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The Beginning of Mobile 2.0: Exploring the determinants of consumer intentions with respect to conversational commerce on the WhatsApp platform

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MASTER'S THESIS

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Abstract

This writing proposes a study that strives to explore the determinants for customer adoption of 5th generation Virtual Assistants (VAs) through the WhatsApp interface. The term 5th generation VA is a variant of many other such as: chatbots, virtual agents, intelligent agents etc. Through the literature we provide reasoning as to why we choose to refer to the phenomena by the term 5th generation VAs.

Because of the global shift in consumer behavior from initially the internet, to the app store, and now messaging, companies increasingly acknowledge VAs as a novel technology for interaction with their customers. This supportive tendency has additionally been encouraged due to the rapid proliferation of natural language processing (NLP) in recent years. The notion of integrating VAs within messaging applications as drivers for commerce is regarded as a logical evolution in the area of m-commerce. This new concept is called conversational commerce, and remains a scarcely researched domain, specifically with respect to information system (IS) adoption research.

This study proposes a research framework on the basis of the limited availability of secondary research, and to a large extent on well-established adoption models such as TAM, DOI and UTAUT(2). Quantitative data was validated from 249 individuals belonging to generation Y in the Netherlands.

Perceived Usefulness was determined as the strongest determinant in the overall model. The latter, along with Compatibility are proven as significant positive predictors of Attitude towards usage. Factors with a direct significant positive impact on Behavioral Intentions are: Attitude, Social Influence, Hedonic Motivation, and Innovativeness. Additionally, Technology Anxiety is proven to have a significant negative effect on Behavioral Intentions towards usage of the specified technology. Apart from path-specific deviations, no significant difference in the overall models' predictive capacity was observed while performing multi-group analyses for the control variables; gender, m-commerce experience and frequency of WhatsApp usage.

Practitioners are advised to lay emphasis on the usefulness of utilizing VAs as tools for procurements. Additionally, the technological design should be compatible with the targeted populations' lifestyle. Furthermore, exploring ways to positively influence the general populations' view towards VAs on WhatsApp is recommended. VAs should be fun to use while at the same time, tendencies that cause anxiety should be mitigated. Besides, practitioners should cherish the observed indifference concerning mobile advertising by distancing themselves from those that can be perceived as intrusive and distracting. Lastly, organizations should remain skeptical by seeking for measures to appease internet privacy concerns by conventional means.

Keywords:

Virtual Assistants, Chatbots, Virtual agents, Conversational Commerce, Mobile commerce, TAM, DOI, IDT, UTAUT, UTAUT2

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List of Abbreviations

α	Significance Level
AI	Artificial Intelligence
AT	Attitude Towards Usage
ATMA	Attitude Towards Mobile Advertising
AVE	Average Variance Extracted
B2B	Business to Business
B2C	Business to Consumer
BBM	BlackBerry Messenger
BI	Behavioral Intention
C	Compatibility
CBS	Centraal Bureau voor de Statistiek
CB-SEM	Covariance-Based Structural Equation Modeling
DOI	Diffusion of Innovations
EE	Effort Expectancy
E-shopping	Electronic Shopping
E-payment	Electronic Payment
HM	Hedonic Motivation
IDT	Innovation Diffusion Theory
IN	Innovativeness
IS	Information System
IT	Information Technology
IPC	Internet Privacy Concerns
MGA	Multi-Group Analysis
MMA	Mobile Marketing Association
MT	Motivation Theory
M-commerce	Mobile Commerce
n	Sample Size
NLP	Natural Language Processing
NN	Neural Network
PE	Performance Expectancy
PEOU	Perceived Ease of Use
PU	Perceived Usefulness
PLS-SEM	Partial Least Square-Structural Equation Modeling
SEM	Structural Equation Modeling
SI	Social Influence
SRMR	Standardized Root Mean Square Residual
SPSS	Statistical Package for the Social Sciences
TA	Technology Anxiety
TAM	Technology Acceptance Model
TAM2	Extended Technology Acceptance Model
TBSS	Technology-Based Self-Service
TRA	Theory of Reasoned Action
TPB	Theory of Planned Behavior
UTAUT	Unified Theory of Acceptance and Use of Technology
UTAUT2	Unified Theory of Acceptance and Use of Technology **2**
VA	Virtual Assistant
VINT	VerkenningsInstituut Nieuwe Technologie

1. Introduction

As the study revolves around a technology that remains at an embryotic stage, an extensive introduction and literature review are provided. The introductory section constitutes three parts. Primarily, we provide an overall background of the subjected phenomenon. Secondly, emphasis is laid on the technological proliferation of Artificial Intelligence (AI) with specific focus on the potential for handheld devices. Finally, we dedicate a section to the Asian paradigm where WeChat is taken as an example. All in all, the Introduction fulfils the requirement of grasping the overall evolution of the technology and the market, while additionally attempting to justify the main research objective of this study.

1.1 Background

Humanity has witnessed an extraordinary technological proliferation since the advent of the internet. As IT (Information Technology) systems have gotten deeply entrenched into the environments of both organizations and individuals, one cannot image a world without them any longer. In fact, one could propose the notion of a widespread demand for even greater IT influence in our daily activities. Think of the exponential growth of smartphones and mobile commerce sales (Sreedharan, 2015). On the other hand, as exposure to data increases along, the term 'information overload' shouldn't sound strange in anyone's ears either. Not to mention the genuine concerns with regard to privacy, security and the effects that new technologies could have on employment rates.

In 1950 Alan Turing proposed that within 50 years, humanity would be able to engage in such conversations with computers that would be indistinguishably from those with human beings (1950). Although that timeframe has surpassed, it seems as if the realization of that prediction is getting nearer by the day. As a result of the second renaissance of machine learning techniques, prospected Natural Language Processing (NLP) capabilities promise to unravel novels approaches for business interactions. Industry observers envision tectonic shifts to take place in the area of specifically mobile commerce as a result of such innovations.

While considering projections of technological hypes that are ought to dominate the near future, we acknowledge exactly these areas that are perceived to trigger industrial transformation. E.g., in Gartner's 2016 recommendation for competitive advantage 'The perceptual smart machine age' theme is considered a key technological trend. The latter entails technologies such as (1) Machine Learning, (2) Virtual Private Assistants, (3) Cognitive Expert Advisors, (4) Conversational User Interfaces and (5) Natural-Language Question Answering (2016).

Not only are we taking notice of such indicators from industry observers, actual finished-product introductions can be taken as elementary evidence to conclude that we are not speaking of a mere fallacy. We refer herewith

to Microsoft's Cortana, Amazon Echo's Alexa, Facebook's M, IBM's Watson etc. In fact, David Markus (VP at Facebook) stated at the April 2016th F8 developers' congress the following while referring to Virtual Assistants (VAs): "Everybody wanted websites when the web was launched. And then everybody wanted apps, this is the start of a new era" (Hempel, 2016). Justifiably one could ask oneself what this new era would look like. In this regard, figure 1 clarifies the evolution of messaging bots in relation to the app-store paradigm (Sheth, 2015). The Asian paradigm can be taken as an example too. WeChat, China's equivalent of WhatsApp, integrated additional functionalities to its core product that allow companies and users to interact with each other through VAs and to execute sales through their platform's payment system. The eventual widespread and exponential growth of WeChat is a primary example of the starting point of platform revolutions in the realm of messaging applications. With regard to the western hemisphere, WhatsApp is the dominant social media platform and therefore it's natural to propose that such a platform could be subjected to a similar evolution. This notion is furtherly backed by Facebook's late 2016 announcement to open up WhatsApp to business services (Russell, 2016).

Further observance of major tech-companies in this respect, reveals that the space wherein touching-points between VAs and end-users are ought to be forged will be in the domain of messaging applications accordingly. In an attempt to indicate the extent that this evolution will effect m-commerce, Gartner goes so far as to state that "…by 2020, smart agents will facilitate 40 percent of mobile interactions, and the post-app era will begin to dominate" (Gartner, 2015).

Although we provided a mere glimpse of the discussion taking place regarding VAs and m-commerce, we have provided an insight of the extent to which major tech-companies strive to strategically incorporate themselves within an emerging technology that may revolutionize current m-commerce conducts.

Such promising and exciting prospects particularly invite researchers to explore the determinants of success. Although hypothetical, this will also be the goal of our study. As we have introduced, and to a certain extent motivated our study, we proceed by providing more concrete evidence with regard to the potential of existing technologies.

Figure 1. Messaging & bots VS Apps. Source: *(Sheth, 2015)*

1.1.1 Technological Proliferation

VAs have been around for a considerable time. However, its relevancy is at an all-time high due to the role the technology could play as an enabler, or better yet, a catalyst for m-commerce. Industry observances led us to the conclusion that companies strategically intent to exploit VA technology as a competitive instrument to either push or pull commerce. This intent is to a greater extent attributable to the proliferation of technological capabilities. The operationalization of AI concepts, drives us to provide an understanding of the basics of AI which allows us to grasp the underlying fundamentals of VA potentials. According to Stair & Reynolds, the building blocks of AI systems constitute (1) data, (2) software and (3) hardware (2016). In this section, we provide an elementary overview of the as-is state of affairs with respect to the proliferation of VA technology in respect to the latterly stated building blocks.

Data

Big data has gone through a metamorphosis with regard to storage, processing and utility. In 2014 it was estimated that a staggering 2.5 quintillion bytes of data was created daily (IBM, 2014). One leaves little room for discussion when stating that this amount will be even higher today. Data science at its turn, continuously proves capable of turning big data into actionable customer insights as a means to strategic decision-making (Liebowitz, 2016). These proliferations with regard to the field of data science have been deterministic for novel resolutions in the areas of both software and hardware.

Software

With regard to software, it's worth mentioning the breakthrough of algorithms capable of establish decision surfaces from sophisticated data inputs. Its proven that by utilizing sub-symbolic processes that combine traditional n-gram models with neural networks, (e.g. convolutional, recurrent, and spiking neural networks) complex NLP problems with big data sets can be solved, research by Mikolov et al. (2013) and Kim (2014) exemplify this notion. These relatively new (software) discoveries have extraordinary potentials. However, conventional hardware processors are restricted in terms of computational power and their inherently high energy consumption.

Hardware

Colloquially speaking, modern-day computers are modularly outfitted with hardware based on the von Neumann architecture. In this context, inherent performance limitations are caused as a result of the restricted transfer rates between the CPU and RAM components, and not the processor speed which has proliferated according to Moore's Law (Somnath & Bhunia, 2014). This restriction of the architecture was initially referred to by Backus as the "Von Neumann Bottleneck" (1977). Although one might reserve the perception of observing continuous developments with regard to conventional hardware, in reality the von Neumann

bottleneck has enforced limitations on the development of AI friendly software and computational systems in general (Schuller & Stevens, 2015).

In attempts to counter von Neumann's inhibiting effects on computing biological sensing such as cochlea and retina, the development of neuromorphic systems was initiated (Ishibuchi, 2015). Alike the NN (Neural Network) paradigm, neuromorphic hardware is brain-inspired. Current-day developments of neuromorphic hardware such as IBM's TrueNorth and Qualcomm's Zeroth processors or DARPA's Synapse project have provided solutions for deep learning problems while at the same time challenging Moore's Law and the von Neumann architecture. Neuromorphic chips simulate brain activity in a sense that its architectural design enforces learning through experience in order to recognize patters in data, whereas, traditional chips solely emphasize the execution of complex calculations (Simonite, 2013). It is prospected that smartphones equipped with hardware alike will become capable of learning about habits, surroundings, understand decisions and encourage needs (Marenko, 2015). Ultimately, it is believed that through the increase of such social intelligence a sense of companionship could be instigated between device and user (Monroe, 2014).

In line with the building blocks of marketing 4.0, wherein the ascension of the increasingly sophisticated human-centric era is acknowledged as one that demands more participative and collaborative approaches, VA technology could provide novel means for companies with commercial intends (Kotler, Kartajaya, & Setiawan, 2017).

1.1.2 The Asian Paradigm

In order to adhere to the fundamental principles of marketing, organizations need to continually map their customers' behavior (Kotler & Armstrong, 2009). With the increasing relevancy of data-driven marketing, the holy grail of marketing is perceived to be achievable through a continuously effective and assistive support system (Pawlak, 2016). In this respect, the previous sections have provided a context from which one may conclude AI technologies' strong potential to fulfill such strategic aspirations. Worthwhile dedicating attention to in this respect, is the Asian paradigm that could be taken as a means to justify such a notion with a practical example.

The Chinese counterpart of WhatsApp; WeChat has recognized the pattern of customer behavior and has subsequently reconfigured its value proposition by adding an array of functionalities to its core product. Apart from instant messaging, VAs now establish communicative channels between customers and companies with the intent to enable mobile commerce and banking. With a state-of-the-art payment platform integrating into the application, companies are enabled to set-up so-called 'official accounts' and establish novel methods to strengthen brand awareness and customer acquisition (Treadgold & Reynolds, 2016). After WeChat's approval of the 'official accounts', people can arrange doctor meetings, search for the latest sales promotions, transfer money, arrange a taxi etc. At the moment, various official account owners engage customers via VAs while

others stick to traditional human-to-human contact. Due to the mobile nature of the platform, companies can also engage in targeted promotion based on location and context (de Leij, 2017). E.g., a just married couple, passing by a physical jewelry store could potentially receive a coupon as a result of selective targeting. WeChat additionally offers search within an 'app-store' wherein official accounts can be found. Out of the 700 million WeChat users, 300 million people are making use of the apps' digital pay services. In fact, on the latest New Year's Eve, WeChat processed 8.1 billion 'red envelopes' (a money transfer bot) while PayPal processed just 4.9 billion transaction throughout the whole year of 2015. According to observers, WeChat is now becoming something like an 'uber-platform', a platform capable of integrating an array of loose platforms into its ecosystem (Moazed & Johnson, 2016).

As a reference to the widespread adoption of the WeChat platform, the drawing of an analogy to the western markets is inevitable. In this respect, Facebook took the initial step at the annual F8 conference by announcing its intent to transform Facebook Messenger into a connective tissue between companies and consumers in quiet the same manner WeChat has done. Subsequently, Facebook announced its plans to open up WhatsApp to become a platform for businesses which is a relatable development to WeChat's transformation (Russell, 2016).

The extensive introduction has provided a multifaceted perspective of the context wherein this study takes place. In the next section we describe our research motivation and subsequently describe the state of current literature in order to finally identify a validated research gap.

1.2 Research Motivation

Technological innovations are perceived to increasingly dominate or disrupt the status-quo (Christensen, Raynor, & Mcdonald, 2015). As was laid out in the introductory sections, there is a consensus between practitioners and observers on the potential integration of NLP products within existing technologies. McKinsey refers to this possible disruptive technology as the practice of automating knowledge work. In case of full-spectrum adoption, it is stated to roughly impact 230 million individuals in the area of knowledge work, this is 9% of the global workforce (2013). On the other hand, they envision a total population of 1.1 billion smartphone users to potentially utilize VAs as a replacement for physical knowledge workers. As a clarification it's noteworthy to mention McKinsey's consideration of the impact of VAs on solely knowledge-workers thus not considering other areas of potential influence. Although McKinsey paints a picture here of what the potential of this disruptions could be, we do contest a scenario wherein unobjectionable, widespread adoption of such a technology is the case. Here lays the intrinsic motivation for our study wherein we strive to explore the determinants of VA adoption to uncover the true sentiments that are ought to drive either acceptance or rejection of VAs as drivers for commerce. Instrumental to such a study is the exploitation of the current knowledgebase regarding technology acceptance and behavioral intent to adopt. Examples of such frameworks

entail the technology acceptance model by Davis et al. (1989) , Innovation Diffusion Theory (Moore & Benbasat, 1991) and the Unified Theory of Acceptance and Understanding of Technology by Venkatesh et al. (2003). In the next section we discuss the scope of our study and provide an analysis of the current state of literature with regard the adoption of the proposed technology.

1.3 Research Gap

This research focuses on the extent to which those that belong to generation Y in the Netherlands, are inclined to utilize 5th generation VAs through the WhatsApp interface as a new technological platform to realize new methods of m-commerce. In an attempt to justify our research orientation, we abide by Hynes by analyzing the boundaries of current knowledge as a means of research justification and relevancy (2006).

Commercial utilization of mobile services as a platform for commerce is referred to as m-commerce, this term at its turn is an integral subset of e-commerce (Omonedo & Bocij, 2014) . With regard to m-commerce and e-commerce adoption, we acknowledge various complementary researches to the one proposed here, such as (Stoel & Ha, 2007) and Lopez-Nicolas et al. (2008). As these domains have an abstractive relation to the specific context of our study, we consider these researches as valuable points for knowledge extraction.

When considering the domain of intelligent agent (i.e. VA) adoption, research conducted by de Ruyter et al. provides us with contemporary insights (2005). However, the intent in their research was to investigate the extent to which social intelligence effects consumer perception regarding physical robots. As we strive to gauge the adoption potential of virtual software in the context of m-commerce, the extent to which this study overlaps with the one presented here is limited. Furthermore, May & Kirwan investigated VA effectiveness in a practical customer support role as a replacement for online forms (2013). However, the study ambitiously extended its methodology to allowing customers to be mediated by an actual VA. Therefore, insufficiencies with regard to expected results can be attributed to a premature and shallow presentation of VA technology. In this respect, we emphasize that our study hypothesizes the notion of fully working, socially intelligent VAs where the focus is therefore not on the extent of practical usability of current VA technology, rather on the perceived inclination to adopt the technology in an envisioned mature state.

Furthermore, Heerink et al. researched the adoption of social agent technology with regard to elderly people (2010). Additional research on 5th generation technology acceptance is published By Bree et al. (2012). Nevertheless, the proposed model is theoretical and has not been empirically tested which makes it daunting to judge the extent of its validity. Another more recent study by Bree concluded a distinct potential for 5th generation VAs in the realm of service delivery (2015). Herein, the authors acknowledged the lack of studies on the adoption of the VAs.

As far as our preliminary review on secondary researches reaches, we acknowledge solely Eeuwen's study as one that has specified its attention to the adoption of chatbots (VAs) as a driver for conversational commerce in the context of Dutch millennials (2017). However, Eeuwen acknowledges a lack of comprehensiveness with respect to the tested model and therefore he recommends studies to explore new constructs that may be complementary to the phenomenon under investigation. In this sense, Moussawi sought to study the user relationship with VAs in pre- and post-adoption context. However, as the complete study remains under embargo within the timeframe of our research, we could extract limited value from it (2016).

The described notion of integrating VAs within messaging platforms as facilitators of m-commerce is widely supported (2017). Research conducted by Newcom indicates that WhatsApp is the biggest social media platform in The Netherlands (2016). Based on this understanding we have chosen to focus the research on the possible utilization of VAs on WhatsApp messenger. Although a hypothetical assumption, press releases about WhatsApp's plans to become a platform by opening up for business services, indicate that the prospected assumption of this study is under serious consideration for implementation (Russell, 2016). This choice is additionally supported by the widespread success of WeChat in China as a result of a similar expansion of its core-functionalities.

The overview of existing literature provided us with the parametric boundaries for the design of our research which starts with the formulation of research questions. In this sense, we intend to build further on existing literature, where the latterly mentioned studies could serve as valuable references for the specification of our final model. The next part dedicates attention to the presentation of our main research question, sub-question and research objectives.

1.4 Research questions & objectives

In line with the recognized methodological approach for research, we are required to acknowledge research questions prior to presenting the forthcoming sections (Saunders, Lewis, & Thornhill, 2009) . Based on the overall purpose of our proposed research scope we introduce the following main research question.

Main RQ: What factors are determinant to behavioral intent with respect to the utilization of 5th generation Virtual Assistants on the WhatsApp platform as a novel method to realize mobile commerce?

In order to answer the main question, a theoretical framework will be designed on the basis of the synthesis of existing adoption models, secondary researches, and possibly new constructs. As a means to provide attributional substance to our main question, we are required to define the following concepts as elementary focus points.

- Define and contextualize 5th generation Virtual Assistants
- Define and characterize mobile commerce
- Define conversational commerce
- Define anthropomorphism

The evaluation of the stated concepts allows for a more holistic approach towards the identification and analysis of secondary literature on adoption for the specified technology. Subsequently, this contributes to our intent to propose an overarching research framework which considers the multi-faceted tendencies that are involved with the adoption of such a technology.

Additionally, the following sub-question allows for a more in-depth evaluation of the eventually obtained results. As opposed to our main question, the sub-question focuses on the possibility of different tendencies relative to unobserved heterogeneity within the unit of analysis under investigation.

Sub RQ: To what extent are there significant differences with respect to results between each control variable and the overall results for the unit of analysis?

To realize the latter, the following should be undertaken:

- Formulate control variables

Table 1 provides an overview of the research objectives and methods that are ought to be fulfilled in order to formulate concrete answers to the presented research questions.

Main Research objective		
Determine the factors that influence behavioral intent with respect to the utilization of 5th generation Virtual Assistants on the WhatsApp platform as a novel method for m-commerce		
Research objective 1	**Research objective 2**	**Research objective 3**
- Define 5th generation VAs - Contextualize 5th generation VAs - Define antrhopomorphism	- Define M-commerce - Define Conversational commerce	- Evaluate consumer acceptance models - Evaluate domain-specific secondary research - Propose final model and control variables
Research method 1	**Research method 2**	**Research method 3**
- Theoretical analysis	- Theoretical analysis	- Theoretical analysis - Secondary analysis
Research objective 4		
- Test research model, hypotheses and control variables		
Methodology		
- Quantitative analysis - Conclusive research design - Cross-Sectional study		
Source		
- See bibliography		

Table 1. Research Framework

1.5 Relevance

As has been clarified, literature focusing on VA technology as a means for m-commerce through messaging platforms (i.e. conversational commerce) is severely lacking. However, the extent to which the current literature did focus on the subject has resulted in elementary models for which future researches were recommended. In this respect, the empirical study on the adoption of conversational commerce on WhatsApp, with the application of an extended framework remains uncharted territory. A distinct research gap is made evident and we therefore consider the intend of this research to be scientifically relevant. In addition, this study is conducted on behalf of Sogeti B.V.'s VINT department. The results of this study could contribute to the enrichment of the departments' perspective and broaden its pool of references to extract knowledge from for future publications.

1.6 Thesis Structure

Chapter 1

This study is initiated with a comprehensive introduction which serves as a clarification for the hypothetical and embryotic technology under investigation. Furthermore, we identify the research gap and therewith, justify our research orientation and the subsequent research questions.

Chapter 2

We proceed by engaging in a literature review which constitutes four main parts. Primarily, 5th generation VAs are defined and contextualized. Anthropomorphism and anxiety towards AI is reviewed. Furthermore, we dedicate attention to mobile commerce and conversational commerce. In the second main part, we evaluate adoption literature by focusing on the state of existence of well-known adoption models. This allows us to refine our scope by focusing on secondary research based on all of the latter, which is the focus of the third part. Finally, we operationalize hypotheses and present our proposed framework in the fourth part.

Chapter 3

In this section we present our research design and strategy. Also, we present the methodological approach for the chosen data analysis technique deployed as part of this study.

Chapter 4

The fourth chapter concerns itself with the evaluation of results in accordance with the latterly mentioned methodological approach for data analysis.

Chapter 5

After obtaining the results, we dedicate attention to discussion, answering the proposed research questions, implications, limitations and conclusions.

2. Literature Review

This part will constitute four main parts. Primarily, the focus will be laid on the characterization of the earlier mentioned concepts. Secondly, we delve into literature on well-established adoption models. Thirdly, secondary research analysis is performed to gather substance for part four wherein, the hypotheses are operationalized and the conceptual model is presented.

2.1 5th Generation VAs

This section strives to provide a synthesis on the definitions of 5th generation VAs. Furthermore, operational space for VAs is justified through the analysis of literature concerning the various types of services.

VAs are also known as: chatbots, virtual agents, conversational agents, virtual servant and intelligent agents. Throughout this study, we have chosen to primarily use the term '5th generation VA' while referring to the phenomenon. Although restrictive in sense that the term holds shallow availability of literary substance, we do however perceive it to convey a unique, timely, profound and personifying characterization of the state of its existence. Nevertheless, within the relevant array of schools of thought, one should indiscriminately consider the various terms as synonymous in order to extract its characteristics and define its true meaning.

The concept of VAs is relatively old. According to many researchers, Turing's Imitation game should be regarded as the starting-point of modern-day intelligent agents (1950). However, others state that the, in 1945 conceived software called Memex, instigated initial research to the phenomenon (Bush, 1945). In either ways, current research has advanced gradually ever since. According to Turban & King, software agents are classified as either resident or mobile agents (2003). Resident agents refer to software embedded into a system to strictly perform tasks there (e.g. computer wizards). Mobile agents, to which 5th generation VAs belong, are capable of transporting themselves through different systems, architectures and platforms. Yeo proceeds to state that mobile agents are well suited within the domains of e-commerce, m-commerce and personal assistance (2002).

Russel & Norvig define a software agent as "...anything that can be viewed as perceiving its environment through sensors and acting on that environment through effectors" (1995) . Although a relatively generalizing description for the phenomenon, it should be regarded as a profound definition too as it doesn't contradict the characteristics relative to the current zeitgeist. In order to extract a more concrete definitions we proceed by discussing additional references. In the 7th International Working Conference on Intelligent Virtual Agents, conversational agents were defined as "graphical representations of humans that are increasingly used in a large variety of applications to help, assist or direct the user in performing a wide number of tasks (Pelachaud, et al., 2007). Furthermore, Perez-Marin & Pacual-Nieto describe the phenomenon as "…a software system that is

able to interact with users in a natural way, and often uses natural language capabilities" (2011). Bree et al., refer to 5th generation VAs as "…technology that incorporates natural-language processing, semantic technologies, dialogue control, domain knowledge and visual appearance" (2012). In the 15th international conference on intelligent virtual agents, Brinkman et al., broadened the definition of the phenomenon by presenting the notion of "...socially adaptive virtual agents" as an extension to prior references (2015). Thus far the definitions provided for VAs are quiet generic. To provide a definite meaning that's both complementary to the context of this dissertation and the provided definitions, we present the following:

"A 5th Generation VA is a socially adaptive and intelligent software, utilizing state-of-the-art NLP processes to assist, stimulate and facilitate (commercial) intents of its users"

2.1.1 Contextualizing VAs

As to adhere to a higher level of abstractions with respect to VA technology as a driver for commerce, we acknowledge 'service' as the main context wherein the technology thrives. According to the Committee on definitions of the American marketing Associations, services are: "activities, benefits or satisfactions which are offered for sale, or are provided in connection with the sale of goods" (1960). The Cambridge dictionary provides the following statement while searching for service: "A government system or private organization that is responsible for a particular type of activity, or for providing a particular thing that people need". One could derive from these definitions the notion that service creation carries economic value from its recipient back to its deliverer while its recipient upholds the perception of having received intangible value, resulting in a win-win outcome.

In an attempt to comprehend the evolution of service marketing literature, we identify the following hierarchically stated areas of research: (1) Service Quality, (2) Service Experiences, (3) Service Design, (4) Customer Retention/Relationship Marketing and (5) Internal Marketing (Fisk & Brown, 1993). As both practitioners and researchers increasingly aligned their attitude towards the distinct importance of services as a means for competitive advantage, customer-centricity gained relevance at the cost of product-centricity. The latter can be exemplified by analyzing the coming-to-existence of two widely renowned strategic theories. Where Porter's Three Generic Strategies tended towards *push* marketing (1983), Treacy & Wiersema's Value Disciplines model slightly shifted towards *pull* by creating awareness for customer intimacy. In this respect, and on a more specific note, Vargo and Lusch (2004) argued that the service-centered view establishes a recognition for the need of customers' deep involvement in the customization of offerings to ascertain co-production. With the advent of the internet, interpersonal communication, processes initiation, monitoring and pivoting has seen tremendous advances (Froehle, 2006). However, organizations remained skeptical about the added-value of

revolutionizing traditional service delivery. As a result, Bitner et al. pointed out the predominant resistance of service deliverers with regard to their unwillingness to focus on non-personal actors throughout the process of interacting with consumers (2000). Nevertheless, companies today are less reluctant to recognize the need for conformance to the digitized world. This notion can be exemplified by the reality that many companies nowadays deploy multi-channel strategies where the nirvana is to offer an omnichannel experience. As available channels proliferate gradually, researchers studied the potential for emerging technologies within this context. In the next paragraphs we will continue by discussing such researches.

Types of Services

In a study to explore the implications of technological implementations on current business models, Bree draws a conclusion regarding the current and future state of service delivery (2015). The author distinguishes three main types of service delivery: (1) Service by humans, (2) by Technology-based self-service (TBSS) and (3) by 5th generation VAs. This section attempts to clarify these types and to provide a reasoning as to why there exists operational space for such means of service delivery. Ultimately, the emphasis is laid on providing scientific substance to prove 5th generation VAs' distinction over other forms of service provision.

1. Services by Humans

In instances where there is specific need for interaction, it is determined that physical presence of individuals is required. Largely, this depends on the service ought to be provided. Whenever a customer segment expects the possibility to negotiate, one is obliged to fulfill that demand accordingly. Also, if the process involves the utilization of human intellect, it greatly enhances the customer experience when guided by experienced personnel (Bree, 2015). Apart from service characteristics, some customer segments simply prefer human interaction over any other form of touching-point (Curran & Meuter, 2005). The underlying reasons can be attributed to the fact that customers perceive that, having a greater possibility to exert influence on the process of fulfilling a service as an important factor. In addition, the way personnel handles the service delivery, allows customers to convey content/discontentment. Attributing this sentiment to physically present individual(s) allows organizations to act accordingly in the presence of customers. This provides the customer with a sense of justice while companies can capitalize on the situation with an intent of service recovery. The instant possibility of service recovery is a positive given, both for the experience of the customer, and the image of the company, even in cases wherein discontentment is not the case (Bitner, Booms, & Tettrault, 1990).

2. Services by TBSS

TBSSs are technological interfaces, initialized by service provider as a touching-point for customers to perform the service without external interference. The core difference lays in the role division during

the interaction (Bitner, Brown, & Meuter, 2000). Where in traditional services, the human element was involved as a facilitator of the process, TBSS replaces this with machines. The continual rise of TBSS is attributed to the increasingly customer centric tendency within organizational strategy along with rapid advances in ICT. However, studies indicate that TBSSs flourish in cases wherein service process have high predictability and simplicity (Simon & Usinier, 2007). Bree concludes a continuous shift from services by humans to TBSSs in the future due to the added value directed to end-users such as price reductions (2015). In addition, certain customer segments seek for new methods of interacting with entities which is referred to as 'Inherent Novelty Seeking' (Dabholkar & Bagozzi, 2002). Moreover, some segments seek human confrontations, others prefer it to be avoided and are more content whilst dealing with technical interfaces (Meuter, Bitner, Ostrom, & Brown, 2005). Although literature concludes increases in respect to company performances, cost reduction and customer experience, the actual desires of the customer segments are ought to be critically assessed before establishing TBSSs as a replacement for traditional service delivery. The introduction of a TBSS brings along change, which entails the inherent resistance that comes along with such endeavors (del Val & Fuentes, 2003).

3. Services by 5th Generation VAs

5th generation VAs, as described earlier, serve as smart agents that allow customers to directly interact with a service provider through an intelligent assistant. Bree's study determines the potential for VAs to penetrate markets where clear added value is perceived by its users (2015). End-user adoption of this technology will result in them interacting with a wide array of assistants that serve multiple industries and thus simplifying the input from the customers' viewpoint. Bree also extracted from his study two business models that are applicable to VAs. Primarily, business-to-business (B2B) which in this context entails companies that develop, sell and maintain VAs on behalf of interested parties. Secondly, business-to-customers (B2C) where a company integrates a VA into another product as an enrichment of its functionalities (2015). In this respect the business model enables the possibility for businesses to engage customers with (location-based) advertisements, m-commerce, payment options, premium services, licensing and so forth. In the case of this study however, we hypothesize a B2C model where VAs are integrated within WhatsApp existing eco-system.

Thus far, little research is conducted with regard to customer acceptance of 5th generation VAs. It is crucial to distinguish VA's from one another as 1st generation VAs are more attributable to TBSS (2015). To clarify the latterly mentioned, we present the following figure that shows the distinction that could be made when analyzing the evolution of VAs. The x-axis describes the touching point of the customer with either a machine or human and the y-axis emphasizes the role taken by the executioner of the service.

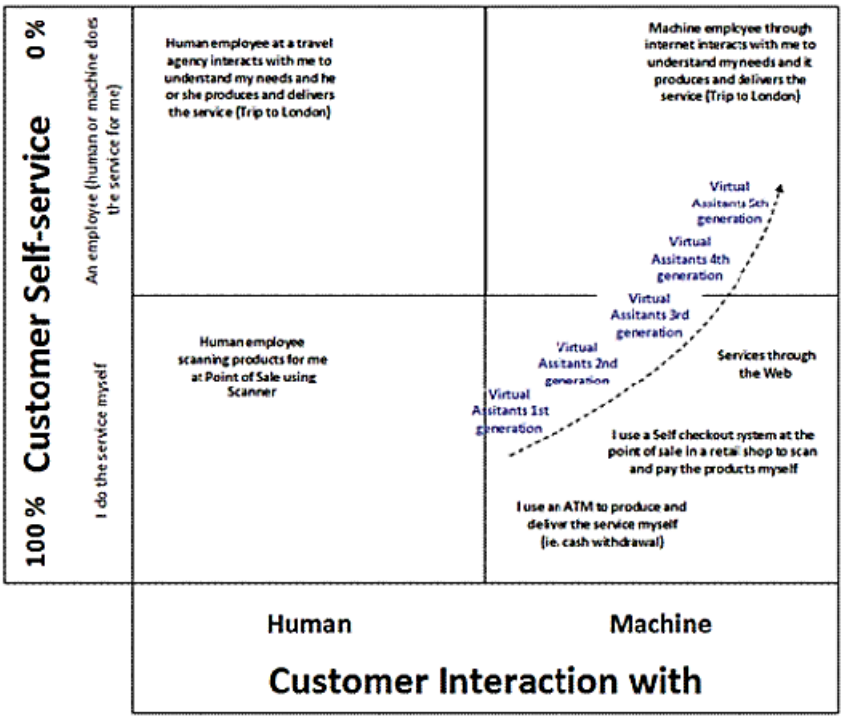

Figure 2. 1st generation VAs to 5th generation VAs. Source *(Bree, 2015)* .

2.1.2 Mobile Commerce

Mobile commerce (M-commerce) is a widely researched topic and considered as an increasingly critical factor in the current business climate. It has proven to be a crucial instrument to safeguard business performance and to remain successful in a globalizing world where companies strive to offer a seamless omnichannel experience (Madan & Arora, 2016). M-commerce evolved as a subset of Electronic Commerce (E-commerce) services where the main differentiating factor is the use of handheld electronics while engaging in services. As its relevance in modern-day business conducts is inevitable, the mitigation of security and trust risks evolving around payment and privacy is crucial to safeguard business continuity. In this section we discuss the characteristics of m-commerce and its proposition in the context of VAs on messaging platforms.

Definitions for m-commerce vary incrementally from another (Omonedo & Bocij, 2014). Clarke defines m-commerce as any shopping activities with a monetary value that is conducted via a mobile device (2001). In line with the stated definition, the existing literature is complementary in a sense that the focus is laid on procurements through mobile handhelds. In more detailed definitions, researchers have included various abstract concepts such as m-commerce's independence from time and space limitations (Mallat N. , 2007). Although, conceivable as mere abstractions they are deterministic characteristics for overall adoption. Helal et al., refer to this as the necessity of being capable to interact in an application at anytime and anyplace in order to safeguard rapid adoption as it contributes to a flawless user experience (1999). The ubiquity of m-commerce along with the intimate co-existence of users and their handhelds provides a unique opportunity for marketers

to leverage on mobile marketing. The Mobile Marketing Association (MMA) defines mobile marketing as "A set of practices that enable organizations to communicate and engage with their audience in an interactive and relevant manner through any mobile device or network (2009) ". Activities ranging within the realm of mobile marketing can be classified as either push or pull marketing (Haig, 2002). We speak of pull marketing when any request initiated by a wireless subscriber directed towards a service deliverer is met by the required responds from that service deliverer. On the contrary, whenever the service deliverer initiates an interaction with a wireless subscriber at any time other than at the subscribers' own request it is regarded as push marketing (Becker & Arnold, 2010). Mobile marketing is subsequently conceived as an effective and relatively cheap channel to identify consumer segments and establish interactions (McDonald, 2011). However, it remains arguable weather mobile marketing techniques such as location-based services and mobile video are positively experienced by recipients. Rodgers & Thorson point out that despite the pro's, users may experience such interactions as intrusive and distracting (2017). In this respect, Teo emphasizes the significance of demographic factors as influential to the value perception (2001). Additionally, Syrett & Lamminman state that in the context of generation Y they should be perceived by marketers as "far more aware of circumstances when they are being deliberately manipulated and have a far lower tolerance of cant and hypocrisy" (2017). In this sense, Venkatesh et al. point out the importance of a deep understanding of customer adoption towards mobile marketing as a deterministic analysis for success (2012).

2.1.3 Conversational Commerce

Despite its increasing relevance, conversational commerce remains a shallowly researched concept. However, Stair & Reynolds define conversational commerce as "A highly personalized form of e-commerce in which consumers and retailers conduct entire transactions within a messaging application" (2016) . Messina goes so far as to define conversational commerce as "...Utilizing chat, messaging, or other natural language interfaces (i.e. voice) to interact with people, brands, or services and bots that heretofore have had no real place in the bidirectional, asynchronous messaging context" (2016). Heikes defines the phenomenon as "...enabling transactions to occur between brands and customers via messaging interfaces such as SMS or through WhatsApp, Facebook Messenger and other mobile messaging platforms" (2017). As one may observe from the definitions of both m-commerce and conversational commerce, the latter focuses exclusively on messaging applications to realize e-commerce, whereas m-commerce is a rather generic term. We can therefore conclude that m-commerce is a subset of e-commerce while conversational commerce is a subset of m-commerce. Holloman contextualizes this novelty with regard to mobile services as an evolution from mobile 1.0 to mobile 2.0. In this regard he states that the era of mobile 1.0 should be perceived as "the constant drive to replicate the web on a mobile screen" (2016). This was mainly attributable to the advent and exponential adoption of smartphones. Mobile 2.0 is a natural shift in approach as the market recognizes that "mobile is bigger than the

desktop web and marketers are taking this on board by grasping messaging as the future, not just an addition to the past" (Holloman, 2016).

2.1.4 Anthropomorphism and Anxiety towards AI

Anthropomorphism is defined as: "the tendency to attribute human characteristics to inanimate objects, animals and others with a view to helping us rationalize their actions" (Duffy, 2003). Mori, in the 'Uncanny Valley' was the initiator of considering the relationship of human affinity towards an increased human-like non-human (1970). According to Moussawi, the effect of anthropomorphism should be one that requires attention in the research on virtual assistant adoption (2016). This section dedicates attention to the phenomenon.

In commerce oriented researches Chandler & Schwarz concluded that people exposed to anthropomorphic products are less reluctant to dispose or replace them (2010). Kim & McGill stress that marketers tend to increasingly treat anthropomorphosis as a phenomenon that requires exploitation in order to enhance customer acquisition (2016). Moreover, Waytz et al. have proven an increased sense of trust towards anthropomorphized autonomous vehicles (2014). On the contrary, researches have also proven the tendency of human behavior to dislike human-like entities. In this sense, Zlotowski et al. (2016) identified the following researches that provided reasoning for the rejection of such artifacts. Saygin et al. considered Neurological reasons (2012), Perception towards experience (Gray & Wegner, 2012), Empathy (MacDorman & Chattopadhyay, 2016), Threat avoidance (Mori, 1970) and terror management (MacDorman & Ishiguro, 2006). Moreover, in a study on the influence of anthropomorphism within the context of self-service technology, Fan, Wi & Matilla concluded a higher degree of customer switching intentions when confronted with a more human-like machine as opposed to less autonomous ones (2015). In this sense, our analysis of the literature on anthropomorphism seems somewhat contradictory. However, a fundamental human instinct which seems to act as a common denominator throughout the school is fear/anxiety.

Technological proliferation isn't always perceived as a positive given. As such, Ricardo analyzed the impact of machinery on the various classes of society and raised arguments as to why the laboring classes had genuine economic concerns towards industrialization (1817). Ever since, fear towards technologies has been discussed widely and presented to us in different forms. The second renaissance of machine learning and the subsequent acknowledgement of the potentials of AI have enriched anxiety towards technology with a new dimension, namely: The fear of superintelligence. In this sense, Sogetilabs VINT presents an extensive research on the anatomy of fear vis-à-vis AI (2017). Overall, the report stresses the necessity for organizations to start learning about the emotions of their customers as only then will they fully get to know them. Apart from the anatomical blocks of fear (figure 3), they presents the phenomenon from a more fundamental angle. Namely, that fear could be seen as a trend of the current zeitgeist and therefore its relevance to technology should not be merely

attributed to AI/technology induced side effects. Supportive to this notion is Moïsi's observations on the 21st century dominance of the culture of fear (2009). In short, the author attributes the current-day dominance of fear in Europe and the United States to geopolitical developments in the world over which the public feels to have no control. As a result, the western society has increasingly perceives these as detrimental to its centrality and therewith giving rise to sentiments such as vulnerability and ultimately, widespread fear.

With respect to underlying fundamentals that allowed the field of psychoanalysis to operationalize 'fear', Freud's contributions are held in high esteem. In 'Beyond the Pleasure Principle' he reasons to declare human behavior as essentially determined by unconscious processes (Freud, 1920). He proceeds to classify human basic instincts into 1. Eros (life instinct) and 2. Thanatos (Death instinct). In short, Freud describes that through the consideration of our Eros and Thanatos we subconsciously give in to either one of the two instinct that takes the overhand. Along with the influence of our already established attitude towards phenomena, actual behavior is ultimately brought to fruition.

Hence, fear ultimately stems from our sub consciousness. Therefore, it should not be regarded as a mere antecedent to certain characteristics but rather as a subset of our basic instinct with an overarching and sometimes unmeasurable extend of influence over decision-making in general. With regard to its operationalization within the context of this study, we dedicate closer attention to the themes discussed in this subchapter in our secondary analysis of adoption research literature.

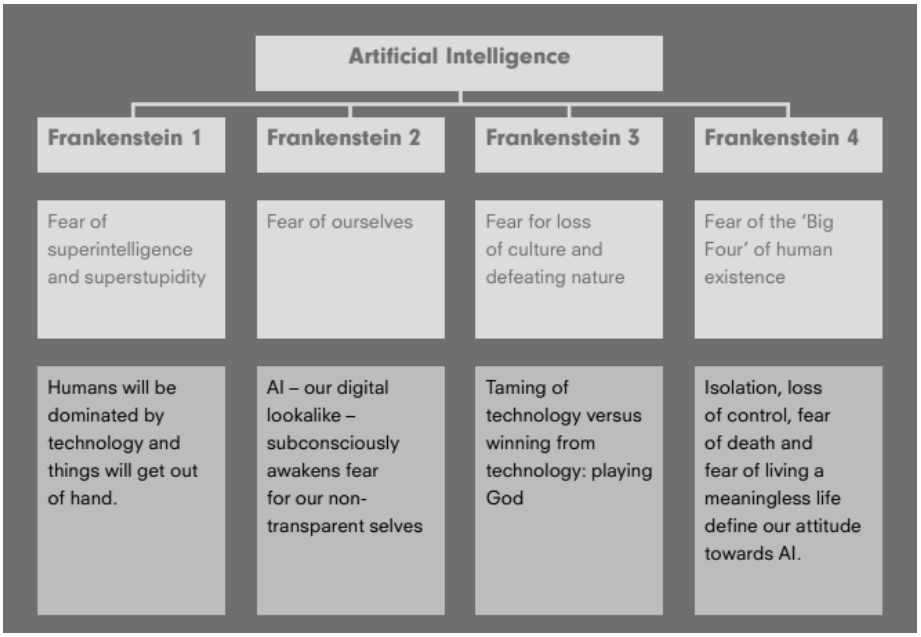

Figure 3. Anatomy of Fear towards AI. Source*: (Doorn, Duivestein, & Pepping, 2017)*

2.2 Evaluating adoption

To construct a theoretical framework from which we can ultimately derive the determinants of adoption for the contextualized technology, a thorough understanding of literature on Information System (IS) adoption should be established first. The following section depicts an overview of the evolution of well-established theoretical frameworks in the broader domain of IS research.

As an elementary point of focus we are inclined to primary enforce that throughout the literature, authors confusingly use the terms 'Adoption' and 'Diffusion' indifferently (Sharma & Mishra, 2014). However, Carr points out that 'Adoption' refers to "the stage in which a technology is selected for use by an individual or an organization" (1999). Whereas, 'Diffusion' emphasizes on "the stage in which the technology spreads to general use and application" (Rogers E. M., 2003). As VA technology remains to be in an embryotic stage, our attention is given to adoption primarily. Furthermore, a logic process for achieving 'Diffusion' is accumulative 'Adoption' and therefore it's natural to establish an understanding on the determinants for adoption first. In order to sketch the dynamics that apply for models that gauge individual adoption, Venkatesh et al. provided the following graphical representation (2003) .

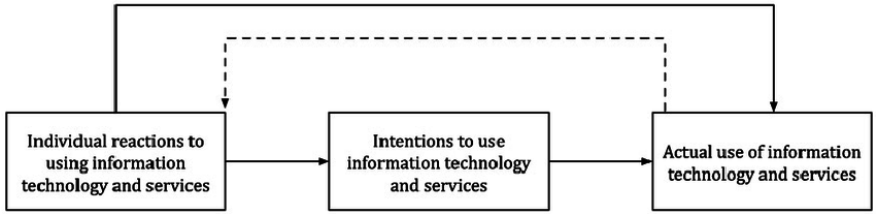

Figure 4. Adoption process for individuals Source*: (Venkantesh, Morris, Davis, & Davis, 2003)*

Naturally, this doesn't mean that we should neglect theories on diffusion. As many adoption studies have incorporated Rogers' theoretical observations into their model we proceed by initiating our evaluation of adoption models with the Diffusion of Innovation (DOI) theory next.

2.2.1 Diffusion of Innovation Theory

As an extensively referred to model, the Diffusion of Innovation Theory i.e. IDT, considers determinants that exert influence on the adoption of innovations. According the theory, diffusion is dependent on the following generic factors: 'the innovation', 'communication channels', 'time' and the 'social system'. With regard to the characteristics of the innovation itself, Rogers' model describes the following factors as crucial elements for rapid diffusion:

1. *Relative advantage:* The degree individuals perceive an innovation to have advantage over the existing one.

2. *Compatibility:* "The extent to which adopting is compatible with what people already do" (Kaasinen, 2005, p. 52).
3. *Complexity:* "the degree to which an innovation is perceived as relatively difficult to understand and use Trialability" (Rogers E. M., 1995, p. 242).
4. *Observability:* "The degree to which the results of an innovation are visible to others" (Rogers E. M., 1995, p. 244).

In general, the theory emphasizes the necessity of decreasing the likelihood of perceived barriers to negatively impact the psychological process of adoption. This process is dissected into 4 stages:

1. *Knowledge:* Individuals gets aware of the innovation and its principle functionalities.
2. *Persuasion:* The formation of a possible positive or negative attitude towards the characteristics of the innovation.
3. *Decision:* The result of an individual's decision-making process for either choosing or dismissing the innovation.
4. *Confirmation:* The potential reversal or reaffirmation of the decision by further exploration of the innovations' characteristics and the perceived general opinion.

2.2.2 Theory of Reasoned Action & Theory of Planned Behavior

The Theory of Reasoned Action (TRA) remains a commonly used framework in the study of human behavior (Fishbein & Ajzen, 1975). Apart from its application in the field of social psychology, TRA has been subjected to IT adoption measurement studies too (2003). The model implies that one's 'Attitude' and 'Subjective Norms' towards behavior trigger 'Behavioral Intention'. In this context 'Attitude' refers to the perceived attitude towards an action and 'Subjective Norms' refers to one's direct environment's perceptual stance on the undertaking of an action. It is proponed that 'Actual behavior' correlates solely with 'Behavioral Intention'. In this respect, the authors assume that if one perceives an action to be relatively profitable it will be executed accordingly. As a responds to the discrepancies with regard to one's control over behavior and voluntariness to behave, Azjen (1985) refined the model and renamed it to the Theory of Planned Behavior (TPB). 'Perceived Behavioral Control' was added as an equally correlating construct to 'Behavioral Intention' next to the ones that had been included in the TRA. 'Perceived Behavioral Control' refers to one's perception of being capable to undertake the action. In addition, the model implies that 'Perceived Behavioral Control' also has an extendable correlation with 'Actual Behavior'. Overall, the authors imply that a higher significance of the correlation from the three constructs to 'Behavioral Intention' should lead to the actual execution of the behavioral action in question.

2.2.3 Technology Acceptance Model

Davis et al. (1989) proceeded by developing one of the, to date, most cited adoption model: The Technology Acceptance Model (TAM). As the name conveys, the framework is primarily intended for the study of technological adoptions. Although stemming from work conducted by Azjen et al., the TAM model attributes the correlation of 'Attitude Towards Using' to the following constructs: 'Perceived Usefulness' and 'Perceived Ease of Use'. According to the authors, these constructs adequately resonate the fundamental substance that impact acceptance of technology. Apart from their strong relation to 'Behavioral Intention', 'Perceived Ease of Use' indirectly correlates with 'Perceived Use'. In this respect, 'Perceived Usefulness' can be defined by a person's perception of experiencing an enhancing effect by a technology when performing a task. 'Perceived Ease of Use' is referred to as one's perceived expectation of using the technology to be free of effort (1989). Through this design the authors attribute a relatively stronger role to 'Perceived Usefulness' as it shares a direct relation with 'Behavioral Intention to Use' as well. In addition TAM introduced 'External Variables' as mediators for 'Perceived Usefulness' and 'Perceived Ease of Use'.

Overall, TAM has proven to be accountable for 40 to 50 % of user acceptance in various contexts of longitudinal studies and is therefore regarded as a robust framework (Park, 2009). Critics however remained skeptical about its ability to encompass a sufficient number of determinants and proponed an investigation to extend the model with holistic experiences that are believed to be explanatory variables for technology adoption. Explementary to this notion are studies conducted by Legris et al. (2003) and (Poon, 2014).

The original TAM model was officially extended by Venkatesh & Davis (2000), and was named the Extended Technology Acceptance Model (TAM2). Additional constructs were added and jointly grouped under the umbrella of social Influence and cognitive instrumental processes. Subsequently, social influence processes constituted 'Subject Norms', 'Voluntaries' and 'Image'. Cognitive instrumental processes encompasses 'Job Relevance', 'Output Quality', 'Result demonstrability' and 'Perceived Ease of Use'.

Longitudinal study results provided a variance of 60% for user adoption which in contrast to TAM's results proved positive significance (Venkatesh & Davis, 2000). As part of a study on the user behavior of m-commerce an adapted TAM2 framework proved applicability. Constructs considered relevant to 'Behavioral Intention to Use' constituted 'Perceived Risk', 'Costs', 'Compatibility', 'Perceived Usefulness' and 'Perceived Ease of Use'.

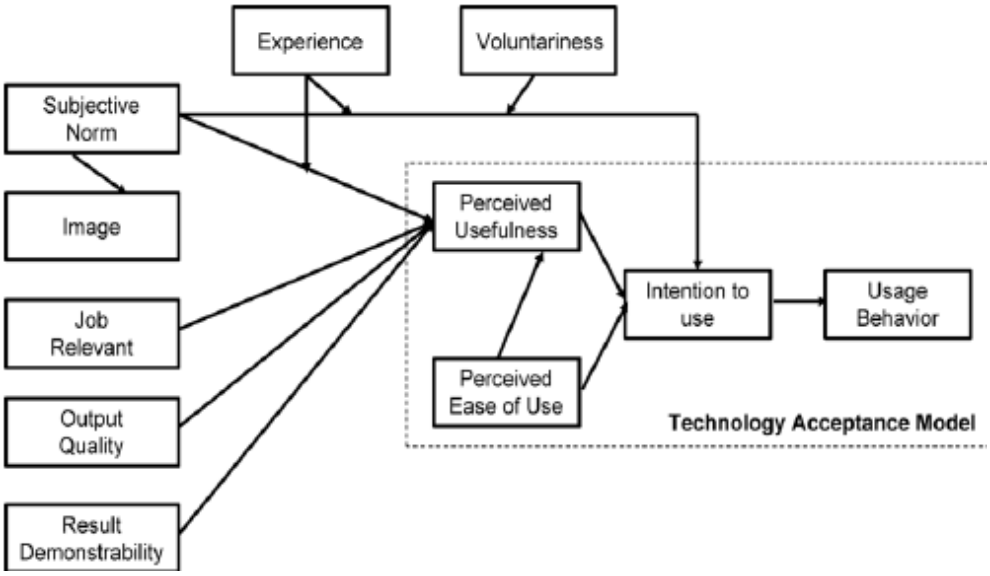

Figure 5. Technology Acceptance Model & Technology Acceptance Model 2. Source: *Venkatesh & Davis (2000)*

2.2.4 Unified Theory and Use of Technology

As a result of an attempt to synthesize earlier adoption models Venkatesh et al. (2003) developed the framework called the Unified Theory of Acceptance and Use of Technology (UTAUT).

The authors based their study on the following eight models:

1. Theory of Reasoned Action (1975)
2. Theory of Planned Behavior (1985)
3. Technology Acceptance Model (1989)
4. Combined TAM and TPB (Taylor & Todd, 1995)
5. Innovation Diffusion Theory (Moore & Benbasat, 1991)
6. Social Cognitive Theory (Compeau & Higgins, 1995)
7. Motivational Theory (Davis, Bagozzi, & Warshaw, 1992)
8. The Model of PC Utilization (Thompson, Higgins, & Howell, 1991)

Seven constructs which were perceived to have a direct relation to 'Behavioral Intention' and 'Use Behavior' were analytically measured. Ultimately, four were concluded to have significance in respect to 'Behavioral Intention' and 'Use Behavior'. 'Social Influence', 'Effort Expectancy' and 'Performance Expectancy' were determined to indirectly exert influence on 'Use Behavior' through 'Behavioral Intention'. 'Facilitating Conditions' however was determined to directly relate to 'Use Behavior' without initial connection to 'Behavioral Intention'.

The tree constructs that had enjoyed relevance in the prior models were; 'Computer Self-Efficacy', 'Computer Anxiety' and 'Attitude Towards Technology'. Venkatesh et al. justified the neglect of these constructs by conveying that 'Self-Efficacy' and 'Anxiety' had an obsolete function due to 'Effort Expectancy's' greater significance on 'Behavioral Intention'. Alike, 'Attitute towards Technology' had proven less significance with relation to 'Behavior Intention' due to both 'Performance' and 'Effort Expactancy'. Furthermore, Venkatesh et al. added 'Gender', 'Age' 'Experience' and 'Voluntariness to Use' as moderating variables with the intend to encourage its predictive power.

As a result of longitudinal studies on the frameworks' performance, the UTAUT confirmed a variance of 70% for 'Usage Intention', whereas, the eight individual models explained 17-53% of variance.

The model was initially intended to study IT adoption within organizational contexts. However, the theoretical origins on which the UTAUT is inspired have fulfilled more general purposes. As such the TRA and TPB have been deployed in various matters on social psychology. Moreover, IDT stems from a study conducted to gain insights on varieties of corn within the context of agriculture (Ryan & Gross, 1950). Not only do UTAUT constructs stem from a wide array of schools of thought, researches have also successfully contested its usefulness outside the realm of the organizational contexts. This notion is also supported by analyzing UTAUT's origins which in general theorized individualized behavioral intentions. In this sense, Mallat states that although its theoretical background is supportive, UTAUT's original design suffers from a lack of attention for analysis of individuals outside organizational contexts (2004). On this basis, researchers have successfully applied extended UTAUT variants with constructs and relations complementary to the specific domains under investigation.

2.2.5 Unified Theory and Use of Technology 2

Subsequently, Venkatesh et al. (2012) proceeded with the introduction of a more comprehensive version of the latter and called it the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). The framework was extended by adding 'Hedonic Motivation', 'Price Value' and 'Habit' to the original UTAUT. The intent of the extension stems from the demand for a friendlier model towards individual behavioral use. The moderating variable 'Voluntariness to Use' was abolished due to its tendency to be predictive within organizational contexts predominantly. Furthermore, apart from having a direct relation with 'Use Behavior', 'Facilitating Conditions' deemed to effect 'Behavioral Intention' as well, and therefore a new connection between the two constructs was established. In consequent studies on the performance of both the UTAUT and UTAUT2 frameworks, the variances for 'Behavioral Intention' and 'Technology Use' saw positive significance from 56-74% and 40-52% respectively. Venkatesh et al. recognized the significance of a consumer-centric model and stated it to be "...a multibillion dollar industry given the number of technology devices, applications, and services targeted at customers" (2012). However, although the model provided significant findings in the subjected context,

recommendations for future research require an extension of the model to fit the domain of the subjected technology and the demographical characteristics.

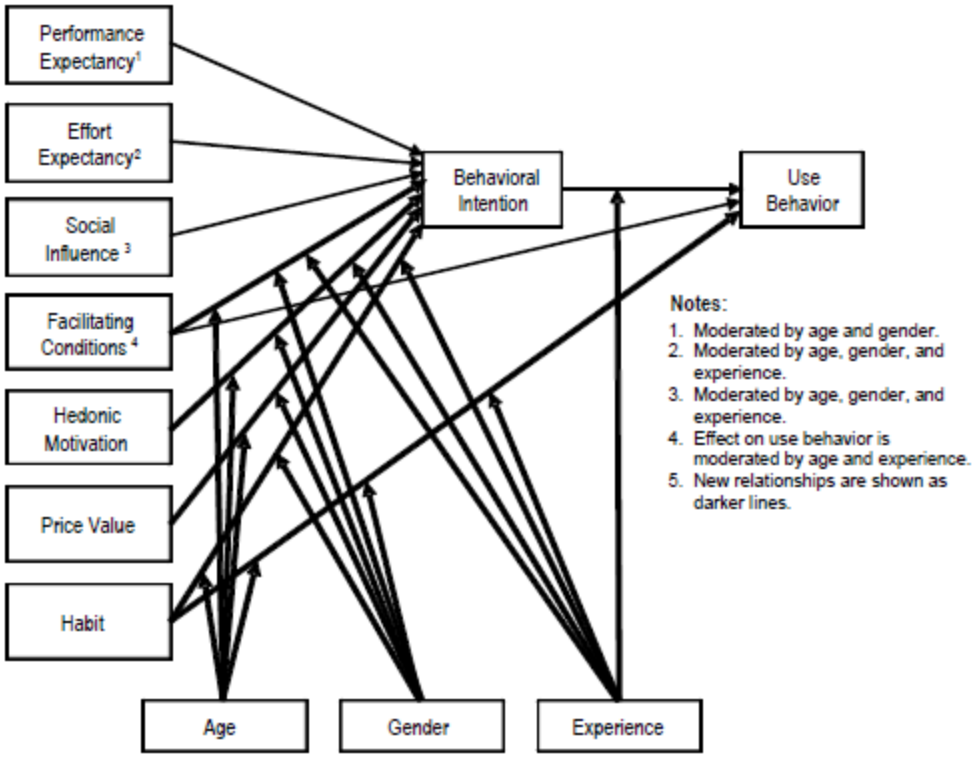

Figure 6. UTAUT2. Source: *(Venkatesh, Thong, & Xu, 2012)*

2.3 Secondary Analysis of Adoption Literature

In the following paragraphs we present and analyze researches that have been conducted on the basis of the latterly presented adoption models. As our literature review thus far has indicated, we dedicated particular attention to TBSS, m-commerce, conversational commerce and VA adoption research. However, if researches within other domains are perceived to enrich our understanding from other angles, these are also incorporated into our analysis.

2.3.1 Setting the Scene

In a study on the assessment of advanced mobile services acceptance, Lopez-Nicolas et al. described TAM's limitations within that context as its design is more complementary to organizational contexts and lacking a detail for social influences (2008). In an attempt to extend the model in order to conform to its contextual shortcomings, the DOI was adapted and combined with TAM. Eventually, 542 respondents (Dutch consumers) were considered valid and a Lisrel, SEM based analysis was performed. Concluded was that social factors have the highest significance on the adoption of advanced mobile services. Throughout the proposed framework the construct 'Social Influence' served as an antecedent to no less than five consecutive constructs. It's therefore

safe to say that the authors attributed the larger extend of their research to prove the significance of social factors within that context. On the contrary, Ha & Stoel's approach towards the antecedents of E-shopping acceptance did not take into account any social factors within their framework but placed a rather greater emphasis on E-shopping Quality and proved robustness as well (2007). The analysis was based on 297 responses and analysis was performed by SEM. The intent of both of these studies exemplifies the various angles that the authors have specifically focused upon where one neglects to incorporate a generic variable, to emphasize the importance of another with the intent to raise attention to that specific tendency. In this respect we highlight that within our study we strive to present an overarching framework that takes into account the multifaceted nature of the phenomenon of conversational commerce where the scarce yet valuable literature serves as a critical foundation.

2.3.2 Secondary Analysis

In a study that assesses robot and human behavior, de Ruyter et al distinguish UTAUT from its predecessors as a validated framework and therefore applicable to the domain (2005). Despite the populations' acknowledgement of the potential invasion of the technology in their daily lives, the study concluded the acceptance of social robots in the context of elderly Dutch people. The authors mainly attribute this acceptance to the concern the population expressed with regard to the increasing complexity that technological proliferation brings along into their surroundings where social robots could serve as a central point to delegating such concerns towards.

Subsequently, Looije, Cnossen & Neerincx took UTAUT as a basis for their research on assessing guidelines for adoption of socially intelligent robots in healthcare (2006). Heerink et al. proceed by complying with the notion of adapting UTAUT within the domain and applied an extended form of the framework in a study on assistive social agent acceptance by older adults and called it The Almere Model (2010). 40 respondents qualified and SEM analysis was performed. The authors defy Vekantesh et al. in a sense that they reintroduce 'Attitude', at the cost of 'Performance Expectancy', and prove it to be the most relevant construct, where 'Perceived Usefulness' shows relatively less significance. This finding is in line with earlier observations by Yang and Yoo who stressed the undeniable significance of 'Attitude' in the domain of IS research in general (2004). They accurately point out some researches interchangeable usage of user beliefs, behavioral intent and attitude as if they entail the same tendencies. As we consider this observation as a sore spot in the domain technology adoption research, we propone herewith the inclusion of the construct of 'Attitude' within our final model which subsequently alters the application of the original UTAUT(2) model significantly. However, Yang and Yoo went further in stressing 'Attitude's' significance and specified the construct into 'Cognitive' and 'Affective Attitude'. In this respect, the domain of VAs lends itself as an ideal fit due to its technical and social nature

which holds relative significance towards cognition and affection. Nevertheless, prioritization drives us to stick to a generic representation of 'Attitude' as overly detailed framework inhibits the generalizability of the study.

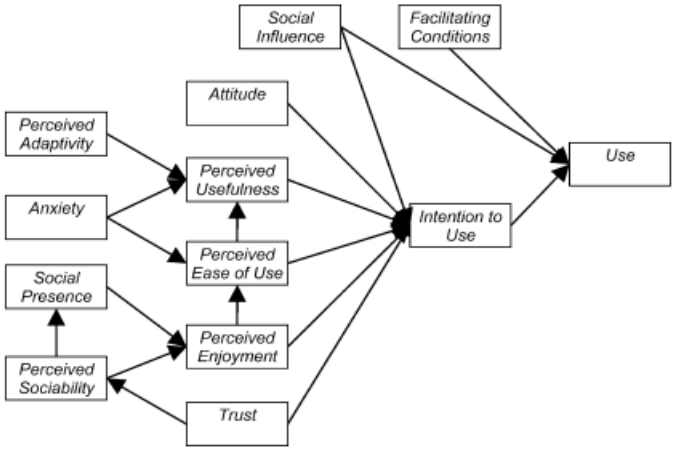

Figure 7. The Almere Model. Source: *(Heerink, Krose, Evers, & Wielinga, 2010)*

In a study on the drivers of mobile commerce, Wu & Wang combined TAM & DOI and performed an SEM based study on 310 respondents (2005). The study contributed to the domain by proving the highest significance of 'Compatibility' on 'Behavioral Intent' followed by 'Perceived Risk'. Eeuwen researched the applicability of messenger chatbots as a means to realize conversational commerce in the context of Dutch millennials. The TAM model was taken as a point of initiation for eventual extension (Eeuwen, 2017). Apart from TAM's constructs the author added DOI's 'Compatibility'. In addition, the framework consists of new constructs such as: 'Attitude Towards Mobile Marketing' and 'Internet Privacy Concerns'. On the basis of 195 respondents and regression analysis, 'Compatibility' proved 59% of variance in 'Attitude' while the addition of 'Internet Privacy Concerns' and 'Perceived Usefulness' increased the variance in 'Attitude' to 66%. As the proposed framework in the specified study proved overall robustness, and due to its relevance to our research goal we intend to include the constructs 'Internet Privacy Concerns', 'Perceived Ease of Use', 'Compatibility', 'Attitude towards Marketing' as predictors to 'Attitude' as well.

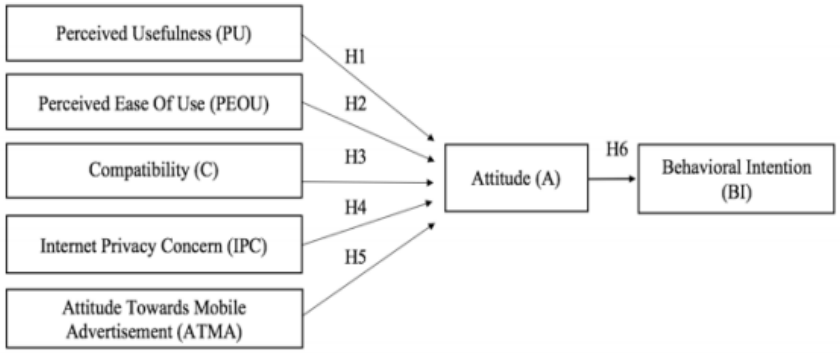

Figure 8. Model on Mobile conversational commerce. Source: *(Eeuwen, 2017)*

Shambare investigated the factors influencing WhatsApp acceptance in developing countries (2014). The TAM framework was used and 192 respondents were considered. It was concluded that the fast paced diffusion of WhatsApp is largely attributable to it's fairly ease of use, cost efficiency and its openness to multiple platforms. Subsequently, these relative advantages that are perceived by its users had been determinant to the steep decline of substitute products such as SMS and BlackBerry Messenger (BBM). Furthermore, Yin studied the adoption of WhatsApp mobile learning in the Malaysian context and concluded a significant positive attitude towards WhatsApp in general (2016). However, the positive tendency towards WhatsApp is internationally supported by multiple other researches such as O'Hara et al. (2014), (Church & Oliviera, 2013), (Dayani Ahad & Lim Ariff, 2014). In this respect, gauging the attitude towards WhatsApp as a platform for conversational commerce proves to be interesting as results may unveil weather the positive attitude towards WhatsApp as-is will either be leveraged or ignored.

Kim & Forsythe performed a study on the adoption of virtual try-on technology for online apparel shopping (2008). 491 responses were collected and consecutively assessed by multiple-group SEM. Their research framework took initial inspiration from TAM and was furtherly extended by the addition of the construct 'Technology Anxiety', 'Innovativeness' and MT's (Motivation Theory) 'Perceived Enjoyment'. Ultimately, the constructs 'Technology Anxiety' and 'Innovativeness' were proven not significant with respect to their immediate effect on 'Intended Use of the Technology' but they did significantly correlate as moderators between 'Attitude' and 'Intended Use'. Herewith, the researchers validated the notion that novel experiences directed towards customers by the utilization of interactive technologies results in increased purchase intentions in contrast to passive product exposure (Kim & Forsythe, 2008, p. 57). In this respect, both 'Technology Anxiety' and 'Innovativeness' are too applicable to the domain of conversational commerce thus the design of the framework of this study is also taken into consideration for the development of our final framework.

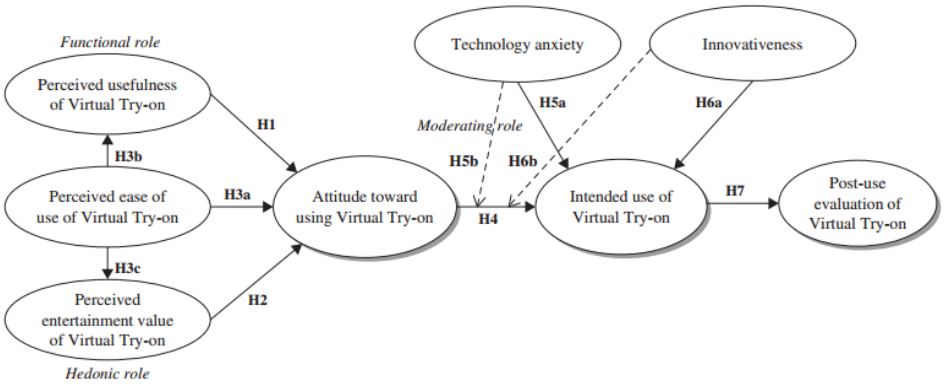

Figure 9. Virtual Try-On Technology model focusing on Technology Anxiety and Innovativeness. *Source: (Kim & Forsythe, 2008)*

Furthermore, while researching the determinants of end-user acceptance of biometric authentication, Miltgen et al. partly combined the TAM, DOI and UTAUT constructs (2013). The study encompassed an analysis of inputs from 326 respondents and analysis was performed by PLS-SEM. Apart from the traditional TAM constructs, UTAUT's 'Social Influence' and 'Facilitating Conditions' were incorporated in the model as having a direct impact on the 'Behavioral Intent'. Furthermore, 'Innovativeness' was included as a prior factor while 'Compatibility' served as an antecedent to the latter. The combination of the so-called 'BIG 3' is recurrent. As such Zhong et al. took TAM, IDT and UTAUT and analyzed their model in the context of mobile payment adoption in China (2013). In total 365 respondents participated in the study where the analysis was performed with the CB-SEM statistical methodology. Noteworthy constructs in this regard are 'E-payment Habit' and 'Interconnection' as direct linkages to 'Intention to use'. Both constructs are inspired on UTAUT's 'Social Influence' however with a specific focus on the domains of commerce and technology environment.

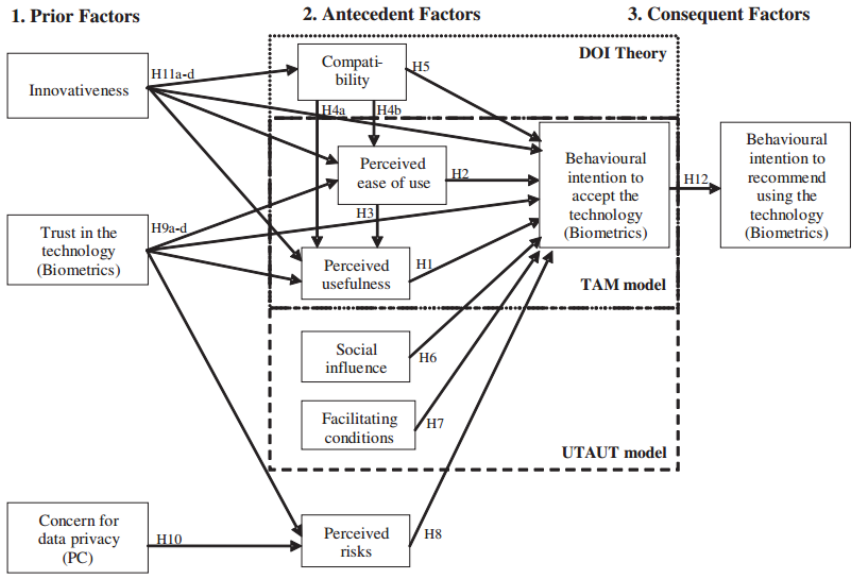

Figure 10. End-user acceptance of biometrics model combining the 'BIG 3'. Source: *(Miltgen, Oliveira, & Popovič, 2013)*

2.3.3 The case against Anthropomorphism

In a study gauging the extent to which increased anthropomorphism has effect on trust towards autonomous vehicles, Waytz et al., (2014) developed the model depicted on figure 11. 100 participants took part in an experiment that involved a driving simulator with three different settings (conditions). Ultimately, it was concluded that a higher degree of anthropomorphism increases trust towards autonomous vehicles. The authors proceed to propone that the findings are representative to the fast paced changing interface between technological capabilities and human interaction, therefore, one shouldn't consider modern technology as mindless tools but rather as socially capable artifacts. Therewith, the authors indirectly imply the validity of their study as one that applies to other domains that deal with anthropomorphism as well.

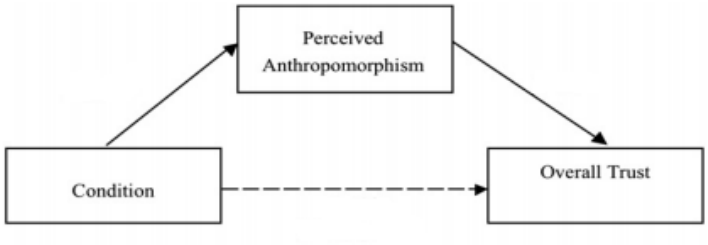

Figure 11. Model on the effect of anthropomorphism on trust for autonomous vehicles. Source: *(Waytz, Heafner, & Epley, 2014)*

However, Fan, Wu & Mattila researched the effect that increased anthropomorphism has on customers' switching intentions in the context of TBSSs (2015). A regression-based moderation analysis was performed to test the hypotheses on the basis of 228 US-based participants. They concluded that an anthropomorphic machine increases the tendency of customers to switch towards traditional service delivery methods. Nevertheless, whenever potential customers are amidst the physical presence of other customers, anthropomorphic TBSS's positively impact their intention which makes the degree of crowdedness a significant positive moderator to the adoption of anthropomorphized TBSS's. On this basis, the research consults service providers to avoid adding human-like features to TBSS's that are heavily utilized in private settings. As 5th generation VAs would serve as highly intimate and subsequently, private companions, it wouldn't be advisable for businesses to dedicate many anthropomorphic features to the virtual entities. However, this notion is based on findings from one study which is limited to an oversimplified generalization of human characteristics in respect to reality. For example, the study acknowledges, but does not take into account, that powerful people are proven to hold agentic views which makes their decision-making process different when compared to less powerful communal individuals (Rucker, Galinsky, & Dubois, 2012). Moreover, anthropomorphic views are proven to differ in the context of contrasting cultures such as individualistic vs collectivistic ones (Epley, Waytz, & Cacioppo, 2007). The neglect of considering such characteristics invokes genuine concerns on the degree of generalizability of such a construct. On this basis we conclude that due the sophistication of human characteristics that influence the acceptance of anthropomorphic artifacts and therewith its inherent tendency to go beyond the scope of our study, we choose not to include the phenomenon within our model. To go more in-depth on this choice, measuring ones attitude towards anthropomorphism in the context of a hypothetical and embryotic technology would forces us to settle with respondents' imagination and assumptions which subsequently raises questions on overall reliability. In this sense, gauging a sample's attitude towards anthropomorphic phenomena should be carried out in the context of experimental studies with physical artifacts, and not with surveys solely. In this respect, the construct 'Technology Anxiety' is to a certain extent complementary to attitude towards anthropomorphism as it may capture generic tendencies with respect to the underlying motives of the adoption of anthropomorphized VAs.

2.4 Operationalizing Hypotheses

The literature review on the initially recognized concepts has primarily contributed to setting the scene for the analysis of relevant adoption literature. Consecutively, the adoption literature analysis has been detrimental to the development of a coherent framework. In the following subchapter we provide an overview of the proposed hypotheses that will undergo final testing. We conclude that on the basis of popularity, robustness and the degree of proven variances the TAM, DOI and UTAUT(2) constructs are of greatest relevance. Moreover, we learned domain-specific constructs and we intend to incorporate these to enhance the frameworks' predictive capacity. The following table provides definitions and sources to each variable.

Constructs	Conceptual Definition	Source
Behavioral Intent (BI)	A person's subjective probability that he will use VAs on WhatsApp for commercial purposes	(Fishbein & Ajzen, 1975), (Eeuwen, 2017)
Attitude (AT)	An individual's positive or negative feelings about using a VA on WhatsApp	Davis et al. (1989), (Eeuwen, 2017)
Perceived Usefulness (PU)	The degree to which a person believes that using VAs on WhatsApp would enhance his or her performance	Davis et al. (1989), (Eeuwen, 2017)
Perceived Ease of Use (PEOU)	The degree to which a person believes that using VAs on WhatsApp would be free of effort	Davis et al. (1989), (Eeuwen, 2017)
Compatibility (C)	The degree to which a VA on WhatsApp is perceived as consistent with existing values, past experiences, and needs of potential adopters	(Rogers E. M., 1983), (Eeuwen, 2017)
Internet Privacy Concerns (IPC)	Concerns opportunistic behavior related to the personal information submitted over VAs on WhatsApp by the respondent in particular	(Dinev, et al., 2006), (Eeuwen, 2017)
Attitude towards Mobile Advertisement (ATMA)	A consumer's positive or negative response towards mobile advertisement send through a VA on WhatsApp	(Ling, Piew, & Chai, 2010), (Eeuwen, 2017)
Social Influence (SI)	The degree to which an individual perceives that important others believe her or she should use VAs on WhatsApp	Venkatesh et al. (2003), Venkatesh et al. (2012)
Perceived Hedonic Motivation (HM)	The perceived fun or pleasure derived from using VAs on WhatsApp	Davis, Bagozzi, & Warshaw, (1992) Venkatesh et al. (2012)
Technology Anxiety (TA)	The fear and apprehension people feel when considering use of or actually using VAs on WhatsApp	(Cambre & Cook, 1985), (Kim & Forsythe, 2008)
Innovativeness (IN)	In a technology context, the willingness of an individual to try VAs on WhatsApp for commercial purposes	(Robinson, Marshall, & Stamps, 2005), (Kim & Forsythe, 2008)

Table 2. Variable definitions

2.4.1 Final Hypotheses

Bidirectional two-tailed hypotheses are deployed in this study. Bidirectional, also known as non-directional hypotheses are ones that don't predict the direction of the outcome, in this context, either positive or negative. On the contrary, directional (i.e. unidirectional) hypotheses inherently tend to predict what direction the impact of a variable can be. (Clark-Carter, 2009) As this study argues to applicability of a proposed model for a hypothetical technology with little complementary secondary researches available, it is only logical to state bidirectional hypotheses two-tailed hypotheses. In essence, the division of statistical significance into two lesser rejection regions allows for a better understanding of the underlying reasons for either positive or negative probability.

TAM constructs

Although, Venkatesh et al. provided that UTAUT's Performance Expectancy (PE) and Effort Expectancy (EE) as better predictors of AT, secondary analysis of the literature on similar technologies indicates a preference to the incorporation of core TAM constructs. In line with Yang & Yoo's (2004) criticism on the neglect of AT in UTAUT research, we reincorporate TAM's core constructs in this study.

H1. Perceived Usefulness will have an effect on Attitude towards using VAs on WhatsApp.
H2. Perceived Ease of Use will have an effect on Attitude towards using VAs on WhatsApp.
H6. Attitude towards Using VAs on WhatsApp will have an effect on behavioral intent to use VAs on WhatsApp

Compatibility (DOI), Attitude towards Mobile Advertisement & Internet Privacy concerns

In line with our literature analysis on the drivers of M-commerce and conversational commerce, we subsequently extracted tendencies with proven significance within existing literature. The operationalization of these constructs led to the following hypotheses.

H3. Compatibility will have an effect on Attitude towards using VAs on WhatsApp.
H4. Attitude towards Mobile Marketing will have an effect on Attitude towards using VAs on WhatsApp
H5. Internet Privacy Concerns will have an effect on Attitude towards using VAs on WhatsApp.

UTAUT constructs

UTAUT2 constructs SI and HM are included as direct antecedents to behavioral intent. The original UTAUT2 model indicates validity of such a design. The two constructs provide a generic representation of angles that lack within the original TAM-based design. Therefore enriching the framework with a blend of the comprehensiveness of UTAUT2 is expected to increase the explanatory power of the model. In this sense,

Bruner & Kumar included 'fun' as an extension of TAM (2005). Several researches however introduce hedonic variables as a determinant to ease of use (Kim & Forsythe, 2008). UTAUT2 however, depicts HM as an independent antecedent to Behavioral Intent. In this sense, we choose to adhere to the UTAUT2's design and not link a hypothesis between EU and HM. In addition, we perceive the explanation of their relationship to add little value to the goal of this study.

H7. Social Influence will have an effect on behavioral intent to use VAs on WhatsApp.
H8. Hedonic Motivation will have an effect on behavioral intent to use VAs on WhatsApp.

Technology Anxiety & Innovativeness

According to Ajzen, individuals won't use technologies unless they feel comfortable with using them (1991). In this sense, ones perception of being able to execute behavior is a major driver (Rogers E. M., 1995). An interesting and domain-specific angle in this respect is ones fears and apprehension in respect to technologies (Cambre & Cook, 1985). As had been described by Freud ones fear is not about cognition, reasoning or even effective attitude, ultimately it's relational to our basic instincts (1920). Hence, TA is incorporate into the framework and translated into H10a & H10b. Moreover, innovativeness is regarded as one of the underlying concepts that influence our desires to undergo new experiences. As such, ones innovativeness is deeply rooted due to its capacity to influence ones attitude and senses (Pearson, 1970). Similarly, researches have considered such sentiments in TBSS research under the umbrella of 'inherent novelty seeking' (Dabholkar & Bagozzi, 2002). In this sense Kim & Forsythe clarified the matter clear by stating that "…adoption of in-home shopping methods is not only a function of attitudes, needs, and experiences, but also personal characteristics such as innovativeness" (2008). Subsequently, we include 'IN' into our framework and translate its relationships into H11a & H11b.

H9a. Technological Anxiety will have an effect on Behavioral Intent to use VAs on WhatsApp.
H9b. Technological Anxiety will moderate the effect of Attitude towards use of VAs on WhatsApp on Behavioral Intent to use VAs on WhatsApp.
H10a. Innovativeness will have an effect on Behavioral Intent to use VAs on WhatsApp.
H10b. Innovativeness will moderate the effect of Attitude towards use of VAs on WhatsApp on Behavioral Intent to use VAs on WhatsApp.

2.4.2 Control Variables

In our hypotheses we have incorporated TA and IN as having a moderating effect on the relationship between AT and BI. Moderating variables, as opposed to control variables, are usually presented in the operationalization of hypotheses as they have been extracted from a literature review. Control variables are rather generic realities which aren't literarily justified. However, their influence on independent and dependent variables is of such importance that one cannot overlook them. On this basis, we present in this section three variables that we perceive to influence the overall model.

M-commerce experience

In a study, on student user acceptance behavior of m-commerce in Taiwan, Peng et al. incorporated m-commerce experience as a control variable and validated associations when analyzing its significance (2011). However, Eeuwen contradicted its explanatory significance by an elaborate consideration of 'Mobile Shopping Behavior'. On the basis of a not so well established understanding of its significance in the context of conversational commerce, we incorporate 'M-commerce Experience' as a control variable where 'Yes' stands for having experience in purchasing products through m-commerce and 'No' stands for having no experience in purchasing via a mobile device.

Gender

The difference in behavior with respect to Gender is been subject to numerous examinations. As such, Venkatesh et al. consider gender to moderate BI and its latent variables as well. As this study doesn't incorporate the UTAUT as it has been intended, we incorporate Gender as a control instead of a moderating variable. In this respect, Eeuwen again concluded the indifference of Gender's relation to BI and AT in the context of conversational commerce. Lee et al. however, prove there is a significant influence of Gender in the context of TBSS usage (2010). On the basis of a not well established common-ground we therefore incorporate Gender as a control variable as well were '1' stands for Male and '2' stands for Female.

WhatsApp usage

Except for Eeuwen's introduction of 'Mobile phone usage' as a control variable, a 'WhatsApp usage' related control variable hasn't been examined as far as our review concerns. In this respect, we adopted Eeuwen's measurements with a slight modification. Intended is to classify frequency of daily WhatsApp usage into three subgroups, where 0-10 times is regarded as 'Light', 10-30 as 'Moderate' and 30> as 'Heavy'.

2.4.3 Proposed Framework

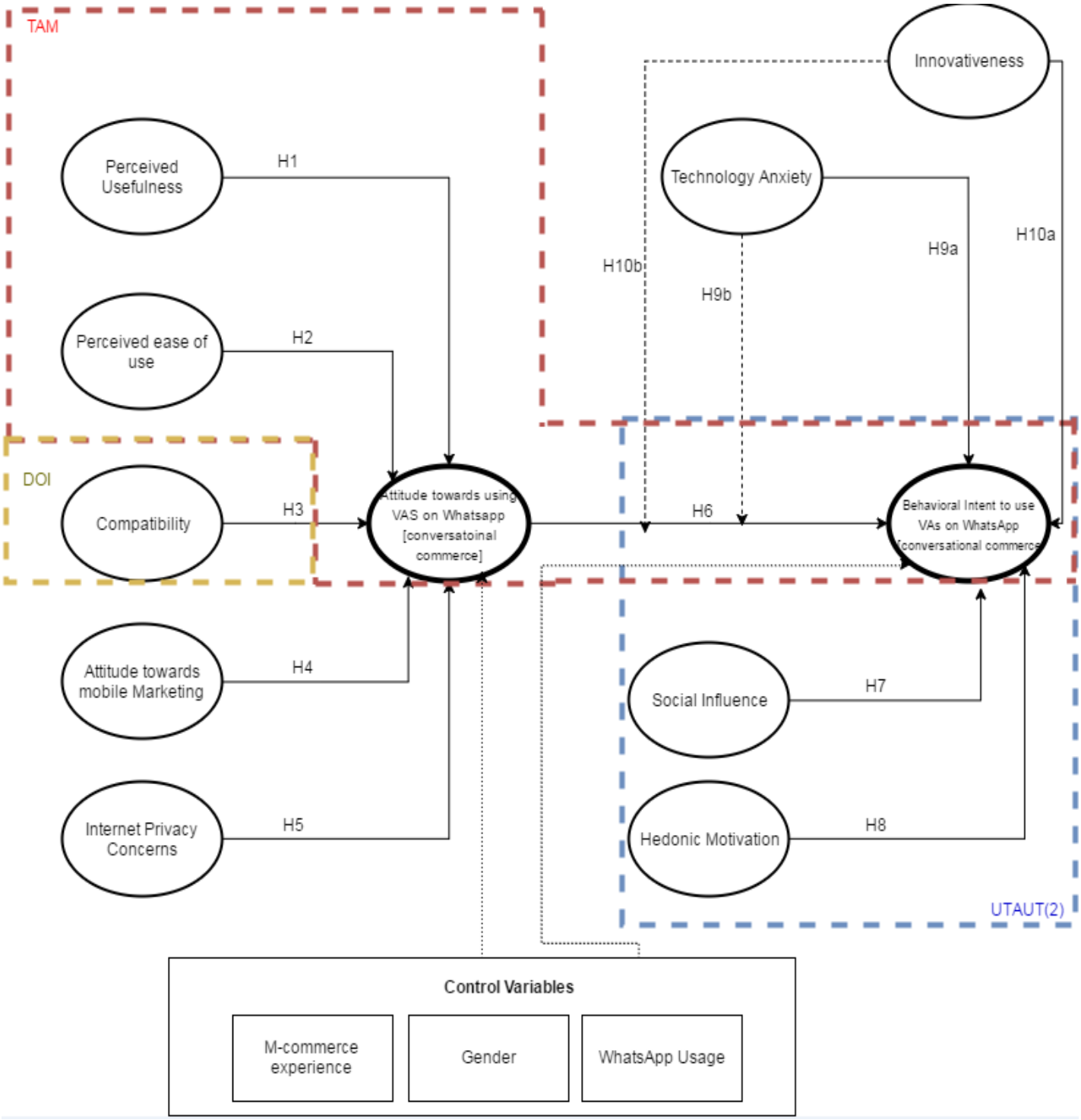

Figure 12. Proposed Model

Constructs	Measure	
Behavioral Intent (BI)	I intend to use VA's through WhatsApp in the future for online shopping	(BI1)
	I Believe my interest in VA's on WhatsApp will increase in the near future	(BI2)
	I recommend others to use VA's on WhatsApp for online shopping	(BI3)
Attitude towards using 5th generation VA's on WhatsApp (AT)	Using VA's on WhatsApp seems a good idea	(A1)
	VA's on WhatsApp make online shopping more interesting	(A2)
	I would like online shopping with VA's on WhatsApp	(A3)
Perceived usefulness (PU)	I think using VA's on WhatsApp would make it easier for me to shop for products	(PU1)
	I think using VA's on WhatsApp would make it easier for me to follow up on my orders	(PU2)
	I think using VA's on WhatsApp enables me to shop for products online more quickly	(PU3)
	I think using VA's on WhatsApp enables me to shop for products online more effectively.	(PU4)
	I find VA's on WhatsApp very useful in shopping for product	(PU5)
Perceived Ease of Use (PEUO)	I think learning to use VA's on WhatsApp is easy	(PEOU1)
	I think becoming skillful at using a VA on WhatsApp is easy	(PEUO2)
	I think using VA's on WhatsApp is easy	(PEUO3)
Compatibility (C)	Using a VA on WhatsApp is compatible with most aspects of my online shopping	(C1)
	Using a VA on WhatsApp fits my lifestyle	(C2)
	Using VA's on WhatsApp fits the way I like to shop or seek for product information online	(C3)
Internet Privacy Concerns (IPC)	I am concerned that the information I submit via VA's on WhatsApp could be misused	(IPC1)
	I am concerned about submitting information via VA's on WhatsApp, because of what others might do with it	(IPC2)
	I am concerned about submitting information via VA's on WhatsApp, because it could be used in a way I did not foresee	(IPC3)
Attitude towards Mobile Advertisement (ATMA)	I consider mobile advertising is useful as it promotes the latest products	(ATMA1)
	Through mobile advertising I got to know more innovative ideas	(ATMA2)
	I refer to mobile advertising because it allows me to enjoy the best deal out of the competing products advertised	(ATMA3)
	I support mobile advertising because it plays an important part in my buying decision	(ATMA4)
	My general opinion of mobile advertising is positive	(ATMA5)
Social Influence (SI)	My family and friends think that VA's on WhatsApp is useful	(SI1)
	People that are important to me think it is advantageous to use VA's on WhatsApp	(SI2)
	If many of my friends would use VA's on WhatsApp, I would probably do it as well	(SI3)
Hedonic Motivation (HM)	Using VA's on WhatsApp would be fun	(HM1)
	Using VA's on WhatsApp would be enjoyable	(HM2)
	Using VA's on WhatsApp would be very entertaining	(HM3)
Technology Anxiety (TA)	If I should use a VA on WhatsApp, I would be afraid to make mistakes with it	(TA1)
	I find the idea of a VA on WhatsApp scary	(TA2)
	I find a VA on WhatsApp intimidating	(TA3)
Innovativeness (IN)	If I heard about a new technology, I would look for ways to experiment with it	(I1)
	Among my peers, I am usually the first to try out new technologies	(I2)
	*****In general, I am hesitant to try out new technologies	(I3)
	I like to experiment with new technologies	(I4)

Table 3. Variables and measurements Note: * = Reverse coded Item

3. Research Methodology

In this chapter we present our research design. Primarily, we summarize our overall methodology. Secondly we proceed by detailing our research strategy. Followed by a description of the participants and means of questionnaire administration. We additionally dedicate attention to the measures undertaken to safeguard data quality. Finally, we delve into the Why's and the How's of the chosen data analysis technique which characterizes the eventual quantitative analysis in this study.

3.1 Overall research design

After concluding the literature review and the subsequent operationalization of deduced hypotheses, a theoretical framework was introduced to explore the determinants of the specified technology in the context of those belonging to generation Y in The Netherlands.

Four constructs find their origins in the TAM model: Perceived Usefulness, Perceived Ease of Use, Attitude towards Usage and Behavioral Intention to use. One Construct was initially introduced in the DOI theory: Compatibility. To this extent, the model complements the one presented by Eeuwen (2017). We extended the model however with four additional constructs from which two were adapted from UTAUT(2): Social Influence and Hedonic Motivation. Lastly, the two remaining constructs were deduced from secondary sources: Technology Anxiety and Innovativeness. In total 11 constructs were incorporated into the model where 38 indicators serve as explanatory items to the latter (table 3).

To test the hypothesized relationships and the overall models' predictive capacity, a questionnaire was designed and a subsequent web-based survey was held. Initially, a pilot survey was conducted which allowed us to validate the quality of the questionnaire. Next, the final survey was launched. Primarily, distribution was initialized via channels provided by company X. The company name is not disclosed due to confidentiality reasons. Eventually, to reach the required amount of respondents, Qualtrics LLC was involved. A more detailed process description of the data collection is available in proceeding sections.

3.1.1 Research Strategy

Throughout the following paragraph we discuss the various stages that are required to be covered in developing a research strategy. In this respect, the Research Onion by Sanders et al. (2009) is regarded as an effective model for the development of an adequate research methodology (Figure 13). In addition, Bryman propones the application of the model due to its usefulness and flexibility of usage for variating types of research (2012).

In our study, the research philosophy is classified as positivistic due to the researchers' intent to test theory that generalizes worldly relationships in a quantitative and possibly repeatable manner (Saunders, Lewis, & Thornhill, 2009). Furthermore, we classify the goal of our study to be in line with behavioristic research due to our intentions to capture the cause-effect relationships between constructs in the context of a technological phenomenon. On the contrary, the goal of design-oriented research is to further innovate information systems or to provide guidelines to enhance effectiveness of such phenomenon which is not the case within this research (Österle & Otto, 2010). As the hypotheses will be derived from theory, and ultimately qualified through observations, our research has a deductive approach. Robson provided the following five sequential stages one is required to abide to in the context of such studies (2002).

Robson's five stages for deductive studies	**Linkage to research objectives**	
1. Deducing hypothesis from theory	Research objective 3, (2), (1)	**Main research Objective**
2. Operationalizing the concepts from the hypotheses	Research objective 3, (2), (1)	
3. Testing the operational hypotheses	Research objective 4	
4. Examining the specific outcome of the inquiry	Research objective 4	
5. If required, modify the theory	Research objective 4	

Table 4. Robson's five stages for deductive studies linked to research objectives

As table 4 clarifies, the literature review is determinant to the realization of steps one & two. From step three on, the study encompasses the execution of an investigation on the derived hypotheses that exert influence on the adoption of the contextualized technology. In this respect, an observational, quantitative conclusive study is ought to be carried out by the distribution of questionnaires as a means to collect empirical data. As the mobile service that is subject to this study remains at an embryotic stage, we cannot expect the population to be acquainted with the actual usage of the technology. Eeuwen points out that consumer ignorance is an issue in user adoption research on new non-existing technology (2017). In this respect respondents are provided with a description of the technology and a scenario which provides a context for their choices. According to Miltgen et al. (2013) and Cheng & Yeh (2010), such hypothetical scenarios are proven effective in the broader technology research and specifically in technology adoption studies. As opposed to the longitudinal nature of researches conducted by Venkatesh et al. this study will gauge inputs at one occasion and we therefore classify the study as cross-sectional (2012). This choice is considered due to the probable escalation of time that is inherent to longitudinal studies.

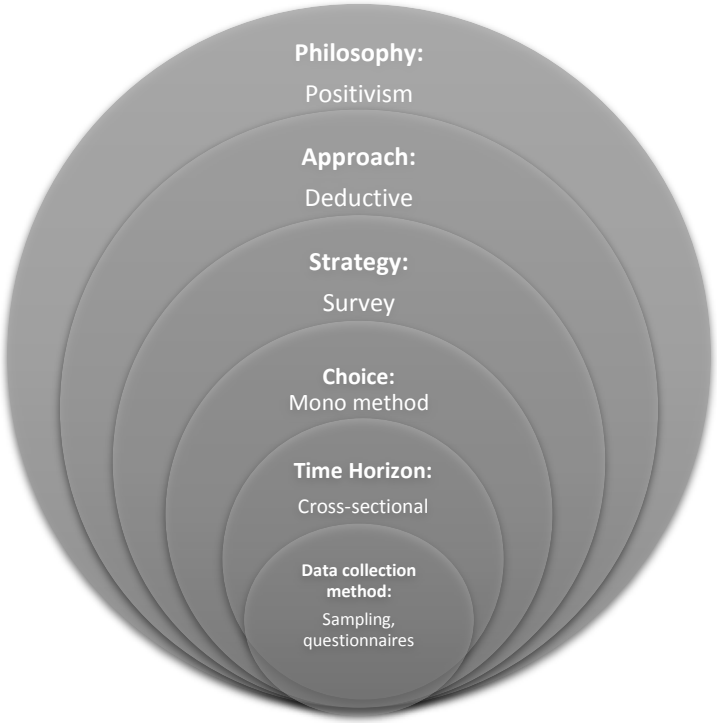

Figure 13. The research 'Onion'. Adapted from: *(Saunders, Lewis, & Thornhill, 2009)*

3.1.2 Sample size

As we face constraints with respect to time and resources, it is necessary to set boundaries to the scope of the study. Therefore, a choice is made to exclusively focus on the Dutch Generation Y population, also known as millennials. We perceive this to be a sufficient segment in order to generalize about potential consumer intentions. This notion is supported by the physical demographic whereabouts of the writer, university and company (The Netherlands) on whose behalf the research is carried out.

Currently, the Dutch population constitutes roughly 17 million inhabitants (World Population Review, 2017). Provided is that within this context, there are 14 million mobile phone users (Statista, 2017). In addition, observances in the Dutch Apps Market-Report indicate a penetration of 78-92% by WhatsApp on Dutch smartphones (Newcom, 2016). For lack of an accurate estimation of the Generation Y population (21-35 years) in the Netherlands we primarily take CBSs (Centraal Bureau voor de Statistiek) figures on the population between 20-40 years which in 2016 constituted 4.163.702 individuals. On this basis we deem Vice's estimation of 4.4 million generation Y individuals in the Netherlands a rather overestimation of the segment (2015). In this sense, we chose to adhere to Heijmans estimation of 3.5 million individuals as it makes more sense relative to CBS's figures (2015). Ruigrok Netpanel indicates a 91% penetration of WhatsApp within the generation Y segment which leads to an eligible population of 3.185.000.

According to McDaniel Jr. & Gates, the formula depicted in figure 14 can be used to provide insight on a sample size where the total population is known (2009). However, such formulas require us to upfront settle with the assumption of a normal distribution. As we aren't certain of that eventually being the case, the reliability of the formula within the context of this study is arguable. Nevertheless, the sample size formula provides us with a preliminary insight and its validity may either be accepted or rejected at the end of this section. Considering a confidence level of 95%, a margin of error of 10% and a spread of 50% the formula depicts a sufficient minimum sample size (n) with 97 observations.

$$moe\ (margin\ of\ error) \pm 1.96\sqrt{\frac{p\ \cdot\ (1-p)}{n^*}} = moe \pm 0.10$$

$$1.96\sqrt{\frac{0.50\ \cdot\ 0.50}{n^*}} = 0.10$$

$$\sqrt{\frac{.25}{n^*}} = \frac{.10}{1.96}$$

$$\frac{.25}{n^*} = \left(\frac{.10}{1.96}\right)^2$$

$$n^* \approx \frac{.25}{0.51^2} \approx 96.1$$

Figure 14. Sample size formula Source: *(McDaniel Jr. & Gates, 2009)* Adapted from*: (Janssen, 2009)*

The previous formula however isn't widely used in PLS-SEM research as it is intended for SPSS studies. Determining the sample-size in PLS-SEM based studies generally allows the consideration of the ten times rule of thumb. Hair et al. indicate that in this sense a sample size should be either greater or equal to: "10 times the largest number of formative indicators used to measure a single construct, or 10 times the largest number of structural paths directed at a particular construct in the structural model" (2014). In the proposed model (figure 12) we observe no formative, but reflective indicators used to measure all constructs. However, the largest structural path directed at a particular construct in the model is 5. Based on the 10 times rule-of-thumb we can therefore conclude a recommended minimum n=50.

Generally, the earlier mentioned rules-of-thumb are considered as rough guidelines for the determination of the eventual sample size. To more accurately put the model background and data characteristics in perspective relative to the eventual sample size, researchers commonly perform G*power analysis (Ringle & Sarstedt, 2011). In a sense similar to the 10 times rule of thumb, G*power analysis focuses on the area within the model with the highest number of antecedents (Hair, Hult, Tomas, Ringe, & Sarstedt, 2014). Cohen's table below illustrates the properties for G*power analysis for 80% statistical power (1992) . In the context of our study, if one takes

a 5% significance level, with a minimum of R^2 of 0.25, we derive a minimum n=70 (red). While for a significance level of 10%, for exploratory studies such as this one, and a minimum R^2 of 0.25 the minimum n=58 (orange).

Exhibit 1.7 Sample Size Recommendation a in PLS-SEM for a Statistical Power of 80%

Maximum Number of Arrows Pointing at a Construct	Significance Level											
	1%				5%				10%			
	Minimum R^2				Minimum R^2				Minimum R^2			
	0.10	0.25	0.50	0.75	0.10	0.25	0.50	0.75	0.10	0.25	0.50	0.75
2	158	75	47	38	110	52	33	26	88	41	26	21
3	176	84	53	42	124	59	38	30	100	48	30	25
4	191	91	58	46	137	65	42	33	111	53	34	27
5	205	98	62	50	147	70	45	36	120	58	37	30
6	217	103	66	53	157	75	48	39	128	62	40	32
7	228	109	69	56	166	80	51	41	136	66	42	35
8	238	114	73	59	174	84	54	44	143	69	45	37
9	247	119	76	62	181	88	57	46	150	73	47	39
10	256	123	79	64	189	91	59	48	156	76	49	41

Figure 15. G*power analysis for 80% statistical power Adapted from: *(Cohen J. A., 1992)*

However, if one considers the latest developments in the domain of PLS-SEM sample size literature, more favorable measurements can be identified. As such, Chin & Dibbern point out that PLS-SEM researches with sample sizes <100, characteristically break down more frequently while sample sizes <500 are determined to output more significant path coefficients (2010). Taking this into account, our previous analyses of the sample size formula, 10 times rule-of-thumb and G*power analysis all provided unsatisfactory results as all minimum sample sizes derived were <100. If one takes into account Chin & Dibbern's recommendations of n = >100 and <500, Kristensen et al. studied the effect of increasing n from 50 - 1000. Concluded was that the benefit of increasing n fades out when n reaches 250 (2010). On this basis, they provide a general recommendation for practitioners that a sample size of 250 is most recommended in PLS-SEM researches. With respect to our study, we therefore adhere to n=250 accordingly. As stratification criteria are defined upfront and distribution will take place randomly, the sample should be classified as a probability random sample.

3.1.3 Survey and Participants

To evaluate the proposed model and hypotheses, a questionnaire was designed using a five-point Likert Scale. Before conducting the final web-based survey, a pilot survey was carried out from which we could enhance the quality of the final questionnaire. Specific details of the pilot survey and the final survey can be found on page 42. Afterwards, distribution of the questionnaires was initiated.

Primarily, we had the opportunity to make use of channels provided by company X to distribute the data to those that satisfy the following stratification criteria:

- Respondents must be between the ages of 21 and 35

- Respondents must be experienced with WhatsApp usage

We have agreed upon not disclosing Company X's name due to confidentiality related reasons. Eventually, Qualtrics LLC was consulted to assist in obtaining additional data from a fixed number respondents that we could not attain ourselves while upholding to the limited timeframe. For this endeavor, the earlier stated stratification criteria were communicated with Qualtrics LLC accordingly.

To ensure willingness to partake and minimize biased answers from respondents, anonymity was guaranteed. Additionally, a description, a clarifying image and the overall objective of the survey was communicated upfront.

3.1.4 Instrumental administration

To adequately administer input from respondents partaking in the survey, the utilization of an appropriate survey software is required. On the basis of personal recommendations and proven robustness we have chosen Qualtrics as the go to survey platform for this study. Inherent to our unit of analysis, the questionnaire is taken in Dutch. As the measures in the original constructs are in English, we engaged into a back translation process. Such a procedure requires a text to be translated, in this case from English to Dutch, and subsequently translated back into English in order to pinpoint any deviations in actual meaning relative to the original text. Ultimately, this process led to 3 minor adjustments.

3.1.5 Data Screening

As part of the analysis of empirical data obtained through surveys, quality of the results has to be ensured timely and methodologically. According to Hair et al., generally one needs to examine missing data, suspicious response patters, outliers screening and data distribution (2014).

With respect to missing data, the questionnaire for this study has 'forced answers' functionality activated for each question. Apart from respondents that quit throughout the questionnaire, this measure prevents missing data completely. Suspicious response patters are examined by calculating the standard deviation (σ) for each response, the closer a respondents' σ to 0, the more suspicious the answers are. Ultimately, we considered the deletion of only highly suspicious responses. In this respect, one is required to be conservative while considering data removal, even though low standard deviations directly inhibit variances which we require for logical predictions (Kumar R. , 2008).

Outliers are defined as extreme responses to particular indicators or to the overall questionnaire. In this respect IBM SPSS statistics 23 allows Boxplot defining based on separated variables. As we analyze latent variables on a 5-point Likert scale along with forced descriptive questions, outliers are not considered as providing insights into bad data (Rodrigues, 2009). Similarly, assessing skewness on 5-point Likert scale (non-parametric statistics)

adds little value. Kurtosis however should be taken into account only as a preliminary indicator of risk-carrying items. The eventual assessment of the Average Variance Extracted (EVA) provides the opportunity to check whether the indicators from the kurtosis analysis are truly problematic, and it is only at this stage that necessary actions should be taken. Therefore, in this study Kurtosis is held into account but not reported, as the AVE will serve as the true determinant of further measures. Furthermore, a data normality test is performed with the application of both the Kolmogorov-Smirnov test and the Shapiro-Wilk test (Appendix A).

3.1.6 Pilot Survey

A pilot survey was carried out to examine the overall integrity of expected future results. According to Baker, pilot surveys should be equal to approximately 10% of the intended sample size (1994). In this pilot survey we collected data from 21 respondents. Excel 2013 and IMB SPSS statistics 23 were used to investigate missing data, unengaged responses and normality of data distribution.

With respect to missing data, zero missing values were detected with the analysis in Excell. As forced responses is checked for each question, the possibility of having missing values is miniscule. For unengaged responses, common pre-survey countermeasures are to reverse-code items or to randomize the order of items so that no one scale is posed consecutively, resulting in rotationally structured items. To test the already obtained responses for unengaged responses, σ were examined. The closer a respondent scores an σ value to zero, the less variance is observed. Two respondents were detected as having extremely unengaged responses ($\sigma=0$). Another respondent ($\sigma=0.5$) raised suspicion as 80% of the values were identical.

As data screening of the pilot survey indicated that 3 out of the 21 respondents (14%) posed risk to our statistical conclusion validity, we choose to randomize the order of the questions, this with the intent to prevent low σ per respondent in the final survey. Also one random item was coded inversely to detect suspicious variance (see table 3).

3.1.7 Final Survey

After optimizing the survey quality, company X provided us with contact details for 855 individuals that satisfied the initially communication stratification criteria. Via this channel, 113 respondents (13%) completed the survey. To reach the desired sample size, Qualtrics LLC was hired. In consultation with Qualtrics, the project was initiated by gathering soft launch data from 20 respondents. The median length of the questionnaire was gauged to be 3 minutes, and a speeding check measured as 2/3 the median soft launch time was added. This allowed for the automatic termination of those not responding thoughtfully. After reaching 160 additional respondents, efforts on the end of Qualtrics were closed down. In total, 263 respondents were eligible for final data screening. After calculating the σ for each, 14 respondents were deleted as their σ scored below 0.1. In

total, 249 respondents qualified for our final analysis. Subsequently, normality test on the final dataset rejects the hypothesis of normality (Appendix A). The results for both the Kolmogorov-Smirnov test and the Shapiro-Wilk test indicate that the significant p-values (α) are .000 while normality can solely be acknowledged when α is >0.05. Therefore, the dataset is herewith classified as not normally distributed.

3.2 Data Analysis

Analysis of data inputs requires the selection of a data analysis technique. Gerow et al. point out that an appropriate approach in this respect would be to select techniques on the basis of applicability, consistency and performance with relation to the overarching theoretical model and data inputs (2010). After all, statistical conclusion validity is crucial as a weak representation of evidence may question the overall purposefulness of our results. In order to rationally explain the preferred analytical technique utilized as part of our study, we primarily distinguish first generation from second generation techniques. Examples of first generation techniques are Linear Regression, ANOVA and MANOVA. Second generation techniques entail Partial Least Square (PLS), Maximum Likelihood and Structural Equation Modelling (SEM).

Studies on the extent to which researchers in the field of IS favor one generation techniques' over the other, reveal a 72% usage of second generation techniques as opposed to 28% in favor of first generation techniques (2010). This study was conducted on articles published in prominent IS journals within 1990 until 2008. However, the depicted trend of increased usage of second-generation techniques is ongoing (Ringle & Sarstedt, 2011) . The increase in relevance of second generation techniques is mainly attributable to its practicability. First generation techniques are restricted to provide insights on the relationship between dependent and independent variables one layer at a time (2010). On the contrary, second generation techniques assess the assumed causal relation between a variety of dissimilar variables and the influence of loadings from indicators on latent variables in a single occasion (2010). On the basis of the portrayed comprehensiveness and applicability of the distinguished techniques we therefore choose to adhere to the utilization of second-generation techniques.

In this study the analysis of data is restricted to the extent to which the proposed theoretical framework and hypotheses are either accepted or rejected. However, the initiated model is new and its evaluation is therefore considered as uncharted territory. In this sense, the analytical part should be characterized as exploratory rather than confirmatory. Commonly used second generation technique in such studies is PLS-SEM (Partial Least Square-Structural Equation Modelling). In SEM based analytics, models are allowed to constitute reflective as well as formative constructs. In case of the presence of a single formative construct Petter et al. suggest a model should be directly classified as formative (2007). As the theoretical framework will be an extension of existing models, where all constructs served as reflective variables, this study revolves around a reflective model overall. Moreover, this study covers a relatively small sample size, according to Hair et al., PLS-SEM is chosen in cases

of small sample sizes, formative measures, focus on prediction and non-normal distributed datasets (2012). On the other hand, CB-SEM (covariance-based Structural Equation Modeling) is utilized in instances where theoretical substance is strong and the intent is to conduct further analysis. Thus, CB-SEM is concerned with the structural relationships of constructs, and therefore more appropriate for cases wherein theory is tested instead of built.

3.2.1 Partial Least Square (PLS)

As has been clarified thus far, this study's objectives, the epistemic view of data to theory, the characteristics of data and the exploratory theoretical development of measurements, signify PLS approach as the most suitable technique. Apart from confirming the proposition of theory, the approach allows making suggestions on the actual existence of assumed relationships (Chin W. , 1998). In this sense, PLS is a multivariate statistical approach wherein dependent and independent variables are compared iteratively. Several applications are developed that aim at facilitating PLS such as SmartPLS, WarpPLS, PLSGraph, VisualPLS and LXSTAT (Wong, 2013). In PLS, both normal and non-normal distributed data are eligible for the evaluation of parameters and predicting causality of relationships. However, PLS-SEM is favored in instances where non-normality is the case. As the evaluation is of a non-parametric nature, the utilization of parametric techniques is no requirement to assess statistical significance. Overall the goal in PLS-SEM based studies is to explain variance (prediction-oriented character of the methodology) instead of covariance as in CB-SEM. The following section provides an overview of the sequential process of evaluation data with PLS, where primarily, the outer model should be tested, followed by the inner model.

3.2.2 Assessing PLS-SEM results

In the development of a methodological approach for PLS-SEM studies, one needs to primarily distinguish, the outer model (Measurement Model) from the inner model (Structural Model). In this respect, evaluation theory with PLS-SEM requires practitioners to rely on measures that provide insights on the models' predictive capabilities so that eventually a judgement can be made on the overall quality of the model. In short, we therefore are required to validate the data in a two-step approach while considering theoretically backed evaluation criteria for which we will provide an assessment in the upcoming sections.

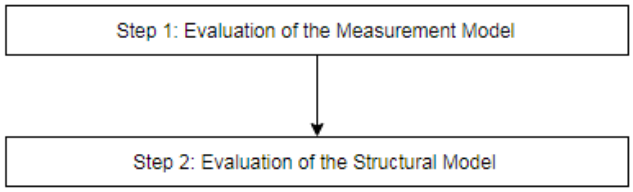

Figure 16. 2-step approach for PLS-SEM

3.2.3 Outer model (Measurement Model)

The evaluation of the outer model concerns itself predominantly with the relationship between latent variables within the model and their measures (i.e. indicators). In this regard, literature stresses the necessity to differentiate between reflective and formative measurement models. According to Hair et al. Reflective measurement models as the one proposed as part of this study, requires the assessment of reliability and validity (2014).

On the basis of proven robustness, it's recommended to initiate the analysis by validating the reliability of indicators. This is done by assessing the extent to which each measurement meets the theoretically backed threshold values. In the context of our specified model we are therefore required to assess the values for: internal consistency (composite reliability), Indicator reliability, Convergent validity (average variance extracted) and Discriminant validity.

3.2.3.1 Data Reliability

Primarily, data reliability, which encompasses the degree to which each indicator satisfies the requirement of measuring the intended construct(s), is determined by assessing indicator reliability and internal consistency reliability. As we utilize SmartPLS 3, indicator reliability is referred to as outer loadings. According to Hair et al. outer loadings which are <0.40 should be deleted, outer loadings that are > 0.40 but < 0.70 should be further analyzed (figure 17) and outer loadings that are > 0.70 are ought to be retained as indicators. In general, a higher outer loading on indicators means that there had been high commonality in answers provided to the indicators in question.

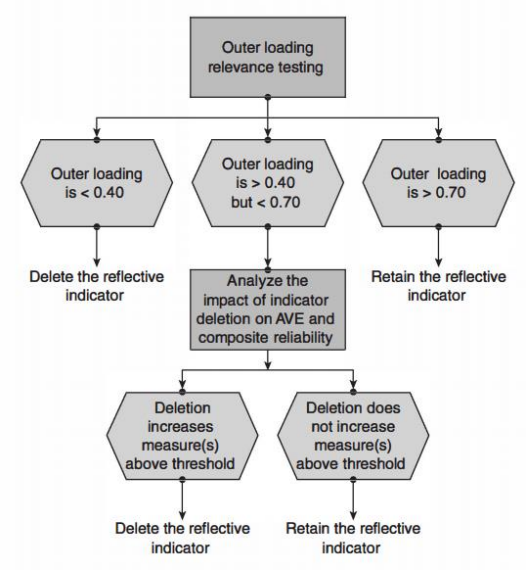

Figure 17. Outer Loadings Relevance Test. Source*: Hair et al. (2014)*

To assess internal consistency reliability, a much referred to criteria is Cronbach's alpha which is not the primary internal consistency reliability evaluation criteria in PLS-SEM studies, wherein composite reliability is

considered as favorable. According to Hair et al. this is attributed to the fact that Cronbach's alpha deals with indicator correlation reliability from a perspective wherein each indicator is considered as equally reliable (2014). Composite reliability however assesses internal reliability while discriminating between the differences of the initially obtained outer loadings. Composite reliability does this by taking into account standardized outer loadings, the measurement errors and denoted measurement errors. Scores between 0.60 until +- 0.90 are admitted in the context of exploratory research, and more mature research respectively (Nunnally & Bernstein, 1994).

3.2.3.2 Data validity

To ascertain data validity, both convergent validity and discriminant validity are required to be assessed as the most important quality criteria. To gauge convergent validity one needs to assess the AVE. In general, convergent validity is established when all measures positively correlate with the remaining measures within a specific construct. When the AVE is >0.50, it's considered as satisfactory to convergent validity. Implying that AVE >50 is explanatory for at least 50% of indicator variance for a specified latent variable.

Subsequently, discriminant validity gauges the extent to which constructs are distinct from others in the same model. Satisfactory discriminant validity therefore implies that a construct captures tendencies that are unique to the model and therefore relevant. A recurring method to assess discriminant validity is by examining the cross loadings. This procedure requires the calculation of outer loadings of each indicator to each construct. Consecutively, the loadings should output the highest values on a specific indicators' associated construct while all loadings for the remaining constructs should be less. A more conservative approach to establish discriminant validity is the Fornell-Larcker criterion wherein the square root of the AVE is correlated all construct correlations. Ultimately, as somehow similar to cross loadings, a diagonal pattern should be visible while the square root AVE of each construct should be higher than the correlating values with latent construct (Fornell & Larcker, 1981).

3.2.4 Inner Model (Structural Model)

After determining reliability and validity as part of evaluation of the outer model, the second step of PLS-SEM analysis requires the evaluation of the inner model. This part of the analysis deals with the theoretical concepts our study seeks to justify with the proposal of the path model. Primarily, significant assessment for path coefficients and t-values is required. These criteria allow for an evaluation of the earlier formulated hypotheses, thus the assumed relationships.

3.2.4.1 R2 values

With the evaluation of the R^2 values (coefficient of determination) one is capable of determining the effect that independent latent variables have on dependent variables within the structural path. In literature this is

commonly translated as the proportion of variance (%), which is the coefficient of determination that can be explained by independent variables in dependent variables (Henseler, Ringle, & Sinkovics, The use of partial least squares path modeling in international marketing, 2009). All R^2 value are in the range of 0 – 1, where 0 suggests no predictive accuracy at all, while 1 defines perfect predictive relevancy. Moore et al. provided the following rules of thumb to assess the strength of R^2 values (2013):

- R^2 value < 0.3, this value is generally considered a None or Very weak effect size.
- R^2 value $0.3 < R^2 < 0.5$, this value is generally considered a weak or low effect size.
- R^2 value $0.5 < R^2 < 0.7$, this value is generally considered a Moderate effect size.
- R^2 value > 0.7, this value is generally considered strong effect size

3.2.4.2 Path Coefficients

Path coefficients are considered to provide a label of value to the strength of the relationship the modelled variables are determined to have. Significant hypotheses are therefore expected to either have positive/negative path coefficient values, where the effect is categorized as small, medium or large by the values 0.02, 0.15 and 0.35 respectively (Cohen J. , 1988). The process of assessing path coefficients can be deceitful at first. In this respect, it's critical to notice that even though effect sizes may be low sometimes, the level of importance cannot be attributed to this as even small interactions can be determinant in the overall decision-making process ofn an individual (Chin, Marcolin, & Newsted, 2003).

3.2.4.3 Hypothesis Testing

To initiate significance testing, SmartPLS's Bootstrapping procedure provides t-statistics for both the inner and the outer model. In this regards, a subsample of preferably 5000, is obtained from the original sample to provide estimates on the standard error of regression paths which at its turn outputs approximate t-values. According to Hair et al. (2014) two-tailed studies, such as this one, are ought to be assessed based on the following critical values: 1.65 ($\alpha = 10\%$), 1.96 ($\alpha = 5\%$) and 2.57 ($\alpha = 1\%$). Two-tailed tests are more favorable, especially in exploratory studies, as the latter is generally considered to provide more appropriate insights with respect to significant effects. In this respect, the significance level (α) is chosen on the basis contributions by Mooi & Sarstedt, who provided the following rule of thumb (2011).

- $\alpha = 0.1$ (10%) in exploratory studies
- $\alpha = 0.01$ (1%) in experimental studies
- $\alpha = 0.05$ (5%) for all other studies

On the basis of the characteristic of our study, which remains to a large extent exploratory, the path coefficients are labeled statistically significant when t-values are > 1.65 and $\alpha < 10\%$ as the most forgiving threshold values.

3.2.5 Standardized Root Mean Square Residual (SRMR) value

As an extension of our analysis of both the inner and the outer model, we intent to measure the overall models' approximate model fit. With respect to the reflective nature of the structural model under investigation, the standardized root mean square residual (SRMR) value is the only approximate model fit criterion for PLS-SEM. In essence, SRMR allows the measurement of the average extent of divergence between expected and observed correlations as a criterion of goodness of fit (Henseler, Hubona, & Ray, 2016). The final SRMR value is obtained by the measurement of both the saturated and the structural model. A final SRMR value between 0 and 0.1 is considered as perfect and good fit respectively (Ringle, Wende, & Becker, 2015).

3.2.6 Moderating effects

Moderating variables are variables that change the strength of causality between two constructs. In this study two variables are hypothesized to have a moderating (indirect) effect on endogenous variables. As has been suggested by Henseler & Chin, the evaluation of moderating effect should be initiated after assessing (direct) hypotheses, better stated as the structural model (2010). In this sense, the product indicator approach is described by Chin as the best technique, especially when dealing with reflective constructs (2003). As opposed to the two-stage and orthogonalization techniques, the product indicator approach utilizes all existing pair combinations of the specified independent and moderating variables in order to provide parametric estimates with respect to the moderating effect between dependent and independent variables (Chin, Marcolin, & Newsted, 2003).

3.2.7 Multi-group analysis

This study proposes the evaluation of specified control variables as literature on the subjected phenomena has suggested heterogeneity of observations for the unit of analysis under investigation. In specific, heterogeneity is theoretically supported for: Gender, Mobile Commerce Experience and Frequency of WhatsApp Usage. In this respect, Partial Least Square-Multi-Group Analysis (PLS-MGA) is utilized as a technique to uncover significant differences in group-specific parameter estimates. As PLS-MGA is categorizes as a non-parametric significance test, SmartPLS constructs its results based on the Bootstrapping procedure. This SmartPLS functionality is largely based on Henseler's MGA method, where MGA's threshold for significance had been set at $\alpha = 0.05$ or larger than 0.95 (2009). The bootstrapping procedure is sequentially conducted by starting off with the division of data into subsamples, in accordance with the level of the grouping variable. Next, the specified amount of bootstrap samples (i.e. 1000-5000) separately analyze the subsamples in a bootstrap analysis. Ultimately, estimate results for the two groups are compared and positive differences are divided by the total amount of comparisons. PLS-MGA significance threshold values are identical to Henseler's MGA methods ($\alpha = 0.05$ or larger than 0.95).

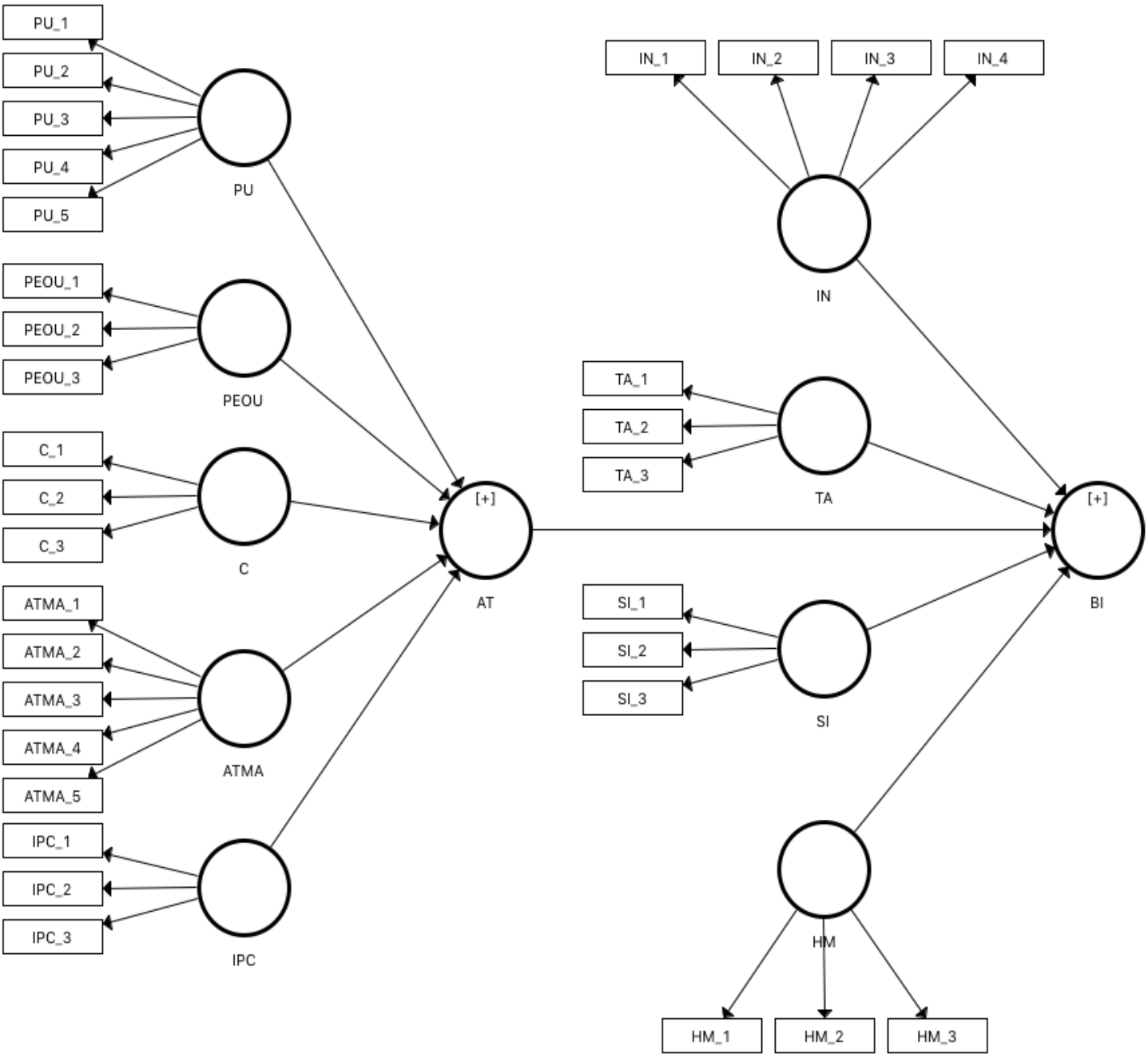

Figure 18. Initial Research Model

4. Results

This chapter dedicates attention to the results obtained and the subsequent evaluation of values in accordance with the earlier described methodology for PLS-SEM. Primarily, sample characteristics are presented. Followed by the evaluation of the measurement model and the structural model. Finally, we conclude this chapter with multi-group analysis on the specified control variables.

4.1 Characteristics of the Sample

On the basis of our final dataset, we proceed by providing an overview of the descriptives of those that took part in the final survey (Table 5). A visual representation of the descriptive statistics based on the sample under investigation can be found in Appendix B.

Variable	**Category**	**Frequency**	**Percentage**
Gender	Male	153	61.45%
	Female	96	38.55%
Age	21-23	33	13.25%
	24-26	55	22.09%
	27-29	63	25.30%
	30-32	50	20.08%
	33-35	48	19.28%
Mobile commerce experience	Yes	212	85.14%
	No	37	14.86%
Daily WhatsApp usage (frequency)	0-10 times a day	59	23.69%
	10-30 times a day	112	44.98%
	30 times or more	78	31.33%

Table 5. Sample Characteristics

4.2 Data Analysis

As has been described in the previous chapter, the data analysis part concerns itself with two main methodologies:

1. Evaluation of the measurement model (outer model)
2. Evaluation of the structural model (inner model)

4.2.1 Evaluation of the measurement model

The PLS algorithm functionality is deployed to primarily extract value criterion on internal reliability. In this respect, outer loadings and composite reliability are gauged first. In case of inconsistencies it is required to further analyze the specified inconsistencies and the inherent deletion of indicators by evaluating the respective variance in AVE and adjusted changes in cross loadings. Ultimately, when outer loadings and composite reliability satisfy the specified thresholds, data reliability is proven. Subsequently, if convergent validity (AVE) and discriminant validity (Fornell-Larcker criterion & Cross loadings) meet the required threshold values, data validity is considered as established.

4.2.2 Data reliability

Table 6 provides a compressed overview of the initial reliability and validity test. As can be seen in table 7, the majority of outer loading values exceed the specified threshold of 0.7. However, IN_3, TA_1 and TA_3 have loading values 0.426, 0.399 and 0.413, respectively. Table 6 highlights the partial inhibiting effects of the latterly mention insufficiencies. Undeterred by the low outer loading of IN_3, IN's overall construct composite reliability (0.817) and convergent validity (0.542) is considered as acceptable. However, if one adheres to Hair et al., indicators >0.4, yet <0.7 should be eliminated, but only if that results in a higher degree of variance with regard to AVE and composite reliability (2014). Furthermore, while evaluating TA, the overall construct composite reliability (0.650) and convergent validity (0.427) is clearly depressed to the point of not meeting the required thresholds. Further analysis of data validity on these indicators will justify any possible necessity of indicator elimination for both IN and TA.

Constructs	Indicators/ Measurement Items	Indicator Reliability (outer loadings)	*Cronbach's Alpha*	Composite Reliability	Convergent Validity (AVE)	Discriminant Validity
Thresholds	**----------**	**> 0.7**	***> 0.7***	**> 0.7**	**> 0.5**	**----------**
Perceived Usefulness (PU)	**PU_1**	**0.823**				
	PU_2	**0.706**				
	PU_3	**0.850**		0.908	0.665	Yes
	PU_4	**0.821**	*0.873*			
	PU_5	**0.868**				
Perceived Ease of Use (PEOU)	**PEO_1**	**0.827**				
	PEO_2	**0.700**	*0.723*	0.840	0.638	Yes
	PEO_3	**0.860**				
Compatibility (C)	**C_1**	**0.780**				
	C_2	**0.855**	*0.796*	0.880	0.710	Yes
	C_3	**0.889**				
Attitude Towards Mobile Advertising (ATMA)	**ATMA_1**	**0.790**				
	ATMA_2	**0.856**				
	ATMA_3	**0.835**	*0.885*	0.916	0.685	Yes
	ATMA_4	**0.840**				
	ATMA_5	**0.815**				
Internet Privacy Concerns (IPC)	**IPC_1**	**0.874**				
	IPC_2	**0.899**	*0.850*	0.908	0.767	Yes
	IPC_3	**0.854**				
Attitude Towards Usage (AT)	**AT_1**	**0.840**				
	AT_2	**0.867**	*0.833*	0.900	0.750	Yes
	AT_3	**0.891**				
Social Influence (SI)	**SI_1**	**0.809**				
	SI_2	**0.880**	*0.776*	0.870	0.691	Yes
	SI_3	**0.803**				
Hedonic Motivation (HM)	**HM_1**	**0.857**				
	HM_2	**0.881**	*0.828*	0.897	0.744	Yes
	HM_3	**0.849**				
Technology Anxiety (TA)	**TA_1**	**0.399**				
	TA_2	**0.976**	*0.769*	0.650	0.427	Yes
	TA_3	**0.413**				
Innovativeness (IN)	**IN_1**	**0.837**				
	IN_2	**0.725**	*0.730*	0.817	0.542	Yes
	IN_3	**0.426**				
	IN_4	**0.871**				

Table 6. Initial results of Reliability and Validity Test Note: Red = Requires removal, Orange = Removal should be considered

4.2.3 Data Validity

The following subheadings describe the procedures deployed as part of assessing data validity, the second part of the evaluation of the measurement model.

4.2.3.1 Convergent Validity

As had been mentioned (table 6), convergent validity is established for each construct except for TA. Primarily, indicator removal for TA_1, as the lowest outer loading (0.399) within TA, is considered. In case, by removing TA_1, the overall composite reliability (>0.7) and AVE (>0.5) do not meet the required thresholds, both TA_1 and TA_2 will be eliminated. However, the latter, more conservative option is only considered if necessary as this would leave TA with one retained indicator.

4.2.3.2 Discriminant Validity (Fornell-Larcker Criterion)

Table 7 provides an overview of discriminant validity values by calculating the Fornell-Larcker quality criteria. On the basis of not a single eliminated indicator, we conclude that discriminant validity is proven for each construct. As a clarification, the AVE for SI is 0.691, by taking its square root (√0.691) 0.831 is derived. While considering 0.831 in the intersection of the Y-and X-axis of the same construct, we observe 0.831 to be the greatest number in the column while also being the greatest in the same row.

	AT	ATMA	BI	C	HM	IN	IPC	PEOU	PU	SI	TA
AT	0.866										
ATMA	0.563	0.828									
BI	0.731	0.527	0.847								
C	0.784	0.620	0.713	0.843							
HM	0.819	0.492	0.697	0.761	0.862						
IN	0.415	0.239	0.392	0.398	0.432	0.736					
IPC	-0.183	-0.101	-0.148	-0.175	-0.205	-0.073	0.876				
PEOU	0.458	0.198	0.417	0.491	0.482	0.347	-0.138	0.798			
PU	0.809	0.565	0.716	0.785	0.750	0.356	-0.139	0.453	0.815		
SI	0.758	0.582	0.672	0.687	0.689	0.332	-0.069	0.389	0.692	0.831	
TA	-0.048	0.169	-0.178	-0.011	-0.052	-0.035	0.368	-0.155	-0.061	0.007	0.654

Table 7. Initial Fornell-Larcker Critereon

4.2.3.3 Discriminant Validity (Cross Loadings)

Table 8 provides an overview of initial cross loadings. Despite IN_3, TA_1 and TA_3's low initial outer loadings, all indicators are proven to be superior on the same row.

	AT	ATMA	BI	C	HM	IN	IPC	PEOU	PU	SI	TA
ATMA_1	0.419	0.790	0.370	0.482	0.400	0.209	-0.072	0.204	0.421	0.391	0.168
ATMA_2	0.537	0.856	0.521	0.612	0.441	0.275	-0.085	0.213	0.503	0.531	0.125
ATMA_3	0.469	0.835	0.456	0.498	0.403	0.159	-0.058	0.110	0.467	0.526	0.123
ATMA_4	0.463	0.840	0.416	0.497	0.392	0.198	-0.087	0.114	0.498	0.457	0.183
ATMA_5	0.426	0.815	0.398	0.459	0.396	0.132	-0.121	0.178	0.439	0.491	0.103
A_1	0.840	0.400	0.646	0.626	0.713	0.391	-0.187	0.447	0.636	0.626	-0.120
A_2	0.867	0.547	0.593	0.675	0.680	0.336	-0.140	0.353	0.754	0.653	0.028
A_3	0.891	0.511	0.662	0.731	0.734	0.354	-0.151	0.392	0.777	0.688	-0.038
BI_1	0.676	0.472	0.870	0.680	0.645	0.352	-0.098	0.384	0.627	0.585	-0.119
BI_2	0.510	0.298	0.821	0.500	0.532	0.359	-0.110	0.310	0.545	0.501	-0.249
BI_3	0.662	0.553	0.851	0.621	0.590	0.290	-0.169	0.362	0.642	0.616	-0.099
C_1	0.534	0.464	0.468	0.780	0.541	0.275	-0.085	0.366	0.574	0.515	0.046
C_2	0.688	0.475	0.629	0.855	0.691	0.371	-0.217	0.441	0.657	0.583	-0.079
C_3	0.736	0.617	0.681	0.889	0.676	0.352	-0.130	0.428	0.737	0.630	0.016
HM_1	0.701	0.409	0.587	0.661	0.857	0.364	-0.156	0.429	0.621	0.562	-0.066
HM_2	0.741	0.417	0.654	0.695	0.881	0.382	-0.216	0.400	0.704	0.627	-0.115
HM_3	0.673	0.449	0.557	0.607	0.849	0.372	-0.151	0.422	0.609	0.590	0.059
IN_1	0.400	0.160	0.383	0.364	0.440	0.837	-0.042	0.360	0.366	0.292	-0.065
IN_2	0.249	0.310	0.231	0.299	0.245	0.725	-0.007	0.134	0.201	0.215	0.137
IN_3	-0.021	-0.311	0.040	-0.071	0.024	0.426	-0.188	0.131	-0.099	-0.099	-0.254
IN_4	0.360	0.208	0.332	0.333	0.352	0.871	-0.099	0.305	0.303	0.320	-0.072
IPC_1	-0.166	-0.147	-0.137	-0.166	-0.172	-0.071	0.874	-0.162	-0.133	-0.087	0.288
IPC_2	-0.183	-0.085	-0.147	-0.174	-0.208	-0.106	0.899	-0.108	-0.134	-0.051	0.324
IPC_3	-0.124	-0.017	-0.097	-0.108	-0.148	0.007	0.854	-0.087	-0.091	-0.039	0.371
PEOU_1	0.366	0.112	0.301	0.384	0.356	0.208	-0.083	0.827	0.337	0.273	-0.128
PEOU_2	0.243	0.076	0.250	0.312	0.325	0.247	-0.046	0.700	0.280	0.239	-0.164
PEOU_3	0.446	0.247	0.417	0.456	0.456	0.361	-0.172	0.860	0.442	0.393	-0.103
PU_1	0.721	0.456	0.636	0.639	0.614	0.298	-0.063	0.393	0.823	0.563	-0.027
PU_2	0.581	0.334	0.492	0.525	0.563	0.353	-0.106	0.347	0.706	0.482	-0.112
PU_3	0.689	0.493	0.607	0.686	0.628	0.312	-0.105	0.400	0.850	0.594	-0.028
PU_4	0.655	0.459	0.532	0.618	0.616	0.235	-0.142	0.310	0.821	0.561	0.004
PU_5	0.748	0.540	0.637	0.714	0.636	0.269	-0.152	0.395	0.868	0.613	-0.092
SI_1	0.589	0.446	0.529	0.520	0.554	0.307	-0.094	0.299	0.506	0.809	-0.064
SI_2	0.625	0.503	0.543	0.561	0.545	0.278	-0.007	0.321	0.593	0.880	0.005
SI_3	0.668	0.498	0.597	0.623	0.611	0.246	-0.070	0.347	0.618	0.803	0.069
TA_1	0.165	0.300	0.020	0.159	0.113	0.054	0.325	-0.095	0.185	0.203	0.399
TA_2	0.001	0.227	-0.147	0.036	-0.017	-0.027	0.394	-0.170	-0.002	0.068	0.976
TA_3	0.129	0.265	0.023	0.150	0.076	-0.029	0.222	-0.159	0.164	0.222	0.413

Table 8. Initial Cross Loadings

As a result of our evaluation of the measurement model, minor indicator adjustments are ought to be performed. While considering the elimination of IN_3, TA_1 and TA_3, we achieved data validity by the elimination of solely TA_1. However, IN_3 is additionally eliminated as the effect of its deletion positively impacts IN's overall composite reliability and convergent validity. According to Hair et al. indicator removal (when <0.4 and >0.7) should be considered when its impact positively impacts the AVE and composite reliability (2014).

4.2.3.4 Adjusted Model

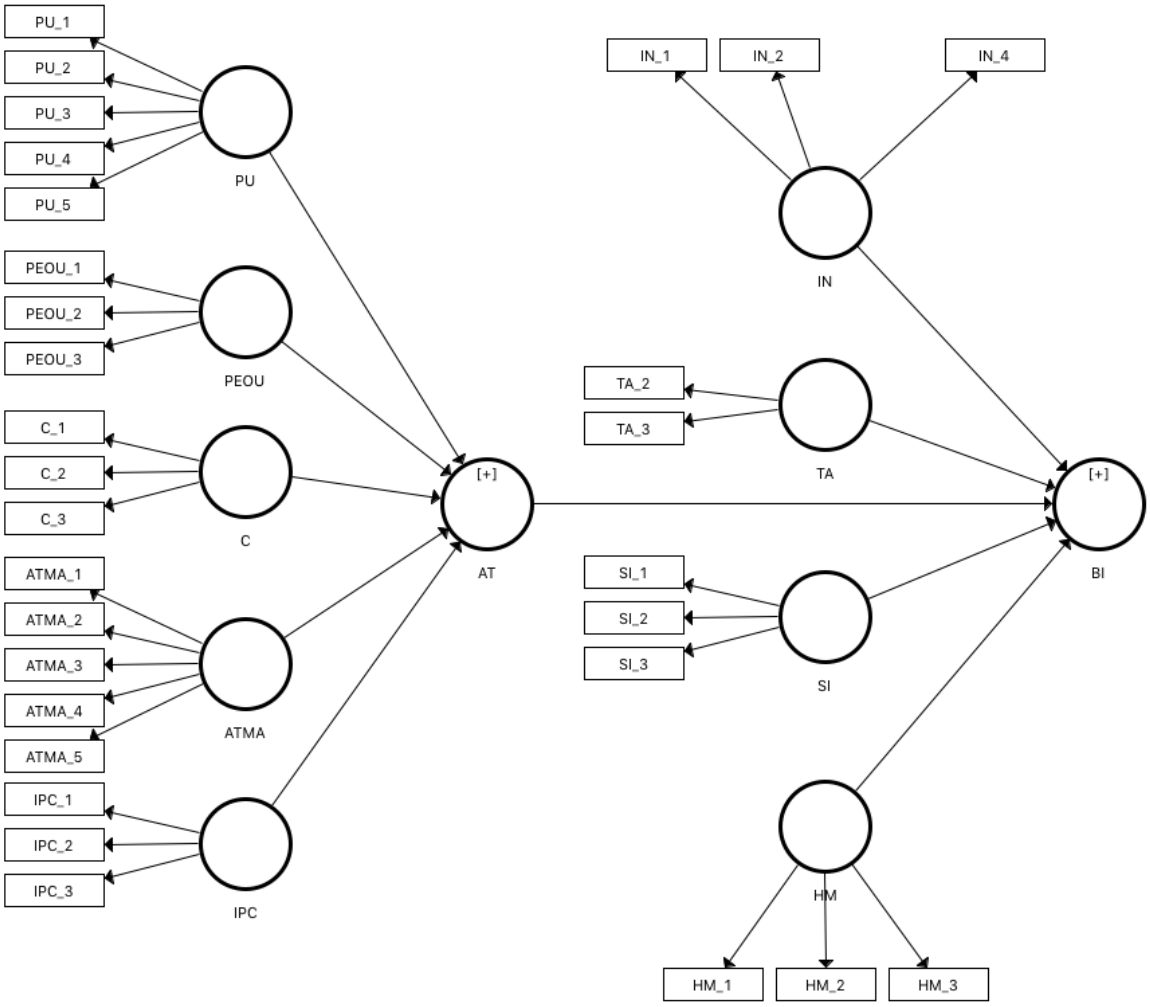

Figure 19. Adjusted Model

4.2.3.5 Adjusted Discriminant Validity (Fornell-Larcker critereon)

Table 9. Fornell-Larcker results after adjustments

	AT	ATMA	BI	C	HM	IN	IPC	PEOU	PU	SI	TA
AT	0.866										
ATMA	0.563	0.828									
BI	0.731	0.527	0.848								
C	0.784	0.620	0.713	0.843							
HM	0.819	0.492	0.697	0.761	0.862						
IN	0.425	0.259	0.398	0.410	0.440	0.814					
IPC	-0.183	-0.101	-0.148	-0.175	-0.205	-0.065	0.876				
PEOU	0.458	0.198	0.417	0.491	0.482	0.347	-0.138	0.798			
PU	0.809	0.565	0.716	0.785	0.750	0.369	-0.139	0.453	0.815		
SI	0.758	0.582	0.672	0.687	0.689	0.344	-0.069	0.389	0.692	0.831	
TA	-0.021	0.201	-0.164	0.013	-0.032	-0.011	0.391	-0.158	-0.030	0.037	0.770

4.2.3.6 Adjusted Discriminant Validity (Cross Loadings)

	AT	ATMA	BI	C	HM	IN	IPC	PEOU	PU	SI	TA
ATMA_1	0.419	0.790	0.369	0.482	0.400	0.222	-0.072	0.204	0.421	0.391	0.189
ATMA_2	0.537	0.856	0.521	0.612	0.441	0.293	-0.085	0.213	0.503	0.531	0.155
ATMA_3	0.469	0.835	0.455	0.498	0.403	0.178	-0.058	0.110	0.467	0.526	0.156
ATMA_4	0.463	0.840	0.416	0.497	0.392	0.215	-0.087	0.114	0.498	0.457	0.211
ATMA_5	0.426	0.815	0.398	0.459	0.396	0.150	-0.121	0.178	0.439	0.491	0.125
A_1	0.840	0.400	0.646	0.626	0.713	0.395	-0.187	0.447	0.636	0.626	-0.106
A_2	0.867	0.547	0.593	0.675	0.680	0.348	-0.140	0.353	0.754	0.653	0.059
A_3	0.891	0.511	0.661	0.731	0.734	0.363	-0.151	0.392	0.777	0.688	-0.011
BI_1	0.676	0.472	0.870	0.680	0.645	0.358	-0.098	0.384	0.627	0.585	-0.105
BI_2	0.510	0.298	0.821	0.500	0.532	0.359	-0.110	0.310	0.545	0.501	-0.242
BI_3	0.662	0.553	0.851	0.621	0.590	0.299	-0.169	0.362	0.642	0.616	-0.082
C_1	0.534	0.464	0.468	0.780	0.541	0.285	-0.085	0.366	0.574	0.515	0.071
C_2	0.688	0.475	0.629	0.855	0.691	0.378	-0.217	0.441	0.657	0.583	-0.066
C_3	0.736	0.617	0.681	0.889	0.676	0.365	-0.130	0.428	0.737	0.630	0.040
HM_1	0.701	0.409	0.587	0.661	0.857	0.370	-0.156	0.429	0.621	0.562	-0.047
HM_2	0.741	0.417	0.654	0.695	0.881	0.387	-0.216	0.400	0.704	0.627	-0.098
HM_3	0.673	0.449	0.557	0.607	0.849	0.381	-0.151	0.422	0.609	0.590	0.076
IN_1	0.400	0.160	0.383	0.364	0.440	0.839	-0.042	0.360	0.366	0.292	-0.057
IN_2	0.249	0.310	0.231	0.299	0.245	0.730	-0.007	0.134	0.201	0.215	0.158
IN_4	0.360	0.208	0.332	0.333	0.352	0.868	-0.099	0.305	0.303	0.320	-0.069
IPC_1	-0.166	-0.147	-0.137	-0.166	-0.172	-0.066	0.874	-0.162	-0.133	-0.087	0.308
IPC_2	-0.183	-0.085	-0.147	-0.174	-0.208	-0.097	0.899	-0.108	-0.134	-0.051	0.342
IPC_3	-0.124	-0.017	-0.097	-0.108	-0.148	0.014	0.854	-0.087	-0.091	-0.039	0.394
PEOU_1	0.366	0.112	0.301	0.384	0.356	0.208	-0.083	0.827	0.337	0.273	-0.133
PEOU_2	0.243	0.076	0.250	0.312	0.325	0.246	-0.046	0.700	0.280	0.239	-0.170
PEOU_3	0.446	0.247	0.417	0.456	0.456	0.362	-0.172	0.860	0.442	0.393	-0.102
PU_1	0.721	0.456	0.635	0.639	0.614	0.307	-0.063	0.393	0.823	0.563	0.002
PU_2	0.581	0.334	0.492	0.525	0.563	0.361	-0.106	0.347	0.706	0.482	-0.097
PU_3	0.689	0.493	0.606	0.686	0.628	0.324	-0.105	0.400	0.850	0.594	0.001
PU_4	0.655	0.459	0.532	0.618	0.616	0.244	-0.142	0.310	0.821	0.561	0.030
PU_5	0.748	0.540	0.637	0.714	0.636	0.280	-0.152	0.395	0.868	0.613	-0.066
SI_1	0.589	0.446	0.529	0.520	0.554	0.314	-0.094	0.299	0.506	0.809	-0.034
SI_2	0.625	0.503	0.543	0.561	0.545	0.289	-0.007	0.321	0.593	0.880	0.029
SI_3	0.668	0.498	0.597	0.623	0.611	0.257	-0.070	0.347	0.618	0.803	0.089
TA_2	0.001	0.227	-0.147	0.036	-0.018	-0.011	0.394	-0.170	-0.002	0.068	0.990
TA_3	0.129	0.265	0.023	0.150	0.076	-0.009	0.222	-0.159	0.164	0.222	0.452

Table 10. Final Cross loadings

4.2.3.7 Final Data Reliability and Validity

Prior to eliminating TA_1, both composite reliability (0.650) and convergent validity (0.427) for TA did not meet the required threshold values >0.7 and >0.5 respectively. However, after deletion, TA performs conform requirements. Moreover, before eliminating IN_3, composite reliability was 0.817 while convergent validity miniscullaly surpassed the threshold with a value of 0.542. After eliminating IN_3, outer loadings and all subsequent values rose to a more reliable level. Overall, removing the least significant indicators has resulted in a more robust measurement model, and therefore, more applicable for the evaluation of the struturcal model.

Constructs	Indicators/ Measurement Items	Indicator Reliability (outer loadings)	*Cronbach's Alpha*	Composite Reliability	Convergent Validity (AVE)	Discriminant Validity
Thresholds	----------	**> 0.7**	***> 0.7***	**> 0.7**	**> 0.5**	----------
Perceived Usefulness (PU)	**PU_1**	**0.823**				
	PU_2	**0.706**				
	PU_3	**0.850**		0.908	0.665	Yes
	PU_4	**0.821**	*0.873*			
	PU_5	**0.868**				
Perceived Ease of Use (PEOU)	**PEO_1**	**0.827**				
	PEO_2	**0.700**	*0.723*	0.840	0.638	Yes
	PEO_3	**0.860**				
Compatibility (C)	**C_1**	**0.780**				
	C_2	**0.855**	*0.796*	0.880	0.710	Yes
	C_3	**0.889**				
Attitude Towards Mobile Advertising (ATMA)	**ATMA_1**	**0.790**				
	ATMA_2	**0.856**				
	ATMA_3	**0.835**	*0.885*	0.916	0.685	Yes
	ATMA_4	**0.840**				
	ATMA_5	**0.815**				
Internet Privacy Concerns (IPC)	**IPC_1**	**0.874**				
	IPC_2	**0.899**	*0.850*	0.908	0.767	Yes
	IPC_3	**0.854**				
Attitude Towards Usage (AT)	**AT_1**	**0.840**				
	AT_2	**0.867**	*0.833*	0.900	0.750	Yes
	AT_3	**0.891**				
Social Influence (SI)	**SI_1**	**0.809**				
	SI_2	**0.880**	*0.776*	0.870	0.691	Yes
	SI_3	**0.803**				
Hedonic Motivation (HM)	**HM_1**	**0.857**				
	HM_2	**0.881**	*0.828*	0.897	0.744	Yes
	HM_3	**0.849**				
Technology Anxiety (TA)	**TA_2**	**0.990 (+)**				
	TA_3	**0.452 (+)**	*0.728 (+)*	0.719 (+)	0.593 (+)	Yes
Innovativeness (IN)	**IN_1**	**0.839**				
	IN_2	**0.730**	*0.751(+)*	0.855(+)	0.663(+)	Yes
	IN_4	**0.868**				

Table 11. Final Results of Reliability and Validity test *Note: (+) indicates increase relative to before indicator elimination*

4.2.4 Evaluation of the structural Model

As part of the evaluation of the inner model, the coefficients of determination are assessed first. Subsequently, the path coefficients are presented to highlight the extended impact. On the basis of the latter, significance of each hypothesis is tested. Ultimately, the overall models' fit for prediction is assessed.

4.2.4.1 R2 values

While adhering to the rule-of-thumb for the classification of coefficients of determination, the calculated path coefficients and R^2 values (figure 20) indicate that the endogenous latent variables of AT own a **strong** effect size. The R^2 value 0.747 is achieved by the explanatory power of all five latent variables linked to AT. Meaning that all five variables linked to AT explain attitude towards using VAs on WhatsApp by 74.7%. Furthermore, endogenous latent variables of BI can be categorized to own a **moderate to nearly strong** effect size. The R^2 value of 0.617 in BI therefore indicates that the five latent variables explain behavioral intentions to use VAs on WhatsApp by 61.7%. Based on the derived R^2 values we conclude that the predictive capability of the proposed model is relatively high. After all, Falk & Miller state in this regard that models with values above 0.10 should be regarded as satisfactory (Falk & Miller, 1992).

4.2.4.2 Path Coefficients

given figure 20 all path coefficients are supported as clearly all exogenous latent variables inflict a bidirectional impact on proceeding endogenous latent variables. The highlighted paths based on relative values show that PU -> AT (O = 0.552) has the strongest path coefficient, followed by, AT->BI (O = 0.323) and C->AT (O = 0.277) while IPC->AT (O = -0.044) and TA->BI (O = -0.158) are supportive of a negative relationship. However, statistical significance of each variable remains undetermined as t-values relative to p-values haven't undergone evaluation yet as part of the actual hypotheses testing.

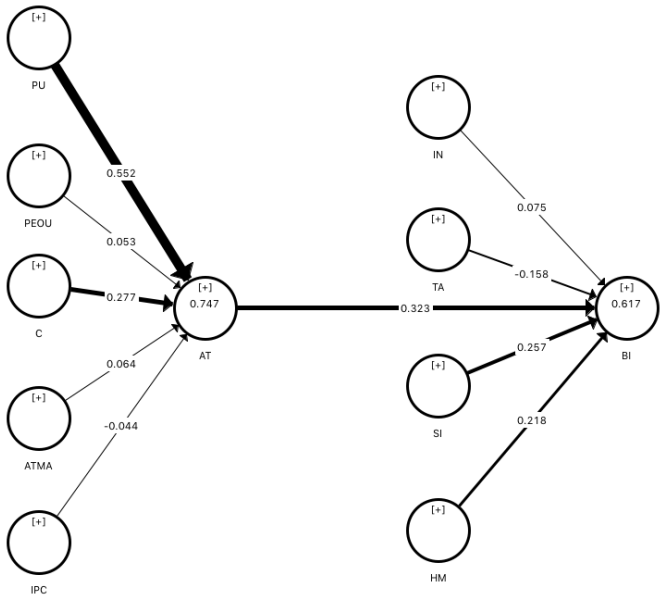

Figure 20. Path coefficients based on relative values

4.2.4.3 Hypotheses testing

Tables 12 and 13 provide an overview of the hypotheses evaluation as a result of the bootstrapping procedure. In this respect, H9b and H10b are separately tested as part of the moderating (indirect) effect analysis.

The null hypothesis (h0) is rejected, in other words the hypothesis is accepted, if the path coefficient is either </>0, with the maximum level of significance set at α =<0.1 and a significant t-value set at >1.65, as is acceptable in exploratory research (Mooi & Sarstedt, 2011).

Table 12. Evaluation of the Structural model (direct effects)

Hypothesis	Structural Path	Path Coefficients (O)	T-statistics values	P values (α)	Result
H1. Perceived Usefulness will have an effect on Attitude towards using VAs on WhatsApp.	**PU → AT**	**0.552**	**9.867**	**0.000**	***
H2. Perceived Ease of Use will have an effect on Attitude towards using VAs on WhatsApp.	**PEUO → AT**	**0.053**	**1.218**	**0.223**	**NS**
H3. Compatibility will have an effect on Attitude towards using VAs on WhatsApp.	**C → AT**	**0.277**	**4.554**	**0.000**	***
H4. Attitude towards Mobile Advertising will have an effect on Attitude towards using VAs on WhatsApp	**ATMA → AT**	**0.064**	**1.252**	**0.211**	**NS**
H5. Internet Privacy Concerns will have an effect on Attitude towards using VAs on WhatsApp.	**IPC → AT**	**-0.044**	**1.223**	**0.221**	**NS**
H6. Attitude towards Using VAs on WhatsApp will have an effect on behavioral intent to use VAs on WhatsApp.	**AT → BI**	**0.323**	**4.207**	**0.000**	***
H7. Social Influence will have an effect on behavioral intent to use VAs on WhatsApp.	**SI → BI**	**0.257**	**3.313**	**0.001**	***
H8. Hedonic Motivation will have an effect on behavioral intent to use VAs on WhatsApp.	**HM → BI**	**0.218**	**2.618**	**0.009**	***
H9a. Technological Anxiety will have an effect on Behavioral Intent to use VAs on WhatsApp.	**TA → BI**	**-0.158**	**1.872**	**0.061**	*
H10a. Innovativeness will have an effect on Behavioral Intent to use VAs on WhatsApp	**IN → BI**	**0.075**	**1.659**	**0.097**	*

Note: NS= Not Significant, * = significant at α < 0.1, *** = significant at α < 0.05

Table 13. Evaluation of the structural model (indirect effects)

Hypothesis	Structural Path	Path Coefficients (O)	T-statistics values	P values (α)	Significance
H9b. Technological Anxiety will moderate the effect of Attitude towards use of VAs on WhatsApp on Behavioral Intent to use VAs on WhatsApp.	**TA moderating: AT→ BI**	**-0.096**	**1.006**	**0.314**	**NS**
H10b. Innovativeness will moderate the effect of Attitude towards use of VAs on WhatsApp on Behavioral Intent to use VAs on WhatsApp.	**IN moderating: AT → BI**	**-0.077**	**1.556**	**0.120**	**NS**

Note: NS= Not Significant, * = significant at α < 0.1, *** = significant at α < 0.05

Based on the results on the previous page, the following findings are formulated in writing:

1. A significant **positive** relationship between Perceived Usefulness and Attitude towards using VAs on WhatsApp is proven.
2. A significant **positive** relationship between Compatibility and Attitude towards using VAs on WhatsApp is proven.
3. A significant **positive** relationship between Attitude towards using VAs on WhatsApp and Behavioral Intent to use VAs on WhatsApp is proven.
4. A significant **positive** relationship between Social Influence and Behavioral Intent to use VAs on WhatsApp is proven.
5. A significant **positive** relationship between Hedonic Motivation and Behavioral Intent to use VAs on WhatsApp is proven.
6. A significant **negative** relationship between Technology Anxiety and Behavioral Intent to use VAs on WhatsApp is proven.
7. A significant **positive** relationship between Innovativeness and Behavioral Intent to use VAs on WhatsApp is proven.

In conclusion, these results imply that the structural paths for:

- Perceived Usefulness and Compatibility to Attitude
- Attitude, Social Influence, Hedonic Motivation and Innovativeness to Behavioral Intent

are significantly positive related, while:

- Technology Anxiety to Behavioral Intent

is significantly negative related, and it is therefore, herewith statistically proven that the hypothesized significant relationships in the proposed model must be accepted. With reference to the degree of significance, Perceived Usefulness (9.867) has the highest explanatory power, followed by Compatibility (4.552), Attitude (4.207) and Social Influence (3.313). Correspondingly, these variables can be interpreted as having the greatest impact on the Behavioral Intention of Dutch generation Y to use VAs on WhatsApp for conversational commerce, within the confines of the factors investigated as part of the proposed framework.

4.2.5 Assessment of the Models' Fit for Prediction - SRMR

Based on the SRMR values presented below, we are enabled to classify the overall model's goodness of fit.

	Saturated Model	Estimated Model
SRMR	0.066	0.069
D_ULS	2.890	3.201
D_G	1.545	1.632
Chi-Square	1,598.460	1,651.784
NFI	0.735	0.726

Table 14. SRMR values

As the SRMR values for the saturated model (0.066) and that of the estimated model (0.069) are below the threshold value of 0.1, we can conclude the model has a good fit for prediction.

4.2.6 Multi-group analysis

This study additionally seeks to uncover significant differences with relation to a set of theoretically deduced control variables. PLS-MGA is used as part of this analysis for Gender (Male/Female), M-commerce Experience (Yes/No) and WhatsApp Usage (Light/Heavy).

4.2.6.1 Gender

The dataset constitutes 153 males (61.4%) and 96 females (38.6%). Table 15 shows the parametric bootstrapping results which enables us to pinpoint a significant difference within the two groups. As highlighted in green, a significant difference is found in relation to the structural path of IN → BI.

Table 15. PLS-MGA parametric results for gender

Structural Path	Path Coefficients-diff (| Male - Female |)	t-Value(Male vs Female)	p-Value α (Male vs Female)
AT -> BI	0.071	0.448	0.655
ATMA -> AT	0.049	0.473	0.637
C -> AT	0.095	0.779	0.437
HM -> BI	0.073	0.429	0.668
IN -> BI	**0.243**	**2.770**	**0.006 *****
IPC -> AT	0.063	0.885	0.377
PEOU -> AT	0.093	1.060	0.290
PU -> AT	0.023	0.205	0.837
SI -> BI	0.128	0.873	0.383
TA -> BI	0.032	0.206	0.837

Note: green = significant at $t > 1.96$, *** = significant at $\alpha < 0.01$, ** = significant at $\alpha < 0.05$

As we take a closer look at the differences within the structural path (table 16), we primarily notice a discrepancy in the t-values for females (3.735) and males (0.197). Subsequently, α for females is found to be significant as opposed to an insignificant α for males.

Table 16. PLS-MGA Path coefficient for specified path

Structural Path	Path Coefficients (Female)	Path Coefficients (Male)	t-Values (Female)	t-Values (Male)	p-Values α (Female)	p-Values α (Male)
IN-> BI	0.254	0.011	3.735	0.197	0.000***	0.844

Note: Green = significant at t = > 1.96, Red = insignificant, *** = significant at α 0.01

Furthermore, no significant differences were found with regard to R^2 values for the specified groups (Appendix C). Nonetheless, based on the results we can conclude that; for females belonging to Dutch generation Y:

- Innovativeness is significantly positive related with Behavioral Intent to use VAs on WhatsApp as a means to realize conversational commerce.

While for males belonging to Dutch generation Y:

- No significant relationship between Innovativeness and Behavioral Intent could be ascertained

4.2.6.2 M-commerce Experience

In our dataset we have 212 (85.1%) respondents with, and 37 (14.9%) respondents without experience with earlier purchases through m-commerce (Yes = experience, No = no experience). Although this representation of m-commerce experience is unequally distributed, the evaluation on significant differences between the two groups is carried out next.

Table 17.PLS-MGA parametric results for M-commerce experience

Structural Path	Path Coefficients-diff (| Yes - No |)	t-Value(Yes vs No)	p-Value α (Yes vs No)
AT -> BI	0.195	0.902	0.368
ATMA -> AT	0.319	2.270	0.024**
C -> AT	0.208	1.185	0.237
HM -> BI	0.377	1.687	0.093
IN -> BI	0.132	0.994	0.321
IPC -> AT	0.001	0.006	0.995
PEOU -> AT	0.054	0.400	0.689
PU -> AT	0.039	0.249	0.804
SI -> BI	0.134	0.618	0.537
TA -> BI	0.273	1.380	0.169

Note: green = significant at t > 1.96, *** = significant at α < 0.01, ** = significant at α <0.05

By singling out the structural path coefficients for ATMA → AT, we are capable of evaluating the discrepancies between the two groups.

Table 18. PLS-MGA Path coefficient for specified path

Structural Path	Path Coefficients (No)	Path Coefficients (Yes)	t-Values (No)	t-Values (Yes)	p-Values α (No)	p-Values α (Yes)
ATMA-> AT	0.349	0.030	2.801	0.554	0.005***	0.580

Note: Green = significant at t = > 1.96, Red = insignificant, *** = significant at α 0.01

Alike our previous multi-group analysis, no significant difference was found with regard to R^2 values (appendix C). However, we conclude on the basis of our evaluation that; for those belonging to Dutch generation Y without m-commerce experience:

- Attitude Towards Mobile Marketing is significantly positive related with Attitude towards using VAs on WhatsApp as a means to realize conversational commerce.

While for those with m-commerce experience belong to generation Y:

- No significant relationship between Attitude Towards Mobile Marketing and Attitude towards usage could be proven.

4.2.6.3 Frequency of WhatsApp usage

SmartPLS-MGA solely allows a two-subgroup evaluation per specified group. Therefore, the two extremes within the scale of WhatsApp Usage where taken. As such, 59 (23.7%) respondents were classified as light users, while 78 (31.1%) respondents as heavy users.

Table 19. PLS-MGA parametric results for Frequency of WhatsApp usage

Structural Path	Path Coefficients-diff (| Heavy - Light |)	t-Value(Heavy vs Light)	p-Value α (Heavy vs Light)
AT -> BI	0.066	0.289	0.773
ATMA -> AT	0.250	1.923	0.057
C -> AT	0.307	1.949	0.053
HM -> BI	0.195	0.800	0.425
IN -> BI	0.171	1.200	0.232
IPC -> AT	0.038	0.411	0.681
PEOU -> AT	0.280	2.433	0.016**
PU -> AT	0.105	0.770	0.443
SI -> BI	0.182	0.906	0.366
TA -> BI	0.183	1.050	0.296

Note: Green = significant at t = > 1.96, Red = insignificant, *** = significant at α 0.01, ** = significant at α < 0.05

The parametric test results indicate that there is a significant difference between heavy and light users for the structural path PEOU → AT. Next, by focusing on the path coefficients of the multi-group analysis, we can gain insights into the dynamics of the specified group difference.

Table 20. PLS-MGA Path coefficient for specified path

Structural Path	Path Coefficients (Heavy_freq)	Path Coefficients (Light_freq)	t-Values (Heavy_freq)	t-Values (Light_freq)	p-Values α (Heavy_freq)	p-Values α (Light_freq)
PEOU-> AT	-0.022	-0.017	0.371	2.378	0.711	0.018**

Note: Green = significant at t = > 1.96, Red = insignificant, *** = significant at α 0.01, ** = significant at α < 0.05

Similarly to the results for two earlier control variables, no significant difference could be proven with regard to the R^2 values (Appendix C). Nevertheless, we can conclude that for heavy WhatsApp users belonging to Dutch generation Y:

- Perceived Ease of Use is significantly positive related with Attitude towards using VAs on WhatsApp as a means to realize conversational commerce.

While for those classified as light WhatsApp users that belong to generation Y:

- No significant relationship between Perceived Ease of Use and Attitude towards usage could be proven.

5. Discussion and Conclusion

In this chapter a summary of findings is provided and subsequently discussed in the context of existing literature. In addition, the specified research questions are answered conform the derived results. Moreover, practical and academic implications are discussed. The chapter is concluded with conclusions on the overall study.

5.1 Discussion

The main objective of this study is to explore the factors determinant to behavioral intent of Dutch generation Y to make use of VAs on the WhatsApp platform as a means to realize conversational commerce. In doing so, a theoretical framework was designed involving constructs adapted primarily from three established theoretical frameworks (TAM, DOI, UTAUT2) and furtherly specified by the consideration of secondary researches.

Sample characteristics indicate that the vast majority of the sample has experience with purchases via m-commerce. Average age is approximately 28 years old, while men slightly overrepresented the overall sample size as opposed to women (Appendix B). WhatsApp usage is skewed towards average to heavy daily usage. Furthermore, the calculated means for both Attitude (3.0750) and Behavioral Intent (3.02288), on a five point Likert scale, resulted in a slightly above neutral score. These results ascertain the lack of a resolute tendency towards the technology. In this sense, the values are complementary to those derived by Eeuwen, wherein single-mindedness in attitude and intention was rejected as well (2017). This implies that the data doesn't provide definitive evidence on the degree to which Dutch generation Y are inclined to adopt 5th generation VAs as a means to realize conversational commerce as an alternative to traditional procurement channels.

Nevertheless, by analyzing the explained variance (R^2), we can judge the latent variables to explain a rather high amount of variance in Attitude towards the technology, which we can subsequently classify as a strong effect size. Moreover, the amount of variance explained by latent variables in Behavioral intent is classified as moderate to strong effect size as well. The eight individual models whereon UTAUT is based were capable of explaining 17-53% of variance in Behavioral Intent, while UTAUT was capable of explaining 60-70% variance (Venkatesh & Davis, 2000). By comparing results from our proposed framework with the latterly mentioned, it is safe to say that the explanatory power of the model designed for this study is relatively high. In general, most of the hypothesized relationships were supported and to a lesser extent found statistically significant (Table 12 & 13). In the context of an embryotic technology which requires further exploration, the proposed model should be regarded as a valuable addition to the current literature.

The variables PU and C, in this order, have the highest explanatory power in the overall model, and in their predictive relation to AT towards usage. Significant factors predictive of BI, in the same order, are: AT, SI, HM, TA and IN.

Dissimilar to Eeuwen's evaluation, our study couldn't prove significant correlation between the hypotheses PEOU -> AT (H2), ATMA -> AT (H4), IPC -> AT (H5). The greatest difference in comparing the results of these two studies is the role of IPC. Eeuwen concluded that C, PU and IPC, in this order, are the most relevant predictors for AT. Our study however suggests that PU explains the highest variance in AT and then followed by C, while both ATMA (O = 0.064) and IPC (O = -0.044) explain only a miniscule additional variance in AT. In their study on the factors determinant for mobile commerce, Wang and Wu, similarly to Eeuwen, were supportive to C being the most important predictor within their TAM-based model. This was also the case for Zhong et al. where C and PU were responsible for the highest amount of variance (2013). Nevertheless, complementary to our results, Wu and Wang didn't conclude PEOU to have a significant direct role in relation to AT or BI, this was also the case for Vijayasrathy while analyzing the determinants for e-commerce (2004).

As opposed to research on virtual try-on technology for online shopping by Kim & Forsythe, in our study TA->BI (H9a) and IN->BI (H10a) were proven to significantly correlate. Notwithstanding that in their role as moderators between AT->BI (H9b, H10b), both relationships could not be supported. In this sense, Wang & Wu found perceived risk to have a significant direct impact on BI. As TA can be associated with perceived risk, we can speak of somehow complementary results in this respect.

Furthermore, in line with results obtained by Lopez-Nicolas et al., SI was proven significant in its relation to BI (2008). This is complementary to Venkatesh et al. who stress the necessity to hold SI into account (2012). Moreover, this study introduced HM as a predictor to BI and subsequently significance was proven. These findings are partly in line with those derived by Bruner & Kumar who found HM of even greater relevance then PU in the context of the drivers of handheld internet devices (2005).

5.2 Answering Research Questions

Main RQ: What factors are determinant to behavioral intent with respect to the utilization of 5th generation Virtual Assistants on the WhatsApp platform as a novel method to realize mobile commerce?

After embarked on a descriptive literature review in order to define domain specific concepts and the subsequent evaluation of well-known adoption literature, we were capable of focusing on domain-specific secondary researches. The eventual model that was designed on the basis of all of the latter has proven to

explain 74.7% of variance in Attitude, and 61.7% in Behavioral Intent. Additionally, by obtaining the SRMR value (0.069) we were capable of validating the proposed models' overall good fit for prediction.

In general, results obtained from our study are largely justifiable in the context of earlier studies. Factors within our model that proved strong significance ($t:>2.56$, $\alpha<0.01$ & $t:>1.96$, $\alpha<0.05$) were: Perceived Usefulness, Compatibility, Attitude, Social Influence and Hedonic Motivation. Factors that are proven significant on the basis of thresholds for the exploratory nature of the study ($t:>1.65$ $\alpha<0.1$) were: Technology Anxiety and Innovativeness. Where Technology Anxiety has a significant negative relation with Behavioral Intentions. Lastly, factors that proved statistically insignificant in any sense were: Perceived Ease of Use, Attitude Towards Mobile Advertising, Internet Privacy Concerns, Technology Anxiety as a moderator and Innovativeness as a moderator.

Sub RQ: To what extent are there significant differences with respect to results between each control variable and the overall results for the unit of analysis?

Initially, we settled with three control variables to be incorporated into the final model as a result of evaluating secondary researches. The Multi-Group analysis performed on Gender, M-commerce experience, Frequency of WhatsApp Usage didn't support a significant difference in R^2 values for Attitude and Behavioral Intent. However, more specific results indicate that the correlation between IN->BI (H9a) is only significant with respect to females, and not for males. This observation is notable as Kim & Forsythe were not able to prove a gender difference within their study on virtual try-on technology in the context of e-commerce (2008). Next, for those without any experience with purchases via m-commerce channels, ATMA->AT (H4) is significantly correlated, while for those without m-commerce experience, the correlation doesn't hold. Lastly, for those classified as heavy WhatsApp users, PEOU->AT (H2) is significantly supported, which is not the case for light users.

5.3 Implications

5.3.1 Academic Implications

This study explored the factors that are determinant to behavioral intent with respect to the utilization of 5th generation Virtual Assistants on the WhatsApp platform as a novel method to realize mobile commerce, with a specific focus on Dutch generation Y. As far as our knowledge reaches, the scope of this study is unique. Therefore, the empirical results obtained and presented here are novel to the school of IS research. We intended to present an overarching model based on generalizable and domain-specific tendencies we deemed to influence behavioral intentions with respect to the contextualized technology.

The somewhat minor differences in results presented in secondary researches that were mentioned throughout the chapters can be mainly attributed to the differing contexts wherein phenomena where studied. For example, from all highlighted studies, Eeuwen's paper was most complementary to ours. However, where we sought to establish an understanding for VAs being used on the WhatsApp platform, Eeuwen contextualized VAs on messaging as a whole. Although, the targeted sample was the same: Dutch Generation Y and millennials respectively, the context wherein conversational commerce was being examined differed. In this sense, the somewhat close results to the latterly mentioned study can be attributed partly to cultural reasons. All of the other studies that were taken into account during our orientation and analysis had not specified specific attention to conversational commerce. As such Wu and Wang studied m-commerce adoption (2005). Looije et al focused on socially intelligent robots as health assistance (2006). De Ruyter et al. explored the effects of socially capable ambient intelligence (2005). Stoel & Ha delved into consumer e-commerce acceptance (2007). Lopez-Nicolas et al. studied the adoption of advanced mobile service acceptance. Kim & Forsythe explored the adoption virtual ty-on in e-commerce (2008). May & Kirwan investigated the effectiveness of adopting VAs as a replacement for online forms (2013). While the list could get infinitely longer, we conclude that apart from one, existing research is sometimes somewhat associative, but has not taken into account VAs on messaging at all.

All-in-all, the model designed as part of this study, and the subsequently presented results can be taken as valuable literature in the quest to further specify more detailed factors that are determinant to the adoption of conversational commerce enabling technologies. In doing so, the validated and the rejected constructs within this model can be adopted to test in different contexts.

5.3.2 Practical Implications

Apart from the academic implications, the results of this study can be translated into actionable measures for decision-makers in organizations aspiring to leverage their strategy for VAs on messaging platforms, specifically on WhatsApp.

Primarily, implementers have to emphasize the benefits that end-users could expect when using their VAs through a platform such as WhatsApp. This perceived usefulness at the end of the user is proven as to most significant determinant towards the overall attitude of Dutch generation Y.

Furthermore, the usage of VAs on WhatsApp should at all times be compatible with their users' lifestyle. Therefore, deviating from that what is considered as the overall norm for making decisions, building relations and eventually making purchases is herewith not advised. However, we judge the integration of VAs on WhatsApp a highly compatible option as assimilation of the technology into an individual's life requires relatively low effort at the end of users. As figures on WhatsApp usage, and secondary researches on

WhatsApp's diffusion, indicate a positive attitude towards its utilization as a standalone messaging platform, this positive sentiment is likely to be leveraged while integrating VAs into the applications' current ecosystem.

Additionally, it's recommended to hold into account the influence from others while seeking to bind customers to ones VA. Apart from emphasizing a VAs usefulness, this social influence could be leveraged by, e.g., engaging in marketing campaigns with opinion leaders while intending a snowball effect for the realization of a more positive perception towards the technology.

Moreover, in the context of our unit of analysis, fun is determined as a fundamental driver. While drawing an analogy with the classic motivational principle that humans seek to attract pleasure and to avoid pain, the design of the interaction between a VA and customer should consistently be efficient, likeable and effective. In doing so, we emphasize that it's crucial not to compromise any aspect of fun.

Next, our study has sought to explore the influence of technological anxiety on behavioral intentions. In this respect, we incorporated a generic scale which did however indicate a significant role for its consideration. Purely form our view, the probable root causes of this apprehension lay within a realm much greater than VAs or the IS domain as a whole. Companies do however need to seek for measures to depress negative tendencies that could be associated with the technology.

Although eventually found insignificant in its relationship with Attitude towards VAs on WhatsApp, mobile advertisement (O = 0.064) with a mean of 2.55 on a 5-point Likert scale indicates a relatively indifferent attitude towards mobile advertisement. In relation to the mean of 2 for the same phenomenon and scale, derived by Eeuwen, our results indicate a slightly more positive attitude (2017). Nevertheless, as bulk of the theory already suggests, practitioners should be cautious in deploying advertising, especially intrusive ones via mobile handheld devices. According to Syrett and Lamminman, deploying mobile advertising should be done with specific consideration, specifically when targeting generation Y as they are less tolerant and see through hypocrisy faster when it comes to advertising (2017). The measured indifferent attitude towards mobile advertising in this study, should be considered as fragile and therefore, cherishing it is crucial in order to realize long-term exploitation.

Furthermore, internet privacy concerns (O = -0.044) with a mean of 3.61 on a 5-point Linkert scale indicates that Dutch generation Y embrace new technologies with a wary eye, and are indeed concerned about internet security and personal data. The mean score for internet privacy concerns is relatively similar to the one derived by Eeuwen (3.39). On this basis, it's recommended for practitioners to remain concerned with the robustness of their data infrastructure as tarnishing ones organizational image in this respect could lead to widespread lack of trust.

Lastly, results obtained from multi-group analysis based on three generic control variables has brought forward contemporary insights, however, not of such a scale that we would consider practical implications for them at this stage.

5.4 Limitations and Future Research

The realization of this study has naturally been compromised due to limited resources. In this respect, time is the most notable constraining factor. Another generic limitation for those that engage in research are researcher biases. Although, one may not like to admit this to be the case, we cannot guarantee this study to be completely free of biases. In this sense, we sought to minimize the likability of biases to blend in with our analysis by dedicating close attention to our survey design, and any deviations from our initially intended methodology.

On a more specific note, our study was of a cross-sectional nature, meaning that observations were recorded at a single point in time. As Venkatesh et al. point out, more concrete and less biased results could be obtained by performing a longitudinal study where results can be compared over a given timeframe (2012). Nonetheless, the variables within the model were capable of explaining 74.7% in variance for Attitude and 61.7% in Behavioral Intentions. Future researches could extent this model in order to increase its predictive capabilities.

Secondly, due to a lack of research focusing on conversational commerce, concrete evidence from secondary resources is scarce. As the technology remains at an embryotic stage, the specification of constructs remains challenging as one is forced to seek a synthesis between generic and specific tendencies. For example, our literature review, alike that of Moussawi (2016), did consider the role of anthropomorphism and that of increased intelligence. Scaling these tendencies to fit within the overall model proves to be daunting as one cannot be measuring generic tendencies with a survey while accomplishing overall reliability for specific tendencies that require a more experimental oriented research. Eventually, we generalized about the role of anthropomorphism and intelligence by exploring the role of technological anxiety according to literature. This has finally proven to be a significant tendency in the context of the studied technology. Therefore, initial steps are herewith undertaken towards a more specified study to the phenomenon within. By dissecting the underlying drivers of technology anxiety which we deem, among others, to be anthropomorphism and the role of increased intelligence, more in-depth and technology-specific studies can be carried out in the future. Moreover, as Yang and Yoo concluded from their study aiming at revisiting the TAM (2004), the specification of Attitude into Cognitive Attitude and Affective Attitude as two separate socio-psychological constructs could enhance overall explanatory power of predictors and therefore, more detailed implications could be raised.

Also, we focused on generation Y in The Netherlands and therefore the results are limited to socio-demographic factors. As regions differ with respect to cultural and social aspects, the generalizability of the

outcomes are naturally limited. Therefore, we suggest conducting future studies on the basis of our research design for regions that differ socio-demographically.

Next, our study hypothesized the notion of fully working, socially intelligent VAs where the focus was therefore not on the extent of practical usability of current VA technology, but rather on the perceived inclination to adopt the technology in an envisioned mature state. A more design-oriented research should therefore be considered where the aim should be to increase effectiveness relative to the underlying technology of VAs.

Furthermore, the original constructs used as part of our survey were English. Back translation procedures were deployed to ascertain minimum deviation relative to the original constructs. However, for lack of evidence, we cannot guarantee the translation to be completely biased free.

In our multi-group analysis we calculated the parametric differences with relation to outcomes based on gender, m-commerce experience and frequency of WhatsApp usage. For m-commerce experience, 85.1% of the respondents were determined to have experience, and only 14.9% didn't. Therefore, this specific analysis should be regarded as one that is based on highly unequally distributed data and therefore its reliability is questionable.

However, the greatest challenge in obtaining results representative to the actual technology is due to the lack of existing VAs on WhatsApp. As this is merely an educated assumption, we cannot confirm this eventually becoming a reality. In consequence, this determined the comprehensiveness of the model to be limited to gauging behavioral intention and not actual usage. We therefore recommend more studies to be carried out in the same context or on the basis of another messaging platform, especially when the technology allows measurement of actual usage. Currently, WhatsApp uses various protocols to filter and ban VAs from its user base. In our survey we provided a written scenario and an image depicting the WhatsApp interface being used for conversational commerce. In consequence, respondents were left to their imagination on the way they felt about using such a technology. Future researches could either make use of existing VAs or developing a VA representative to what the technological capabilities are. In this way, respondents could get a better feel of the technology, and subsequently reflect this on their choices throughout the questionnaire.

5.5 Conclusion

This study began by putting the study in appropriate context. This was done by the provision of a detailed introduction, along with the formulation of research questions. We then engaged in a literature survey wherein a set of concepts were defined from where targeted secondary researches could be identified and analyzed. The latter enriched our understanding of the overall requirements for the feasibility of our research objectives. We then proceeded by specifying the final research model. Subsequently, we collected data from 249 respondents, and analyzed and interpreted findings accordingly.

In conclusion, this study has proven the proposed model as capable to explain the Attitude and Behavioral Intentions of Dutch Generation Y to make use of VAs on WhatsApp as a means to exercise conversational commerce. Therefore, the overall research should be considered as an empirical addition to the scarce availability of literature focusing on this specific phenomenon.

The overall design of the research is primarily based on secondary resources which have proven to resonate with literature on established adoption model literature. In general, research conducted on the adoption of VAs, robotics, TBSS's and m-commerce are largely based on TAM, UTAUT and DOI, which subsequently influenced our orientation towards the development of the final proposal. In doing so, we took initial inspiration from the study conducted by Eeuwen who utilized TAM as a basis for his design (2017). By extending Eeuwen's base model with four additional constructs and three control variables, we initiated an exploratory analysis as none of these variables had been studied in this context before.

The final results indicate that the variables linked to Attitude towards usage explain 74.7% of variance, while the ones with linkages to Behavioral Intentions were capable of explaining 61.7% of variance. Together, the average R^2 value for the proposed model is 0.682 (68.2%), which positions the explanatory power of this model, in the context of the specified technology as one of the strongest ones to date, if not the strongest.

As such, Attitude towards usage of VAs on WhatsApp was significantly determined by two variables, Perceived Usefulness, originating from Davis et al. their widely known TAM framework (1989), and Compatibility which was initially introduced in the renowned DOI theory (Rogers E. M., 1983). The significance for these variables was based on the thresholds values used in regular studies ($t < 1.96$ and $p < 0.05$). Secondly, Behavioral Intention towards using VAs on WhatsApp was explained by four variables. Herein, the UTAUT(2) constructs; Social Influence and Hedonic Motivation were found significant at the same threshold values (Venkatesh & Davis, 2000). However, Technology Anxiety and Innovativeness were found significant at threshold values for exploratory research only ($t < 1.65$ and $p < 0.1$).

Results for the moderating effect of Technology Anxiety and Innovativeness on the relationship between Attitude and Behavioral Intentions however didn't prove significant at the generally accepted threshold values for moderation ($t < 1.96$ and $p < 0.05$).

The results for constructs used in prior research on associative technologies are to a large extent complementary. However, constructs that were added with an exploratory intent could not be thoroughly compared with additional secondary sources. Overall, the sequence beginning with the strongest significant factors and ending with the least significant ones for Behavioral Intention is as follows: Perceived Usefulness, Compatibility, Attitude, Social Influence, Hedonic Motivation, Technology Anxiety, and lastly Innovativeness.

Moreover, multi-group analysis on three control variables (Gender, M-commerce experience, and Frequency of WhatsApp usage) didn't conceive a significant difference with regard to R^2 values for Attitude and Behavioral Intentions. Nevertheless, a more specified focus on the interrelationships throughout the model proved the existence of significant differences with regard to females and males within the structural path between Innovativeness and Behavioral Intentions. Subsequently, those with M-commerce Experience have proven to have a significant positive Attitude Towards Mobile Advertising in the structural path with Attitude. Lastly, those that are classified as Light WhatsApp users prove to have a positive significant tendency for Perceived Ease of Use in the structural path between Attitude, as opposed to Heavy users.

With regard to both academic and practical implications, we deem our research design as a valuable addition to existing literature. Specifically, the incorporation of constructs that haven't been studied in the context of this technology are evidently an added value. As a result, practitioners are advised to recognize our findings on significant drivers for the adoption of the specified technology, and to strategize accordingly.

Future research on the basis of our research design is advisable, however, with the consideration of the specified key limitations of our study. The lack of a proper school of research towards the phenomenon studied as part of this thesis drives us to elicit potential research to delve into generic tendencies and to subsequently specify those in the context of differing research strategies as well. For example, this could be realized by the initiation of design-oriented studies intending to raise the effectiveness of VAs relative to our derived findings. Another example could be by experimental studies gauging the effect of specific tendencies that fall under the umbrella of Technology Anxiety such as the effect of increased anthropomorphism or the effect of increased intelligence in the context of conversational commerce.

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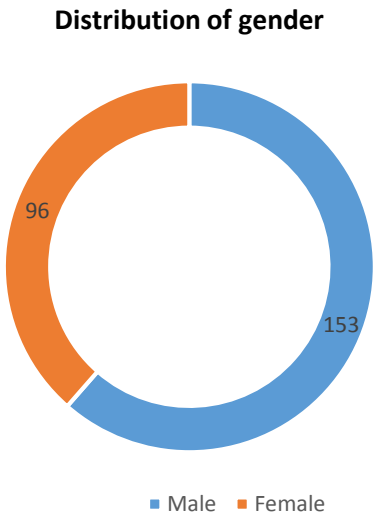
APPENDIX A. Data distribution Test

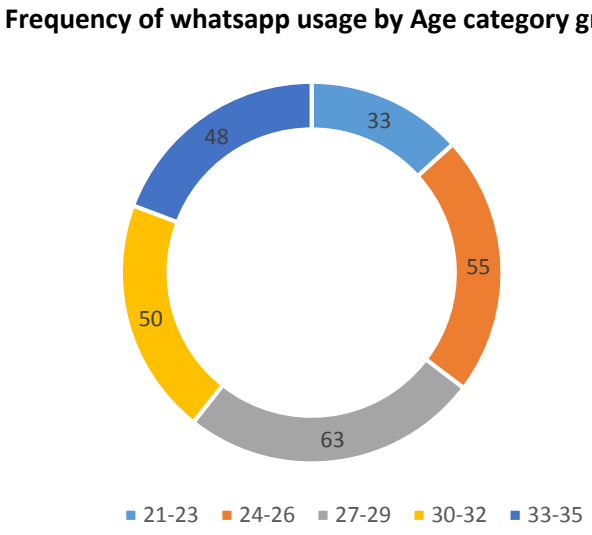
Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Gender	.400	249	.000	.617	249	.000
Age	.087	249	.000	.962	249	.000
Experience	.513	249	.000	.424	249	.000
Frequency	.228	249	.000	.807	249	.000
PU_1	.198	249	.000	.906	249	.000
PEOU_1	.295	249	.000	.856	249	.000
C_1	.201	249	.000	.895	249	.000
ATMA_1	.174	249	.000	.908	249	.000
IPC_1	.263	249	.000	.877	249	.000
A_1	.204	249	.000	.902	249	.000
SI_1	.235	249	.000	.894	249	.000
HM_1	.232	249	.000	.889	249	.000
IN_1	.296	249	.000	.853	249	.000
BI_1	.193	249	.000	.900	249	.000
TA_1	.196	249	.000	.909	249	.000
PU_2	.241	249	.000	.888	249	.000
PEOU_2	.292	249	.000	.837	249	.000
C_2	.185	249	.000	.909	249	.000
ATMA_2	.170	249	.000	.909	249	.000
IPC_2	.274	249	.000	.872	249	.000
A_2	.204	249	.000	.902	249	.000
SI_2	.249	249	.000	.890	249	.000
HM_2	.222	249	.000	.878	249	.000
IN_2	.177	249	.000	.914	249	.000
BI_2	.259	249	.000	.873	249	.000
TA_2	.176	249	.000	.914	249	.000
PU_3	.206	249	.000	.907	249	.000
PEOU_3	.314	249	.000	.824	249	.000
C_3	.172	249	.000	.908	249	.000
ATMA_3	.176	249	.000	.902	249	.000
IPC_3	.262	249	.000	.879	249	.000
A_3	.180	249	.000	.907	249	.000
SI_3	.190	249	.000	.907	249	.000
HM_3	.209	249	.000	.893	249	.000
IN_3	.238	249	.000	.894	249	.000
BI_3	.196	249	.000	.910	249	.000
TA_3	.218	249	.000	.905	249	.000
PU_4	.192	249	.000	.908	249	.000
ATMA_4	.199	249	.000	.902	249	.000
IN_4	.276	249	.000	.871	249	.000
PU_5	.206	249	.000	.901	249	.000
ATMA_5	.180	249	.000	.906	249	.000

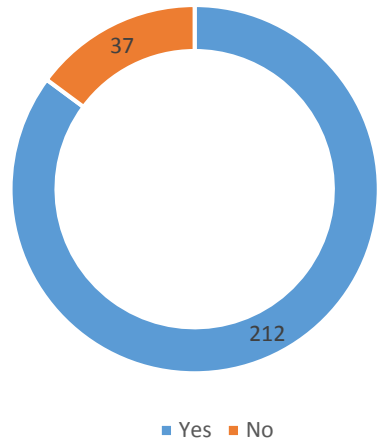
a. Lilliefors Significance Correction

Appendix B. Additional Descriptive Statistics

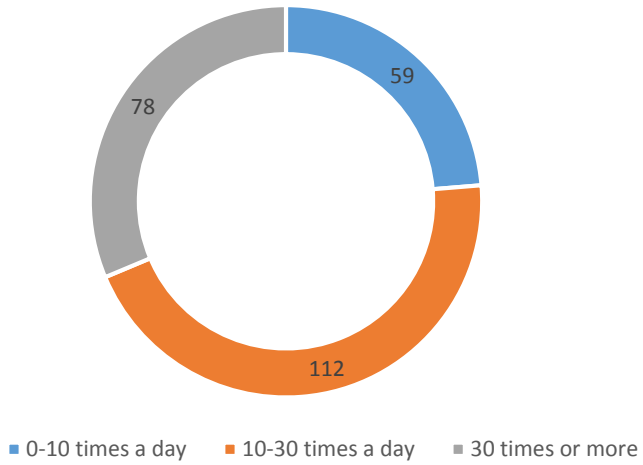




Previous mobile commerce experience



Frequency of Daily WhatsApp usage



Means for Frequency, M-commerce Experience, Age & gender

		Mean_Freq	Mean_Exp	Mean_age	Mean_gen
N	Valid	249	249	249	249
	Scale	1-3	1-2	1-15	1-2
Mean		2.0763	1.1486	28.2530	1.3855

Mean Attitude & Behavioral Intent

		Mean Attitude score	Mean Behavioral Intent score
N	Valid	249	249
	Scale	1-5	1-5
Mean		3.0750	3.0228

Appendix C: MGA R2 values

Gender (Female-Male)

	R Square Original (Female)	R Square Original (Male)	R Square Mean (Female)	R Square Mean (Male)	STDEV (Female)	STDEV (Male)	t-Values (Female)	t-Values (Male)	p-Values (Female)	p-Values (Male)
AT	0.776	0.747	0.795	0.758	0.034	0.034	23.105	22.088	0.000	0.000
BI	0.736	0.586	0.751	0.604	0.067	0.072	10.975	8.088	0.000	0.000

M-Commerce Experience (Yes-No)

	R Square Original (No)	R Square Original (Yes)	R Square Mean (No)	R Square Mean (Yes)	STDEV (No)	STDEV (Yes)	t-Values (No)	t-Values (Yes)	p-Values (No)	p-Values (Yes)
AT	0.807	0.713	0.849	0.724	0.045	0.033	18.036	21.946	0.000	0.000
BI	0.774	0.553	0.815	0.568	0.051	0.068	15.186	8.183	0.000	0.000

Frequency of daily WhatsApp usage (Light-Heavy)

	R Square Original (HIGH)	R Square Original (LOW)	R Square Mean (HIGH)	R Square Mean (LOW)	STDEV (HIGH)	STDEV (LOW)	t-Values (HIGH)	t-Values (LOW)	p-Values (HIGH)	p-Values (LOW)
AT	0.851	0.772	0.860	0.803	0.027	0.045	31.138	17.286	0.000	0.000
BI	0.650	0.636	0.684	0.679	0.097	0.105	6.731	6.080	0.000	0.000

Appendix D: Web-Based Questionnaire

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Inleiding

Niemand zal ontkennen dat technologie tot dusver radicale veranderingen gebracht heeft in de manier waarop we onze levens leiden. Ook jij wacht daarom waarschijnlijk vol verwachting af wat de volgende grote stap zal zijn.

Vanwege technologische ontwikkelingen binnen het domein van artificiële intelligentie is het nu al mogelijk om ingewikkelde conversaties met chatbots (i.e. virtuele assistenten) te voeren. Een Chatbot is een computer programma waar gebruikers gesprekken mee kunnen voeren binnen messaging applicaties, chat applicaties of in toenemende mate door middel van spraak.

Bedrijven zijn momenteel volop bezig om de gebruikerservaring met chatbots te verfijnen zodat de technologie vervolgens massaal geïmplementeerd kan worden. Volgens trendwatchers zullen chatbots een platform revolutie teweeg brengen waardoor chatbots uiteindelijk geïntegreerd zullen worden in messaging applicaties. Er wordt doorgaans voorspeld dat door massale adoptie van deze technologie het gros van de aankopen in de nabije toekomst via deze chatbots zullen worden gedaan. Dit zou betekenen dat je, door het simpelweg toevoegen van een bedrijf aan je contactenlijst, per direct je vragen beantwoord kan krijgen en dat je vervolgens je potentiele aankoop kan bevestigen en betalen zonder enige externe interventie.

Los van de praktische voordelen die deze chatbots je te bieden hebben, zullen ze in staat zijn om jouw gedragspatronen aan te leren om je vervolgens nog beter van dienst te kunnen zijn, vandaar ook de benaming: Virtuele Assistenten. Bedrijven zullen deze data onder meer kunnen gebruiken om je selectieve advertenties te sturen op basis van bijvoorbeeld je locatie. Door de combinatie van jouw data en de toenemende mate van intelligentie van virtuele assistenten, zou je in de nabije toekomst één persoonlijke virtuele assistent kunnen krijgen, een digitale verlengstuk van jezelf, je digitale jij.

Stel jezelf eens voor dat je geconfronteerd wordt met deze technologie in je dagelijks leven. Wij proberen uit te zoeken, aan de hand van deze enquête, hoe mensen zouden staan ten opzichte van het gebruik van Chatbot technologie op het WhatsApp platform om hun aankopen te doen.

Deze vragenlijst maakt deel uit van mijn masterscriptie ICT in Business aan de Universiteit Leiden. Indien anders verzocht, gaarne één antwoord per vraag geven, en zo eerlijk mogelijk beantwoorden. Alle ingewonnen enquêtes worden anoniem behandeld, en alleen gebruikt voor dit onderzoek. Ik dank u hartelijk voor uw deelname aan deze enquête.

Navid Malikbaba
ICT in Business – Universiteit Leiden
I.S.M Sogeti - verkenningsinstituut nieuwe technologie (VINT)

Universiteit Leiden
The Netherlands

Wat is uw geslacht?

Mannelijk	Vrouwelijk

What is uw leeftijd?

▼

>>

Heeft u ervaring in het aankopen doen dmv uw mobiele telefoon?

Ja	Nee

Hoevaak maakt u gebruik van WhatsApp op een dag?

0-10 keer	10-30 keer	30 keer of meer

>>

Stelling 1

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Ik denk dat het gebruik van Virtual Assistants (VAs) op WhatsApp het makkelijker zou maken voor mij om producten te kopen	○	○	○	○	○

Stelling 2

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Ik denk dat het leren om VAs te gebruiken op WhatsApp makkelijk is	○	○	○	○	○

Stelling 3

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Het gebruik van een VA op WhatsApp is compatibel met de meeste aspecten van mijn online winkelen	○	○	○	○	○

Stelling 4

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Ik denk dat mobiele reclame nuttig is aangezien het de nieuwste producten belicht	○	○	○	○	○

Stelling 5

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Ik ben bezorgd dat de informatie die ik via VAs op WhatsApp verstuur misbruikt kan worden	○	○	○	○	○

Stelling 6

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Het gebruik van VAs op WhatsApp lijkt me een goed idee	○	○	○	○	○

Stelling 7

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Mijn familie en vrienden denken dat VAs op WhatsApp nuttig zouden kunnen zijn (Als u niet zeker weet wat uw familie en vrienden ervan vinden, graag een inschatting maken)	○	○	○	○	○

Stelling 8

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Het gebruik van VAs op WhatsApp zou leuk zijn	○	○	○	○	○

Stelling 9

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Als ik over een nieuwe technologie zou horen, zou ik zoeken naar manieren om ermee te experimenteren	○	○	○	○	○

Stelling 10

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Ik wil de VAs via WhatsApp in de toekomst gebruiken om online te winkelen	○	○	○	○	○

Stelling 11

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Als ik een VA op WhatsApp zou gebruiken, zou ik bang zijn om er fouten mee te maken	○	○	○	○	○

Stelling 12

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Ik denk dat het gebruik van VAs op WhatsApp het makkelijker zou maken voor mij om mijn bestellingen te volgen	○	○	○	○	○

Stelling 13

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Ik denk dat je makkelijk vaardig kan worden met het gebruik van een VA op WhatsApp	○	○	○	○	○

Stelling 14

	Helemaal oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Het gebruik van een VA op WhatsApp past bij mijn levensstijl	○	○	○	○	○

Stelling 15

	Helemaal oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Door middel van mobiele reclame heb ik kennis gekregen van innovatievere ideeën	○	○	○	○	○

Stelling 16

	Helemaal oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Ik ben bezorgd over het verstrekken van informatie via VAs op WhatsApp vanwege wat anderen ermee zouden kunnen doen	○	○	○	○	○

Stelling 17

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
VAs op WhatsApp maken online winkelen interessanter	○	○	○	○	○

Stelling 18

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Mensen die belangrijk zijn voor mij vinden het handig om VAs op WhatsApp te gebruiken (Als u niet zeker weet wat uw familie en vrienden ervan vinden, graag een inschatting maken)	○	○	○	○	○

Stelling 19

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Het gebruik van VAs op WhatsApp zou aangenaam zijn	○	○	○	○	○

Stelling 20

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Onder mijn leeftijdsgenoten ben ik meestal de eerste om nieuwe technologieën uit te proberen	○	○	○	○	○

Stelling 21

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Ik geloof dat mijn interesse voor VAs op WhatsApp in de nabije toekomst zal toenemen	○	○	○	○	○

Stelling 22

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Ik vind het idee van een VA op WhatsApp eng	○	○	○	○	○

Stelling 23

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Ik denk dat ik door het gebruik van VAs op WhatsApp sneller online kan winkelen	○	○	○	○	○

stelling 24

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Ik denk dat het gebruik van VAs op WhatsApp makkelijk is	○	○	○	○	○

Stelling 25

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Het gebruik van VAs op WhatsApp past bij de manier waarop ik graag online productinformatie wil kopen of zoeken	○	○	○	○	○

Stelling 26

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Ik maak gebruik van mobiele reclame omdat het mij de beste deal biedt uit concurrerende producten die geadverteerd worden	○	○	○	○	○

Stelling 27

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Ik ben bezorgd over het verstrekken van informatie via VAs op WhatsApp omdat het zou kunnen worden gebruikt op een manier die ik niet had voorzien	○	○	○	○	○

Stelling 28

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Ik zou graag online winkelen met VAs op WhatsApp	○	○	○	○	○

Stelling 29

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Als veel van mijn vrienden VAs op WhatsApp zouden gebruiken, zou ik het waarschijnlijk ook doen	○	○	○	○	○

Stelling 30

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Het gebruik van VAs op WhatsApp zou heel vermakelijk zijn	○	○	○	○	○

Stelling 31

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Over het algemeen ben ik aarzelend om nieuwe technologieën uit te proberen	○	○	○	○	○

Stelling 32

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Ik raad andere aan om VAs op WhatsApp te gebruiken om online te winkelen	○	○	○	○	○

Stelling 33

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Ik vind een VA op WhatsApp intimiderend	○	○	○	○	○

Stelling 34

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Ik denk dat het gebruik van VAs op WhatsApp mij in staat stelt om effectiever online te winkelen	○	○	○	○	○

Stelling 35

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Ik ben een voorstander van mobiele reclame omdat het een belangrijk onderdeel speelt in mijn koopbeslissing	○	○	○	○	○

Stelling 36

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Ik experimenteer graag met nieuwe technologieën	○	○	○	○	○

Stelling 37

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee eens (4)	Helemaal mee eens (5)
Ik denk dat VAs op WhatsApp erg handig zou zijn bij het winkelen voor producten	○	○	○	○	○

Stelling 38

	Helemaal mee oneens (1)	Mee oneens (2)	Neutraal (3)	Mee oneens (4)	Helemaal mee oneens (5)
Mijn algemene mening over mobiele reclame is positief	○	○	○	○	○

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Bedankt voor uw tijd om aan deze enquête deel te nemen.
Uw antwoord is geregistreerd.

Uitgevoerd met Qualtrics