaseofUse	,095[b]	2,705	,007	,160	,830	1,205	,830
	CentGender	,026[b]	,779	,437	,047	,981	1,020	,981
	CentBHa	-,128[b]	-4,030	,000	-,234	,987	1,013	,987
	CentBHb	,195[b]	6,392	,000	,357	,992	1,008	,992
	CGenEase	,048[b]	1,451	,148	,086	,968	1,033	,968
	CGenUsef	,020[b]	,610	,542	,036	1,000	1,000	1,000
	CGenSubj	,009[b]	,280	,779	,017	,972	1,029	,972
	CExpSubj	,054[b]	1,662	,098	,099	1,000	1,000	1,000
	CExpUsef	-,074[b]	-2,270	,024	-,134	,978	1,022	,978
	CExpEase	-,136[b]	-4,324	,000	-,250	,999	1,001	,999
	CBHaSubj	,049[b]	1,505	,133	,090	,992	1,008	,992
	CBHaUsef	,006[b]	,176	,860	,011	,994	1,006	,994
	CBHaEase	,022[b]	,680	,497	,041	,972	1,029	,972
	CBHbEase	-,124[b]	-3,920	,000	-,228	,991	1,009	,991
	CBHbUsef	-,054[b]	-1,651	,100	-,098	,990	1,010	,990
	CBHbSubj	-,042[b]	-1,282	,201	-,076	1,000	1,000	1,000
2	CentAge	-,088[c]	-2,762	,006	-,163	,882	1,133	,882
	CAgeUsef	,084[c]	2,804	,005	,166	,991	1,009	,986
	CAgeEase	,043[c]	1,382	,168	,082	,937	1,067	,937
	CAgeSubj	,031[c]	1,004	,316	,060	,980	1,020	,973
	CentExperience	,026[c]	,776	,439	,046	,832	1,202	,832
	CentSubjNorm	-,075[c]	-2,464	,014	-,146	,978	1,022	,976
	CentEaseofUse	,029[c]	,834	,405	,050	,743	1,346	,743
	CentGender	,008[c]	,252	,802	,015	,973	1,028	,973
	CentBHa	,127[c]	2,251	,025	,134	,284	3,517	,284
	CGenEase	,033[c]	1,079	,281	,064	,962	1,039	,962

	CGenUsef	,012[c]	,389	,697	,023	,998	1,002	,991
	CGenSubj	-,005[c]	-,167	,868	-,010	,967	1,034	,962
	CExpSubj	,063[c]	2,076	,039	,123	,998	1,002	,990
	CExpUsef	-,084[c]	-2,757	,006	-,163	,976	1,025	,970
	CExpEase	-,101[c]	-3,302	,001	-,194	,957	1,045	,951
	CBHaSubj	,042[c]	1,390	,166	,083	,991	1,010	,983
	CBHaUsef	,043[c]	1,395	,164	,083	,960	1,042	,958
	CBHaEase	,072[c]	2,279	,023	,135	,920	1,086	,920
	CBHbEase	-,129[c]	-4,353	,000	-,252	,991	1,009	,983
	CBHbUsef	-,056[c]	-1,843	,066	-,110	,990	1,010	,983
	CBHbSubj	-,042[c]	-1,397	,164	-,083	1,000	1,000	,992
3	CentAge	-,062[d]	-1,946	,053	-,116	,843	1,187	,843
	CAgeUsef	,052[d]	1,676	,095	,100	,908	1,101	,908
	CAgeEase	-,021[d]	-,609	,543	-,037	,746	1,341	,746
	CAgeSubj	,018[d]	,614	,539	,037	,971	1,030	,971
	CentExperience	-,001[d]	-,025	,980	-,001	,802	1,247	,802
	CentSubjNorm	-,065[d]	-2,182	,030	-,130	,972	1,029	,972
	CentEaseofUse	,027[d]	,780	,436	,047	,743	1,346	,743
	CentGender	,022[d]	,729	,467	,044	,961	1,040	,961
	CentBHa	,036[d]	,596	,551	,036	,238	4,203	,238
	CGenEase	,031[d]	1,051	,294	,063	,962	1,039	,954
	CGenUsef	,009[d]	,291	,771	,017	,997	1,003	,983
	CGenSubj	-,023[d]	-,759	,448	-,045	,950	1,053	,949
	CExpSubj	,068[d]	2,325	,021	,138	,996	1,004	,983
	CExpUsef	-,055[d]	-1,796	,074	-,107	,916	1,092	,916
	CExpEase	-,063[d]	-1,993	,047	-,119	,846	1,182	,846
	CBHaSubj	,040[d]	1,340	,181	,080	,990	1,010	,974
	CBHaUsef	,022[d]	,719	,473	,043	,933	1,072	,933
	CBHaEase	-,013[d]	-,335	,738	-,020	,592	1,690	,592
	CBHbUsef	-,005[d]	-,168	,867	-,010	,832	1,201	,832
	CBHbSubj	-,037[d]	-1,268	,206	-,076	,998	1,002	,983
4	CentAge	-,066[e]	-2,092	,037	-,125	,840	1,190	,840
	CAgeUsef	,055[e]	1,786	,075	,107	,907	1,103	,907
	CAgeEase	-,026[e]	-,775	,439	-,047	,742	1,347	,742
	CAgeSubj	,028[e]	,949	,343	,057	,952	1,050	,952
	CentExperience	,009[e]	,261	,794	,016	,790	1,266	,790
	CentSubjNorm	-,059[e]	-2,007	,046	-,120	,965	1,036	,965
	CentEaseofUse	,040[e]	1,171	,243	,070	,724	1,381	,724
	CentGender	,023[e]	,765	,445	,046	,961	1,040	,961

	CentBHa	,039[e]	,645	,519	,039	,238	4,204	,238
	CGenEase	,038[e]	1,277	,203	,077	,954	1,048	,954
	CGenUsef	,022[e]	,727	,468	,044	,964	1,037	,964
	CGenSubj	-,016[e]	-,533	,594	-,032	,940	1,064	,940
	CExpUsef	-,057[e]	-1,867	,063	-,111	,916	1,092	,916
	CExpEase	-,059[e]	-1,853	,065	-,111	,842	1,188	,842
	CBHaSubj	,048[e]	1,615	,107	,097	,978	1,022	,974
	CBHaUsef	,017[e]	,573	,567	,034	,929	1,077	,929
	CBHaEase	-,008[e]	-,207	,836	-,012	,590	1,696	,590
	CBHbUsef	-,004[e]	-,139	,890	-,008	,832	1,202	,831
	CBHbSubj	-,066[e]	-2,148	,033	-,128	,896	1,116	,894
5	CentAge	-,083[f]	-2,590	,010	-,154	,808	1,238	,808
	CAgeUsef	,049[f]	1,616	,107	,097	,900	1,111	,889
	CAgeEase	-,028[f]	-,828	,409	-,050	,742	1,348	,742
	CAgeSubj	,013[f]	,409	,683	,025	,888	1,127	,835
	CentExperience	,008[f]	,250	,803	,015	,790	1,266	,790
	CentSubjNorm	-,061[f]	-2,071	,039	-,124	,964	1,037	,889
	CentEaseofUse	,051[f]	1,497	,135	,090	,710	1,409	,710
	CentGender	,027[f]	,901	,368	,054	,958	1,044	,893
	CentBHa	,050[f]	,837	,403	,050	,236	4,236	,236
	CGenEase	,031[f]	1,038	,300	,062	,941	1,063	,883
	CGenUsef	,025[f]	,844	,399	,051	,962	1,040	,862
	CGenSubj	-,021[f]	-,699	,485	-,042	,935	1,070	,889
	CExpUsef	-,062[f]	-2,050	,041	-,122	,910	1,099	,891
	CExpEase	-,059[f]	-1,882	,061	-,113	,842	1,188	,842
	CBHaSubj	-,005[f]	-,110	,912	-,007	,373	2,681	,342
	CBHaUsef	,017[f]	,562	,574	,034	,929	1,077	,890
	CBHaEase	-,010[f]	-,253	,800	-,015	,589	1,697	,589
	CBHbUsef	,000[f]	-,013	,990	-,001	,829	1,206	,829
6	CAgeUsef	,038[g]	1,243	,215	,075	,879	1,138	,789
	CAgeEase	-,041[g]	-1,209	,228	-,073	,728	1,374	,728
	CAgeSubj	,020[g]	,642	,521	,039	,881	1,135	,802
	CentExperience	,011[g]	,341	,733	,021	,789	1,267	,789
	CentSubjNorm	-,053[g]	-1,795	,074	-,108	,951	1,052	,797
	CentEaseofUse	,027[g]	,748	,455	,045	,643	1,556	,643
	CentGender	,033[g]	1,130	,259	,068	,951	1,051	,802
	CentBHa	-,004[g]	-,059	,953	-,004	,207	4,820	,207
	CGenEase	,031[g]	1,048	,296	,063	,941	1,063	,808
	CGenUsef	,020[g]	,689	,491	,042	,958	1,044	,805

	CGenSubj	-,027[g]	-,914	,361	-,055	,929	1,077	,803
	CExpUsef	-,055[g]	-1,842	,067	-,110	,903	1,107	,802
	CExpEase	-,049[g]	-1,563	,119	-,094	,827	1,209	,793
	CBHaSubj	-,003[g]	-,072	,942	-,004	,373	2,682	,337
	CBHaUsef	,033[g]	1,087	,278	,065	,895	1,118	,778
	CBHaEase	,015[g]	,383	,702	,023	,555	1,802	,555
	CBHbUsef	-,005[g]	-,151	,880	-,009	,827	1,209	,790

a. Dependent Variable: Usage Intention

b. Predictors in the Model: (Constant), CentUseful

c. Predictors in the Model: (Constant), CentUseful, CentBHb

d. Predictors in the Model: (Constant), CentUseful, CentBHb, CBHbEase

e. Predictors in the Model: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj

f. Predictors in the Model: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj, CBHbSubj

g. Predictors in the Model: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj, CBHbSubj, CentAge

Collinearity Diagnostics[a]

				Variance Proportions		
Model	Dimension	Eigenvalue	Condition Index	(Constant)	CentUseful	CentBHb
1	1	1,000	1,000	,50	,50	
	2	1,000	1,000	,50	,50	
2	1	1,088	1,000	,00	,46	,46
	2	1,000	1,043	1,00	,00	,00
	3	,912	1,092	,00	,54	,54
3	1	1,343	1,000	,31	,03	,00
	2	1,086	1,112	,02	,42	,46
	3	,916	1,211	,05	,49	,53
	4	,656	1,431	,62	,06	,01
4	1	1,346	1,000	,30	,03	,00
	2	1,094	1,109	,03	,33	,46
	3	1,003	1,158	,00	,20	,00
	4	,904	1,220	,06	,38	,52
	5	,654	1,435	,61	,06	,01
5	1	1,464	1,000	,17	,01	,00
	2	1,213	1,098	,13	,03	,00
	3	1,090	1,159	,02	,42	,46
	4	,911	1,268	,06	,48	,52
	5	,703	1,443	,17	,04	,00
	6	,619	1,538	,46	,03	,02
6	1	1,532	1,000	,08	,09	,06

	2	1,414	1,041	,08	,05	,05
	3	1,192	1,134	,17	,01	,10
	4	,911	1,296	,05	,53	,43
	5	,801	1,383	,09	,24	,20
	6	,619	1,573	,49	,02	,02
	7	,532	1,697	,05	,06	,14

Collinearity Diagnostics[a]

		Variance Proportions			
Model	Dimension	CBHbEase	CExpSubj	CBHbSubj	CentAge
1	1				
	2				
2	1				
	2				
	3				
3	1	,33			
	2	,00			
	3	,00			
	4	,67			
4	1	,33	,01		
	2	,00	,07		
	3	,00	,79		
	4	,00	,13		
	5	,67	,01		
5	1	,16	,10	,17	
	2	,16	,26	,15	
	3	,00	,01	,00	
	4	,00	,01	,01	
	5	,36	,33	,36	
	6	,32	,29	,32	
6	1	,15	,03	,01	,14
	2	,02	,10	,22	,09
	3	,13	,24	,08	,01
	4	,00	,00	,01	,00
	5	,09	,19	,11	,16
	6	,35	,25	,26	,00
	7	,26	,18	,30	,59

a. Dependent Variable: Usage Intention

Casewise Diagnostics[a]

Case Number	Std. Residual	Usage Intention	Predicted Value	Residual
18	3,030	6,75	4,8714	1,87859
34	3,045	5,50	3,6123	1,88774
127	3,575	5,75	3,4836	2,26638
200	3,042	5,25	3,3639	1,88615

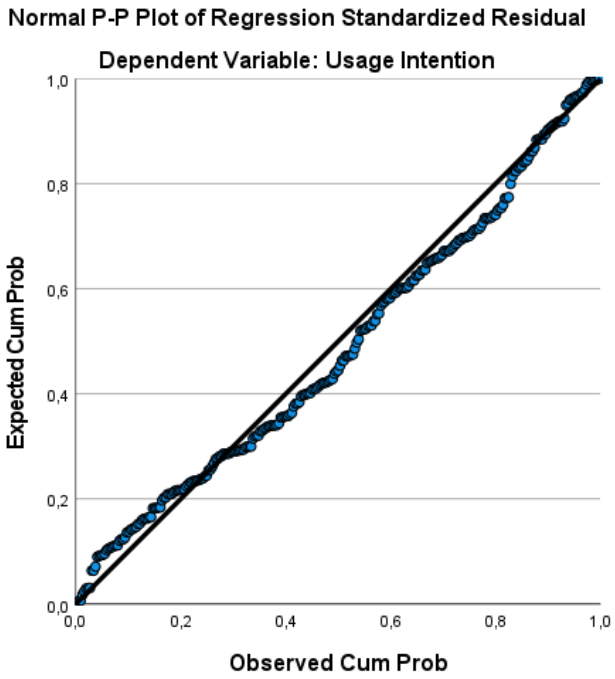
a. Dependent Variable: Usage Intention

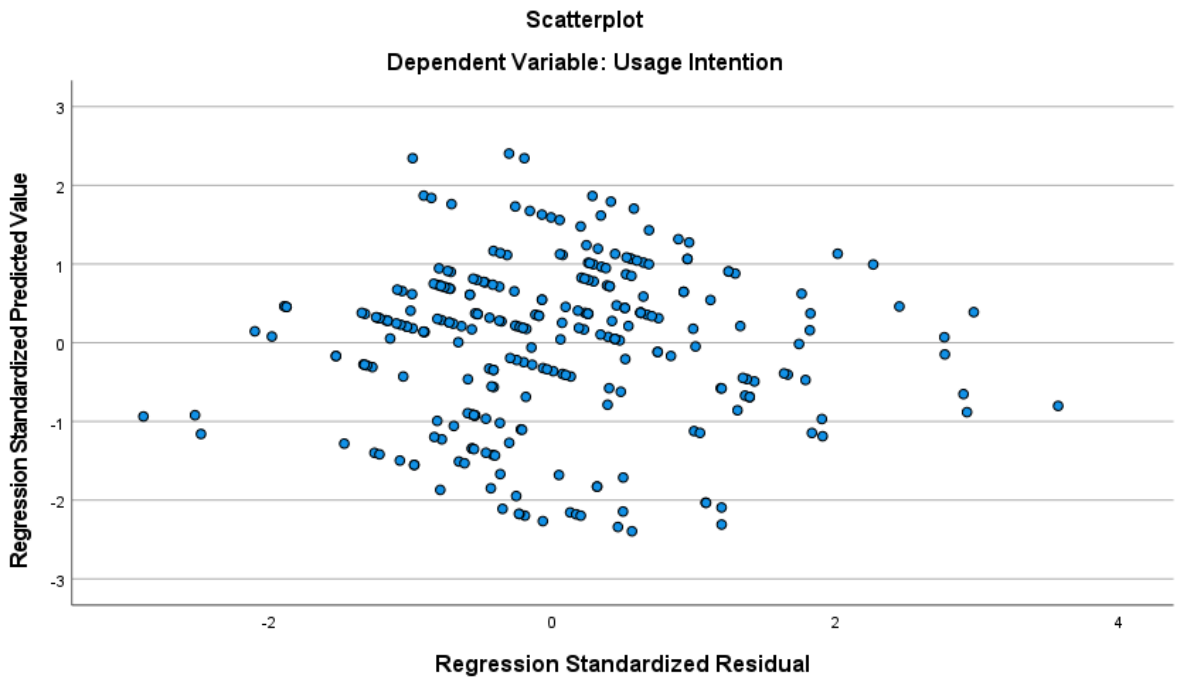
Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1,6414	7,1918	4,4108	1,15661	283
Residual	-1,82847	2,26638	,00000	,62722	283
Std. Predicted Value	-2,394	2,404	,000	1,000	283
Std. Residual	-2,884	3,575	,000	,989	283

a. Dependent Variable: Usage Intention

Charts





2. <u>Second regression</u>

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	CentUseful	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
2	CentBHb	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

3	CBHbEase	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
4	CExpSubj	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
5	CBHbSubj	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
6	CExpUsef	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Usage Intention

Model Summary[g]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,856[a]	,733	,732	,67934	
2	,878[b]	,771	,769	,63059	
3	,887[c]	,788	,785	,60825	
4	,890[d]	,793	,790	,60207	
5	,894[e]	,799	,796	,59345	
6	,896[f]	,802	,798	,59004	1,589

a. Predictors: (Constant), CentUseful

b. Predictors: (Constant), CentUseful, CentBHb

c. Predictors: (Constant), CentUseful, CentBHb, CBHbEase

d. Predictors: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj

e. Predictors: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj, CBHbSubj

f. Predictors: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj, CBHbSubj, CExpUsef

g. Dependent Variable: Usage Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	351,081	1	351,081	760,746	,000[b]
	Residual	127,834	277	,461		
	Total	478,916	278			
2	Regression	369,166	2	184,583	464,191	,000[c]
	Residual	109,750	276	,398		
	Total	478,916	278			
3	Regression	377,175	3	125,725	339,827	,000[d]
	Residual	101,741	275	,370		
	Total	478,916	278			
4	Regression	379,594	4	94,898	261,796	,000[e]
	Residual	99,322	274	,362		
	Total	478,916	278			
5	Regression	382,769	5	76,554	217,369	,000[f]
	Residual	96,146	273	,352		
	Total	478,916	278			
6	Regression	384,220	6	64,037	183,935	,000[g]
	Residual	94,696	272	,348		
	Total	478,916	278			

a. Dependent Variable: Usage Intention

b. Predictors: (Constant), CentUseful

c. Predictors: (Constant), CentUseful, CentBHb

d. Predictors: (Constant), CentUseful, CentBHb, CBHbEase

e. Predictors: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj

f. Predictors: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj, CBHbSubj

g. Predictors: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj, CBHbSubj, CExpUsef

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	4,382	,041		107,744	,000
	CentUseful	,934	,034	,856	27,582	,000
2	(Constant)	4,382	,038		116,079	,000
	CentUseful	,915	,032	,839	29,000	,000
	CentBHb	,511	,076	,195	6,744	,000
3	(Constant)	4,442	,039		115,087	,000
	CentUseful	,901	,031	,826	29,456	,000
	CentBHb	,515	,073	,197	7,047	,000
	CBHbEase	-,263	,056	-,130	-4,653	,000
4	(Constant)	4,442	,038		116,277	,000
	CentUseful	,901	,030	,826	29,742	,000
	CentBHb	,524	,072	,200	7,230	,000
	CBHbEase	-,268	,056	-,132	-4,789	,000
	CExpSubj	,057	,022	,071	2,583	,010
5	(Constant)	4,455	,038		117,601	,000
	CentUseful	,903	,030	,827	30,230	,000
	CentBHb	,530	,071	,202	7,418	,000
	CBHbEase	-,261	,055	-,129	-4,731	,000
	CExpSubj	,080	,023	,100	3,469	,001
	CBHbSubj	-,184	,061	-,086	-3,003	,003
6	(Constant)	4,480	,040		112,852	,000
	CentUseful	,895	,030	,820	29,892	,000
	CentBHb	,537	,071	,205	7,550	,000
	CBHbEase	-,232	,057	-,115	-4,087	,000
	CExpSubj	,082	,023	,103	3,593	,000
	CBHbSubj	-,194	,061	-,091	-3,173	,002
	CExpUsef	-,049	,024	-,058	-2,041	,042

Coefficients[a]

Model		Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)		
	CentUseful	1,000	1,000
2	(Constant)		
	CentUseful	,992	1,008

	CentBHb	,992	1,008
3	(Constant)		
	CentUseful	,982	1,018
	CentBHb	,992	1,008
	CBHbEase	,990	1,010
4	(Constant)		
	CentUseful	,982	1,018
	CentBHb	,990	1,010
	CBHbEase	,989	1,011
	CExpSubj	,997	1,003
5	(Constant)		
	CentUseful	,982	1,018
	CentBHb	,989	1,011
	CBHbEase	,987	1,013
	CExpSubj	,887	1,128
	CBHbSubj	,887	1,127
6	(Constant)		
	CentUseful	,966	1,035
	CentBHb	,987	1,013
	CBHbEase	,924	1,082
	CExpSubj	,884	1,131
	CBHbSubj	,881	1,135
	CExpUsef	,909	1,101

a. Dependent Variable: Usage Intention

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance	VIF	Minimum Tolerance
1	CentAge	-,111[b]	-3,537	,000	-,208	,935	1,070	,935
	CAgeUsef	,075[b]	2,431	,016	,145	,991	1,009	,991
	CAgeEase	,079[b]	2,524	,012	,150	,970	1,031	,970
	CAgeSubj	-,002[b]	-,067	,947	-,004	1,000	1,000	1,000
	CentExperience	,068[b]	2,020	,044	,121	,852	1,174	,852
	CentSubjNorm	-,037[b]	-1,200	,231	-,072	,995	1,005	,995
	CentEaseofUse	,074[b]	2,188	,029	,131	,826	1,211	,826
	CentGender	,022[b]	,704	,482	,042	,981	1,019	,981

	CentBHa	-,134[b]	-4,436	,000	-,258	,986	1,014	,986
	CentBHb	,195[b]	6,744	,000	,376	,992	1,008	,992
	CGenEase	,040[b]	1,283	,201	,077	,968	1,033	,968
	CGenUsef	,018[b]	,571	,568	,034	,999	1,001	,999
	CGenSubj	,021[b]	,656	,513	,039	,970	1,031	,970
	CExpSubj	,058[b]	1,861	,064	,111	1,000	1,000	1,000
	CExpUsef	-,069[b]	-2,216	,028	-,132	,978	1,022	,978
	CExpEase	-,115[b]	-3,795	,000	-,223	,999	1,001	,999
	CBHaSubj	,069[b]	2,228	,027	,133	,989	1,011	,989
	CBHaUsef	,012[b]	,391	,696	,024	,993	1,007	,993
	CBHaEase	,031[b]	,985	,326	,059	,972	1,029	,972
	CBHbEase	-,128[b]	-4,213	,000	-,246	,990	1,010	,990
	CBHbUsef	-,052[b]	-1,664	,097	-,100	,990	1,010	,990
	CBHbSubj	-,057[b]	-1,854	,065	-,111	1,000	1,000	1,000
2	CentAge	-,065[c]	-2,139	,033	-,128	,877	1,140	,877
	CAgeUsef	,068[c]	2,368	,019	,141	,989	1,011	,984
	CAgeEase	,043[c]	1,436	,152	,086	,934	1,070	,934
	CAgeSubj	,024[c]	,827	,409	,050	,982	1,018	,975
	CentExperience	,034[c]	1,067	,287	,064	,829	1,206	,829
	CentSubjNorm	-,061[c]	-2,117	,035	-,127	,981	1,019	,978
	CentEaseofUse	,006[c]	,175	,861	,011	,740	1,352	,740
	CentGender	,004[c]	,135	,893	,008	,973	1,028	,973
	CentBHa	,105[c]	1,963	,051	,118	,287	3,486	,287
	CGenEase	,027[c]	,914	,361	,055	,964	1,038	,963
	CGenUsef	,011[c]	,373	,710	,022	,998	1,002	,991
	CGenSubj	,005[c]	,159	,874	,010	,963	1,038	,960
	CExpSubj	,066[c]	2,324	,021	,139	,998	1,002	,990
	CExpUsef	-,078[c]	-2,711	,007	-,161	,976	1,024	,970
	CExpEase	-,080[c]	-2,740	,007	-,163	,959	1,043	,953
	CBHaSubj	,064[c]	2,238	,026	,134	,989	1,011	,981
	CBHaUsef	,052[c]	1,775	,077	,106	,956	1,046	,955
	CBHaEase	,079[c]	2,672	,008	,159	,923	1,083	,923
	CBHbEase	-,130[c]	-4,653	,000	-,270	,990	1,010	,982
	CBHbUsef	-,056[c]	-1,931	,054	-,116	,989	1,011	,982
	CBHbSubj	-,060[c]	-2,084	,038	-,125	1,000	1,000	,992
3	CentAge	-,038[d]	-1,249	,213	-,075	,838	1,193	,838
	CAgeUsef	,033[d]	1,139	,256	,069	,907	1,103	,907
	CAgeEase	-,022[d]	-,670	,503	-,040	,747	1,339	,747
	CAgeSubj	,012[d]	,409	,683	,025	,973	1,028	,973

	CentExperience	,008[d]	,264	,792	,016	,801	1,248	,801
	CentSubjNorm	-,051[d]	-1,818	,070	-,109	,974	1,026	,974
	CentEaseofUse	,003[d]	,083	,934	,005	,740	1,352	,740
	CentGender	,018[d]	,624	,533	,038	,962	1,039	,962
	CentBHa	,009[d]	,163	,870	,010	,240	4,162	,240
	CGenEase	,024[d]	,845	,399	,051	,963	1,038	,954
	CGenUsef	,007[d]	,267	,790	,016	,997	1,003	,982
	CGenSubj	-,013[d]	-,449	,654	-,027	,947	1,056	,946
	CExpSubj	,071[d]	2,583	,010	,154	,997	1,003	,982
	CExpUsef	-,048[d]	-1,672	,096	-,101	,915	1,093	,915
	CExpEase	-,038[d]	-1,237	,217	-,075	,838	1,193	,838
	CBHaSubj	,060[d]	2,163	,031	,130	,988	1,012	,971
	CBHaUsef	,030[d]	1,043	,298	,063	,927	1,079	,927
	CBHaEase	-,002[d]	-,043	,966	-,003	,595	1,681	,595
	CBHbUsef	-,004[d]	-,121	,904	-,007	,828	1,208	,828
	CBHbSubj	-,053[d]	-1,923	,055	-,115	,997	1,003	,982
4	CentAge	-,042[e]	-1,394	,164	-,084	,836	1,196	,836
	CAgeUsef	,036[e]	1,243	,215	,075	,906	1,104	,906
	CAgeEase	-,027[e]	-,859	,391	-,052	,743	1,346	,743
	CAgeSubj	,022[e]	,793	,429	,048	,953	1,049	,953
	CentExperience	,018[e]	,587	,558	,036	,789	1,267	,789
	CentSubjNorm	-,045[e]	-1,631	,104	-,098	,968	1,033	,968
	CentEaseofUse	,016[e]	,505	,614	,031	,720	1,388	,720
	CentGender	,019[e]	,682	,496	,041	,962	1,039	,962
	CentBHa	,012[e]	,212	,832	,013	,240	4,163	,240
	CGenEase	,031[e]	1,111	,267	,067	,954	1,048	,954
	CGenUsef	,021[e]	,742	,459	,045	,966	1,036	,965
	CGenSubj	-,005[e]	-,187	,852	-,011	,937	1,068	,937
	CExpUsef	-,051[e]	-1,765	,079	-,106	,914	1,094	,914
	CExpEase	-,033[e]	-1,086	,278	-,066	,835	1,198	,835
	CBHaSubj	,070[e]	2,518	,012	,151	,974	1,027	,971
	CBHaUsef	,025[e]	,879	,380	,053	,923	1,084	,923
	CBHaEase	,004[e]	,104	,917	,006	,593	1,687	,593
	CBHbUsef	-,002[e]	-,081	,936	-,005	,827	1,209	,827
	CBHbSubj	-,086[e]	-3,003	,003	-,179	,887	1,127	,887
5	CentAge	-,061[f]	-2,015	,045	-,121	,807	1,239	,807
	CAgeUsef	,028[f]	,962	,337	,058	,897	1,115	,878
	CAgeEase	-,030[f]	-,953	,341	-,058	,742	1,347	,742
	CAgeSubj	,000[f]	,006	,995	,000	,886	1,129	,824

	CentExperience	,017[f]	,563	,574	,034	,789	1,267	,789
	CentSubjNorm	-,047[f]	-1,701	,090	-,103	,968	1,033	,882
	CentEaseofUse	,030[f]	,936	,350	,057	,707	1,415	,707
	CentGender	,025[f]	,898	,370	,054	,958	1,044	,883
	CentBHa	,025[f]	,457	,648	,028	,239	4,190	,239
	CGenEase	,022[f]	,798	,426	,048	,942	1,061	,876
	CGenUsef	,025[f]	,909	,364	,055	,963	1,038	,856
	CGenSubj	-,012[f]	-,414	,679	-,025	,932	1,074	,882
	CExpUsef	-,058[f]	-2,041	,042	-,123	,909	1,101	,881
	CExpEase	-,034[f]	-1,139	,256	-,069	,835	1,198	,835
	CBHaSubj	,013[f]	,294	,769	,018	,380	2,633	,346
	CBHaUsef	,025[f]	,898	,370	,054	,923	1,084	,883
	CBHaEase	,002[f]	,057	,954	,003	,593	1,687	,593
	CBHbUsef	,003[f]	,088	,930	,005	,825	1,213	,825
6	CentAge	-,056[g]	-1,853	,065	-,112	,801	1,249	,801
	CAgeUsef	,020[g]	,687	,493	,042	,879	1,138	,868
	CAgeEase	-,029[g]	-,927	,355	-,056	,742	1,347	,742
	CAgeSubj	-,004[g]	-,134	,894	-,008	,882	1,134	,817
	CentExperience	,028[g]	,920	,358	,056	,767	1,303	,767
	CentSubjNorm	-,048[g]	-1,753	,081	-,106	,968	1,034	,880
	CentEaseofUse	,033[g]	1,030	,304	,062	,705	1,417	,705
	CentGender	,029[g]	1,039	,300	,063	,954	1,049	,877
	CentBHa	,007[g]	,123	,902	,007	,232	4,309	,232
	CGenEase	,026[g]	,937	,350	,057	,938	1,066	,871
	CGenUsef	,032[g]	1,144	,254	,069	,952	1,051	,852
	CGenSubj	-,022[g]	-,781	,436	-,047	,904	1,107	,874
	CExpEase	-,013[g]	-,416	,677	-,025	,720	1,389	,720
	CBHaSubj	,023[g]	,514	,608	,031	,376	2,662	,346
	CBHaUsef	,033[g]	1,163	,246	,070	,909	1,100	,881
	CBHaEase	,013[g]	,357	,722	,022	,580	1,723	,580
	CBHbUsef	,006[g]	,211	,833	,013	,822	1,217	,790

a. Dependent Variable: Usage Intention

b. Predictors in the Model: (Constant), CentUseful

c. Predictors in the Model: (Constant), CentUseful, CentBHb

d. Predictors in the Model: (Constant), CentUseful, CentBHb, CBHbEase

e. Predictors in the Model: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj

f. Predictors in the Model: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj, CBHbSubj

g. Predictors in the Model: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj, CBHbSubj, CExpUsef

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	CentUseful	CentBHb
1	1	1,008	1,000	,50	,50	
	2	,992	1,008	,50	,50	
2	1	1,089	1,000	,00	,46	,45
	2	1,000	1,043	,99	,00	,01
	3	,911	1,093	,00	,54	,54
3	1	1,340	1,000	,31	,02	,00
	2	1,087	1,110	,03	,43	,45
	3	,917	1,209	,04	,48	,55
	4	,655	1,430	,62	,07	,01
4	1	1,343	1,000	,30	,03	,00
	2	1,097	1,107	,04	,33	,44
	3	1,000	1,159	,00	,21	,00
	4	,906	1,217	,05	,37	,55
	5	,654	1,433	,61	,07	,01
5	1	1,465	1,000	,16	,00	,00
	2	1,220	1,096	,14	,04	,00
	3	1,094	1,157	,03	,41	,45
	4	,913	1,266	,05	,48	,53
	5	,683	1,464	,22	,06	,00
	6	,625	1,531	,40	,02	,02
6	1	1,765	1,000	,14	,01	,00
	2	1,311	1,160	,00	,01	,00
	3	1,094	1,270	,02	,40	,45
	4	,916	1,388	,07	,44	,53
	5	,704	1,584	,07	,06	,00
	6	,670	1,624	,26	,02	,00
	7	,540	1,807	,44	,05	,02

Collinearity Diagnostics[a]

Model	Dimension	CBHbEase	Variance Proportions CExpSubj	CBHbSubj	CExpUsef
1	1				
	2				
2	1				
	2				
	3				

3	1	,33			
	2	,00			
	3	,00			
	4	,66			
4	1	,33	,01		
	2	,00	,08		
	3	,00	,79		
	4	,00	,12		
	5	,67	,01		
5	1	,16	,11	,17	
	2	,17	,24	,14	
	3	,00	,01	,00	
	4	,00	,00	,01	
	5	,42	,28	,31	
	6	,26	,35	,37	
6	1	,14	,01	,02	,14
	2	,01	,31	,30	,03
	3	,00	,01	,00	,00
	4	,00	,01	,00	,00
	5	,01	,48	,41	,19
	6	,84	,00	,00	,10
	7	,01	,17	,26	,54

a. Dependent Variable: Usage Intention

Casewise Diagnostics[a]

Case Number	Std. Residual	Usage Intention	Predicted Value	Residual
26	3,072	6,25	4,4727	1,77734
105	3,296	6,00	4,0551	1,94489

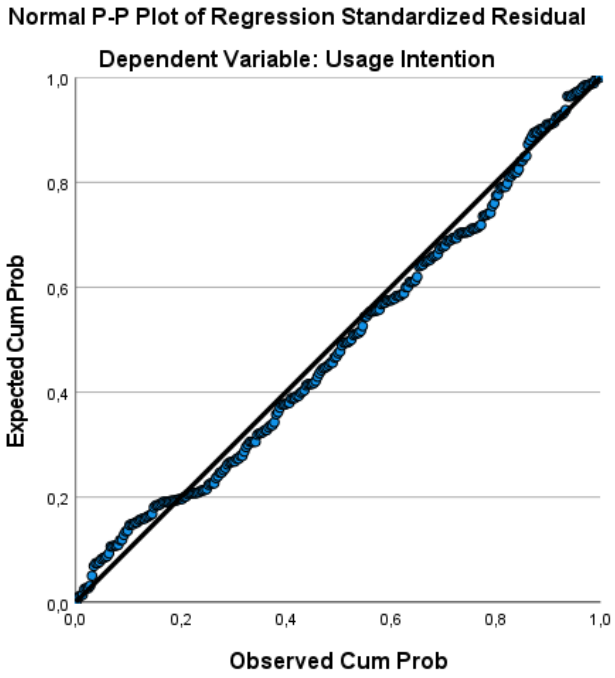
a. Dependent Variable: Usage Intention

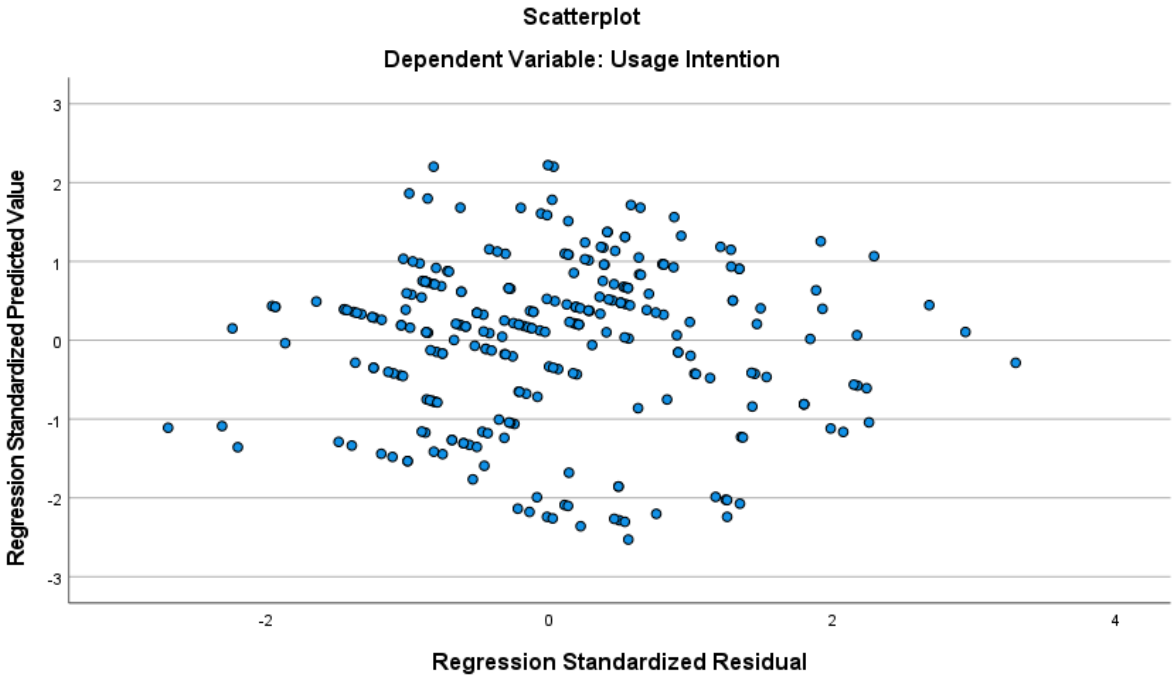
Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1,4190	7,0036	4,3907	1,17562	279
Residual	-1,58641	1,94489	,00000	,58364	279
Std. Predicted Value	-2,528	2,223	,000	1,000	279
Std. Residual	-2,689	3,296	,000	,989	279

a. Dependent Variable: Usage Intention

Charts


Normal P-P Plot of Regression Standardized Residual
Dependent Variable: Usage Intention
Expected Cum Prob
Observed Cum Prob
0,0
0,2
0,4
0,6
0,8
1,0


Scatterplot
Dependent Variable: Usage Intention
Regression Standardized Predicted Value
Regression Standardized Residual
3
2
1
0
-1
-2
-3
-2
0
2
4

3. Third regression

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	CentUseful	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
2	CentBHb	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
3	CBHbEase	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
4	CExpSubj	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

5	CBHbSubj	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
6	CExpUsef	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Usage Intention

Model Summary[g]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,871[a]	,759	,758	,64340	
2	,890[b]	,792	,790	,59947	
3	,897[c]	,805	,803	,58043	
4	,899[d]	,809	,806	,57634	
5	,901[e]	,812	,809	,57258	
6	,903[f]	,815	,811	,56889	1,633

a. Predictors: (Constant), CentUseful

b. Predictors: (Constant), CentUseful, CentBHb

c. Predictors: (Constant), CentUseful, CentBHb, CBHbEase

d. Predictors: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj

e. Predictors: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj, CBHbSubj

f. Predictors: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj, CBHbSubj, CExpUsef

g. Dependent Variable: Usage Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	358,984	1	358,984	867,173	,000[b]
	Residual	113,842	275	,414		

	Total	472,825	276			
2	Regression	374,361	2	187,181	520,874	,000[c]
	Residual	98,464	274	,359		
	Total	472,825	276			
3	Regression	380,851	3	126,950	376,816	,000[d]
	Residual	91,974	273	,337		
	Total	472,825	276			
4	Regression	382,475	4	95,619	287,860	,000[e]
	Residual	90,350	272	,332		
	Total	472,825	276			
5	Regression	383,979	5	76,796	234,244	,000[f]
	Residual	88,846	271	,328		
	Total	472,825	276			
6	Regression	385,445	6	64,241	198,501	,000[g]
	Residual	87,380	270	,324		
	Total	472,825	276			

a. Dependent Variable: Usage Intention

b. Predictors: (Constant), CentUseful

c. Predictors: (Constant), CentUseful, CentBHb

d. Predictors: (Constant), CentUseful, CentBHb, CBHbEase

e. Predictors: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj

f. Predictors: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj, CBHbSubj

g. Predictors: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj, CBHbSubj, CExpUsef

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	4,363	,039		112,849	,000
	CentUseful	,947	,032	,871	29,448	,000
2	(Constant)	4,365	,036		121,174	,000
	CentUseful	,928	,030	,854	30,842	,000
	CentBHb	,474	,072	,181	6,542	,000
3	(Constant)	4,421	,037		119,145	,000
	CentUseful	,914	,029	,842	31,209	,000
	CentBHb	,480	,070	,184	6,846	,000
	CBHbEase	-,240	,055	-,118	-4,389	,000
4	(Constant)	4,421	,037		120,006	,000
	CentUseful	,914	,029	,841	31,399	,000

	CentBHb	,488	,070	,187	7,003	,000
	CBHbEase	-,243	,054	-,120	-4,483	,000
	CExpSubj	,047	,021	,059	2,211	,028
5	(Constant)	4,431	,037		120,063	,000
	CentUseful	,914	,029	,841	31,615	,000
	CentBHb	,495	,069	,190	7,145	,000
	CBHbEase	-,240	,054	-,118	-4,450	,000
	CExpSubj	,064	,023	,080	2,838	,005
	CBHbSubj	-,129	,060	-,060	-2,142	,033
6	(Constant)	4,457	,039		115,398	,000
	CentUseful	,906	,029	,834	31,287	,000
	CentBHb	,502	,069	,192	7,283	,000
	CBHbEase	-,211	,055	-,104	-3,811	,000
	CExpSubj	,066	,022	,083	2,960	,003
	CBHbSubj	-,139	,060	-,065	-2,314	,021
	CExpUsef	-,050	,023	-,058	-2,128	,034

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	(Constant)		
	CentUseful	1,000	1,000
2	(Constant)		
	CentUseful	,991	1,009
	CentBHb	,991	1,009
3	(Constant)		
	CentUseful	,980	1,021
	CentBHb	,991	1,010
	CBHbEase	,989	1,011
4	(Constant)		
	CentUseful	,980	1,021
	CentBHb	,988	1,012
	CBHbEase	,988	1,012
	CExpSubj	,996	1,004
5	(Constant)		
	CentUseful	,980	1,021
	CentBHb	,985	1,015
	CBHbEase	,987	1,013
	CExpSubj	,873	1,146
	CBHbSubj	,874	1,144

6	(Constant)		
	CentUseful	,964	1,038
	CentBHb	,983	1,017
	CBHbEase	,926	1,080
	CExpSubj	,870	1,149
	CBHbSubj	,869	1,151
	CExpUsef	,911	1,097

a. Dependent Variable: Usage Intention

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance	VIF	Minimum Tolerance
1	CentAge	-,098[b]	-3,238	,001	-,192	,932	1,073	,932
	CAgeUsef	,062[b]	2,084	,038	,125	,990	1,011	,990
	CAgeEase	,075[b]	2,520	,012	,150	,969	1,032	,969
	CAgeSubj	-,018[b]	-,616	,539	-,037	1,000	1,000	1,000
	CentExperience	,072[b]	2,256	,025	,135	,853	1,172	,853
	CentSubjNorm	-,014[b]	-,472	,637	-,029	,996	1,004	,996
	CentEaseofUse	,080[b]	2,486	,014	,149	,824	1,214	,824
	CentGender	,035[b]	1,181	,238	,071	,983	1,018	,983
	CentBHa	-,124[b]	-4,302	,000	-,252	,987	1,013	,987
	CentBHb	,181[b]	6,542	,000	,368	,991	1,009	,991
	CGenEase	,031[b]	1,020	,309	,061	,967	1,034	,967
	CGenUsef	,008[b]	,277	,782	,017	,999	1,001	,999
	CGenSubj	-,002[b]	-,080	,937	-,005	,972	1,028	,972
	CExpSubj	,045[b]	1,540	,125	,093	1,000	1,000	1,000
	CExpUsef	-,069[b]	-2,339	,020	-,140	,979	1,022	,979
	CExpEase	-,098[b]	-3,376	,001	-,200	,998	1,002	,998
	CBHaSubj	,048[b]	1,629	,105	,098	,991	1,009	,991
	CBHaUsef	,005[b]	,169	,866	,010	,994	1,006	,994
	CBHaEase	,025[b]	,819	,413	,049	,972	1,029	,972
	CBHbEase	-,114[b]	-3,931	,000	-,231	,989	1,011	,989
	CBHbUsef	-,038[b]	-1,270	,205	-,077	,989	1,012	,989
	CBHbSubj	-,032[b]	-1,067	,287	-,064	1,000	1,000	1,000
2	CentAge	-,056[c]	-1,895	,059	-,114	,877	1,140	,877
	CAgeUsef	,056[c]	2,043	,042	,123	,989	1,011	,981

	CAgeEase	,042[c]	1,468	,143	,088	,934	1,070	,934
	CAgeSubj	,008[c]	,274	,785	,017	,980	1,021	,971
	CentExperience	,040[c]	1,327	,186	,080	,829	1,206	,829
	CentSubjNorm	-,039[c]	-1,392	,165	-,084	,978	1,022	,973
	CentEaseofUse	,017[c]	,517	,606	,031	,734	1,362	,734
	CentGender	,017[c]	,613	,540	,037	,973	1,028	,973
	CentBHa	,098[c]	1,912	,057	,115	,288	3,471	,288
	CGenEase	,019[c]	,670	,503	,041	,963	1,039	,960
	CGenUsef	,003[c]	,095	,924	,006	,998	1,002	,990
	CGenSubj	-,015[c]	-,544	,587	-,033	,968	1,033	,962
	CExpSubj	,055[c]	2,011	,045	,121	,997	1,003	,988
	CExpUsef	-,078[c]	-2,829	,005	-,169	,977	1,024	,969
	CExpEase	-,066[c]	-2,373	,018	-,142	,962	1,040	,955
	CBHaSubj	,046[c]	1,666	,097	,100	,991	1,009	,982
	CBHaUsef	,043[c]	1,521	,129	,092	,954	1,048	,952
	CBHaEase	,071[c]	2,478	,014	,148	,921	1,086	,921
	CBHbEase	-,118[c]	-4,389	,000	-,257	,989	1,011	,980
	CBHbUsef	-,043[c]	-1,549	,122	-,093	,988	1,012	,979
	CBHbSubj	-,036[c]	-1,324	,187	-,080	,999	1,001	,990
3	CentAge	-,030[d]	-1,027	,305	-,062	,836	1,196	,836
	CAgeUsef	,024[d]	,854	,394	,052	,904	1,106	,904
	CAgeEase	-,015[d]	-,496	,620	-,030	,749	1,336	,749
	CAgeSubj	-,004[d]	-,146	,884	-,009	,970	1,031	,970
	CentExperience	,018[d]	,590	,556	,036	,802	1,246	,802
	CentSubjNorm	-,031[d]	-1,138	,256	-,069	,974	1,027	,973
	CentEaseofUse	,010[d]	,327	,744	,020	,733	1,365	,733
	CentGender	,029[d]	1,065	,288	,064	,964	1,038	,963
	CentBHa	,011[d]	,198	,843	,012	,241	4,158	,241
	CGenEase	,019[d]	,687	,493	,042	,963	1,039	,950
	CGenUsef	,000[d]	,001	,999	,000	,998	1,002	,979
	CGenSubj	-,030[d]	-1,105	,270	-,067	,953	1,049	,946
	CExpSubj	,059[d]	2,211	,028	,133	,996	1,004	,980
	CExpUsef	-,052[d]	-1,871	,062	-,113	,917	1,090	,917
	CExpEase	-,027[d]	-,924	,356	-,056	,839	1,192	,839
	CBHaSubj	,043[d]	1,623	,106	,098	,990	1,010	,970
	CBHaUsef	,023[d]	,829	,408	,050	,926	1,079	,926
	CBHaEase	-,002[d]	-,056	,955	-,003	,602	1,661	,602
	CBHbUsef	,006[d]	,196	,845	,012	,826	1,210	,826
	CBHbSubj	-,032[d]	-1,205	,229	-,073	,998	1,002	,980

4	CentAge	-,034[e]	-1,176	,241	-,071	,833	1,201	,833
	CAgeUsef	,027[e]	,969	,333	,059	,902	1,108	,902
	CAgeEase	-,020[e]	-,665	,507	-,040	,745	1,343	,745
	CAgeSubj	,006[e]	,215	,830	,013	,945	1,059	,945
	CentExperience	,025[e]	,854	,394	,052	,792	1,263	,792
	CentSubjNorm	-,027[e]	-,994	,321	-,060	,969	1,032	,969
	CentEaseofUse	,023[e]	,727	,468	,044	,710	1,408	,710
	CentGender	,030[e]	1,101	,272	,067	,963	1,038	,962
	CentBHa	,014[e]	,252	,801	,015	,240	4,160	,240
	CGenEase	,024[e]	,897	,371	,054	,955	1,047	,949
	CGenUsef	,011[e]	,418	,676	,025	,963	1,038	,962
	CGenSubj	-,024[e]	-,860	,390	-,052	,940	1,063	,940
	CExpUsef	-,053[e]	-1,940	,053	-,117	,917	1,091	,917
	CExpEase	-,024[e]	-,819	,413	-,050	,837	1,195	,837
	CBHaSubj	,052[e]	1,944	,053	,117	,973	1,027	,970
	CBHaUsef	,019[e]	,699	,485	,042	,923	1,084	,923
	CBHaEase	,002[e]	,062	,951	,004	,600	1,665	,600
	CBHbUsef	,006[e]	,207	,836	,013	,826	1,210	,826
	CBHbSubj	-,060[e]	-2,142	,033	-,129	,874	1,144	,873
5	CentAge	-,049[f]	-1,659	,098	-,100	,798	1,252	,798
	CAgeUsef	,022[f]	,790	,430	,048	,895	1,117	,867
	CAgeEase	-,023[f]	-,748	,455	-,045	,744	1,345	,744
	CAgeSubj	-,009[f]	-,324	,746	-,020	,887	1,128	,820
	CentExperience	,024[f]	,815	,416	,050	,792	1,263	,792
	CentSubjNorm	-,029[f]	-1,094	,275	-,066	,967	1,034	,870
	CentEaseofUse	,033[f]	1,045	,297	,063	,696	1,436	,696
	CentGender	,033[f]	1,228	,221	,075	,961	1,041	,871
	CentBHa	,023[f]	,432	,666	,026	,239	4,189	,239
	CGenEase	,018[f]	,676	,499	,041	,944	1,060	,864
	CGenUsef	,015[f]	,566	,572	,034	,959	1,043	,839
	CGenSubj	-,027[f]	-,976	,330	-,059	,938	1,066	,865
	CExpUsef	-,058[f]	-2,128	,034	-,128	,911	1,097	,869
	CExpEase	-,025[f]	-,882	,378	-,054	,836	1,196	,836
	CBHaSubj	,019[f]	,448	,655	,027	,386	2,592	,346
	CBHaUsef	,020[f]	,727	,468	,044	,923	1,084	,870
	CBHaEase	,001[f]	,028	,978	,002	,600	1,666	,600
	CBHbUsef	,009[f]	,305	,760	,019	,824	1,213	,824
6	CentAge	-,043[g]	-1,482	,140	-,090	,792	1,263	,792
	CAgeUsef	,014[g]	,496	,620	,030	,877	1,140	,860

CAgeEase	-,022[g]	-,719	,473	-,044	,743	1,345	,743
CAgeSubj	-,013[g]	-,478	,633	-,029	,882	1,134	,813
CentExperience	,036[g]	1,195	,233	,073	,769	1,300	,769
CentSubjNorm	-,030[g]	-1,144	,254	-,070	,967	1,034	,867
CentEaseofUse	,036[g]	1,139	,256	,069	,695	1,439	,695
CentGender	,037[g]	1,380	,169	,084	,956	1,046	,866
CentBHa	,004[g]	,080	,936	,005	,232	4,310	,232
CGenEase	,022[g]	,826	,409	,050	,939	1,064	,860
CGenUsef	,022[g]	,805	,422	,049	,948	1,055	,834
CGenSubj	-,038[g]	-1,378	,169	-,084	,909	1,100	,864
CExpEase	-,003[g]	-,098	,922	-,006	,719	1,391	,719
CBHaSubj	,029[g]	,680	,497	,041	,381	2,622	,346
CBHaUsef	,027[g]	,999	,319	,061	,909	1,100	,868
CBHaEase	,012[g]	,342	,733	,021	,588	1,702	,588
CBHbUsef	,013[g]	,438	,661	,027	,821	1,217	,791

a. Dependent Variable: Usage Intention

b. Predictors in the Model: (Constant), CentUseful

c. Predictors in the Model: (Constant), CentUseful, CentBHb

d. Predictors in the Model: (Constant), CentUseful, CentBHb, CBHbEase

e. Predictors in the Model: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj

f. Predictors in the Model: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj, CBHbSubj

g. Predictors in the Model: (Constant), CentUseful, CentBHb, CBHbEase, CExpSubj, CBHbSubj, CExpUsef

Collinearity Diagnostics[a]

				Variance Proportions		
Model	Dimension	Eigenvalue	Condition Index	(Constant)	CentUseful	CentBHb
1	1	1,013	1,000	,49	,49	
	2	,987	1,013	,51	,51	
2	1	1,095	1,000	,00	,45	,45
	2	1,002	1,045	,97	,01	,02
	3	,903	1,101	,03	,54	,53
3	1	1,348	1,000	,30	,02	,00
	2	1,093	1,111	,03	,43	,44
	3	,916	1,213	,05	,46	,55
	4	,643	1,448	,62	,08	,01
4	1	1,350	1,000	,30	,02	,00
	2	1,104	1,106	,03	,33	,44
	3	1,005	1,159	,00	,23	,00

	4	,900	1,224	,05	,34	,54
	5	,641	1,451	,61	,08	,02
5	1	1,475	1,000	,15	,00	,00
	2	1,237	1,092	,14	,03	,00
	3	1,100	1,158	,02	,40	,45
	4	,914	1,271	,06	,48	,52
	5	,679	1,474	,25	,05	,00
	6	,595	1,575	,38	,03	,04
6	1	1,770	1,000	,14	,01	,00
	2	1,328	1,154	,00	,01	,00
	3	1,100	1,268	,02	,40	,44
	4	,916	1,390	,07	,44	,51
	5	,695	1,596	,13	,06	,00
	6	,663	1,634	,17	,01	,00
	7	,529	1,830	,47	,06	,04

Collinearity Diagnostics[a]

		Variance Proportions			
Model	Dimension	CBHbEase	CExpSubj	CBHbSubj	CExpUsef
1	1				
	2				
2	1				
	2				
	3				
3	1	,33			
	2	,00			
	3	,01			
	4	,66			
4	1	,32	,00		
	2	,00	,09		
	3	,00	,75		
	4	,01	,15		
	5	,66	,01		
5	1	,15	,11	,17	
	2	,17	,24	,13	
	3	,00	,01	,00	
	4	,00	,00	,01	
	5	,46	,26	,26	
	6	,22	,38	,42	
6	1	,14	,01	,02	,14

2	,01	,31	,29	,03
3	,00	,01	,00	,00
4	,00	,00	,01	,00
5	,00	,44	,37	,21
6	,85	,00	,00	,19
7	,00	,22	,31	,44

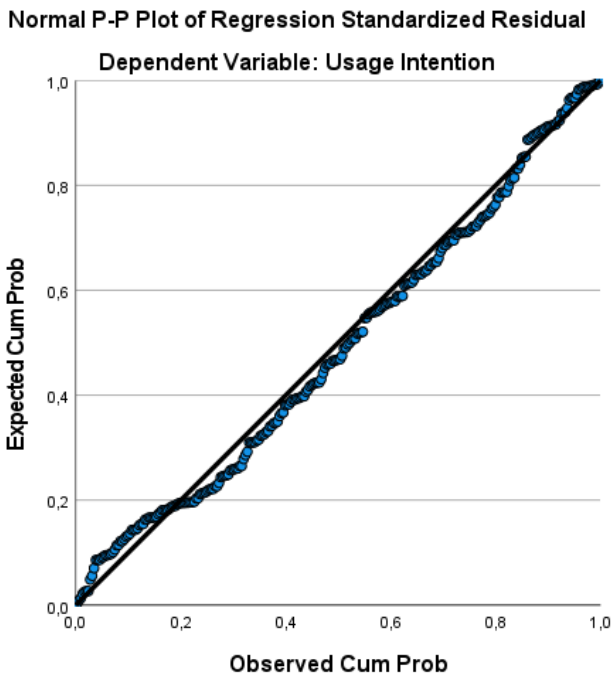
a. Dependent Variable: Usage Intention

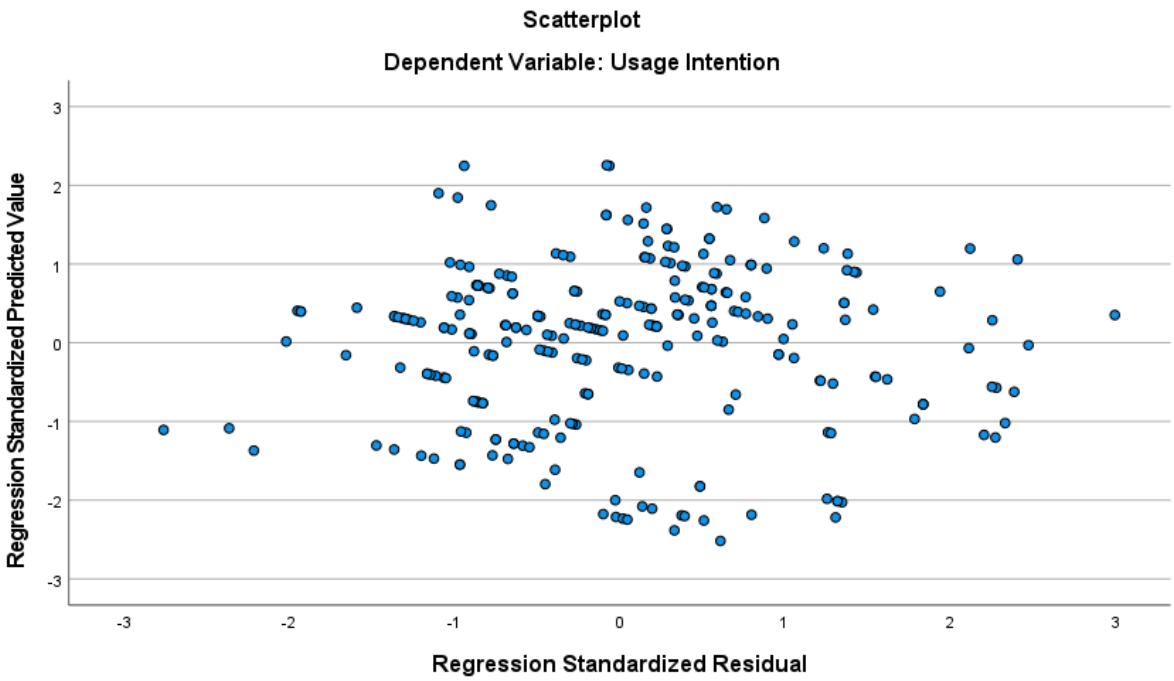
Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1,4031	7,0447	4,3782	1,18175	277
Residual	-1,57039	1,70488	,00000	,56267	277
Std. Predicted Value	-2,518	2,256	,000	1,000	277
Std. Residual	-2,760	2,997	,000	,989	277

a. Dependent Variable: Usage Intention

Charts




Scatterplot
Dependent Variable: Usage Intention
Regression Standardized Predicted Value
Regression Standardized Residual
3
2
1
0
-1
-2
-3
-3
-2
-1
0
1
2
3

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