We need to talk… – Acceptance of Digital Voice Assistants among Millennials and older people

Dissertation

zur Erlangung des Grades eines Doktors der Wirtschaftswissenschaft

der Rechts- und Wirtschaftswissenschaftlichen Fakultät

der Universität Bayreuth

vorgelegt

von

Karolina Ewers

aus

Lodz

Dekan: Herr Prof. Dr. Jörg Schlüchtermann

Erstberichterstatter: Herr Prof. Dr. Daniel Baier

Zweitberichterstatter: Herr Prof. Dr. Claas Christian Germelmann

Tag der mündlichen Prüfung: 17.12.2021

To Leo and Alex

Danksagung

Während meiner Promotionszeit haben mich einige Menschen begleitet, die mit mir durch Dick und Dünn gelaufen sind und mich auf vielerlei Art und Weise unterstützt haben. Hiermit möchte ich die Gelegenheit nutzen, um ihnen für die letzten drei Jahre vom ganzen Herzen zu danken.

Besonders danken möchte ich meinem Doktorvater, Herrn Prof. Dr. D. Baier, für die ständige Unterstützung, ein offenes Ohr sowie zahlreiche Ratschläge während meiner gesamten Zeit am Lehrstuhl für Marketing & Innovation (BWL XIV). Ich danke ihm vor allem dafür, dass er immer in mich und das Thema meiner Dissertation geglaubt hat. Er hat es mir auch ermöglicht, die European Conference on Data Analysis (ECDA2019) zu mitorganisieren. Dadurch habe ich erkannt, welche Richtung ich in meinem Berufsleben einschlagen möchte. Einen besseren Mentor und Doktorvater hätte ich mir nicht wünschen können!

Weiterhin möchte ich mich bei Herrn Prof. Dr. C. C. Germelmann für die Übernahme der Rolle des Zweitgutachters bedanken. Ich danke ihm für unsere tollen Gespräche, seine Begeisterung für mein Forschungsgebiet sowie für seine Bachelor- und Master-Veranstaltungen, die mich inspiriert haben, das Marketing-Wissen im Rahmen des MuSe-Schwerpunktes weiter zu vertiefen.

Ebenfalls möchte ich meinen Lehrstuhl-Kollegen ein „Dankeschön“ für die unvergesslichen drei Jahre aussprechen; Theresa Rausch, Benedikt Brand und Cristopher Kopplin – ich bin sehr froh, dass wir so ein gutes Team waren. Ihr wart immer offen für wissenschaftliche sowie private Gespräche und standet mir oft mit guten Ratschlägen zur Seite. Des Weiteren möchte ich an dieser Stelle PD Dr. Alexandra Rese für ihre Unterstützung danken. Ein besonderer Dank auch für Jessica Kiesswetter, die uns einen reibungslosen Ablauf des Lehrstuhlalltags ermöglicht hat und immer eine gute Lösung für alle Angelegenheiten hatte.

Zum Schluss möchte ich meinem Ehemann meine größte Dankbarkeit entgegenbringen. Er steht mir immer beiseite und unterstützt mich in allen Lebensphasen. Bei allen Höhen und Tiefen, in jedem fröhlichen aber auch in jedem traurigen Moment meines Lebens war und ist er immer für mich da und glaubt an mich, auch wenn ich oft selbst an mich nicht glaube.

Zu guter Letzt möchte ich die Gelegenheit nutzen und mich bei meiner Mutter, meinem größten Vorbild, in unserer Muttersprache, Polnisch, zu bedanken: Dziekuje, ze jestes i ze zawsze we mnie wierzylas! To Ty pokazalas mi, ze kazdego dnia trzeba ciezko pracowac na swoj sukces i nigdy nie mozna sie poddawac. Dziekuje za kazda rade, wspolnie spedzony czas, smaczne obiady, telefony 24/7, dowcipy oraz cieplo i bezgraniczna milosc, ktorymi mnie obdarzasz. Zawsze bylas, jestes i bedziesz moja bohaterka i najwiekszym autorytetem. Jestes najlepsza mama i przyjaciolka na swiecie. Kocham Cie!

Abstract

When Alan Turing formulated the Turing test in 1950, he certainly would not have thought that 70 years later, new trends and technology would change the way we experience our everyday life. Digital Voice Assistants are rapidly conquering the market and offer consumers simple, voice-based usability. Companies from various industries, such as the retail or the health sector, have recognized their potential and are already offering services digitally with the support of Digital Voice Assistants. It is only a matter of time that voice assistant will soon, at least to a certain extent, find their way into consumers' everyday lives.

Against this background, the present thesis offers a good basis for better assessing the acceptance of Digital Voice Assistants and dealing more precisely with the influencing factors among the age cohorts - Millennials and older people. Three surveys of Millennials and one of older people were nearly examined under investigation of carefully selected technology acceptance models – the modified TAM and the modified UTAUT2. Those two models have proven to be reliable theories for testing the acceptance of new media.

When analyzing the predictors among Millennials, Pastime is the most important aspect that influences the acceptance of Digital Voice Assistants. Moreover, Enjoyment, Image, Expediency, and Social Influence also positively impact the intention to use the system. Nonetheless, privacy concerns and the fear of being intercepted negatively affect Millennials' acceptance and the use of such new technologies. Within the second investigated group – older people, Performance Expectancy, Facilitating Conditions and Hedonic Motivation have the strongest influence on the acceptance of Digital Voice Assistants. Although, it should be noted that there are noticeable differences between individuals aged 55 to 64 years and those beyond the age of 65 years.

The qualitative analysis shows that Digital Voice Assistants are very helpful while quickly looking for short information, navigating a car, traveling, or using a mobile phone, especially when manual input is impossible. People in both target groups mainly use their Digital Voice Assistants for time-saving and increase their image among friends and family, who strongly influence their decisions and behavior. Many users, especially those older ones, turn to Digital Voice Assistants when they feel lonely and need a conversation with somebody.

Future studies should examine further age cohorts in different countries. A specific subdivision of older people will also be recommended. Another interesting aspect, which will certainly provide meaningful findings, is to examine differences between Behavioral Intention to Use and different education levels.

Table of Contents

List of Tables

List of Abbreviations

CUI – Conversational User Interface

DVA – Digital Voice Assistant

UGA – Uses and Gratifications Approach

UTAUT2 – Unified Theory of Acceptance and Use of Technology 2

1 Introduction

1.1 Theoretical background and motivation

The idea of having a conversation with a computer fascinated people for quite some time. Also, the implementation of a Conversational User Interface (CUI), a conversation interface between the user and the system, has long been the vision of many researchers in speech technology and artificial intelligence. By definition, CUI represents the front end of chatbots or Digital Voice Assistants, which enables the user to interact with an app with the help of speech, text or other input and output (McTear 2017). Joseph Weizenbaum's ELIZA is considered the first chatbot able to create deceptively real human communication for test subjects. This inspired many scientists to develop a CUI that will pass the Turing test (Dale 2016; Luger and Sellen 2016). Digital Voice Assistants (DVA), which have been available to the general public since the late 2010s, also form a part of CUI (McTear et al. 2016; Yang and Lee 2018). With the technological advances, the possibility of controlling devices with the help of voice commands, which was once only a topic in science fiction films, has become a reality (McTear et al. 2016). Mainly large corporations such as Siri (Apple), S Voice (Samsung), Cortana (Windows), Google Now (Google) and Echo (Amazon) have contributed to the rapid growth of DVAs (Coskun-Setirek and Mardikyan 2017). Since the commercialization of DVAs they have made their way into the households of many users. While according to the consulting company Deloitte (2018), the worldwide turnover generated by smart speakers was 4.4 billion US dollars in 2017, such enormous market growth can also be assumed in the future. Experts estimate a turnover of 27.8 billion US dollars in 2022 as realistic (Deloitte 2018; Statista 2019).

A successful introduction and establishment of DVAs largely depends on consumer acceptance (Rese et al. 2017). Acceptance is a multidimensional and complex process that depends, among other things, on psychological, sociodemographic, physical and social factors (Lee and Coughlin 2015; Williams et al. 2015). DVAs are particularly more popular among younger people (Statista 2017d). Market research studies show that the technology-savvy generation, Millennials, particularly see advantages in using DVAs (Vantiv LLC 2018). Many people know the flexibility associated with DVAs and their multiple-usage potential as useful (Yang and Lee 2018). On the other hand, older people (especially the Boomer Generation) still do not exploit the potential of the DVAs (Statista 2017d).

A precise examination of the influencing factors which significantly determine the acceptance has not taken place so far. For this reason, this thesis builds on the research gap. It examines the intention to use the DVAs within the framework of the target groups: Millennials and older people, considering various technology acceptance models and their extensions.

1.2 Acceptance research

Acceptance research was established in the 1960s and dealt with the effects of innovative technologies on the individual and society (Klauser 2006). Due to the increasing spread of information technologies, acceptance research has been increasingly concerned with users' customer acceptance of information technologies since the 1980s (Klauser 2006). The state of research regarding technology acceptance models is already well advanced, and the variety of literature is very wide. There are many different models for predicting technology adoption and usage. These models aim to explain the individual actions of people and thus predict the behavior or use. To explain the development of the technology acceptance models, the important ones are discussed in the table 1. Modifications of two of them (TAM and UTAUT2) are closely examined in this thesis.

Source	Model	Core constructs	Main information
Fishbein and Ajzen (1975)	Theory of Reasoned Action (TRA)	Attitude Toward Behavior Subjective Norm	- Starting point: Desire to understand and predict human behavior. - Clear structuring through a few determinants.
Ajzen (1985)	Theory of Planned Behavior (TPB)	Attitude Toward Behavior Subjective Norm Perceived Behavioral Control	- Supplementing the TRA to include Perceived Behavioral Control, which considers that voluntary control over one's behavior can be restricted.
Davis (1989)	Technology Acceptance Model (TAM)	Perceived Usefulness Perceived Ease of Use	- Development for acceptance research of IT devices in an organizational context.
Thompson et al. (1991)	Model of PC Utilization (MPCU)	Job-fit Complexity Long-term Consequences Affect Towards Use Social Factors Facilitating Conditions	- To predict the individual acceptance and the usage behavior (not usage intention) of many information technologies. - MPCU was originally used for the behavioral prediction of computer usage.
Davis, et al. (1992)	Motivational Model (MM)	Extrinsic Motivation Intrinsic Motivation	- Extrinsic and intrinsic motivation are key factors in determining whether a technology is intended to be used.
Compeau and Higgins (1995a; 1995b)	Social Cognitive Theory (SCT)	Outcome Expectations (Performance and Personal) Self-efficacy Affect Anxiety	- Originally, it was used to study computer usage. - The model and the underlying theory extend the acceptance and usage analysis of IT equipment in general.
Rogers (1995)	Innovation Diffusion Theory (IDT)	Relative Advantage Ease of Use Image Visibility Compatibility Results Demonstrability Voluntariness of Use	- The aim is to study the distribution and use of innovation in a population.
Taylor and Todd (1995)	Combined TAM-TPB (C-TAM-TPB)	Attitude Toward Behavior Subjective Norm Perceived Behavioral Control Perceived Usefulness	- Adding Perceived Usefulness to the TPB. - The combination of the TAM and the TPB offers an adequate model for IT users.
Venkatesh and Davis (2000)	TAM 2	Perceived Usefulness Perceived Ease of Use Subjective Norm Image Job Relevance Output Quality Result Demonstrability Moderator variables: Experience, Voluntariness	- Further development of the TAM to include social process variables and cognitive instrumental variables, which significantly influence user acceptance.
Venkatesh et al. (2003)	UTAUT	Performance Expectancy Effort Expectancy Social Influence Facilitating Conditions Moderator variables: Gender, Age, Experience and Voluntariness of Use	- It helps to understand the acceptance drivers and to be able to take proactive measures. - Due to its construction, the UTAUT can explain up to 70% of the variance of the intended use.
Venkatesh et al. (2012)	UTAUT2	Performance Expectancy Effort Expectancy Social Influence Facilitating Conditions Hedonic Motivation Price Value Habit Moderator variables: Age, Gender, Experience	- UTAUT2 is the most advanced theory → it can explain 74% of the variance of the intended use and 52% of the variance of the usage behavior (significant improvement compared to the previous models). - The model is tailored to research user acceptance and use of technology from the consumer's point of view.

Table 1: Selection of the models and theories of technology acceptance research from the last 50 years

1.3 Generational gap in the acceptance of Digital Voice Assistants

1.3.1 General information

Well-known representatives of smart home devices are Digital Voice Assistants in the form of autonomous loudspeakers, which receive questions or commands via voice input and can, for example, predict the current weather or control smart sockets to switch the lighting. With Google (Alphabet), Apple, Microsoft, and Amazon, well-known IT companies are trying to secure market shares with their specially marketed Digital Voice Assistants. Intelligent personal assistants are software applications based on artificial intelligence, receive voice inputs, and answer them via loudspeakers. The end devices on which the digital helpers are used are diverse. Starting with PCs (e.g., Cortana) via smartphones (e.g., Siri and Alexa) to autonomous devices (e.g., smart speakers or smartwatches), more and more internet-capable end devices are interacting with the software. Since the market launch in Germany in early 2017, Amazon's smart speakers, the Echo series, have secured a market share of 64% alongside Google Home devices with 29% (Pakalski 2018). According to Statista, only 4% do not know Alexa. However, the user numbers are rather low at 18% (Statista 2017d). It is mainly younger age groups who use the Digital Voice Assistants (BVDW e.V. 2017). While there is already a very high level of awareness and a high usage rate among younger age groups, e.g. Millennials, Digital Voice Assistants have so far only been used by a small number of older people (Sovie et al. 2017; Vantiv LLC 2018). Due to the demographic change, however, there is enormous potential for use and sales, especially for older people. The question inevitably arises whether such new technologies are accepted by older generations, who did not grow up with the achievements of digitization, and which factors lead to acceptance. From a scientific perspective, the acceptance of digital language assistants has so far not been adequately researched (Coskun-Setirek and Mardikyan 2017). Although there are some publications on the topic and its acceptance, the age range of these studies is in the lower third of the average life expectancy (Coskun-Setirek and Mardikyan 2017). For this reason, this thesis focuses on the two largest generation groups - millennials and older people. Finally, the findings of all the studies presented are summarized to see the reasons for use or non-use.

1.3.2 Millennials

One of the two target groups examined in more detail in this thesis are people assigned to the group of Millennials, also known as Generation Y (Govindarajo and Kumar 2013). Even if there is a lack of clarity about a uniform definition of the term Millennials, people born between the 1980s and 2000s are often classified in this generation cohort. Members of such a

group are often similar because they have had the same cultural experiences in their lifetime. Accordingly, they have similar values, beliefs, preferences, motivations and behaviors (Young and Hinesly 2012). In contrast to other generations, the Millennials present themselves as particularly technophile, are very enthusiastic about technological progress and therefore have higher rates of adaptation of Internet technologies than previous generations. Mobile technology and network connectivity describe this generation best and represent a particularly characteristic property (Eastman et al. 2014). Above all, digital media and social media development make it possible for Generation Y to contact online communities in previously unthinkable ways with friends and acquaintances or even strangers who show the same interests (Viswanathan and Jain 2013). As a result, Generation Y has a more professional approach to technological innovations than previous generations (Deal et al. 2010). Rather, the major innovations in software and hardware in recent years have resulted in a completely different understanding of connectivity and communication in everyday life for Generation Y (Deal et al. 2010). Since the Millennials grew up with technology, they are also called “Digital Natives” (Eastman et al. 2014; Lissitsa and Kol 2016; Young and Hinesly 2012). Generation Y is currently the second-largest generation cohort after the Baby Boomers. Due to their size and high purchasing power, they represent an attractive target group for many companies (Lissitsa and Kol 2016; Taken Smith 2012). Nevertheless, only a few studies in the literature specifically cite Millennials as an object of investigation.

1.3.3 Older people

Demographic change has the world firmly under control. Older people are already shaping the image of society around the world. According to the United Nations, almost 962 million people over the age of 60 lived on earth in 2017, which corresponds to around 13% of the total population (United Nations 2017). It is estimated that this number will increase to a quarter for almost all regions of the world by 2050. For the European Union and Germany, however, this relationship already applies today (Federal Ministry for Family Affairs, Senior Citizens, Women and Youth 2016). In an EU-wide comparison, Germany is the country with the highest proportion of over 65-year-olds after Italy. However, seniors alone do not make up the lion's share of society. The actual population pyramid shows that the population increases significantly from around 50 years of age (Destatis 2019a). The reason for this is the so-called Baby Boomer generation. Applied to Germany, this cohort denotes the Baby Boomers who died after World War II. A uniform definition of the period cannot be found in the literature. The reason for this lies in the various socio-economic factors that lead to this phenomenon. In the USA, for example, those born after 1945 are included in this cohort,

while in Germany, the start year is defined as 1955 (Knickmann and Snell 2002; Destatis 2019b).

However, a significant increase in the number of newborns from 1945 can also be identified for the most European countries from the birth statistics (Federal Ministry for Family Affairs, Senior Citizens, Women and Youth 2016). As a result, the generation over 50 is most frequently represented within the population and represents an interesting research cohort. But how does this age group deal with the achievements of digitization? In contrast to Generation Y, Millennials, or Generation Z, people aged 50 and over did not grow up with digitization. Telephone and television were the technological achievements of the Boomer Generation. The Internet did not develop into a mass medium until the early 1990s and is considered the pioneer of digitization. This has continuously grown over the past few years and decades. Apart from Industry 4.0, which describes the usage of digital technologies, such as the 5G-supported transmission of data, an evolution in technology is also taking place in the private sector. Mobile phone became the smartphone, and the laptop increasingly replaces the desktop PC (Haas 2018). Fast broadband connections and ever smaller and more powerful electronic components also lead to ever more compact devices that are in constant communication through the Internet. The prerequisites for the smart home, the networked house, were born (Bendel 2019).

1.4 Research questions and thesis organization

New technologies and innovations increasingly shape today's world. Digital Voice Assistants represent one of the most important changes in the interaction with technologies. However, there has not been sufficient scientific research into how high the current level of acceptance of Digital Voice Assistants in private use is and what factors influence this acceptance. Research into usage and user acceptance represents a central field of investigation in the IT context and is also the main research subject of this thesis, which aims to answer the following overarching research questions:

RQ1: *Which factors influence the acceptance of Digital Voice Assistants by Millennials vs. by older people?*

RQ2: *Which technology acceptance model is best suited to investigate the technology acceptance of Digital Voice Assistants?*

Table 2 and table 3 sum up the most relevant findings to both research questions and give a structured comparison of the answers to the research questions for all research papers mentioned in this thesis.

	Research paper/ Chapter	Author(s)	Target group/ Sample	Applied methodologies and fit measures	Relevant findings
Research Paper #1 [Chapter 2]	UGA or TAM: Which Approach Explains Digital Voice Assistant Acceptance Better?	Ewers, K., Baier, D.	Millennials n= 173	TAM and UGA	- Pastime has a positive influence on Actual System Use. - Image, Expediency and Enjoyment have a positive influence on Behavioral Intention to Use DVAs.
Research Paper #2 [Chapter 3]	Acceptance of Digital Voice Assistants in Customer Communication: An Application of the Technology Acceptance Model and the Uses and Gratifications Approach	Ewers, K.	Millennials n= 173	Modified TAM (integration of TAM an UGA)	- Pastime is the most important aspect that influence the users' acceptance of DVAs.
Research Paper #3 [Chapter 4]	Siri, Do I like You? Digital Voice Assistants and Their Acceptance by Consumers	Ewers, K., Baier, D., Höhn, N.	Millennials n= 283	Modified TAM	- Enjoyment, Social Status and Social Influence have a positive impact on the acceptance of DVAs. - Privacy concerns and the fear of being intercepted negatively influence the acceptance and the use of DVAs by Millennials.
Research Paper #4 [Chapter 5]	How about older people and Digital Voice Assistants? – An empirical investigation of Amazon's Alexa based on UTAUT2	Ewers, K.	Older people n= 223	Modified UTAUT	- Performance Expectancy, Social Influence, Facilitating Conditions and Hedonic Motivation play an essential role in the acceptance of DVAs by older people. - Noticeable differences between people aged 55 to 64 years and people over the age of 65 years: older people cannot be seen as a largely homogenous group.

***Notes: TAM**- Technology Acceptance Model, **UGA**- Uses and Gratifications Approach, **UTAUT2**- Unified Theory of Acceptance and Use of Technology 2), **DVA**- Digital Voice Assistant*

Table 2: Applied methodologies and relevant findings of the four research papers to answer the research question 1 (RQ1): Which factors influence the acceptance of Digital Voice Assistants by Millennials vs. by older people?

Summing up the outcome of table 2, it can be said that Pastime, Enjoyment and Social status/Image have the strongest influence on Millennials' acceptance of using DVAs. In the

group of older people, Performance Expectancy, Social Influence, Facilitating Conditions, and Hedonic Motivation are the most relevant factors influencing the acceptance of DVAs.

	Research paper/ Chapter	Author(s)	Target group/ Sample	Applied methodologies and fit measures	Relevant findings
Research Paper #1 [Chapter 2]	UGA or TAM: Which Approach Explains Digital Voice Assistant Acceptance Better?	Ewers, K., Baier, D.	Millennials n= 173	Technology Acceptance Model and Uses and Gratifications Approach UGA: BIU: R^2= 0.561, ASU: R^2= 0.812. TAM: ATU: R^2= 0.656, BIU: R^2= 0.680, ASU: R^2= 0.640.	- The integration of the two methods (UGA and TAM) to measure customers' acceptance leads to meaningful results and is recommended for further studies.
Research Paper #2 [Chapter 3]	Acceptance of Digital Voice Assistants in Customer Communication: An Application of the Technology Acceptance Model and the Uses and Gratifications Approach	Ewers, K.	Millennials n= 173	Modified TAM (integration of TAM and UGA) Research model: ATU: R^2= 0.481, BIU: R^2= 0.569, ASU: R^2= 0.476.	- The Items of the original TAM show a positive influence on all its constructs. - TAM is a useful theoretical approach to understand and explain the behavioral intention of consumers to use DVAs. - The model should be extended by Pastime. - Other constructs/gratifications should be found based on the current literature.
Research Paper #3 [Chapter 4]	Siri, Do I like You? Digital Voice Assistants and Their Acceptance by Consumers	Ewers, K., Baier, D., Höhn, N.	Millennials n= 283	Modified TAM Research model: PU: R^2= 0.681, BIU: R^2= 0.686, ASU: R^2= 0.805.	The research model shows a moderate predictive power. - It can also be considered as relevant for the prediction of the Millennials' acceptance for using DVAs. - Suitable gratifications have been found. - The level of information content and the adjustment effort is high.
Research Paper #4 [Chapter 5]	How about older people and Digital Voice Assistants? – An empirical investigation of Amazon's Alexa based on UTAUT2	Ewers, K.	Older people n= 223	Modified UTAUT Research model: BIU: R^2= 0.507.	- The research model has a high level of prognostic relevance for the endogenous construct of intended use.

***Notes: TAM**- Technology Acceptance Model, **UGA**- Uses and Gratifications Approach, **UTAUT2**- Unified Theory of Acceptance and Use of Technology 2), **DVA**- Digital Voice Assistant*

Table 3: Applied methodologies and relevant findings of the four research papers to answer the research question 2 (RQ2): Which technology acceptance model is best suited to investigate the technology acceptance of Digital Voice Assistants?

The examined models, modified TAM and modified UTAUT2, have a moderate or high predictive power and are recommended for further research. A special focus is on UTAUT2, which is tailored for the technology acceptance research from the consumers' point of view. Henceforth, UTAUT2 (best possible expanded by other constructs tailored for the used medium) will be recommended for future research in the field of Conversational User Interface.

Table 4 summarizes all research papers, which are included in the following chapters 2-5 and their publication status. Chapter 6 provides the conclusion of this thesis. Table 4 presents the publication status of all research papers.

	Title	Author(s)	Research question	Metho-dology, sample size	Findings	Medium	Publication status
Research Paper #1 [Chapter 2]	UGA or TAM: Which Approach Explains Digital Voice Assistant Acceptance Better?	Ewers, K., Baier, D.	UGA or TAM: Which Approach Explains Digital Voice Assistant Acceptance Better?	Survey, n=173	- DVAs are an interesting and useful innovation. - DVAs are helpful, while quickly looking for some information, navigating a car, or traveling, especially when a manual input is not possible. - Customers mainly use their DVAs for time-saving and to increase their image among friends and family. - Many users also turn to DVAs, when they want to talk to somebody. - On the other hand, people have some concerns about the usage of DVAs in public. - The integration of the two methods (UGA and TAM) to measure customers' acceptance leads to meaningful results and is recommended for further studies.	Archives of Data Science Series A	Published
Research Paper #2 [Chapter 3]	Acceptance of Digital Voice Assistants in Customer Communication: An Application of the Technology Acceptance Model and the Uses and Gratifications Approach	Ewers, K.	Which factors influence the users' acceptance of digital voice assistants?	Survey, n=173	- Millennials use a DVA when they primarily want to have a good time and also to save some time. - Many of the DVAs' users turn to DVAs when looking for a conversation with somebody. - Users of DVAs mainly use them to obtain brief information, navigate, or travel. - DVAs are mainly used on the go or when a manual operation of the smartphone is not possible. - In the future, people will use digital voice assistants, especially to obtain brief information or while driving a car. - Siri is preferred for iOS smartphones and the Google Assistant for Android phones depending on the smartphone software.	Journal of Retailing and Consumer Service	Submitted
Research Paper #3 [Chapter 4]	Siri, Do I like You? Digital Voice Assistants and Their Acceptance by Consumers	Ewers, K., Baier, D., Höhn, N.	Which factors positively or negatively influence the acceptance of DVAs?	Survey, n=283	- Enjoyment, Social Status and Social Influence have a positive impact on the acceptance of DVAs. - Consumers, who enjoy talking through their mobile devices, are indeed more likely to use DVAs. - When some colleagues, friends or students use a DVA, it will be very likely, that their friends will also do so. People use DVAs in some life situations, e.g., navigating a car, receiving quick answers, and setting the timer. - DVAs are rather used at home than in public. - Among Digital Natives, privacy concerns are indeed an issue, but not to the extent as they would adversely affect the acceptance of the usage of Siri. - Fear of being intercepted and unexplained legal situation of DVAs are further reasons for not using such devices. - Consumers are concerned about companies who can easily get too much personal information about the consumers and eventually misuse them.	Journal of Service Management Research	Published
Research Paper #4 [Chapter 5]	How about older people and Digital Voice Assistants? – An empirical investigation of Amazon's Alexa based on UTAUT2	Ewers, K.	Which factors play an essential role in accepting DVAs by older people?	Survey, n=223	- Performance Expectancy, Social Influence, Facilitating Conditions and Hedonic Motivation play an essential role in the acceptance of DVAs by older people. - Especially older women are strongly influenced by the opinion and behavior of family and friends in the decision-making process. - Family members or related persons play in the decision-making process an important role. - Primary conditions must be created for older people, so they can decide, whether to use DVAs (e.g., customer support). - Noticeable differences between people aged 55 to 64 years and people aged 65 years and older → older people cannot be seen as a largely homogenous group.	Journal of Service Management Research	Submitted

Table 4: Publication status, (paper-specific) research question, and (paper-specific) findings of the four research papers

2 Research paper #1: UGA or TAM: Which Approach Explains Digital Voice Assistant Acceptance Better?

Authors: Ewers, K., Baier, D.

Published in: Archives of Data Science Series A, Vol. 6 (2020), Issue 2

Abstract: Digital Voice Assistants (DVAs) have the potential to radically change the communication between companies and their customers in the near future. However, despite enormous cost and convenience reduction advantages for both sides, their acceptance is still limited and even tools for measuring their acceptance are missing. Consequently, in this paper, we investigate whether the Uses and Gratifications Approach (UGA) and/or the Technology Acceptance Model (TAM) is better suited for this purpose. We have a closer look on a popular DVA – Google Assistant – and investigate DVA acceptance in a navigation and sightseeing context using a field experiment and a follow-up questionnaire (n=173). The results are promising: Both approaches (UGA and TAM) are valid tools. Pastime, expediency, and enjoyment demonstrate to be important drivers for using DVAs.

2.1 Introduction

Year by year, more digital data is generated worldwide. It is predicted that the yearly amount of digital data generated will increase to 163 zettabytes in 2025 (Statista, 2017a). The omnipresence of smartphones that support users in various contexts (e.g., mobile search for information and orientation, shopping, navigation, taking and sharing photos, videos, comments) is an important trig- ger for this development but – at the same time – also promises easy access to this interesting but more and more confusing knowledge source. So, e.g., Digital Voice Assistants (DVAs) like e.g. Google Assistant or Siri and augmented reality (AR) apps like e.g. Google Maps AR (Rese et al, 2014) are wide-spread sample offers (see, e.g., Statista, 2017b).

However, at the same time, users are becoming more and more demanding (Macronomy, 2018). In order to make apps acceptable, providers must under- stand, whether and why their customers accept or reject them. Since this topic has not yet been sufficiently researched, this paper examines how DVA acceptance can be measured and whether the Uses and Gratifications Approach (UGA) or the Technology Acceptance Model (TAM) provides more clarity.

The paper is organized as follows: After this short introduction (section 1), we discuss UGA and TAM (section 2). Then, we apply these two approaches to measure DVA acceptance using Google Assistant as a sample DVA and com- pare the results (section 3). The paper ends with conclusions and an outlook (section 4).

2.2 UGA and TAM: Two alternatives for acceptance measurement

UGA was originally developed and applied in the field of media exploitation research (see, e.g., Katz, 1959; DeFleur, 2016). UGA examines fundamentally the interaction between the consumer and the media he/she uses (DeFleur, 2016). However, the focus lies on the consumer, who freely acts by integrating the media into her/his daily life (Rauschnabel, 2018). UGA assumes that viewers are not only passive consumers of media but rather responsible for choosing media that suit their needs and satisfy them (Katz, 1974). This approach suggests that the media must compete with other sources to meet the needs of the viewer, which is why the media should not have too much power over its consumers. UGA examines exact consumers' reasons for an active search for specific media (Rauschnabel, 2018). UGA explains, which media the user subconsciously prefers and what are the reasons for doing so. This approach assumes that intelligence, as well as self-esteem of the individual, basically affect her/his choice of media (Knobloch, 2003).

Contrary to previous criticisms (see, e.g., Knobloch, 2003), UGA can be used in the context of modern communication technologies. In the field of the Internet-based media, UGA already found its application. In this context, re- searchers often explored benefits that consumers of social media (such as Facebook, Twitter, Instagram) can derive from using them (Stafford et al, 2004). UGA was also used as a basis for further investigations, e.g. using this approach, motives for using online or mobile games and the use of augmented reality applications were further explored (see, e.g., Lin and Chen, 2017). All of these studies point to the versatility of UGA and imply that the approach is also applicable and, therefore, can be extremely helpful in supposedly ”young” application fields, such as the Internet and video games (Li et al, 2015). Table 1 shows some recent studies based on UGA from main digital fields.

Technology (sample size)	Found gratifications	Reference
Mobile phones (n=834)	Approp., social connectedness, calming	Leung and Wei (2000)
Internet (n=498)	Inf. search, distraction, personal status	Song et al (2004)
Social networks (n=167)	Social benefit, inf. exchange, entertainment	Ancu and Cosma (2009)
Instant messaging (n=150)	Pastime, inf. search, contact maintenance	Ku et al (2013)
Online/mob. games (n=237)	Individual (enyojment, int. with others)	Wei and Lu (2014)
Social networks (n=3,172)	Entertainment, inf. exchange, self-portrayal	Alhabash et al (2014)
Online/mob. games (n=3,919)	Hedonic (enjoyment, fantasy), social (social int., social presence), utilitarian (success)	Li et al (2015)
Social networks (n=368)	Interest, inf. exchange, social influence	Malik et al (2016)
Chatbots (n=146)	Productivity, pastime, social advantages	Brandtzaeg and Følstad (2017)
Online/mob. games (n=642)	Hedonic (enjoyment, physical activity), social (image), emotional (nostalgia)	Rauschnabel et al (2017)
Instant messaging (n=297)	Hedonic (enjoyment), utilitarian (exchange inf.), technological (appeal of medium)	Gan and Li (2018)

approp.=appropriateness, inf.=information, int.=interaction, mob.=mobile

Table 1 Applications of the uses and gratifications approach (UGA)

The best known model used in the area of technology acceptance is TAM developed in 1985 by Fred D. Davis (Davis, 1985; Davis et al, 1989). TAM is a theoretical approach, which tries

to explain and predict whether a new technology will be adopted or rejected (Rauschnabel and Ro, 2016; Easwara Moorthy and Vu, 2015). TAM was firstly used within computer-based information systems (Davis, 1985). The flexibility of the model has already been shown in many other research fields, so that it will currently be used in e.g. various industries to research the acceptance of new technologies (see, e.g., Rese et al, 2014). Moreover, this model has already been used in several studies about DVAs (Easwara Moorthy and Vu, 2015) (see also Table 2). Basic attitude of the user, the so called "Attitude Toward Using" construct decides whether the new technology will in fact be used by its user in the near future. According to Davis (1985), "Attitude Toward Using" depends on two other constructs: "Perceived Usefulness" and "Perceived Ease of Use". The first one is defined as a subjective feeling of an individual, that using a new technology will increase her/his productivity (Chu and Chu, 2011). The second, on the other hand, indicates to what extent the interviewee supposes that learning to use new technologies without physical exertion is possible (Davis, 1985). Both constructs have to be individually considered depending on consumer's perspective. Moreover, they have a direct impact on "Attitude Toward Using" in relation to the construct "Actual System Use" and "Perceived Ease of Use" is assumed to have a direct impact on "Perceived Usefulness" (Chu and Chu, 2011). "Perceived Usefulness" and "Perceived Ease of Use" can also be influenced by external factors, e.g. demographic variables or some personality traits (Davis et al, 1989). Moreover, both – "Perceived Usefulness" and "Attitude Toward Using", are related to "Behavioral Intention to Use", which finally influences "Actual System Use".

Technology (sample size)	**Found effects**	**Reference**
E-commerce (n=310)	Perceived usefulness, compatibility, costs, perceived risk influence behavioral intention to use	Wu and Wang (2005)
Customer support chat (–)	Perceived usefulness and ease of use influence acceptance	Elmorshidy (2013)
Customer support chat (n=327)	Perceived usefulness, ease of use and attitude towards using influence the behavioral intention to use	Elmorshidy et al. (2015)
Customer support chat (n=302)	Perceived usefulness, ease of use, wait time, response capacity influence the behavioral intention to use	McLean and Osei-Frimpong (2017)
Smart home (n=304)	Security technologies are perceived as "useful" whereas the convenience apps are perceived as "pleasant"	Chen et al. (2018)

Table 2 Application of the technology acceptance model (TAM)

2.3 Application to DVA acceptance measurement

Voice input makes it possible to use (mobile) devices without any manual act. And so, searching for some information, sending a message or making a call are now possible without even touching a (mobile) device. This feature is getting more popular, and it is essential in smartphones, smartwatches, laptops and others (Bitkom, 2017). That is the reason, why large international companies already developed their own DVAs. Siri (from Apple), Cortana (from Microsoft) or Google Assistant (from Google) can make everyday life easier, as they start the navigation on call, set an alarm clock, set a timer, play music from a playlist and much more. In this study Google Assistant will be used as an example of a DVA. It receives and processes spoken language and constantly learns from already posed and answered questions. As a result, it gets to know the user better, and so, in most cases, it can answer her/his questions very precisely. The device not only handles simple questions, but also more complex voice commands and it can e.g. understand semantic connections. Once Google Assistant has met the user, it will regularly display user-specific information. All this happens without an explicit request from the user (Digital Trends, 2018).

Despite many benefits of DVAs, concerns have been noted regarding the ethical and social issues caused by the AI technology (Statista, 2017a). For example, some users do not notice that they are talking to a digital robot, which some critics consider unethical or even deceitful (see, e.g., van der Heijden, 2004). Privacy concerns have also been noted as conversations with some DVAs were recorded so that the virtual assistant could analyze it and respond (Easwara Moorthy and Vu, 2015). Fortunately, users with privacy concerns can automatically turn off the voice control (Gao et al, 2010). As a result of these concerns, a mobile phone no longer constantly listens, but also prevents the use of voice control. Proponents of data protection also expressed concern that millions of language samples collected by consumers are being fed into virtual assistant algorithms (Easwara Moorthy and Vu, 2015). Although these features personalize user experience, critics are uncertain about the long-term implications of giving companies unlimited access to human patterns and preferences that are critical to the next phase of AI. This could lead to the situation, where AI tricks its creators (Chen et al, 2018).

Figures 1 and 2 describe the assumed factors and dependencies (hypotheses) in each model based on studies from the last section (see, e.g., Davis et al.,1989; Hu et al., 1999; Venkatesh and Davis, 2000). There, the relevant, recent studies were summarized in an overview. From the totality of the various fac- tors that appear in the literature, five were ultimately chosen for this study based on teleological ethics (Thomas, 2015). Here, hedonistic (pastime, enjoyment) and utilitarian gratifications (image, expediency) as well as barriers (fear of data misuse) were nearly considered. Within these groups, all users' motives were queried

extensively regarding the use of Google Assistant. For TAM, the unchanged assumption of classical constructs seemed applicable.

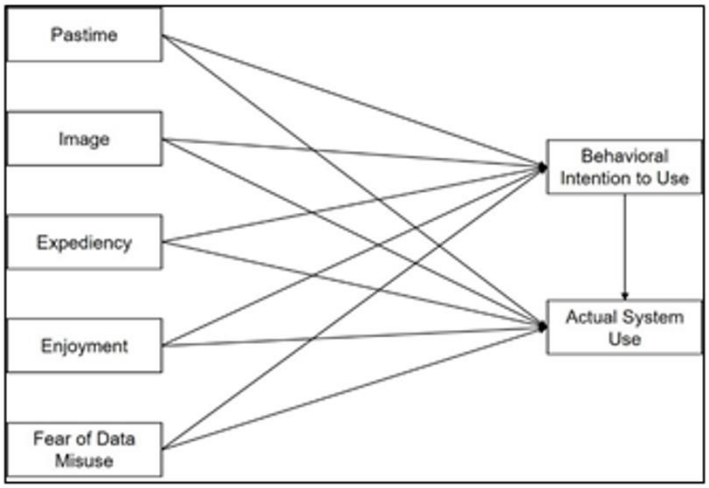


Fig. 1 UGA structural model for DVA acceptance measurement

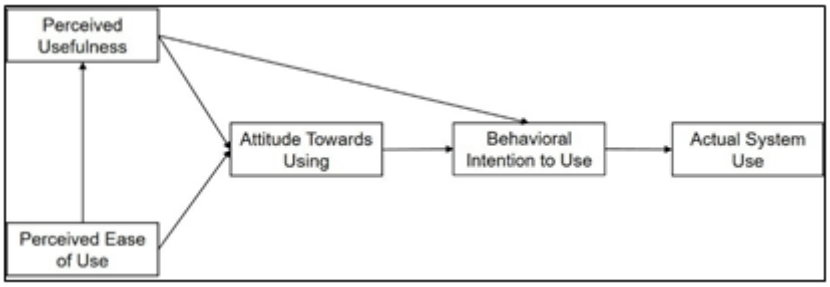


Fig. 2 TAM structural model for DVA acceptance measurement

The study design is based both on a field experiment and on a quantitative research method. The field experiment, called ”On the traces of Richard Wagner”, is intended to explore the city – Bayreuth, Germany – in an interesting way using the DVA Google Assistant. Participants are given several small tasks and are expected to solve them by only using voice input (e.g. navigating to Villa Wahnfried – the house of Richard Wagner – or finding out some important information about Richard Wagner, his family and his operas). The questionnaire used for this study mainly consists of closed questions with the exception of two open ones (”In which situation in everyday life is the use of Google Assistant helpful?”, ”In which situation will you use Google Assistant in the future?”). This allows respondents to easily comment on their observations and ideas on the topic. With the help of the electronic questionnaire provider Qualtrics, the questionnaire was drafted and checked by five test persons for possible errors, the duration of the survey, possible problems with comprehension and the correctness of the structure. Afterwards, the questionnaire was refined. Finally, it was com-

pletely designed on June 25, 2018. The survey period was between June 26 and August 4, 2018 and it was only available in German. For the measurement of UGA and TAM constructs, 5- point Likert scales were used for the items ranging from ”1=totally disagree” to ”5=totally agree”. Respondents also had the opportunity to take a neutral position. Open questions were also included to get a deeper insight into drivers of acceptance.

Finally, some socio-demographic questions, such as age and gender of the respondents, were asked. These are evaluated as a part of the descriptive statistics. The survey reached a total of 173 people. 173 respondents filled out the questionnaire, which corresponds to a completion rate of 88.7%. These evaluated data are the basis of the further empirical investigation. 50.3% of the respondents are female and 48% are male. Another three people gave no information about their gender. The target group of the study are millennials (21 to 35 years old) from a middle-sized German city (population: about 75,000 inhabitants), who will start the working life soon. Even though companies try to appeal to all age groups with their products and ser- vices, people aged 21-35 are the most interesting ones to the digital information market. They are open to new technologies and have sufficient incomes to afford them. Out of 173 participants, 126 (72.8%) were between 21 and 25 years old and 45 (26.0%) between the age of 26 and 30. Two persons (1.2%) represented the age group older than 31 but not older than 35 years. In order to be able to analyze and evaluate the data collected in the online survey, it is essential to check in advance the indicators of model quality (for UGA and TAM). This is followed by the evaluation of structural equation models and the examination of previously formulated hypotheses. Focusing of the causal- predictive nature of the analysis, PLS-SEM was chosen for a validation of the data (Rigdon et al, 2017; Hair et al, 2019). All calculations were performed using IBM SPSS Statistics 25.0 and SmartPLS 3.

First, the quality criteria of the measurement model were verified. The focus is on ensuring reliability and validity. Reliability as such is an important indicator for a formally accurate or reliable measurement (Olbrich et al, 2012). Validity indicates whether a measurement is valid: Whether there is a compatibility between the measuring instrument and the examined case (Rigdon et al, 2017). In order to be able to ensure these basic requirements, a number of quality criteria are analyzed in the course of this work (see Tables 3 and 4). While analyzing the outcomes, it was necessary to constantly check the data and adjust and control the thresholds thereafter. In addition, the insufficient items were taken out of consideration. For the evaluation of all quality criteria, threshold values were used that were already proved in the current literature and are valid. Furthermore, the average variance extracted and Cronbach’s alpha are used to accordingly validate the construct reliability. All values correspond to the prerequisites for the quality criteria can be found in Table 4. Thus, the data used are reliable and can easily be used in further data analysis. The average means show that the attitude of the recipients to the topic Google Assistant is relatively inconclusive (in some

cases even skeptical) and in principle does not outweigh any extreme opinions. The mean values across relevant items of a construct and respondents range from 1.35 (near ”1=totally disagree”) to 4.31 (near ”5=totally agree”). In the next step, the quality criteria of the second generation were analyzed. Here all calculated quantities are sufficient. Outter Loadings of the two models also show no abnormalities and can therefore be considered as sufficient.

Construct(No. of items)	R2	R^2 adj.	CA	CR	AVE	Val. (Std.)	References
Pastime (3)	—	—	.717	.724	.469	2.55 (1.042)	Gan and Li (2018)
Image (4)	—	—	.871	.864	.617	1.50 (0.859)	Rauschnabel et al (2017)
Expediency (2)	—	—	.759	.768	.626	3.03 (1.083)	Leung and Wei (2000)
Enjoyment (4)	—	—	.825	.818	.539	3.61 (1.007)	Rauschnabel et al (2017)
Fear of Data Misuse (3)	—	—	.960	.964	.902	3.66 (1.193)	Rauschnabel et al (2017)
Behavioral Intention (3)	.561	.548	.861	.868	.691	2.72 (1.115)	Moon, Kim (2001), Venkatesh et al (2012)
Actual System Usage (3)	.812	.805	.725	.725	.468	1.35 (0.781)	Venkatesh and Davis (2000)

Notes: adj.=adjusted, CA=Cronbach’s α, CR=composite realibility, AVE=average variance explained; val.=mean construct values; std.=standard deviation

Table 3 UGA results: Quality of measurement scales and construct values (1=totally disagree,. . . ,5=totally agree)

The existence of the reliability is the precondition for the validity. Therefore, validity can now be checked by looking at the means of the discriminant validity and the collinearity. For that Fornell-Larcker Criterion (Fornell and Larcker, 1981) and Heterotrait-Monotrait Ratio (HTMT) (Hair et al, 2017) will be nearly investigated. Fornell-Larcker Criterion examines the constructs for their separability (Fornell and Larcker, 1981). In this study, all square roots of Average Variance Extracted (AVE) of each constructs are higher than the largest correlation with any of the other constructs. By closely looking at HTMT (see Tables 5 and 6), a treshold of 0.85 (Henseler et al, 2015) is fulfilled by all constructs. In the context of the effect size (f^2), exogenous variables have a significant effect on the respective constructs of the model (Hair et al. 2017).

Tables 5 and 6 show whether the influence is low, medium or high. Furthermore, the model is examined for multicollinearity using Variance Inflation Factor (VIF) (Hair et al., 2017). Here,

all examined VIF-values are below the threshold of 5 and so they meet the acceptance range.

Construct (No. of items)	R2	R^2 adj.	CA	CR	AVE	Val. (Std.)	References
Perceived Usefulness (3)	.172	.167	.807	.807	.515	3.39 (0.919)	Venkatesh and Davis (2000)
Perceived Ease of Use (4)	—	—	.694	.691	.428	4.31 (0.891)	Venkatesh and Davis (2000), Gefen et al. (2003)
Attitude Toward Using (3)	.656	.652	.862	.864	.619	2.62 (1.027)	Venkatesh and Davis (2000), Porter and Donthu (2006)
Behavioral Intention (3)	.680	.677	.861	.869	.692	2.72 (1.115)	Moon, Kim (2001), Venkatesh et al. (2012)
Actual System Use (1)	.640	.638	.725	.721	.463	1.35 (0.781)	Venkatesh and Davis (2000)

Notes: adj.=adjusted, CA=Cronbach's *α*, CR=composite reliability, AVE=average variance explained; val.=mean construct values; std.=standard deviation

Table 4 TAM results: Quality of measurement scales and construct values (1=totally disagree,. . . ,5=totally agree)

In order to be able to interpret the structural equation model accordingly, an examination of R^2, R^2Adjusted and f^2 is indispensable (Chin and Marcoulides, 1998). All these values can be seen in Tables 5 and 6. Furthermore, Stone-Geisser Criterion (Q^2) will also be closely looked at. The criterion can be used to check the prognostic relevance for latent endogenous variables (Stone, 1974). Thus, only values greater than zero are prognostically relevant. Here, Q^2 for all examined variables, was higher than 0.057, and it met the acceptance range.

	BIU	ASU
Pastime (PA)	0.009	.854
Image (IM)	.023	.109
Expediency (EX)	.048	.334
Enjoyment (EN)	.065	.024
Fear of Data Misuse (FDM)	.005	.000
Behavior Intention to Use (BIU)	.902	
Actual System Use (ASU)		

	PA	IM	EX	EN	FDM	BIU
PA						
IM	.774					
EX	.843	.540				
EN	.726	.640	.641			
FDM	.228	.288	.134	.341		
BIU	.708	.593	.675	.641	.158	
ASU	.789	.580	.568	.545	.148	.797

Table 5 UGA: Effect size and discriminant validity assessment using f^2 (left) HTMT (right)

	PU	ATU	BIU	ASU
Perceived Ease of Use (PEOU)	.207	.019		
Perceived Usefulness (PU)		1.424	.048	
Attitude Toward Using (ATU)			.460	
Behavioral Intention to Use (BIU)				1.781
Actual System Use (ASU)				

	PEOU	PU	ATU	BIU
PEOU				
PU	.412			
ATU	.408	.797		
BIU	.366	.728	.819	
ASU	.321	.735	.753	.797

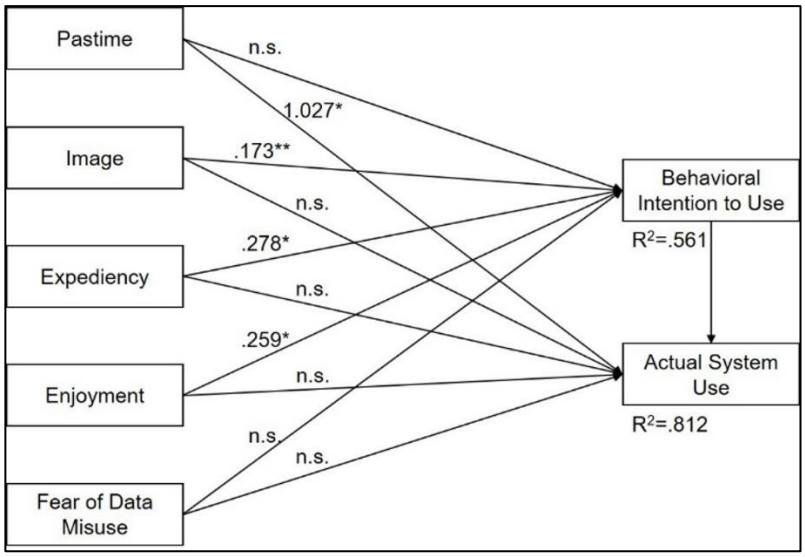
Table 6 TAM: Effect size and discriminant validity assessment using f^2 (left) HTMT (right)

Even though the models were compared contrasting them on the grounds of explanatory power, it should be mentioned, that they differ in their complexity, so that the explanatory power cannot be the only comparing criterion. In such cases is the Bayesian Information Criterion for model selection (BIC) particularly a better choice for PLS-SEM-based model selection tasks – from an explanatory as well as a predictive perspective (Sharma et al, 2019). In terms of predicting “Actual System Use“ and “Behavioral Intention to Use“ with UGA it is -76.275 and with TAM is -82.918. According to Sharma et al (2019) the model with the lowest BIC is preferred, so in this case, TAM has more informative power than UGA. Furthermore, in order to assess a model’s out- of-sample predictive power, PLSpredict was used for both models (Shmueli et al, 2019). Comparing UGA and TAM from a prediction-only perspective shows, that UGA tends to be a better model (lower RMSE-values). All in all, it cannot be clearly said, which model has more information power.

After the completion of all the evaluations presented above, the findings can be summarized as follows:

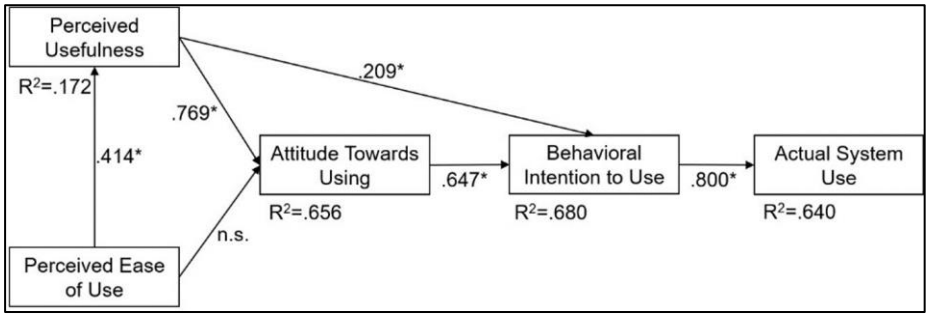
1. “Pastime“ has a positive influence on actual system use,
2. “Image“, “Expediency“ and “Enjoyment“ have a positive influence on “Behavioral Intention to Use“ a DVA,
3. “Behavioral Intention to Use“ itself has a positive influence on “Actual System Use“, “Fear of Data Misuse“ has no influence on neither “Behavioral Intention to Use“ nor “Actual System Use“.

Relating to TAM, all constructs show a significant correlation between each other. Whereas in UGA, correlations between “Image“, “Expediency“, “Enjoyment“ and “Fear of Data Misuse“ and “Actual System Use“ are not significant. This leads to the consideration, whether the relationship between constructs mentioned above and “Actual System Use“ are relevant or even, whether “Actual System Use“ needs to be integrated in this model at all.



* (**) denotes significant at the p=0.01 (0.001) level; n.s.=not significant

Fig. 3 UGA structural model with standardized path coefficients



* denotes significant at the p=0.01 level; n.s.=not significant

Fig. 4 TAM structural model with standardized path coefficients

By closely looking at the answers to the open questions, it is clear, that people use DVAs to save some time, to increase their productivity and/or to improve their image. They expect from DVAs, that they will make the everyday life easier and be entertained by such devices.

With regard to TAM a positive influence of almost all its constructs (with an exception of the correlation between “Perceived Ease of Use“ and “Attitude Toward Using“) could be confirmed. The outcomes show, that TAM is a helpful theoretical tool to understand and explain consumers’ intention to use DVAs. In order to answer the research question in the title (“UGA or TAM: Which Approach Better Explains Digital Voice Assistant Acceptance? “), several prerequisites must be considered.

Firstly, the models have to be compared from both – an explanatory and a predictive – perspective. Therefore, the coefficient of determination dependent variables were firstly examined. The variables of TAM explain “Behavioral Intention to Use“ by 9.3% better than those of

UGA (R^2 for UGA: 46.1% vs. R^2 for TAM: 55.4%). On the other hand, “Actual System Use“ will be better explained by the variables of UGA rather than by TAM (R^2 for UGA: 47.5% vs. R^2 for TAM: 41.3%). Because of different complexity of both models, BIC was closely examined, as a better choice for model selection tasks. In terms of “Actual System Use“ and “Behavioral Intention to Use“ for TAM is -82.918 and for UGA it is -76.275. Here, TAM has more informative power than UGA. Furthermore, in order to assess a model’s out-of-sample predictive power, RMSE-values were nearly investigated. Comparing these two models from a prediction-only perspective, UGA seems to be a better one (lower RMSE-values). So only by looking at the explanatory and a predictive perspective of UGA and TAM, it cannot be clearly said, which of the two models is better suited in this case.

Regarding the information content, constructs of UGA have a more specific character than those of TAM. In case of UGA, more specific, user-adapted constructs (e.g. “Pastime“, “Enjoyment“, “Fear of Data Misuse“) were asked. With regard to the effort of adapting to the research context, apparently TAM seems to be easier in the usage due to the easier application of existing scales to the research object whereas the adaptation of UGA items tends to be more extensive. Concerning UGA, the development of new constructs is required. These are adapted to the respective circumstances more closely, though. All in all, it cannot be clearly stated which of the two models seems to be better suited for measuring the acceptance of DVAs. A combination of the two models will be rather recommended for future researches, as this leads to more meaningful

and precise results. Such a wide range of tested constructs would not be possible by using only one of the models. Contrary to other studies (see, e.g., PwC, 2018), this study does not show any difference in acceptance of DVAs between men and women. Both genders equally accept and use those devices.

2.4 Conclusion and outlook

The first goal of this study was to highlight the factors that cause customers’ acceptance of DVAs (here on the example of Google Assistant). In addition, it was also important to characterize main functions of DVAs, that are interesting and useful for consumers. To do so, two approaches, UGA and TAM, were closely examined. Results show that customers mainly use their DVAs for time-saving. Furthermore, they also use DVAs, because they want to increase their image among friends and family and such a modern device, like DVAs, can be very useful. Many users also turn to DVAs, when they want to talk to somebody. On the other hand, people have some concerns about the usage of DVAs in public (e.g. they do not want to talk too loud with their smart devices) because they do not want to be laughed at. Survey results also show, that DVAs are helpful, while quickly looking for some information, navi-

gating a car, or traveling, especially when a manual input is not possible. Furthermore, in some of the comments on the survey, the software was nearly discussed. Depending on the smartphone software, Google Assistant is preferred mainly for Android and Siri is used on iOS devices. The integration of the two methods (UGA and TAM) to measure customers' acceptance leads to meaningful results and is recommended for further studies. For this reason, in-depth research, which has its origins in UGA and TAM, is recommended. An interesting extension of this study would eventually be to determine, how the research model can be adapted to incorporate the perception of non-users.

All in all, DVAs are an interesting and useful innovation. The idea of a personal assistant in the digital age is very contemporary, convincing and more than comprehensible. In order to meet the needs of an individual, DVAs should continually be improved. New functions should be added, which can make the everyday life much easier.

Future studies are encouraged to interview a larger, heterogeneous sample. Due to a rather small sample in this study (n=173) as well as the data collection at a certain time (six weeks), the data cannot be seen as representative.

It is also advisable to compare UGA with some recent versions of TAM, e.g. UTAUT2 or technology readiness model, which are mainly based on other, more specified constructs. Finally, results of the study are primarily for the use of Google Assistant and make no demands on the completeness. To improve the data quality, it would be advisable to conduct the survey for other DVAs (e.g. Siri, Cortana, Alexa).

2.5 References

Alhabash S., Yh. Chiang, K. Huang (2014), “TAM & U&G in Taiwan: Differences in the uses and gratifications of facebook as a function of motivational reactivity”. Computers in Human Behavior 35:423–430, DOI 10.1016/j.chb.2014.03.033

Ancu M., R. Cozma (2009), “Myspace politics: Uses and gratifications of befriending candidates”. Journal of Broadcasting & Electronic Media 53(4):567–583, DOI 10.1080/08838150903333064

Bitkom (2017),“Das smartphone gehorcht aufs wort”. URL https://www.bitkom.org/Presse/Presseinformation/Das-Smartphone-gehorcht-aufs-Wort.html

Brandtzaeg P., A. Følstad (2017), “Why people use chatbots”. In: International Conference on Internet Science, Springer, pp 377–392

Chen R., Z. Tian, H. Liu, F. Zhao, S. Zhang, H. Liu (2018), “Construction of a voice driven life assistant system for visually impaired people”. In: 2018 International Conference on Artificial Intelligence and Big Data, IEEE Press, Piscataway, NJ, pp 87–92, DOI 10.1109/ICAIBD.2018.8396172

Chin W., G. Marcoulides (1998), “The partial least squares approach to structural equation modeling”. Modern Methods for Business Research 8

Chu A. Z. C., R. J. C. Chu (2011), “The intranet’s role in newcomer socialization in the hotel industry in Taiwan – technology acceptance model analysis”. The International Journal of Human Resource Management 22(5):1163–1179, DOI 10.1080/09585192.2011.556795

Davis F. D. (1985), “A technology acceptance model for empirically testing new end-user information systems: Theory and results”. PhD thesis, Massachusetts Institute of Technology

Davis F. D., R. P. Bagozzi, P. R. Warshaw (1989), “User acceptance of computer technology: A comparison of two theoretical models”. Management Science 35(8):982–1003, DOI 10.1287/mnsc.35.8.982 DeFleur ML (2016) Mass communication theories: Explaining origins, processes, and effects. Routledge Taylor & Francis Group, London and New York

Digital Trends (2018), “Google assistant: The complete history of the voice of android”. URL https://www.digitaltrends.com/mobile/google-assistant/

Easwara Moorthy A., K. P. L. Vu (2015), “Privacy concerns for use of voice activated personal assistant in the public space”. International Journal of Human-Computer Interaction 31(4):307–335, DOI 10.1080/10447318.2014.986642

Elmorshidy A. (2013), “Applying the technology acceptance and service quality models to live customer support chat for e-commerce websites”. Journal of Applied Business Research (JABR) 29(2):589, DOI 10.19030/jabr.v29i2.7659

Elmorshidy A., M. M. Mostafa, I. El-Moughrabi, H. Al-Mezen (2015), “Factors influencing live customer support chat services: An empirical investigation in Kuwait”. Journal of theoretical and applied electronic commerce research 10(3):63–76, DOI 10.4067/S0718-18762015000300006

Fornell C., D. F. Larcker (1981), “Evaluating structural equation models with unobservable variables and measurement error”. Journal of Marketing Research 18(1):39–50, DOI 10.1177/002224378101800104

Gan C., H. Li (2018), “Understanding the effects of gratifications on the continuance intention to use WeChat in china: A perspective on uses and gratifications”. Computers in Human Behavior 78:306– 315, DOI 10.1016/j.chb.2017.10.003

Gao T., F. Sultan, A. J. Rohm (2010), “Factors influencing chinese youth consumers’ acceptance of mobile marketing”. Journal of Consumer Marketing 27(7):574–583, DOI 10.1108/07363761011086326

Hair J. F., G. T. M. Hult, C. M. Ringle, M. Sarstedt, N. F. Richter, S. Hauff (2017), “Partial Least Squares Strukturgleichungsmodellierung (PLS-SEM): Eine anwendungsorientierte Einführung“, 1st edn. Franz Vahlen, München, DOI 10.15358/9783800653614, URL http://dx.doi.org/10.15358/9783800653614

Hair J. F., M. Sarstedt, C. M. Ringle (2019), “Rethinking some of the rethinking of partial least squares”. European Journal of Marketing 53(4):566–584

Henseler J., C. M. Ringle, M. Sarstedt (2015), “A new criterion for assessing discriminant validity in variance-based structural equation modeling”. Journal of the Academy of Marketing Science 43(1):115–135

Hu P.J., P. Y. Chau, O. R. L. Sheng, K. Y. Tam (1999), “Examining the technology acceptance model using physician acceptance of telemedicine technology”. Journal of Management Information Systems 16(2):91–112, DOI 10.1080/07421222.1999.11518247

Katz E. (1959), “Mass communications research and the study of popular culture: An editorial note on a possible future for this journal”. Departmental Papers (ASC) 2

Katz E. (1974), “The uses of mass communications: Current perspectives on gratifications research”, Sage annual reviews of communication research, vol 3. Sage Publ, Beverly Hills, Calif., URL http://www.loc.gov/catdir/enhancements/fy0660/73090713-d.html

Knobloch S. (2003), “Mood adjustment via mass communication”. Journal of Communication 53(2):233–250, DOI 10.1111/j.1460-2466.2003.tb02588.x

Ku Y.C., T. H. Chu, C. H. Tseng (2013), “Gratifications for using cmc technologies: A comparison among sns, im, and e-mail”. Computers in Human Behavior 29(1):226–234, DOI 10.1016/j.chb.2012.08.009

Leung L., R. Wei (2000), “More than just talk on the move: Uses and gratifications of the cellular phone”. Journalism & Mass Communication Quarterly 77(2):308–320, DOI 10.1177/107769900007700206

Li H., Y. Liu, X. Xu, J. Heikkilä, H. van der Heijden (2015), “Modeling hedonic is continuance through the uses and gratifications theory: An empirical study in online games”. Computers in Human Behavior 48:261–272, DOI 10.1016/j.chb.2015.01.053

Lin H.F., C. H. Chen (2017), “Combining the technology acceptance model and uses and gratifications theory to examine the usage behavior of an augmented reality tour-sharing application”. Symmetry 9(7):113, DOI 10.3390/sym9070113

Macronomy (2018), “Digitale Sprachassistentennutzung von Alexa, Siri und Co. nimmt zu“. URL https://www.marconomy.de/digitale-sprachassistenten-nutzung-von-alexa-siri-und-co-nimmt-zu-a-722632/

Malik A., A.Dhir, M. Nieminen (2016), “Uses and gratifications of digital photo sharing on facebook”. Telematics and Informatics 33(1):129–138, DOI 10.1016/j.tele.2015.06.009

McLean G., K. Osei-Frimpong (2017), “Examining satisfaction with the experience during a live chat service encounter-implications for website providers”. Computers in Human Behavior 76:494–508, DOI 10.1016/j.chb.2017.08.005

Olbrich R., D. Battenfeld, C. C. Buhr (2012), “Marktforschung: Ein einführendes Lehr- und Übungsbuch“. Springer-Lehrbuch, Springer Berlin Heidelberg, Berlin, Heidelberg, DOI 10.1007/978-3-642- 24345-5, URL http://dx.doi.org/10.1007/978-3-642-24345-5

PwC (2018), “Consumer intelligence series: Prepare for the voice revolution”. URL https://www.pwc.com/us/en/services/consulting/library/consumer-intelligence-series/voice-assistants.html

Rauschnabel P. A. (2018), “A conceptual uses & gratification framework on the use of augmented reality smart glasses”. In: Jung T, tom Dieck MC (eds) Augmented Reality and Virtual Reality, Progress in IS, vol 11, Springer International Publishing, Cham, pp 211–227, DOI 10.1007/978-3-319-64027- 3 15

Rauschnabel P.A., Y. K. Ro (2016), “Augmented reality smart glasses: an investigation of tech- nology acceptance drivers”. International Journal of Technology Marketing 11(2):123, DOI 10.1504/IJTMKT.2016.075690

Rauschnabel P. A., A. Rossmann, M. C. tom Dieck (2017), “An adoption framework for mobile aug- mented reality games: The case of Pokemon go”. Computers in Human Behavior 76:276–286, DOI 10.1016/j.chb.2017.07.030

Rese A., S. Schreiber, D. Baier (2014), “Technology acceptance modeling of augmented reality at the point of sale: Can surveys be replaced by an analysis of online reviews?” Journal of Retailing and Consumer Services 21(5):869–876, DOI 10.1016/j.jretconser.2014.02.011

Rigdon E. E., M. Sarstedt, C. M. Ringle (2017), “On comparing results from CB-SEM and PLS-SEM: Five perspectives and five recommendations”. Marketing ZFP 39(3):4–16

Sharma P.N., G. Shmueli, M. Sarstedt, N. Danks, S. Ray (2019), “Prediction-oriented model selection in partial least squares path modeling”. Decision Sciences Forthcoming

Shmueli G., M. Sarstedt, J. H. Cheah, S. Vaithilingam, C. M. Ringle (2019), “Predictive model assessment in pls-sem: guidelines for using PLSPredict”. European Journal of Marketing Forthcoming

Song I., R. LaRose, M. S. Eastin, C. A. Lin (2004), “Internet gratifications and internet addiction: on the uses and abuses of new media”. Cyberpsychology & behavior : the impact of the Internet, multimedia and virtual reality on behavior and society 7(4):384–394, DOI 10.1089/cpb.2004.7.384

Stafford T. F., M. R. Stafford, L. L. Schkade (2004), “Determining uses and gratifications for the internet”. Decision Sciences 35(2):259–288, DOI 10.1111/j.00117315.2004.02524.x

Statista (2017a), “In immer mehr Bereichen des Lebens spielen digitale Sprachassistenten eine rolle“. URL https://de.statista.com/statistik/daten/studie/739040/umfrage/umfrage-zur- bekanntheit-ausgewaehlter-sprachassistenten-in-deutschland/

Statista (2017b), “Prognose zum Volumen der jährlich generierten digitalen Datenmenge weltweit in den Jahren 2016 und 2025“. URL https://de.statista.com/statistik/daten/studie/267974/umfrage/prognose-zum-weltweit- generierten-datenvolumen/

Stone M. (1974), “Cross-validation and multinomial prediction”. Biometrika 61(3):509, DOI 10.2307/2334733

Thomas J. A. (2015), “Deontology, consequentialism and moral realism”. Journal of Philosophy 19:1–24 van der Heijden H (2004) User acceptance of hedonic information systems. MIS Quarterly 28(4):695, DOI 10.2307/25148660

Venkatesh V., Davis F. D. (2000), “A theoretical extension of the technology acceptance model: Four longitudinal field studies”. Management Science 46(2):186–204, DOI 10.1287/mnsc.46.2.186.11926

Wei P. S., H. P. Lu (2014), “Why do people play mobile social games? an examination of network externalities and of uses and gratifications”. Internet Research 24(3):313–331, DOI 10.1108/IntR-04- 2013-0082

Wu J. H., S. C. Wang (2005), “What drives mobile commerce?” Information & Management 42(5):719– 729, DOI 10.1016/j.im.2004.07.001

3 Research paper #2: Acceptance of Digital Voice Assistants in Customer Communication: An Application of the Uses and Gratifications Approach and the Technology Acceptance Model

Author: Ewers, K.

Submitted in: Journal of Retailing and Consumer Services

Note: A shorter version of this research paper was submitted and published in the conference proceedings of the 26th International Conference on Recent Advances in Retailing and Consumer Services (RARCS2019/EIRASS2019), and was also presented there by the author. The research paper and its presentation at the conference were awarded by the program committee of the conference with the price for the "**Most Innovative Paper on the 26th International Conference on Recent Advances in Retailing and Consumer Services (RARCS2019/EIRASS2019), Tallinn, Estonia**". The author was invited to submit the full version of the paper to be published in the Journal of Retailing and Consumer Services, which is closely connected to the conference. The publication is currently under review.

Abstract: Digital Voice Assistants are conquering nowadays numerous areas of our everyday life. It is predicted that their functions and capabilities will enormously grow in the future. Therefore, it is relevant to examine the researches of user acceptance of Digital Voice Assistants (DVAs) in the context of customer communication. Our paper makes an empirical contribution to this topic under the consideration of the Uses and Gratifications Approach (UGA) and the Technology Acceptance Model (TAM). The outcomes proved the developed model (that consists out of constructs from UGA and TAM) to be good theoretical tool to understand users' acceptance of DVAs. Pastime was the most important aspect that influence the users' acceptance of DVAs. Our study offers numerous practical implications. To increase users' satisfaction and assure higher intention to use, DVA designer should focus on improving entertainment service and skills of DVAs, which will give stronger feeling of communicating (only with the voice) with a human, rather than a robot.

Keywords: Acceptance, Digital Voice Assistants, Google Assistant, Uses and Gratifications Approach, Technology Acceptance Model (TAM)

3.1 Introduction

The era of information technology has fundamentally changed everyday life and work structures (Niehaves and Plattfaut 2014). An enormous amount of digital content is created around the world every year. In 2016 alone, 16.1 zettabytes of digital information were generated (Statista 2017c). According to Statista, the data volume will rise to 163 zettabytes in 2025 (Statista 2017c). This expected amount of data makes the digitization of numerous everyday and business activities indispensable. Similar growth figures can also be seen in artificial intelligence (BMWi 2018).

A life without a computer, smartphone, or the internet is hard to imagine these days. Since the market launch of the first computer, people wanted to be able to talk to them (Hoy 2018). Due to the fast pace of products and many opportunities to develop new technologies, it was only a matter of time before new technologies were developed that put the most original and natural form of communication, the verbal exchange among themselves, in the foreground (Shankar 2018). And so, the Digital Voice Assistant (DVA) was created and it was used as an everyday helper (Mari 2019). Since DVAs are now built into every smartphone, the spread of the technology is by no means a problem, and it makes sense to use DVAs daily in private life and at work. However, the media often speak of data protection aspects that prevent people from using DVAs since the internal company and private data should not be leaked to strangers (Macronomy 2018). It is used, for example, in Digital Voice Assistants, which are increasingly gaining more areas of application (Statista 2017b). With the widespread use of smartphones, there is also growing interest in Digital Voice Assistants, which are now preinstalled in almost every smartphone. According to the online survey by Splendid Research (2018), 91 percent of Germans know what a Digital Voice Assistant is. Thirty-seven percent of the recipients even use one of the voice assistants available on the market (Splendid Research 2018). The market leader in this area is Google Assistant, which is used by 29 percent of the recipients. In second place is Siri, the voice assistant from Apple, operated by 22% of those surveyed (Statista 2017a). Due to the increased interest in the use of voice assistants, consumers are becoming choosier and placing ever higher demands on new functions (Macronomy 2018). To make the parts customer-friendly, the provider must know the preferred areas of application. The provider needs to know when its customers will accept or reject an innovative information or communication technology (Bundesverband Digitale Wirtschaft e.V. 2017). Since this topic has not been sufficiently investigated yet, this study deals with the acceptance of Digital Voice Assistants in customer communication. As a matter of fact, the following research question will be answered: “Which factors influence the users’ acceptance of Digital Voice Assistants?”.

The present study is divided into eight parts. The first part introduces the topic of the acceptance of Digital Voice Assistants in customer communication. Both the initial situation and the current problems are discussed there. In the second part of the study, two theoretical components are explained in more detail - the Uses and Gratifications Approach (UGA) and the Technology Acceptance Model (TAM). Building on this, the theoretical framework, a modified TAM, is discussed in the further course of the study. The next step is a detailed presentation of Digital Voice Assistants. Some functions of the best-known voice assistants, statistical data, and the latest studies on the topic are mentioned here. In part 4, a research design of the study, including research hypotheses, is presented. After that (part 5), the target group is shown. Subsequently, research hypotheses are formulated, and a questionnaire is created. The data collection is also described here. Part 6 focuses on all the answers obtained in the primary analysis and evaluates the quantitative survey. Then, part 7 shows the limitations of the present study. The final part of the study (part 8) deals with the observations made so far and summarizes the results. Finally, a research outlook is given.

3.2 Literature review

3.2.1 Technology Acceptance Model (TAM)

One of the best known and most widely used models of technology acceptance is the Technology Acceptance Model (TAM), which Fred D. Davis developed in 1986 (Davis, Bagozzi and Warshaw 1989). TAM is a theoretical model that explains and predicts when a new technology will be accepted and used or rejected (Rauschnabel and Ro 2016). The basis of the TAM is the socio-psychological model by Icek Ajzen and Martin Fishbein from 1980, the Theory of Reasoned Action (TRA) (Davis and Venkatesh 1996). It is an attitude model that predicts the behavior of the observed object with its attitudes and social norms concerning this behavior (Marangunic and Granic 2015).

The TAM aims to map a wide range of end-user behavior to explain as many computer technologies as possible. As a result, it also accepts that it is not very specific (Davis 1989, 319–322). Due to this objective, compared to the TRA, one can assume that the TAM is less general, requiring few statements. Nevertheless, this model has found its theoretical justification and established itself in science (Taherdoost 2018).

Fred D. Davis used TAM first within computer-based information systems (Davis 1985). The model's flexibility has also been showed in other areas, with the result that it is now being used in a wide variety of industries to research technology acceptance (Rese et al. 2014). The TAM has also already been used to study Digital Voice Assistants (Easwara and Vu 2015).

When the user first comes into contact with new technology, various factors arise that play a major role in deciding whether and when the new technology is accepted and used. Voice assistants can also be understood as such young technology for which the TAM can draw good conclusions about user acceptance (Moorthy and Vu 2014). In particular, the relationship between the observable, actual behavior of users and the external variables that affect user acceptance is shown (Taherdoost 2018). The external variables do not have a direct effect on the use of computer-based technologies, but only indirectly through the factors "Perceived Usefulness" (PU) and "Perceived Ease of Use" (PEOU) (Davis 1989).

The user's Attitude Toward technology acceptance/use (Attitude Toward Using, ATU) determines if the user will use the new technology in the future. In line with Davis (1985), the ATU depends, as already mentioned, on two characteristics: the Perceived Usefulness (PU) and the Perceived Ease of Use (PEOU) (Davis 1985). The PU is understood to be the subjective perception of an individual, which gives the user the feeling that using a new technology increases their productivity (Chu and Chu 2011). The PEOU, in turn, indicates the extent to which the respondent believes that learning to use new technologies goes hand in hand with no physical strain (Davis 1985). Both variables, PU and PEOU, must always be viewed from the consumers' point of view and have a direct effect on the ATU with regard to the use of a system (Actual System Use, ASU). Moreover, they are influenced by external variables such as demographic aspects and personality traits (Davis et al. 1989). Simultaneously, PEOU also affects PU (Park 2009). However, some scientific studies consider this dependency irrelevant for the studies' overall results (Almahamid et al. 2010, 32). Therefore, the relationship between PEOU and PU is not a mandatory requirement (Almahamid et al. 2010). Additionally, both the PU and the ATU once again affect the Behavioral Intention to Use (BIU), which in turn influences the Actual System Use (ASU). An original TAM as well as an overview of exemplary studies based on TAM are shown in figure 1. Moreover, table 1 presents a selection of technology acceptance models over the last 40 years.

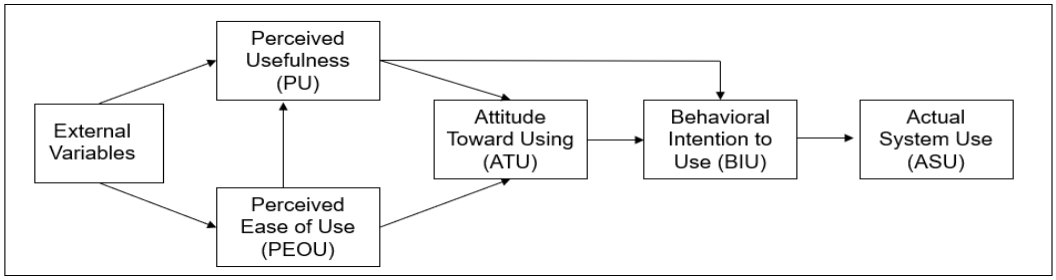


Fig. 1: Original Technology Acceptance Model; **Source:** Davis 1985

Source	Model	Constructs	Key findings
Fishbein and Ajzen (1975)	Theory of Reasoned Action (TRA)	- Attitude Toward Behavior - Subjective Norm	- Starting point: desire to understand and predict human behavior - Clear structuring through a few determinants
Ajzen (1985)	Theory of Planned Behavior (TPB)	- Attitude Toward Behavior - Subjective Norm - Perceived Behavioral Control	- Supplementing the TRA with Perceived Behavioral Control, which considers the fact that voluntary control over one's own behavior can be restricted
Davis (1989)	Technology Acceptance Model (TAM)	- Perceived Usefulness - Perceived Ease of Use - Subjective Norm	- Development for acceptance research of IT devices in an organizational context
Thompson, Higgins and Howell (1991)	Model of PC Utilization (MPCU)	- Job-fit - Complexity - Long-term Consequences - Affect Towards Use - Social Factors - Facilitating Conditions	- To predict the individual acceptance and usage behavior (not usage intention) of many information technologies - It was originally used to predict computer usage behavior
Davis, Bagozzi and Warshaw (1992)	Motivational Model (MM)	- Extrinsic Motivation - Intrinsic Motivation	- Extrinsic and intrinsic motivation are key factors for the intended use of a technology
Compeau and Higgins (1995a; 1995b)	Social Cognitive Theory (SCT)	- Outcome Expectations (Performance and Personal) - Self-efficacy - Affect - Anxiety	- Computer usage was originally studied - The model and the underlying theory allow an extension to the acceptance and usage analysis of IT equipment in general
Rogers (1995)	Innovation Diffusion Theory (IDT)	- Relative Advantage - Ease of Use - Image - Visibility - Compatibility - Results Demonstrability - Voluntariness of Use	- The aim is to study the distribution and use of innovation in a population
Taylor and Todd (1995)	Combined TAM-TPB (C-TAM-TPB)	- Attitude Toward Behavior - Subjective Norm - Perceived Behavioral Control - Perceived Usefulness	- Extension of the TPB to include Perceived Usefulness - The combination of the TAM and TPB models offers an adequate model for IT users
Venkatesh and Davis (2000)	TAM 2	- Perceived Usefulness - Perceived Ease of Use - Subjective Norm - Image, Job Relevance, Output Quality, Result Demonstrability	- Further development of the TAM to include social process variables and cognitive instrumental variables, which significantly affect user acceptance

Tab. 1: Selection of technology acceptance models over the last 40 years
Source: Own depiction

3.2.2 Uses and Gratifications Approach (UGA)

The UGA is considered one of the most influential theories in acceptance research, as it clarifies which needs the media should meet by individuals (Curras-Perez et al. 2014). It explores why an individual uses a specific medium and how it uses it to meet certain needs (Brandtzaeg and Følstad 2017). The approach was developed by Katz et al. in the early 1960s (Katz et al. 1974). It was initially used for research into mass media and their content (Kaye 1998). The UGA assumes that people have innate needs known to them and which

can be met through the targeted use of a new medium (Katz et al. 1974; Lin and Chen 2017). The motivation to use the new technology depends on the so-called gratuities, i.e., reasons that put the user in a state of satisfaction through use (Rauschnabel 2018).

Gratifications are independent variables of the theoretical model. The UGA states that every user is motivated based on their individual needs and characteristics (Brandtzaeg and Følstad 2017, 381; Rauschnabel 2018). There are sometimes big differences between the new technologies, e.g., in use itself or in the purpose of use, which is why it is essential for each medium or for each technology to identify the most important gratuities that are relevant to this context (Brandtzaeg and Følstad 2017). Accordingly, the approach does not consist of fixed constructs but must be individually adapted to the respective facts and context (Rauschnabel 2018).

Frequently seen components of the model are, on the one hand, the Behavioral Intention to Use a technology (BIU), which, if the Actual System Use (ASU) is also part of the model, functions as a semi-dependent variable and, on the other hand, the ASU represents the fully dependent variable (Rauschnabel 2018; Rauschnabel and Ro 2016; Venkatesh et al. 2012). With these two constructs, the classic elements of the TAM were integrated into the UGA.

Research object	Method	Sample	Main Results (Researched gratifications - selection)	Reference
Online/ Mobile Games	Uses and Gratifications Approach	n=237	Individual gratifications: Enyojment, interaction with others	Wei and Lu, 2014
		n=3919	Hedonic g.: Enjoyment, fantasy Social g.: Social interaction, social presence Utilitarian g.: Success	Li et al., 2015
		n=642	Hedonic g.: Enjoyment, physical activity Social g.: Image Emotional g.: Nostalgia	Rauschnabel, Rossmann and Dieck, 2017
Instant Messaging		n=150	Pastime, information search, contact maintenance	Ku, Chu and Tseng, 2013
		n=297	Hedonic g.: Enjoyment Utilitarian g.: Exchange of information Technological g.: Appeal of medium	Gan and Li, 2018
Chatbot		n=146	Productivity, pastime, social advantages	Brandtzaeg und Følstad, 2017
Mobile phone		n=834	Appropriateness, social connectedness, calming	Leung and Wie, 2000
Internet		n=498	Information search, distraction, personal status	Song et al., 2004
Social Networks		n=167	Social benefit, exchange of information, entertainment	Ancu and Cozma, 2009
		n=3172	Entertainment, exchange of information, self-portrayal	Alhabash, Chiang and Huang, 2014
		n=368	Interest, exchange of information, social influence	Malik, Dhir and Nieminen, 2016

Tab. 2: Exemplary studies based on UGA
Source: Own depiction

In previous studies, the UGA has been successfully applied to a wide variety of technologies. Originally, the approach was used shortly after its development to the current mass media of the time, such as the newspaper, radio, or television (Greenberg 1974; McQuail et al. 1972). In recent years, researchers explored the most important gratitudes for the use of augmented reality smart glasses (Rauschnabel 2018), smartphones (Joo and Sang 2013), internet (Staf-

ford et al. 2004), social media (Whiting and Williams 2013), and chatbots (Brandtzaeg and Følstad 2017). Table 2 gives an outline of some studies based on UGA.

3.3 Digital Voice Assistants

In the last few years, speech-based DVAs have become more of a talking point (Sayago et al. 2019). According to statistics, over a billion Digital Voice Assistants were used worldwide in 2018, increasing to 1.8 billion expected by 2021 (Statista 2019b). The focus of research has, on the one hand, to do with the technological advances in the field of Artificial Intelligence, but also with the increasing interest of large technology companies in investing in new technologies (Klopfenstein et al. 2017).

A DVA is a computer or software with which the user can communicate using the voice (Hoy 2018; Jiang et al. 2015; Kepuska and Bohouta 2018). This technology can help users complete tasks more efficiently and faster through spoken instructions (Kepuska and Bohouta 2018). The user thus has the option of no longer typing in and sending certain commands but simply giving them verbally. The more the user communicates with the voice assistant, the more personalized it becomes since it learns more about the user with increasing communication (Jones 2018). The present technology relies on artificial intelligence, machine learning, and the processing of natural language to give the user the desired information (Gaggioli 2018; Hoy 2018; McLean and Osei-Frimpong 2019). Using these processing methods, Digital Voice Assistants try to place the information given to them in a context and thus improve their answers (Nasirian et al. 2017).

Voice Assistants are often built into smartphones as applications (Klopfenstein et al. 2017). But they can also be found in smart TVs and laptops (Sarikaya 2017). For some time now, Digital Voice Assistants have also been available for use at home in the form of hardware, the so-called smart speakers, e.g., Google Home or Amazon Echo (Herrero et al. 2018). You can use them to convert your home into a smart home, a so-called intelligent home (Han and Yang 2018). Like Google, Apple, or Microsoft, many of the biggest international companies already launched their DVAs (EY 2018). In our study, we use Google Assistant as an example of a DVA.

Voice Assistants differ, among other things, in their design and their functions (Kepuska and Bohouta 2018). Nevertheless, every Voice Assistant performs the same basic functions, for example, everyday tasks such as reading and sending text messages and emails and making phone calls, or ordering food (Hoy 2018; Han and Yang 2018). In addition, the Voice Assistant can set an alarm clock, remind the user of important things and add calendar entries. DVAs can also be used for simple conversations by reproducing some knowledge or jokes

(Yang and Lee 2019). The range of tasks of a DVA is constantly expanding, as research and further development are not completed yet (Wagner et al. 2019). A great advantage of Digital Voice Assistants is their flexibility, as they can be used anytime and anywhere (Han and Yang 2018). Since they can be used for various tasks, they have a great potential for the future (Yang and Lee 2019).

However, there are also negative aspects of using such devices. One problem that arises when using DVAs is data security and privacy protection (Hoy 2018). By operating the voice control, personal data can be read out more easily by third parties, and processes can be carried out. In addition, DVAs can always overhear, as they are always on call to answer inquiries. As soon as the user says a keyword, the Voice Assistant will activate (McLean and Osei-Frimpong 2019). Due to the constant availability of Voice Assistants, it is conceivable that private data will be saved and fall into the wrong hands, or the user will be spied on. Appropriate technical measures must prevent this. However, there will always be a certain residual risk that personal data will be stolen and used without authorization (Brill 2018). The first table in Appendix (Appendix 1) summarizes important findings on Digital Voice Assistants in recent years.

3.4 Research Design and Hypotheses

Although the TAM has proven useful in numerous research areas to identify the factors that influence a person's technology acceptance and use, the model, as Park et al. (2007), does not fully explain why people ultimately accept and use a technology (Park et al. 2007). Furthermore, Bagozzi (2007) and Coskun-Setirek and Mardikyan (2017) show that the original TAM by Davis (1989) ignores external factors affecting the overall context (Coskun-Setirek and Mardikyan 2017). As a result, the previous model should be modified by further factors to make its application possible and consolidate it in the field of new and innovative technologies. Benbasat and Barki (2007) also criticize that the focus in acceptance research is too much on the TAM without considering another approaches (Benbasat and Barki 2007). To overcome such significant limitations, our study uses the Technology Acceptance Model and the Uses and Gratifications Approach examining consumers' acceptance of Digital Voice Assistants.

Based on the theoretical contribution, the following hypotheses are built to examine the acceptance of DVAs in the context of customer communication. These are then discussed in the further course of the study. Which studies were ultimately decisive for the choice of gratuities is described in table 3. There, the relevant studies are summarized in an overview. From the totality of the various factors that appear in the literature, we modified the original TAM by adding five further factors: Pastime (PA), Image (IM), Enjoyment (EN), Expediency (EX) and

Fear of Data Misuse (FDM). Following hypotheses were made for the presented research model (see figure 2):

Hedonic gratuities:

Pastime has a positive effect on the behavioral intention to use the DVA (**H1a**) and on the actual system use (**H1b**).

Enjoyment has a positive effect on the behavioral intention to use the DVA (**H2a**) and on the actual system use (**H2b**).

Utilitarian gratuities:

Image has a positive effect on the intention to use the DVA (**H3a**) and on the actual system use (**H3b**).

Expediency has a positive effect on the intention to use the DVA (**H4a**) and on the actual system use (**H4b**).

Barriers:

Fear of data misuse has a negative effect on the intention to use the DVA (**H5a**) and on the actual system use (**H5b**).

Perceived Usefulness (PU):

The behavioral intention of users to use an information system is strongly influenced by the perceived usefulness of the examined system (Davis et al. 1989). Numerous researchers have already proven the significant effect of the perceived benefit on behavioral intent (Hu et al. 1999); (Davis et al. 1989); (Venkatesh and Davis 2000). As a logical consequence of this, it seems likely that the perceived usefulness can lead to a positive assessment of the Voice Assistant by the respondents. The following hypotheses are presented:

H7a: Perceived usefulness has a positive effect on Attitude Toward using the Google Assistant.

H7b: Perceived usefulness has a positive effect on the intention to use the Google Assistant.

Perceived Ease of Use (PEOU):

Over the past few decades, a significant amount of research has provided substantial support in examining the effects of perceived usability on behavioral intent, either directly or indirectly, through its impact on perceived benefit (Hu et al. 1999, 92–95). Therefore, two hypotheses are proposed: the perceived ease of use of the Google Assistant positively affects both the perceived usefulness (H8a) and the behavioral intention to use Digital Voice Assistants.

H8a: Perceived ease of use positively affects the perceived usefulness of Digital Voice Assistants.

H8b: Perceived ease of use positively affects the behavioral intention to use Digital Voice Assistants.

Attitude Toward Using (ATU):

Furthermore, it is assumed that the attitude toward using Voice Assistants has a positive effect on the behavioral intention to use them. Rauschnabel et al. (2017), in their study, the results of which are associated with the classic TAM (Rauschnabel et al. 2017). For this reason, the following research hypothesis is made:

H9: Attitude Toward using DVAs has a positive effect on the intention to continue using Google Assistant.

Behavioral Intention to Use (BIU)

Intention to use represents a person's intention to use something (here: Digital Voice Assistants). It represents a probability that the person will engage in certain behavior. The following hypothesis was formulated in this context:

H10: Behavioral Intention to use DVAs has a positive effect on the actual use of Digital Voice Assistants (ASU).

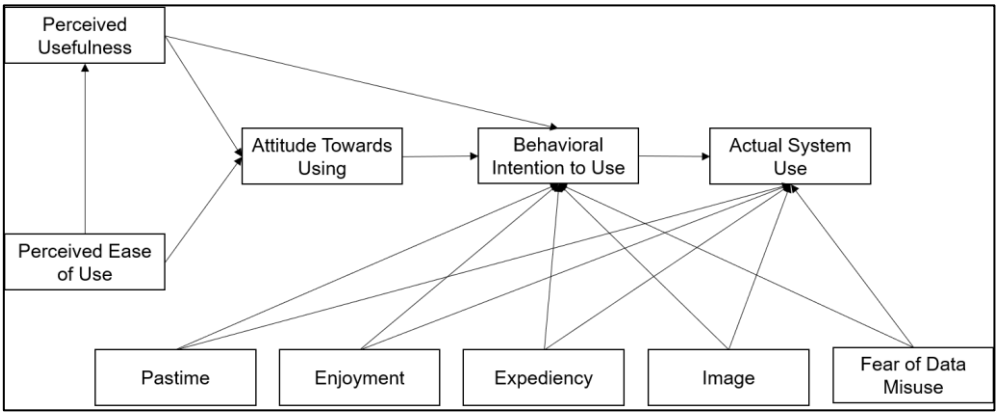


Fig. 2: Modified TAM – structural model for the acceptance of DVAs
Source: Own depiction

Constructs	Number of items	References
Pastime (PA)	3 Items	Gan and Li, 2018; Rauschnabel et al., 2017; Ku et al., 2013; Papacharissi and Rubin, 2000
Enjoyment (EN)	3 Items	Rauschnabel et al., 2017; Wei and Lu, 2014; Li et al., 2015
Image (IM)	4 Items	Rauschnabel et al., 2017; Song et al., 2004; Malik et al., 2016
Expediency (EX)	2 Item	Leung and Wei, 2000
Fear of Data Misuse (FDM)	3 Items	Rauschnabel et al., 2017; Kayak, 2017; YouGov, 2017
Perceived Usefulness (PU)	4 Items	Venkatesh and Davis, 2000
Perceived Ease of Use (PEOU)	3 Items	Venkatesh and Davis, 2000; Gefen, Karahanna and Straub, 2003
Attitude Toward Using (ATU)	4 Items	Venkatesh and Davis, 2000; Porter and Donthu, 2006
Behavioral Intention to Use (BIU)	3 Items	Moon and Kim, 2001; Venkatesh, Thong and Xu, 2012
Actual System Use (ASU)	3 Item	Venkatesh and Davis, 2000

Tab. 3: Constructs used in the research model and references
Source: Own depiction

3.5 Questionnaire Development and Data Collection

Mobile technology and network connectivity represent Generation Y, also known as Millennials - the target group for our study (Eastman 2014). Compared to previous generations, Generation Y has no difficulties in dealing with technological communication and sees this more as a potential to maximize their productivity (Myers and Sadaghiani 2010). According to Tuzovic and Paluch (2018) “Millennials are four times as likely to use virtual assistants compared to baby boomers” (Tuzovic and Paluch 2018). Rather, the major innovations in software and hardware in recent years have resulted in a completely different understanding of connectivity and communication in everyday life for Generation Y (Deal et al. 2010). Above all, digital media and social media development make it possible for this generation to come into contact in online communities in previously unthinkable ways with friends and acquaintances or even strangers who show the same interests (Viswanathan and Jain 2013). As a result, Generation Y has a more professional approach to technological innovations than the previous generations (Deal et al. 2010) and represents a suitable target group for the innovative subject of this study. In summary, it can be stated that DVAs are now integrated into numerous devices and that third-party providers increasingly see new opportunities in the application of the technology in their products.

With the help of the "Qualtrics" survey software, the questionnaire was designed and, after it was created, checked by five test persons for possible errors, the duration of the survey, potential comprehension problems, and the structure's correctness. The questionnaire was then refined through targeted adjustments. Finally, it was freely designed on June 25th, 2018, and made available on June 26th, 2018, via the eLearning platform to all students who took part in the "Dialog Marketing" event at the University of Bayreuth in the 2018 summer semester. The survey period was between June 26th and August 4th, 2018. Since the survey took place internally at the University of Bayreuth as part of the German-language event "Dialog Marketing", the questionnaire was only available in German.

The research design is based on a quantitative research method. In light of the beforehand shown research models and the subsequent research hypotheses, an online survey, which primarily consists of closed questions, has been conducted. An exception are two open-ended questions: "In which situation in everyday life is the use of Google Assistant helpful?", "In which situation will you use Google Assistant in the future?". The survey took place from June 26th to August 4th, 2018. The greater part of the survey was designed utilizing the 5-point Likert scale (Stavropoulos et al. 2016). The range of the scale stretches from "strongly agree" to "strongly disagree". The respondents could also choose an impartial position "neutral" within the survey.

Before the participants started the online survey, they were welcomed and briefly introduced to the subject area. It was also made clear to them what the ultimate goal of the survey is. The questions at the beginning of the questionnaire are based on the research model**.** The style of the questions is based on previous studies on TAM (Venkatesh and Davis 2000) and on the Uses and Gratifications approach (Brandtzaeg and Følstad 2017; Rauschnabel et al. 2017). With the help of the opening questions, variables that have an influence on users' acceptance towards DVAs were found. It was also helpful to find out to what extent and how these variables correlate with one another. Building on the theoretical considerations of the research model, the questionnaire is structured as follows (three to eight questions in each group):

At the beginning of the questionnaire, the first construct of the TAM, the Perceived Usefulness of the Digital Voice Assistant "Google Assistant", was examined based on five questions. Subsequently, the respondents were able to indicate in a free field some everyday situations when using Google Assistant is helpful. In the second step, questions were asked about the usability of Google Assistant. Questions were asked about i.e., the required knowledge of the users, the comprehensibility, user-friendliness of the device, and any support in using the assistant.

The next part of the questionnaire contains the influencing factors (in the context of UGA), which were subsequently divided into three categories (personal and social factors, satisfaction of needs, and risks). Personal and social factors, such as the incentive (questions about, e.g., increasing productivity or loss of time), the image (positive perception from the environment, self-development, image improvement), as well as social influence (from acquaintances and certain institutions). The second group focuses on the satisfaction of needs (e.g., Google Assistant is interesting or entertaining, Google Assistant gives me pleasure, etc.). The third group focuses on the possible risks, such as distraction, data abuse, or tracking.

Subsequently, other TAM constructs - the attitude of the users towards the Google Assistant as well as the intention to use it (e.g., "I intend to use Google Assistant more often in the future.") were asked. The second open question dealt with the conceivable situations in which the DVA can be used. Finally, in this part of the survey, the actual use of the device was asked. Here, the respondents were able to indicate, i.e., how often they use the Digital Voice Assistant.

At the end of the survey, socio-demographic data such as gender or age were asked to gain a deeper understanding of the age-related or attitude-related influences of the test persons (Wixom and Todd 2005). The respondents also had the opportunity to submit their comments on the use of Google Assistant, Digital Voice Assistants in general, and comment on the survey in open fields at the end of the survey.

The survey was answered by 195 respondents. One hundred seventy-three respondents filled out the questionnaire completely, which corresponds to a completion rate of 88.7 percent. These evaluated data are the premise of further empirical examination. Of the respondents, 50.3 percent are female, and 48 percent are male. Another three individuals did not provide any information about their sexual orientation.

The target group of the study are Millennials (21 to 35 years old) who will begin their professional life soon.

Despite the fact the companies try to address all age groups with their products and services, it is precisely individuals between the ages of 21 and 35 who are most attractive for the market for digital innovations. They are open to the new on the market and have the means to afford these goods. Of the 173 survey participants, 126 people (72.8 percent) were between 21 and 25 years old and 45 people (26.0 percent) between 26 and 30. Two people (1.2 percent) represented the age group of 31 and younger than 35. None of the respondents was older than 35 years.

3.6 Analysis and Results

3.6.1 Quality assessment of the Research Model

To evaluate, analyze and interpret the collected data, the variance-based, consistent Partial Least Square (PLS) approach was used and applied with the help of the SmartPLS software (version 3.3.3). The PLS approach developed by Wold (1975) aims to maximize the explained variance of the latent constructs to enable an optimal prognosis and explainability for the dependent variables (Hair et al. 2012; Wold, 1975). An advantage of using a PLS structural equation analysis (PLS-SEM) in contrast to the likewise popular covariance-based approach (used e.g., by Amos or LISREL) is that PLS enables complex models with comparatively small sample size, as in the present case (Hair et al. 2012; Jahn 2007; Ringle et al. 2012). In addition, this approach often provides more robust estimates of the model. It is particularly helpful if the research study aims to identify key drivers for a construct, as it is in the present case for the intended use (Hair et al. 2011; Hair et al. 2017).

An extension of the PLS approach is the consistent PLS approach, correcting the estimation errors for reflective models (Dijkstra & Henseler 2015). The advantage here is that it follows the composite logic of the PLS. Still, it provides comparable results of the more confirmatory covariance-based approach (Hair et al. 2019) PLS-SEM are very popular today and, thanks to their diverse applications, have been used in different disciplines established as a standard for marketing research (Hair et al. 2012; Henseler et al. 2015). In addition, Ringle and Sarstedt (2016) state in the context of their work that this approach and the SmartPLS software package are particularly well suited to the analysis of acceptance models so that the use of this approach appeared expedient for the present situation (Ringle and Sarstedt 2016).

To ensure the informative value and interpretability of the collected data, the quality of the measurement process must first be checked in empirical structural equation analyses. The aim is to assess the measurement quality and to minimize any measurement errors that occur. Therefore, it is essential to check the reliability and validity using appropriate quality criteria (Hair et al. 2017; Himme 2007). Hair et al. (2019) examines different quality criteria in the following: indicator reliability, internal consistency, convergent reliability, and discriminant validity (Hair et al. 2019). To test the indicator reliability, factor loading (FL) is used in the study and can be taken from the table in Appendix (Appendix 2). FL indicates the degree to which the variance of the indicators can be explained by the corresponding construct (Hair et al. 2017). An evaluation of the internal consistency is carried out according to Hair et al. (2017) based on the quality criteria Cronbach's Alpha (CA) and the composite reliability (CR) (Hair et al. 2017; Cleff 2015). In the second table in Appendix (s. Appendix 2), the respective

values of Cronbach's alpha and composite reliability that exceed their respective threshold values, what means that a sufficient internal consistency can be assumed.

In the next step, the convergent validity is examined more closely (Hair et al. 2019; Hair et al. 2017; Himme 2007). The measured variable for determining the convergent validity is the average variance extracted (AVE). Since both the AVE for each construct has a value greater than 0.5 and the factor loadings have also proven to be significant, the convergent validity can be assumed for the available data.

In many studies, the Fornell-Larcker criterion measures discriminant validity (Fornell and Larcker 1981; Hair et al. 2017). It can be seen in table 4, according to the Fornell-Larcker criterion, that in this study there is a sufficient discriminant validity.

	ASU	ATU	BIU	EN	EX	FDM	IM	PA	PEOU	PU
ASU	0.805									
ATU	0.607	0.841								
BIU	0.639	0.723	0.885							
EN	0.464	0.735	0.583	0.827						
EX	0.431	0.656	0.554	0.526	0.897					
FDM	-0.129	-0.311	-0.145	-0.287	-0.114	0.962				
IM	0.466	0.581	0.532	0.577	0.452	-0.264	0.849			
PA	0.571	0.664	0.566	0.577	0.631	-0.187	0.623	0.800		
PEOU	0.228	0.319	0.285	0.316	0.285	-0.055	0.318	0.318	0.787	
PU	0.562	0.685	0.624	0.641	0.676	-0.127	0.575	0.714	0.312	0.795

Tab. 4: UGA – Fornell-Larcker Criterion

Some research articles suggest an alternative to assessing discriminant validity - the heterotrait monotrait (HTMT) criterion developed by Henseler et al. (Hair et al. 2019; Hair et al. 2017; Henseler et al. 2015). According to Table 5, none of the correlations takes a value greater than 0.85, which means that a sufficient discriminant validity can also be assumed according to the HTMT criterion.

	ASU	ATU	BIU	EN	EX	FDM	IM	PA	PEOU	PU
ASU										
ATU	0.753									
BIU	0.797	0.819								
EN	0.621	0.884	0.710							
EX	0.568	0.807	0.675	0.683						
FDM	0.148	0.331	0.158	0.329	0.134					
IM	0.580	0.638	0.593	0.700	0.540	0.288				
PA	0.789	0.829	0.708	0.780	0.843	0.228	0.774			
PEOU	0.321	0.408	0.366	0.428	0.386	0.066	0.387	0.448		
PU	0.735	0.797	0.728	0.811	0.842	0.145	0.691	0.827	0.412	

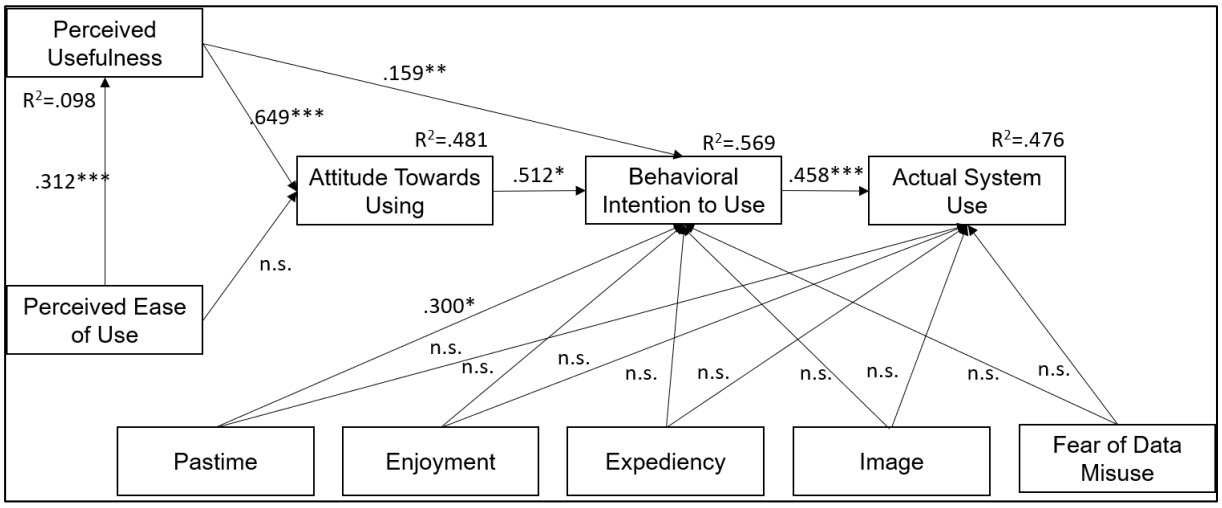
Tab. 5: HTMT – UGA

According to the quality criteria that have just been evaluated, the data collected can be viewed as valid and reliable.

3.6.2 Consideration of the Structural Model

The following consideration of the structural model examines the predictability of the present model more precisely and analyzes the relationships between the individual constructs (Hair et al. 2017). Accordingly, the collinearity is first examined to exclude an excessive correlation of the constructs in the context of the regression analysis. For this purpose, the Variance Inflation Factor (VIF) is examined more closely (Hair et al. 2017). In this study, all constructs take VIF values lower than 5 so that multicollinearity between the constructs can be excluded.

The next step is to examine the path coefficients, which describe the theoretically assumed relationships between the constructs. In the context of the study, the t-values are used for this purpose, which can be estimated in the light of defined threshold values (Hair et al. 2017). The calculated path coefficients, including the respective significance, can be found in Table 6. This means that seven hypotheses can be supported (H1b, H6a, H6b, H7a, H7b, H8, and H9). As part of the effect size (f^2), it is examined whether an exogenous variable significantly affects a construct of the model (Hair et al. 2017). In the present study, the effect size of the assumed hypotheses can be assessed as high for H1b, H6a, H6b, H7a, H8, H9. For all other hypotheses, a rather smaller effect can be seen. The Stone-Geisser criterion (Q^2) is used as a further model assessment method to identify the prognostic relevance of the constructs (Geisser 1974; Hair et al. 2017, 174; Stone 1974). Here a Q^2 value results beyond zero, so that one can speak of a good forecast relevance. Figure 3 summarizes all findings described above. So far, the research model as well as the hypotheses have been tested and adjusted to the conditions.



Note: *** p < .001; ** p<.05; * p<.01; R^2 values are shown in parentheses

Fig. 3: Standardized path coefficients

Answering the research question ("Which factors influence the users' acceptance of Digital Voice Assistants?"), it can be said that:

• Pastime has a positive influence on Actual System Use of DVAs,

• Enjoyment, Image, Expediency, and Fear of Data Misuse have no effect on neither Behavioral Intention to Use DVAs nor on Actual Use of DVAs.

Investigating the open questions confirms the results of our current findings – Millennials mainly use DVAs for fun and/or for entertainment. Even though Millennials use DVAs mainly as a pastime, it is still very important, that the customers' needs, are met (Chung et al. 2018). Potential risks associated with using DVAs (e.g. data misuse) do not play a significant role for this age group.

The Items of the original TAM (Perceived Usefulness, Perceived Ease of Use, Attitude Toward Using, Behavioral Intention to Use, Actual System Use) show a positive influence on all its constructs. The results confirm that TAM is a useful theoretical approach to understand and explain the behavioral intention of consumers to use DVAs.

As part of the questionnaire, two open questions were asked. Their evaluation is based on the frequency with which various terms are mentioned. The first question, "In which everyday situation is the use of the Google Assistant helpful?", was answered by 134 people out of 173 respondents. A catchphrase that was mentioned most frequently in the answers is information acquisition – Millennials use Google Assistant to receive answers to simple and spontaneous questions (41 responses). Numerous statistics are also queried more often (15 mentions). Calling up the news using the DVA is less important for the respondents (4 responses). The evaluation also shows that users of DVAs want to obtain information as quickly as possible (38 mentions). Another focus in the responses of the survey participants is the navigation of vehicles with the help of their DVA (32 mentions). It involves route planning and the determination of the current location of the smartphone owner. Apart from the three large subject areas, other terms are mentioned that are important for the users of Voice Assistants. These include weather forecast, use without manual operation, use of the DVA when traveling or driving. Based on the answers to the first open question, it can be said that the users of DVAs already use them mainly for quickly obtaining (brief) information, for navigation, weather forecasting, and when traveling. Customers mainly use DVAs when they cannot operate their smartphone by hand. In addition, DVAs are mainly used by users on the go.

The second open question deals with the topic of the future use of DVAs("In which situation will you use Google Assistant in the future?"). From a total of 173 respondents, 118 people answered this question. The answers given were not distributed as homogeneously as in the first question. This created a wider range of responses. As with the first open question, it

turns out that most of the respondents will also use DVAs in the future for driving a car (i.e. navigation and traffic information - 34 mentions), for weather forecasting (17 mentions), as well as for obtaining short and simple information or will use factual knowledge (15 mentions each). In addition, it turns out that the fast processing of the command is of great importance for the Google Assistant consumer (16 mentions). Fifteen responses were made to the area of application “use when traveling”. Despite the above-mentioned possible uses, a further 22 people say that they do not want to use Google Assistant at all in the future. Twelve participants prefer to use another DVA (e.g., Siri) in the future.

3.7 Limitations

This study has some limitations that researchers may consider in future studies, although the findings of our study nevertheless provide meaningful insights into the technology acceptance of Digital Voice Assistants.

Firstly, key findings of this study are based on data distributed among the students of the University of Bayreuth (Millennials) in Germany. In order to ensure generalizability, a future study should attempt to gather data from a geographically and also ethnically diverse group.

Secondly, we did not examine individual discrepancies among the survey respondents. In the future, the findings could be expanded and refined by investigating the moderating effects of individual differences such as, e.g., gender, age, level of education, and occupation. Future studies should also pay attention to how peoples’ emotions, which they experience during the implementation of new technologies, relate to the use of such technologies (Beaudry and Pinsonneault 2010).

Moreover, access to comparative studies is unfortunately limited. There is no known longitudinal study that is comparable to the survey carried out. Due to the one-time online survey available, the data may lead to results that are not representative.

Furthermore, the survey does not consider all factors that influence customer acceptance of DVAs. Such a questionnaire, which includes all of these factors, would be too large and could lead to excessive demands on the recipient.

Lastly, the survey results mainly apply to the use of the Google Assistant and do not claim to be exhaustive. To improve the information quality of the data, it would be advisable to conduct the survey for other DVAs (e.g., Siri). In addition, other data collection methods, such as surveying focus groups, could also be used in this context. In this way, one could go even better into the rather complex and novel instruments.

Although our study has a few limitations, it adds a more systematic comprehension of the acceptance of DVAs. In this regard, we trust that our research will help to build a foundation for future research on related studies.

3.8 Conclusion and Discussion

The results of this study offer important theoretical insights and practical implications. This is the first empirical academic study, which shed light on which factors lead to customer acceptance of Google Assistant and which areas of application of DVAs consumers find particularly interesting and useful. Mindmeld (2016) examined DVAs usage patterns such as time, frequency, and purpose of use as well as satisfaction. However, it was limited to a descriptive survey report.

The evaluation of the measurement showed that the influence of six hypotheses could be confirmed. Our study verified the robustness of the proposed model by applying it in the context of Digital Voice Assistants. The empirical results showed that the research model has moderate explanatory power. This implies that it creates a useful framework and theoretical basis to explain the acceptance of DVAs, and show that the application of traditional theories is appropriate to reflect the attributes of such a new technology.

The results show that Millennials use a DVA when they primarily want to have a good time and also to save some time. Many of the DVAs' users also turn to such devices when looking for a conversation with somebody. These findings are in line with Rase et al. (2018).

Other variables positively influence the use of Digital Voice Assistants (within the framework of the TAM). These include the perceived usefulness, the Attitude Toward use, and the intention to use it. However, no significant effect of the construct Perceived Ease of Use on Attitude Toward Using DVAs could be ascertained. It can be concluded that Perceived Usefulness and Perceived Ease of Use DVAs lead to their acceptance by customers.

Open questions also show that users of DVAs mainly use them to obtain brief information, navigate, or travel. Our findings are in line with McLean and Osei-Frimpongb 2019). Moreover, the DVA is mainly used on the go or when a manual operation of the smartphone is not possible. It was also found that in the future, recipients will use Digital Voice Assistants, especially to obtain brief information or while driving a car. Siri is preferred for iOS smartphones and the Google Assistant for Android phones depending on the smartphone software.

This study offers especially large corporations, such as car manufacturers and technology developers, numerous practical implications. To increase users' satisfaction (Baier et al. 2018) and assure higher intention to use, DVA designer should focus on developing "human-like" and more "professional" Voice Assistant, which will give stronger feeling of communi-

cating with a human, rather than a robot. The results of our study outline the importance of Digital Voice Assistants in a daily life. Practitioners should note that Digital Voice Assistants can be used in almost every situation, not only at home but also in the city, in cars, shops, etc. This makes out of DVAs a very powerful tool. Since nowadays people want to use their smartphones anytime and anywhere, but this can sometimes be very dangerous, the use of DVAs, especially in cars, would be a useful idea. It would give the opportunity to operate a smartphone – to make phone calls, to start navigation or to turn on music – without using hands. Furthermore, DVA designers should carefully consider their target group. The results of our study have shown that millennials are very tech-savvy and like to reach for DVAs. Based on the results, one could also say that people in general who have little contact with other people, e.g., older people, could benefit from DVAs, which could provide in such case e.g., some enjoyment in the life of older and/or ill people.

For future research, data collection with a larger, heterogeneous sample or with the help of other methods is recommended. Future studies are encouraged to include larger heterogeneous target group. In addition, random sampling should take place. Ultimately, the survey results are primarily for the use of Google Assistant and make no demands on completeness. To improve the quality of the data, it would be advisable to explore other DVAs (e.g., Siri, Cortana). Future studies should highlight the social aspect of DVAs because they will resemble humans more, as AI technology advances.

Modifying the original TAM by integrating five constructs based on UGA leads to meaningful results and is recommended for further studies to measure customers' acceptance. For this reason, in-depth research originating in UGA and TAM is recommended. Finally, an interesting extension of this study would be to determine how the research model can be adapted to include the perceptions of non-users.

In summary, it can be said that Digital Voice Assistants are an interesting and useful innovation. The idea of a personal assistant in the digital age is very contemporary, convincing, and more than understandable. To respond more to the needs of the individual, Digital Voice Assistants are continuously being developed. New functions are constantly being added that can make everyday life much easier for smartphone users.

3.9 Appendix

Appendix 1: Studies on the acceptance of Digital Voice Assistants; **Source:** Own depiction

Source (Year)	Title	Key findings
Yang and Lee (2019)	Understanding user behavior of virtual personal assistant devices	The authors examine the reasons why digital voice assistants are used in everyday life. The following findings were made: Fun and usefulness are two reasons for using the technology, with the influence of fun on the intended use is stronger. The usefulness of the assistant is influenced by the level of automation and the quality of the information. The mobility, i.e., the flexibility to use the assistant anywhere, has no significant influence on its usefulness. The fun factor is determined by the visual attractiveness, i.e., the appearance, of the assistant, but also by the quality of the information.
pwc (2018)	Consumer Intelligence Series: Prepare for the voice revolution	- Three out of four consumers (74 percent of respondents) use their mobile voice assistants at home; - Men and younger consumers are more likely to get involved in newer, innovative functions of the voice assistant; - Consumers see voice assistants as a faster and easier way of getting things done on a daily basis (e.g., 71 percent of respondents look for information using digital voice assistants); - When it comes to money matters (shopping, reimbursement of a flight ticket, etc.), consumers prefer to keep it personally dealt with; - 50 percent of the respondents purchased everyday items through their voice assistant, and another 25 percent would do so in the future. Most of the purchases were of little value, the quality of which is already known.
Han and Yang (2018)	Understanding adoption of intelligent personal assistants	The acceptance of the digital voice assistant is also evident in the acceptance of the hardware devices for the home. The trend towards the smart home is increasing. The market research institute Gartner shows that more and more households are bringing wireless assistants into their homes.
Bitkom (2018)	Zukunft der Consumer Technology - 2018: Marktentwicklung, Trends, Mediennutzung, Technologien, Geschäftsmodelle	- 13 percent of the respondents (this corresponds to 8.7 million German citizens) already use intelligent loudspeakers with digital voice assistants; - Four out of five German citizens (84%) are already familiar with digital voice assistants; - More than one in four respondents can imagine using various devices verbally in the future; - 4 percent of the recipients plan to acquire a language assistant within the coming year; - A third of respondents (33 percent) can imagine using digital voice assistants for navigation and travel.
Kepuska and Bohouta (2018)	Next-Generation of virtual personal assistants (Microsoft Cortana, Apple Siri, Amazon Alexa and Google Home)	Digital voice assistants have so far been used in healthcare, education, or at work. They are also installed in vehicles, making the onboard computer easier to use. The latest trend in digital voice assistants is to use them for a so-called smart home and increase, e.g., security in the house.
EY (2018)	Intelligente Sprachassistenten: Ergebnisse der Kundenbedürfnisanalyse"	- 50 percent of the respondents either rarely or do not at all use digital voice assistants; voice assistants are used frequently by 10 percent of those surveyed; - The digital voice assistant is particularly popular within younger people; - More than 80% of the respondents consider data security and privacy to be important; - More than 50% attach great importance to human interaction with the voice assistant; - For half of the respondents, information retrieval is the most important function of a digital voice assistant; - A quarter of the recipients can imagine carrying out monetary transactions with the voice assistant; - 25% of customers are ready to purchase digital voice assistants. They prefer a one-off payment.
pwc United States (2018)	Prepare for the voice revolution	Digital voice assistants are popular because they are often the easiest, most convenient, and the fastest way to get information or carry out certain activities. Instead of talking to a person, virtual assistants are used for reasons of efficiency. For non-everyday activities in which money plays a role, such as online shopping or mobile banking, digital voice assistants have so far been used less and reluctantly.
Snell (2018)	Siri: What Apple needs to do to improve voice-activated digital assistant	The author delves into the drawbacks of Siri. For one thing, Siri users are bored and annoyed by its nature. Many users do not want to build a personal bond with Siri but rather use it for efficiency reasons and not to hear jokes - they want an exchange of knowledge on a factual basis. Furthermore, unlike other voice assistants, Siri cannot distinguish the people who speak to it because there is no voice training and no personalized information. This becomes problematic when several people use Siri, for example, with the HomePod.
Chung et al. (2017)	„Alexa, Can I Trust You?"	Potential users are discouraged from using digital voice assistants because it is too risky for them. They fear for their privacy if certain activities can be carried out through verbal commands. That's why some assistants have voice training so that they only react to the owner. Unfortunately, it will be difficult for the system to filter out the wrong ones between voices that sound similar. There is always a risk when using the voice assistant.
Capgemini Digital Transformation Institute (2017)	Conversational Commerce: Why consumers are embracing voice assistants in their lives	- More than two-thirds (69 percent) prefer using voice assistants at home, while only 32 percent of users want to use voice assistants in public; - The majority of respondents (71 percent) consider the security of their data very important; - 44 percent of users are interested in doing banking with the help of voice assistants.
Guzman (2017)	Making AI safe for humans: A conversation with Siri	Many digital voice assistants are female. When Apple launched Siri, the discussion arose as to whether the portrayal of Siri as a woman is brilliant or misogynistic since one could think of a secretary when thinking of a female assistant doing everyday tasks. However, the female Siri was quickly accepted, among other things, because a woman's voice is more pleasant. Apple also deliberately never referred to Siri as a secretary.

Appendix 2: Quality assessment of the measurement model; **Source:** Own depiction

Construct / Items	N	Mean	SD	FL	AVE	CA	CR
Pastime					0.640	0.717	0.841
PA1	172	2.547	1.042	0.877			
PA2	172	2.238	0.992	0.773			
PA3	172	2.831	1.126	0.745			
Enjoyment					0.683	0.767	0.866
EN1	172	3.607	1.007	0.818			
EN2	172	3.532	1.062	0.888			
EN3	172	2.890	1.000	0.770			
Image					0.721	0.871	0.812
IM1	172	1.500	0.859	0.864			
IM2	172	2.616	1.143	0.767			
IM3	172	1.523	0.859	0.894			
IM4	172	1.640	0.933	0.867			
Expediency					0.804	0.759	0.891
EX1	172	3.029	1.083	0.920			
EX2	172	3.156	1.093	0.873			
Fear of Data Misuse					0.925	0.960	0.974
FDM1	171	3.657	1.193	0.975			
FDM2	171	3.671	1.193	0.977			
FDM3	171	3.751	1.193	0.933			
Perceived Usefulness					0.633	0.807	0.873
PU1	170	3.386	0.919	0.817			
PU2	170	2.747	0.977	0.764			
PU3	170	2.708	1.018	0.846			
PU4	170	1.982	0.958	0.751			
Perceived Ease of Use					0.620	0.694	0.830
PEOU1	171	3.994	0.873	0.797			
PEOU2	171	3.483	0.899	0.789			
PEOU3	171	3.076	0.928	0.775			
Attitude Toward Using					0.707	0.862	0.906
ATU1	172	2.630	1.027	0.889			
ATU2	172	2.965	0.949	0.873			
ATU3	172	3.399	0.978	0.844			
ATU4	172	3.873	0.816	0.751			
Behavioral Intention to Use					0.783	0.861	0.915
BIU1	172	2.728	1.113	0.925			
BIU2	172	2.613	1.067	0.923			
BIU3	172	2.514	1.136	0.800			
Actual System Use					0.648	0.725	0.846
ASU1	172	1.353	0.781	0.810			
ASU2	172	1.671	1.193	0.862			
ASU3	172	2.711	1.485	0.737			

Scale: 1= strongly disagree; 5= strongly agree. Abbreviations: **SD**= Standard Deviation; **FL**= Factor Loading; **AVE**= Average Variance Extracted; **CA**= Cronbach Alpha; **KMO**= Kaiser-Meyer-Olkin Criteriom; **TVE**= Total Variance Explained; **CR**= Composite Reliability.

3.10 References

Ajzen, I. (1985), „From Intentions to Actions: A Theory of Planned Behavior“, in Action Control - From Cognition to Behavior, (Hrsg.) J. Kuhl and J. Beckmann, Berlin, Heidelberg, Springer Verlag: 11-39.

Alhabash, S., Y. Chiang and K. Huang (2014), „TAM & U&G in Taiwan: Differences in the uses and gratifications of Facebook as a function of motivational reactivity”, Computers in Human Behavior, 35, 423–430.

Ancu, M. and R. Cozma (2009), „MySpace Politics: Uses and Gratifications of Befriending Candidates”, Journal of Broadcasting & Electronic Media, 53 (4), 567–583.

Bagozzi, R.P. (2007), „The Legacy of the Technology Acceptance Model and a Proposal for a Paradigm Shift”, Journal of the Association for Information Systems, 8 (4), 244-254.

Baier, D., A. Rese and M. Röglinger (2018), „Conversational user interfaces for online shops? A categorization of use cases”, International Conference on Information Systems 2018, ICIS 2018.

Bass, F. M. (1969), „A new product growth model for consumer durables”, Management Science, 15, 215–227.

Beaudry, A. and A. Pinsonneault (2010), „The Other Side of Acceptance: Studying the Direct and Indirect Effects of Emotions on Information Technology Use'', MIS Quarterly, 34 (4), 689-710.

Benbasat, I. and H. Barki (2007), „Quo vadis, TAM?”, Journal of the Association for Information Systems, 8 (4), 211-218.

Bitkom (2018), „Zukunft der Consumer Technology - 2018: Marktentwicklung, Trends, Mediennutzung, Technologien, Geschäftsmodelle”.

Bitkom (2017), „Das Smartphone gehorcht aufs Wort”, https://www.bitkom.org/Presse/Presseinformation/Das-Smartphone-gehorcht-aufs-Wort.html.

Brandtzaeg, P. B. and A. Følstad (2017), „Why People Use Chatbots”, in Internet Science: 4th International Conference, INSCI 2017, Thessaloniki, Greece, November 22-24, 2017, Proceedings. Lecture Notes in Computer Science, 10673. Aufl., (Hrsg.) Y. Kompatsiaris, J. Cave, Anna Satsiou, G. Carle, A. Passani, E. Kontopoulos, S. Diplaris and D. McMillan, Cham: Springer International Publishing, 377–392.

BMWi – Bundesministerium für Wirtschaft und Energie (2018), „Altmaier: „Künstliche Intelligenz maßgeblich für Wachstum im produzierenden Gewerbe“”,

https://www.bmwi.de/Redaktion/DE/Pressemitteilungen/2018/20180719-altmaier-kuenstliche-intelligenz-massgeblich-fuer-wachstum-im-produzierenden-gewerbe.html.

BVDW - Bundesverband Digitale Wirtschaft e.V. (2017), „Digital Trends: Umfrage zu digitalen Sprachassistenten".

Capgemini Digital Transformation Institute (2017), „Conversational Commerce: Why consumers are embracing voice assistants in their lives".

Chen, J.-Y. and Ma, Y.-P., Jeng, T.S., Chang, C.-C. (2011), „An assessment of user needs for intelligent living space", Intelligent Buildings International, 2 (1), 20–40.

Chen, R., Z. Tian, H. Liu, F. Zhao and S. Zhang (2018), „Construction of a voice driven life assistant system for visually impaired people", in 2018 International Conference on Artificial Intelligence and Big Data: ICAIBD 2018, May 26-28, 2018, Chengdu, China, Piscataway, NJ: IEEE Press, 87–92.

Chin, W. W. (1998), „The partial least squares approach to structural equation modeling", in Modern methods for business research, (Hrsg.) G. A. Marcoulides and N. J. Mahwah: Lawrence Erlbaum, 295–358.

Chu, A. and R. Chu (2011), „The intranet's role in newcomer socialization in the hotel industry in Taiwan - technology acceptance model analysis", The International Journal of Human Resource Management, 22 (5), 1163–1179.

Chung, M., E. Ko, H. Joung and S.J. Kim (2018), „Chatbot e-service and customer satisfaction regarding luxury brands". Journal of Business Research, Elsevier, vol. 117(C), 587-595.

Chung, H., M. Iorga, J. Voas and S. Lee (2017), „Alexa, Can I Trust You?", Computer, 50 (9), 100–104.

Cleff, T. (2015), „Deskriptive Statistik und Explorative Datenanalyse", Wiesbaden, Gabler Verlag.

Cohen, J. (1992), „A Power Primer", Psychological Bulletin, 112 (1), 155–159.

Compeau, D. R. and C. A. Higgins (1995a), „Application of Social Cognitive Theory to Training for Computer Skills", Information Systems Re-search, 6 (2), 118-143.

Compeau, D. R. and C. A. Higgins (1995b), „Computer Self-Efficacy: Development of a Measure and Initial Test", Medical Reference Services Quarterly, 19 (2), 189-211.

Coskun-Setirek, A. and S. Mardikyan (2017), „Understanding the Adoption of Activated Personal Assistants", International Journal of E-Services and Mobile Applications, 9 (3), 1-21.

Curras-Perez, R., C. Ruiz-Mafe and S. Sanz-Blas (2014), „Determinant of user behaviour and recommendation in social networks: An integrative approach from the uses and gratifications perspective", Industrial Management & Data Systems, 114 (9), 1477–1498.

Davis, F. D. (1985), „A technology acceptance model for empirically testing new end-user information systems: theory and results.", Massachusetts Institute of Technology.

Davis, F. D. (1989), „Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology", MIS Quarterly, 13 (3), 319–340.

Davis, F. D., R. P. Bagozzi and P. R. Warshaw (1989), „User Acceptance of Computer Technology: A Comparison of Two Theoretical Models", Management Science, 35 (8), 982–1003.

Davis, F. D., R. P. Bagozzi and P. R. Warshaw (1992), „Extrinsic and Intrinsic Motivation to Use Computers in the Workplace", Journal of Applied Social Psychology, 22 (14), 1111-1132.

Deal, J. J., D. G. Altman and S. G. Rogelberg (2010), „Millennials at Work: What We Know and What We Need to Do (If Anything)", Journal of Business and Psychology, 25, 191-199.

DeFleur, M. L. (2016), Mass communication theories: Explaining origins, processes, and effects, London, New York: Routledge Taylor & Francis Group.

Digital Trends (2018), „Google Assistant: The complete history of the voice of Android".

Dijkstra, T. K., and J. Henseler (2015), „Consistent Partial Least Squares Path Modeling", MIS Quarterly, 39 (2), 297–316.

Drosdowski, G. (1997), Das Herkunftswörterbuch: Etymologie der deutschen Sprache, Mannheim.

Eastman, J. K., R. Iyer, S. Liao-Troth, D. F. Williams and M. Griffin (2014), „The Role of Involvement on Millennials' Mobile Technology Behaviors: The Moderating Impact of Status Consumption, Innovation, and Opinion Leadership", Journal of Marketing Theory and Practice, 22 (4), 455-470.

Easwara, M. A. and K.-P. L. Vu (2015), „Privacy Concerns for Use of Voice Activated Personal Assistant in the Public Space", International Journal of Human-Computer Interaction, 31 (4), 307–335.

Elmorshidy, A. (2013), „Applying the Technology Acceptance and Service Quality Models to Live Customer Support Chat for E-Commerce Websites", The Journal of Applied Business Research, 29 (2), 589–595.

Elmorshidy, A., M. M. Mostafa, I. El-Moughrabi and H. Al-Mezen (2015), „Factors Influencing Live Customer Support Chat Services: An Empirical Investigation in Kuwait", Journal of Theoretical and Applied Electronic Commerce Research, 10 (3), 63–76.

EY (2018), „Intelligente Sprachassistenten: Ergebnisse der Kundenbedürfnisanalyse".

Fishbein, M. and I. Ajzen (1975), „Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research", Reading, Mass: Addison-Wesley.

Fornell, C. and D. F. Larcker (1981), „Evaluating Structural Equation Models with Unobservable Variables and Measurement Error", Journal of Marketing Research, 18 (1), 39.

Gaggioli, A. (2018), „Virtual Personal Assistants: An Emerging Trend in Artificial Intelligence", Cyberpsychology, behavior and social networking, 21 (12), 803–804.

Gao, T., F. Sultan and A. J. Rohn (2010), „Factors influencing Chinese youth consumers' acceptance of mobile marketing", Journal of Consumer Marketing, 574–583.

Gan, C. and H. Li (2018), „Understanding the effects of gratifications on the continuance intention to use WeChat in China: A perspective on uses and gratifications", Computers in Human Behavior, 78, 306–315.

Gefen, D., E. Karahanna and D. W. Straub (2003), „Trust and TAM in online shopping: An integrated model", Management Information Systems Quarterly, 27 (1), 51–90.

Greenberg, B. S. (1974), „Gratifications of television viewing and their correlates for British children", in The uses of mass communications: Current perspectives on gratifications research, (Hrsg.) J. G. Blumler and E. Katz, Beverly Hills, CA: Sage, 71–92.

Guzman, A. L. (2017), „Making AI safe for humans: A conversation with Siri", in Socialbots and their friends: Digital media and the automation of sociality, (Hrsg.) R. W. Gehl und M. Bakardjieva, New York, NY: Routledge, 69–85.

Hair, J. F., M. Sarstedt, and C. M. Ringle (2019), „Rethinking some of the rethinking of partial least squares", European Journal of Marketing, 53 (4), 566–584.

Hair, J. F., G. T. M. Hult, C. M. Ringle, M. Sarstedt, N. F. Richter and S. Hauff (2017), „Partial Least Squares Strukturgleichungsmodellierung (PLS-SEM): Eine anwendungsorientierte Einführung", München: Franz Vahlen.

Hair, J. F., M. Sarstedt, C. M. Ringle and J. A. Mena (2012), „An assessment of the use of partial least squares structural equation modeling in marketing research", Journal of the Academy of Marketing Science, 40 (3), 414-433.

Hair, J. F., C. M. Ringle and M. Sarstedt (2011), „PLSSEM: Indeed a Silver Bullet", Journal of Marketing Theory and Practice, 19 (2), 139-152.

Han, S., and Yang, H. (2018). „Understanding adoption of intelligent personal assistants: a parasocial relationship perspective", Industrial Management & Data Systems, 118 (3), 618-636.

Henseler, J., C. M. Ringle and M. Sarstedt (2015), „A new criterion for assessing discriminant validity in variance-based structural equation modeling", Journal of the Academy of Marketing Science, 43 (1), 115-135.

Herrero, S. T., Nicholls, L., and Strengers, Y. (2018). „Smart home technologies in everyday life: do they address key energy challenges in households?", Current Opinion in Environmental Sustainability, 31, 65-70.

Himme, A. (2007), „Gütekriterien der Messung: Reliabilität, Validität und Generalisierbarkeit" in Methodik der empirischen Forschung, (Hrsg.) S. Albers, Wiesbaden, Gabler Verlag, 485-500.

Hoy, M. B. (2018), „Alexa, Siri, Cortana, and More: An Introduction to Voice Assistants", Medical reference services quarterly, 37 (1), 81–88.

Hu, P. J., P. Y. K. Chau, O. R. L. Sheng and K. Y. Tam (1999), „Examining the Technology Acceptance Model Using Physician Acceptance of Telemedicine Technology", Journal of Management Information Systems, 16 (2), 91–112.

Huber, F., A. Herrmann, F. Meyer, J. Vogel and K. Vollhardt (2007), Kausalmodellierung mit Partial Least Squares, Wiesbaden: Gabler Verlag.

Jahn, S. (2007), „Strukturgleichungsmodellierung mit LISREL, AMOS und SmartPLS: Eine Einführung (An Introduction to Structural Equation Modeling with LISREL, AMOS and SmartPLS)" SSRN Electronic Journal, 26 (2), 1-46.

Jiang, J., A. H. Awadallah, R. Jones, U. Ozertem, I. Zitouni, R. G. Kulkarni and O. Z. Khan (2015), „Automatic Online Evaluation of Intelligent Assistants", in Proceedings of the 24th International Conference on World Wide Web, (Hrsg.) World Wide Web Conference, Florence, Italy, 506–516.

Jones, V. K. (2018), „Voice-activated Change: Marketing in the age of artificial intelligence and virtual assistants", Journal of brand strategy, 7 (3).

Joo, J. and Y. Sang (2013), „Exploring Koreans' smartphone usage: An integrated model of the technology acceptance model and uses and gratifications theory", Computers in Human Behavior, 29 (6), 2512–2518.

Katz, E. (1959), „Mass Communications Research and the Study of Popular Culture: An Editorial Note on a Possible Future for This Journal", Departmental Papers (ASC).

Katz, E., J. G. Blumler and M. Gurevitch, (Hrsg.) (1974), Utilization of Mass Communication by the Individual.

Kayak (2017), „Mobile Travel Report", https://www.kayak.co.uk/news/mobile-travel-report-2017/.

Kaye, B. K. (1998), „Uses and gratifications of the World Wide Web: From couch potato to web potato", New Jersey Journal of Communication, 6 (1), 21–40.

Kepuska, V. and G. Bohouta (2018), „Next-generation of virtual personal assistants (Microsoft Cortana, Apple Siri, Amazon Alexa and Google Home)", in Proceedings of the 8th annual Computing and Communication Workshop and Conference, (Hrsg.) IEEE, Las Vegas, NV, 99–103.

Klopfenstein, L. C., S. Delpriori, S. Malatini and A. Bogliolo (2017), „The Rise of Bots", Proceedings of the Conference on Designing Interactive Systems, (Hrsg.) DIS, Edinburgh, UK, 555–565.

Knobloch, S. (2003), „Mood adjustment via mass communication", Journal of Communication, 53, 233–250.

Ku, Y. C., T. H. Chu and C. H. Tseng (2013), „Gratifications for using CMC technologies: A comparison among SNS, IM, and e-mail", Computers in Human Behavior, 29 (1), 226–234.

Legris, P., J. Ingham and P. Collerette (2003), „Why do people use information technology? A critical review of the technology acceptance model", Information & Management, 40 (3), 191–204.

Leung, L. and R. Wei (2000), „More Than Just Talk on the Move: Uses and Gratifications of the Cellular Phone", Journalism & Mass Communication Quarterly, 77 (2), 308–320.

Li, H., Y. Liu, X. Xu, J. Heikkilä and H. van der Heijden (2015), „Modeling hedonic is continuance through the uses and gratifications theory: An empirical study in online games", Computers in Human Behavior (48), 261–272.

Likert, Rensis (1932), "A technique for the measurement of attitudes", Archives of Psychology, 22 (140), 55.

Lin, H.-F. and C.-H. Chen (2017), „Combining the Technology Acceptance Model and Uses and Gratifications Theory to examine the usage behavior of an Augmented Reality Tour-sharing Application", Symmetry, 7 (9), 1–22.

Lometti, G. E., B. Reeves and C. R. Bybee (1977), „Investigating the Assumptions of Uses and Gratifications Research", Communication Research, 4 (3), 321–338.

Macronomy (2018), „Digitale Sprachassistenten – Nutzung von Alexa, Siri und Co. nimmt zu", https://www.marconomy.de/digitale-sprachassistenten-nutzung-von-alexa-siri-und-co-nimmt-zu-a-722632/.

Malik, A., A. Dhir and M. Nieminen (2016), „Uses and Gratifications of digital photo sharing on Facebook", Telematics and Informatics, 33 (1), 129–138.

Mari, A. (2019, October), „Voice Commerce: Understanding shopping-related voice assistants and their effect on brands" In IMMAA Annual Conference. Northwestern University in Qatar, Doha (Qatar).

McLean, G. and K. Osei-Frimpong (2017), „Examining satisfaction with the experience during a live chat service encounter-implications for website providers", Computers in Human Behavior, 76, 494–508.

McQuail, D., J. G. Blumler und J. R. Brown (1972), „The television audience: a revised perspective", in Sociology of Mass Communications, (Hrsg.) D. McQuail, Middlesex: Penguin, 135–165.

MindMeld 2016. „Intelligent Voice Assistants - Q1 2016 User Adoption Survey".

Moon, J-W and Y.G. Kim (2001), „Extending the TAM for a World-Wide-Web context", Information & Management, 38 (4), 217–230.

Myers, K. K. and K. Sadaghiani (2010), „Millennials in the Workplace: A Communication Perspective on Millennials' Organizational relationships and Performance", Journal of Business and Psychology, Vol. 25 No.2, Special Issue June 2010, 225-238.

Nasirian, F., Ahmadian, M., and Lee, O. K. D. (2017), „AI-based voice assistant systems: Evaluating from the interaction and trust perspectives", Twenty-third Americas Conference on Information Systems, Boston, 2017.

Niehaves, B. and R. Plattfaut (2014), „Internet adoption by the elderly: Employing IS technology acceptance theories for understanding the age-related digital divide", European Journal of Information Systems, 23 (6), 708–726.

Olbrich, R., D. Battenfeld and C.-C. Buhr (2012), Marktforschung: Ein einführendes Lehr- und Übungsbuch, Berlin, Heidelberg: Springer Berlin Heidelberg.

Papacharissi, Z. and A. M. Rubin (2000), „Predictors of Internet Use", Journal of Broadcasting & Electronic Media, 44 (2), 175–196.

Park, S. Y. (2009), „An Analysis of the Technology Acceptance Model in Understanding University Students' Behavioral Intention to Use e-Learning", Educational Technology & Society, 3 (12), 150–162.

PEW Research Center (2017), „American Trends Panel".

Porter, C. E. and N. Donthu (2006), „Using the technology acceptance model to explain how attitudes determine Internet usage: The role of perceived access barriers and demographics", Journal of Business Research, 59 (9), 999–1007.

Pwc (2018), „Consumer Intelligence Series: Prepare for the voice revolution".

pwc United States (2018), „Prepare for the voice revolution", https://www.pwc.com/us/en/services/consulting/library/consumer-intelligence-series/voice-assistants.html.

Rase, Y., A. Ormaza Cuadra, and C. de Moerloose (2018), „The use of personal voice assistants in the context of retail digitalization: An empirical study of consumers' attitude and privacy concerns" (Doctoral dissertation, Master's thesis). Louvain School of Management, Université catholique de Louvain, Louvain-la-Neuve. Supervisor: de Moerloose, Chantal).

Rauschnabel, P. A. and Y. K. Ro (2016), „Augmented reality smart glas-ses: an investigation of technology acceptance drivers", International Journal of Technology Marketing, 11 (2), 123–148.

Rauschnabel, P. A., A. Rossmann and M. C. Tom Dieck (2017), „An adoption framework for mobile augmented reality games: The case of Pokemon Go", Computers in Human Behavior (76), 276–286.

Rauschnabel, P. A. (2018), „A Conceptual Uses & Gratification Frame-work on the Use of Augmented Reality Smart Glasses", in Augmented Reality and Virtual Reality: Empowering Human, Place and Business. Progress in IS, (Hrsg.) T. Jung and M. C. Tom Dieck, Cham: Springer International Publishing, 211–227.

Rese, A., S. Schreiber and D. Baier (2014), „Technology acceptance modeling of augmented reality at the point of sale: Can surveys be replaced by an analysis of online reviews?", Journal of Retailing and Consumer Services, 1–8.

Ringle, C. M. and M. Sarstedt (2016), „Gain more insight from your PLS-SEM results: The importance-performance map analysis", Industrial Management & Data Systems, 116 (9), 1865–1886.

Ringle, C. M., M. Sarstedt and D. W. Straub (2012), „Editor's Comments: A Critical Look at the Use of PLS-SEM in MIS Quarterly", MIS Quarterly, 36 (1), iii.

Rogers, E. M. (1995), Diffusion of Innovations, New York: Free Press.

Sarikaya, R. (2017), „The Technology Behind Personal Digital Assistants: An overview of the system architecture and key components", IEEE Signal Processing Magazine, 34 (1), 67–81.

Sayago, S., Neves, B. B., and Cowan, B. R. (2019), „Voice assistants and older people: some open issues", In Proceedings of the 1st International Conference on Conversational User Interfaces (7), ACM.

Shankar, V. (2018). „How Artificial Intelligence (AI) is reshaping retail". Journal of Retailing, 94(4), VI-XI.

Snell, J. (2018), „Siri: What apple needs to do to improve its voice-activated digital assistant", Macworld, 95–99.

Song, I., R. LaRose, Eastin M. S. and C. A. Lin (2004), „Internet Gratifications and Internet Addiction: On the Uses and Abuses of New Media", Cyberpsychology & behavior, 7 (4), 384–394.

Stafford, T. F., M. R. Stafford and L. L. Schkade (2004), „Determining Uses and Gratifications for the Internet", Decision Sciences, 35 (2).

Statista (2017a), „In immer mehr Bereichen des Lebens spielen digitale Sprachassistenten eine Rolle. Welche dieser Sprachassistenten kennen Sie?", https://de.statista.com/statistik/daten/studie/739040/umfrage/umfrage-zur-bekanntheit-ausgewaehlter-sprachassistenten-in-deutschland/.

Statista (2017b), „Prognose zum Volumen der jährlich generierten digitalen Datenmenge weltweit in den Jahren 2016 und 2025", https://de.statista.com/statistik/daten/studie/267974/umfrage/prognose-zum-weltweit-generierten-datenvolumen/.

Statista (2017c), „Prognose zum Volumen der jährlich generierten digitalen Datenmenge weltweit in den Jahren 2016 und 2025", https://de.statista.com/statistik/daten/studie/267974/umfrage/prognose-zum-welt-weit-generierten-datenvolumen/.

Stavropoulos, V., D. Kuss, M. Griffiths and F. Motti-Stefanidi (2016), „A Longitudinal Study of Adolescent Internet Addiction", Journal of Adolescent Research, 31 (4), 442–473.

Stone, M. (1974), „Cross-validation and multinomial prediction", Biometrika, 61 (3), 509–515.

Sundar, S. S. and Anthony M. Limperos (2013), „Uses and Grats 2.0: New Gratifications for New Media", Journal of Broadcasting & Electronic Media, 57 (4), 504–525.

Taylor, S. and P. Todd (1995), „Assessing IT Usage: The Role of Prior Experience", Management Information Systems Quarterly, 19(4), 561–570.

Thompson, R. L., C. A. Higgins and J. M. Howell (1991), „Personal Computing: Toward a Conceptual Model of Utilization", Management Information Systems Quarterly, 15(1), 125-143.

Tuzovic, S. and Paluch, S. (2018), „Alexa–What's on my shopping list? Investigating consumer perceptions of voice-controlled services", In SERVSIG Conference Proceedings 2018 Paris: Opportunities for services in a challenging world. SERVSIG, France, 107-110.

van der Heijden, H. (2004), „User Acceptance of Hedonic Information Systems", MIS Quarterly, 28 (4), 695–704.

Venkatesh, V. and F. D. Davis (2000), „A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies", Management Science, 46 (2), 186–204.

Venkatesh, V., J. Y. L. Thong and X. Xu (2012), „Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology", MIS Quarterly, 36 (1), 157–178.

Wagner, K., Nimmermann, F. and Schramm-Klein, H. (2019), „Is It Human? The Role of Anthropomorphism as a Driver for the Successful Acceptance of Digital Voice Assistants", In Proceedings of the 52nd Hawaii International Conference on System Sciences.

Wei, P. S. and H. P. Lu (2014), „Why do people play mobile social games? An examination of network externalities and of uses and gratifications", Internet Research, 24 (3), 313–331.

Weiber, R. and D. Mühlhaus (2014), Strukturgleichungsmodellierung, Berlin, Heidelberg: Springer Berlin Heidelberg.

Whiting, A. and D. Williams (2013), „Why people use social media: a uses and gratifications approach", Qualitative Market Research: An International Journal, 16 (4), 362–369.

Wold, H. (1975), „Path Models with Latent Variables: The NIPALS Approach", Quantitative Sociology, Academic Press, 307–357.

Wu, J.-H. and S.-C. Wang (2005), „What drives mobile commerce? An empirical evaluation of the revised technology acceptance model", Information & Management (42), 719–729.

Yang, H. und H. Lee (2019), „Understanding user behavior of virtual personal assistant devices", Information Systems and e-Business Management, 17, 65–87.

YouGov (2017), „Kommunikation per Chatbot: Sind Ihre Kunden bereit für das nächste Level des Kundenservice?", https://campaign.yougov.com/DE_2017_08_Reports_Chatbots .html ?utm _source=press&utm_medium=media&utm_campaign=report_chatbot.

4 Research paper #3: Siri, Do I like You? Digital Voice Assistants and Their Acceptance by Consumers

Authors: Ewers, K., Baier, D., Höhn, N.

Published in: Journal of Service Management Research. Vol. 4 (2020) Issue 1, pp. 52-66.

DOI: 10.15358/2511-8676-2020-1-52

Abstract: Nowadays, Digital Voice Assistants (DVAs) such as Amazon's Alexa, Google's Assistant, or Apple's Siri provide speech-oriented human-computer inter- faces that have the potential to make consumers' interaction with other consumers, firms, or devices more convenient, enjoyable, and productive. How- ever, at least currently, DVA acceptance is limited, even among digital natives and corresponding explanations are missing. This paper seeks to close this gap by investigating which factors have an impact on DVA acceptance. Therefore, we develop a new approach that combines elements of the Technology Acceptance Model (TAM) as well as the Uses and Gratifications Approach (UGA). A sample of 283 digital natives participated in a Siri field experiment. The results demonstrate that especially enjoyment, but also social status and social influence are main DVA acceptance drivers. Nevertheless, Millennials have some privacy concerns about companies getting too much personal information while using DVAs. This study provides valuable insights into main drivers of DVA acceptance. Theoretical and practical implications are discussed.

Keywords: Acceptance, Digital Voice Assistants (DVAs), Uses and Gratifications Approach (UGA), Technology Acceptance Model (TAM).

4.1 Introduction

The idea to communicate with devices in spoken natural language and to control them in this way is not new. Already in 1966, Joseph Weizenbaum invented ELIZA, an early chatbot that mainly consisted of a database of keywords and contents as well as a pattern matching and substitution methodology that gave users the illusion as if the program is able to understand asked questions in natural language and to provide meaningful answers (Weizenbaum 1966). Since then (and triggered by massive advances in linguistics, data computing and storage as well as speech-to-text and text-to-speech converters) the capabilities of such chatbots have rapidly evolved (Wünderlich & Paluch 2017, Čaić et al. 2018; Wirtz et al. 2018; Ivanov 2019a). Nowadays, large, internationally operating companies such as Amazon, Apple, and Google are making their way into everyday consumers' life, providing powerful Digital Voice Assistants (DVAs) like Alexa, Siri, or Google Assistant for everyone. Companies distribute impressing numbers of DVAs (pre-)installed on smartphones (e.g. Siri, Google Assistant) or smart speakers (e.g. Alexa). However, it is unclear, to what extent DVAs – especially their speech features – are used by the consumers and which are the determining factors for their acceptance.

Besides this lack of in-depth usage studies, DVA acceptance has rarely been discussed from a theoretical point of view. Our study tries to fill this gap and examines DVA acceptance based on two well-known theoretical models. We develop customized gratuities, which are tailored for DVAs – hedonic and utilitarian reasons as well as risks regarding to the DVA acceptance. By using such a wide range of probable reasons for DVA usage (or not usage), our results contribute towards a better understanding of their acceptance. Until now, only few research in this direction has been published (Joo and Sang 2013; Park et al. 2014). In our study we rely on a new, integrated measurement approach based on the Technology Acceptance Model (TAM) and on five gratuities derived from the Uses and Gratifications Approach (UGA). We aim to suggest a model, which can explain and even predict DVA acceptance. The main research objective is to confirm that these factors positively or negatively influence the acceptance of DVAs. In order to answer this question, we apply the approach using Siri's speech features as an example. Through our findings, future research is stimulated to recognize, define, and interpret reasons for the usage of DVAs. Not only researchers, but also practitioners may profit from the study outcomes.

The paper is structured as follows: In section 2, two approaches (TAM and UGA) for measuring technology acceptance are described in detail. Section 3 discusses DVAs and the development of the new approach. Section 4 describes the empirical study: data collection and analysis as well as the results. Sections 5 and 6 close with a discussion and implications as well as a conclusion and an outlook.

4.2 Approaches for measuring technology acceptance

4.2.1 Technology Acceptance Model (TAM)

TAM and its numerous extensions are wide-spread approaches for exploring the acceptance of new technologies. Being developed by Davis in 1986 (Davis 1986), the origin of the model can be found in behavioral psychology, especially in the Theory of Reasoned Action (TRA) by Ajzen and Fishbein (Davis et al. 1989). TRA makes the basic assumption that an individual's behavior is determined by both – behavioral intention and attitude (Joo and Sang 2013). Building on TRA's assumptions, TAM seeks to pinpoint factors, which influence an individual's behavioral intent towards the use of a technology (Park et al. 2007). Davis initially created TAM for computer-based information systems to explore the acceptance and the adoption of traditional technologies in the workplace (Davis 1986; Kim et al. 2007). Because of its flexibility, TAM has been extended as well as adopted and applied to many different contexts, e.g. in mobile commerce (Ko et al. 2007), smartphones (Joo and Sang 2013), mobile cloud services (Park and Kim 2014), mobile navigation Systems (Park et al. 2014), autonomous vehicles (Lee et al. 2019), smartwatches (Kim and Shin 2015), smart glasses (Rauchnabel and Ro 2016) and recently also in the field of DVAs (Coskun-Setirek and Mardikyan 2017; Easwara and Vu 2015).

In general, TAM assumes that potential users are influenced by external factors when they communicate with a new technology (Elmorshidy 2013). However, these external variables do not have a direct impact on the actual behavior of the potential users, but an indirect one, that can be measured using constructs like Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) (Davis 1986; Venkatesh and Morris 2000). Davis defines PU as the subjective perception of an individual that the use of a particular technology improves her/his performance in the workplace (Davis 1989). PEOU, on the other hand, indicates the extent to which the individual believes that the use of a technology is not associated with physical effort. This implies an easy usage of a technology, or an application is easy to use (Davis 1989). Both constructs, PEOU and PU, are positively related to the user's Attitude Toward Using a technology (ATU), which determines further usage of a new technology (Park et al. 2007; Lee et al. 2015). Furthermore, PU and ATU have a positive impact on Behavioral Intention to Use (BIU) (Srite and Karahanna 2006), whereas BIU is positively related to Actual System Usage (ASU) (Wu and Wang 2005; Lee et al. 2015). Therefore, BIU is determined by PU and ATU, which in turn is determined by PU and PEOU (Davis et al., 1989). Furthermore, as a tool, which explains and predicts user behavior, TAM was optimized to include only three basic constructs: PU, PEOU and BIU. In such case a direct impact of PU and PEOU on BIU shows a strong, direct effect. Moreover, PEOU has then a small (but significant) indirect effect on BIU, even if the latter effect decreases over time (Onobhayedo 2017). Even though

including ATU into the equation has a small effect on the coefficients of PU and PEOU, ATU does not fully mediate these relationships (Onobhayedo 2017)**.** Therefore, it is not surprising that TAM will be often mentioned in the literature without ATU (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). Therefore, in our study this more parsimonious model structure is assumed.

Despite the vast and successful application of TAM in investigating the factors of technology acceptance and usage, Park et al. (2007) cannot fully explain why individuals ultimately accept and use certain technologies. Coskun-Setirek and Mardikyan (2017) also point out that the original TAM ignores external, overall context factors. Therefore, the original model should be completed with additional components in order to make it applicable for new, innovative technologies as well. Furthermore, Benbasat and Barki (2007) criticize that acceptance research puts too much emphasis on TAM without considering the approaches of other theories in acceptance research. In order to overcome these significant limitations, the study also draws on another approach – UGA – to investigate DVA acceptance.

TAM is also a precursor to many other approaches in technology acceptance research (van der Heijden 2004; Taherdoost 2018). Accordingly, Venkatesh and Davis developed TAM2 in 2000, summing up the basic model to include social and cognitive-instrumental variables (Venkatesh and Davis 2000). In addition, TAM also forms the basis for the development of Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al. 2003 and TAM3 (Venkatesh and Bala 2008). Since UTAUT was primarily created for the organizational rather than for consumer context, Venkatesh et al. (2012) modified the model and expanded it to UTAUT2 (extended by the factors: hedonic motivations, price value and habit). On the other hand, there are also some other technology acceptance models, that will be used by researchers, e.g. the Technology Readiness Model with "people's propensity to embrace and use new technologies to accomplish goals in home life and at work" (Parasuraman 2000, p. 308) or the Hedonic-Motivation System Adoption Model (HMSAM) with factors: perceived ease of use, perceived usefulness, curiosity, joy, control, behavioral intention to use and immersion (Lowry et al. 2013).

Although TAM has proven to be useful in identifying factors that influence a person's technology acceptance and use (Lee et al. 2015), the model, as Park et al. (2007) states, does not fully explain, why individuals ultimately accept and use a technology. Bagozzi (2007) as well as Coskun-Setirek and Mardikyan (2017) point out that the original TAM ignores external, overall context factors. Consequently, the existing model should be supplemented with other factors in order to make it possible to apply it in the area of new technologies as well. Benbasat and Barki (2007) criticize that the focus in acceptance research lies too much on the technology acceptance model without considering the approaches of other theories. In

order to overcome these significant limitations, this study draws on UGA in addition to the original TAM in order to investigate the acceptance of DVAs. The original TAM-items fulfill the aim of the study, namely to investigate the acceptance of DVAs, having impact on Behavioral Intention to Use DVAs and Actual Use of modern technologies, such as DVAs. The model exclusively concentrates on beliefs about the technology (here: DVAs). Moreover, instead of using already established items (e.g. in TAM2 or UTAUT), we invent, based on literature on UGA, additional constructs (see section 2.2), which are more suited for such a new technology like DVAs. Otherwise to HMSAM, we do not only want to investigate heterogeneous variables, but also utilitarian ones as well as some risks.

4.2.2 Uses and Gratifications Approach (UGA)

UGA has its origins in media and communication research. It tries to explain and describe, why people choose and use media for their own purposes (Rauschnabel et al. 2018). Based on first studies in gratification research from the 1940s, the American communication scientist and sociologist Elihu Katz (1959) developed UGA. His development has resulted in a thoroughly significant paradigm shift for media and communication research. In contrast to the classical media research, UGA does not ask "what the media do to people", but "what people do to the media" (Rubin 2002). The approach also examines the correlation between the consumer and the available media offer. However, UGA focuses on consciously acting consumers and their active and goal-oriented role in dealing with the media. Based on their needs and expectations, consumers decide, whether and which of the existing media will be used. According to Katz et al. (1974), UGA deals with social and psychological origins of needs, which conduct to different expectations towards media and non-media sources. These expectations however lead to different media usage patterns, resulting in a satisfaction of needs or other consequences (Katz et al. 1974).

Despite many extensions and further developments, UGA is not without criticism. Frequently mentioned limitations are:

- The approach focuses too much on the individual itself without considering other fundamental factors such as its social environment (Nabi et al. 2006).
- Assuming an omnipresent and always active audience is not sustainable, as an individuals' behavior always depends on its mood and the situation in general (Dunne et al. 2010). Schweiger (2007) adds that recipients usually turn to the media implicitly and unconsciously.
- The approach is not based on a valid theory and shows a theoretical weakness (Ruggiero 2000).

Contrary to the criticism, UGA is still a suitable approach to explain the acceptance and the use of media. Sheldon et al. (2017) suggest that the approach is suitable for both – traditional and highly innovative new technologies. *Tab. 1* presents recent studies that have used UGA to examine the acceptance of different modern technologies. In addition to the research object and the sample size, researched gratuities are shown in the overview. The literature (see *Tab. 1*) shows that UGA has diverse applicabilities and utilities. Quan-Haase and Young (2010) share this view and confirm that the approach plays an important role in the digital age in order to investigate the acceptance of such young technologies, like e.g. DVAs. While voice control cannot per se be classified in the mass media field, it can still be helpful and useful in the usage of some mass media (such as smartphones). In our study, Siri is deliberately selected based on consumer gratuities to be determined from a variety of conversational interfaces. Gratuities used in our study are written using bold fonts in *Tab. 1*.

Research object	Research study	Sample size	Selection of researched gratuities
Chatbot	Brandtzaeg and Følstad (2017)	146	Productivity, Pastime, **Social Motivations,** Entertainment
Internet	Song et al. (2004)	498	Distraction, Information Search, **Social Status**
Messaging Services	Gan and Li (2018)	297	**Enjoyment**, Attraction of the medium, Information Exchange
Mobile/Online Games	Li et al. (2015)	3919	**Enjoyment**, Reality Escapism, Social Presence, Success
	Rauschnabel et al. (2017)	642	**Enjoyment**, Image, Nostalgia, **Physical Risks, Privacy Concerns**
Mobile Phone	Leung and Wei (2000)	834	Mobility, Immediacy, Expediency
Social Networks	Malik, Dhir and Nieminen (2016)	368	Attention, **Social Impact**, Pastime
	Papacharissi and Mendelson (2010)	344	**Enjoyment**, Pastime
	Valenzuela et al. (2009)	1715	Information search, **Social Status**, Entertainment
	Xu et al. (2012)	160	Coordination (Expediency), Immediacy
Tablet	Leung and Zhang (2016)	948	Relaxation, Information Search, **Social Status**, Time Management

Tab. 1: UGA-based studies with researched gratuities

4.3 Digital Voice Assistants and an approach for measuring their acceptance

4.3.1 Digital Voice Assistants (DVAs)

DVAs are software applications based on Artificial Intelligence (AI), which communicate with people through natural, spoken language (Griol et al. 2013). They may be integrated in a smartphone (e.g. Apple's DVA Siri or Google's Assistant). In addition, DVAs are also available in form of smart speakers (e.g. Amazon's Alexa). Tasks, such as making calls, sending messages, receiving reminders, or opening an application, can be fulfilled by DVAs using voice control without any manual intervention (Bitkom 2018). In their interaction with DVAs

consumers can nowadays assess a wide range of functions, which is constantly being increased by new skills (Bitkom 2018). This opens up various possibilities for users in their everyday life. According to Statista (2017), almost half of the respondents see DVAs as an obviousness in everyday life. Despite the vast application of DVAs in different fields and their function as an everyday helper, there are also doubts about the use of DVAs. According to a study by BVDW (2017), about 80% of respondents are concerned about the use of DVAs in their daily lifes: 30% fear misuse of their data or third-party monitoring and 29% state that communication with a Voice Assistant is strange and impersonal to them. *Tab. 2* provides an overview of the most important findings of the discussed (and selected other) studies on DVA usage which make clear that DVAs are wide-spread among consumers – especially when integrated into smartphones – but their everyday usage is up-to-now limited – among other reasons – by data security and privacy concerns.

Source (Year)	Type of study (Country)	Sample size	Findings
Bitkom e.V. (2018)	Online survey (DE)	n = 1.007	- 13% of respondents already use a DVAs in their households; - 4% plan to purchase a DVA in a period of up to 12 months; - DVAs have a wide range of so-called actions or skills and their application area permanently increases; - More than half of non-users are concerned about data protection (58%) and their privacy (57%), while 56% of non-users say they do not need a DVA.
Deutsche TV-Plattform e.V. (2018)	Online survey (DE)	n = 1.006	- High degree of fame of DVAs; - Relatively low usage rate of DVAs (on average only 15% of respondents use a DVA); - Especially the voice control via smartphones is used (38%).
EY (2018)	Online survey (DE)	n = 1.015	- More than half of respondents (53%) use DVAs at least occasionally; - High affinity for DVAs in the younger age groups; - Large proportion of potential users (70%); - Data security and privacy concerns are essential for 80% of respondents in the context of using DVAs.
PwC (2018)	Online survey (US)	n = 1.000	- Previous usage rate of DVA is 72% among the US-population; - 57% of respondents use DVAs on their smartphones; - Young adults (18-24 year) are a driver of the adoption of DVAs; - Consistency of such technology as a crucial factor for ultimately broad adoption among consumers.
SPLENDID RESEARCH GmbH (2018)	Online survey (DE)	n = 1.024	- 37% of respondents already use DVAs; - Google Assistant and Siri are the most popular DVAs (both 15% each); - 22% of respondents are interested in the technology behind DVAs.
BVDW e.V. (2017)	Online survey (DE)	n = 1.038	- Google Assistant (29%) and Siri (22%) enjoy great popularity among DVAs; - high affinity for DVAs in the age group of 16-24-year-olds.
Capgemini S.E. (2017)	Online survey (DE, FR, UK, US)	n = 5.041	- Half of respondents (51%) have already used DVAs; - Consumers especially appreciate the ease of use and the multitasking capability of DVAs; - 65% of non-users are concerned about data protection and privacy as a reason, why they do not use DVAs.
Pew Research Center (2017)	Online survey (US)	n = 4.135	- 42% of respondents use DVAs on their smartphones; - 55% of the US-citizens sees a great advantage of such technology, especially in the voice-driven interaction; - For 23%, the fun factor is crucial in using DVA.
PwC (2017)	Online survey (DE)	n = 1.012	- High awareness of DVAs (e.g. Siri: 70%) - 20% of Germans plan to use Siri in a timely manner; - Users still have concerns about data misuse and too much transparency.
Wavestone (2017)	Online survey (US)	n = 1.000	- Technical improvements as a key factor in the continued adoption of DVAs.

Notes: DE = Germany, FR = France, UK = United Kingdom, US = United States of America

Tab. 2: Studies on DVA usage

One of the best-known DVA is Apple's Siri (Speech Interpretation and Recognition Interface). Siri learns steadily through questions or commands of its user and gains in competence in order to answering questions more purposeful. Furthermore, Siri learns about consumers'

usage behavior on different devices by Apple. This allows the Voice Assistant to make suggestions, so-called shortcuts (Apple 2019). The entire learning process contributes to a personalization of the human-voice assistant relationship. Siri can thus become in many ways more and more useful to consumers – both at work and in private life. In addition, Apple is steadily expanding the stock of features for its DVA and is constantly working on its quality (Apple 2019).

4.3.2 Approach for measuring DVA acceptance

Based on the discussions above, in the following we develop an approach for measuring DVA acceptance. Our approach not only makes a use of TAM and its extensions but also integrates selected gratuities derived from UGA. Apple's Siri is used as a DVA example when formulating the items for an online survey.

As already discussed in section 2, TAM (as well as UGA) can be adapted for measuring technology acceptance in many application fields (Park 2010; Venkatesh 2000). Therefore, also, for measuring DVA acceptance, original TAM constructs can be taken over unchanged for our approach. When building the UGA-based gratifications, in contrast to TAM, which considers PEOU and PU as primary factors influencing the final usage decision, it is obvious that UGA draws on a large number of different and freely selectable gratuities. According to Li et al. (2015), gratifications obtained through the use of a communication medium always depend on the type of the communication medium. Therefore, it is necessary to consider new gratifications for each new medium or communication technology (Li et al. 2015; Simon 2007). This approach can cover a wide range of customer needs and explore an equally wide variety of motivations (Luo et al. 2011). Gratifications used in our study come from recent research papers shown in *Tab. 1.* From a large selection of different gratifications in the literature, five of them were selected for this study. In addition to a hedonistic gratification "Enjoyment" (EN) and utilitarian gratifications "Social Status" (SS) and "Social Influence" (SI), also "Physical Risks" (PR) and "Privacy Concerns" (PC) find their place in our approach. Based on both, the original TAM and five gratuities derived from UGA, a research model is developed (see *Fig. 1*). The integrated factors and their relationships (hypotheses) as well as the items used in the measurement model are discussed in the following.

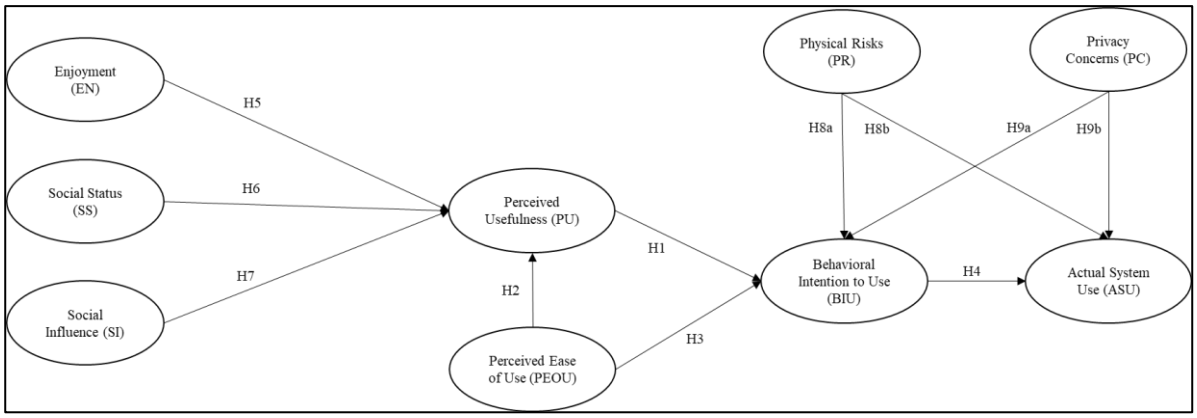


Fig. 1: Theory-based structural model – Approach for measuring DVA acceptance

TAM assumes that both, Perceived Usefulness (PU) and Perceived Ease of Use to be of decisive relevance for the technology acceptance (Davis et al. 1989). In line with Davis (1989), PU will be here understood as the degree to which users believe that the DVA can be useful in private and professional everyday life (Davis 1989). Moreover, various studies have shown that PU not only influences Attitude Toward Using a technology (ATU), but also in further step – Behavioral Intention to Use a technology (BIU) (Park et al. 2007; Davis et al. 1989; Venkatesh 2000). Based on the following theoretical considerations with regard to the DVA Siri, we hypothesized the following:

- Perceived Usefulness of a DVA has a positive impact on Behavioral Intention to Use a DVA (Hypothesis H1).

Based on the definition by Davis (1989), Perceived Ease of Use (PEOU) describes the extent to which the consumer believes that the use of a DVA is not associated with physical exertion for him/her. This implies that the DVA is easy to use (Davis 1989). Various studies have proved so far, that PEOU has a significant influence on Perceived Usefulness of a technology (Davis et al. 1989; Venkatesh 2000). The easier the usage of a technology, the larger the PU of the technology will be (Venkatesh and Davis 2000). In the case of the DVA Siri, this leads to the following hypothesis:

- Perceived Ease of Use of a DVA has a positive impact on Perceived Usefulness of a DVA (H2).

Based on the literature, PEOU has an indirect (via Attitude Toward Using a technology) impact on the Behavioral Intention to Use a technology (Srite and Karahanna 2006). This basic attitude of an individual is ultimately decisive for whether the DVA will be used or not. Therefore, the following causal relationship can be assumed:

- Perceived Ease of Use a DVA has a positive impact on Behavioral Intention to Use a DVA (H3).

In addition to the previous interdependencies, it is also assumed that the Behavioral Intention to Use has a significant influence on the Actual System Use (Wu and Wang 2005). Transferred to our study, intention to use means the decision of the consumer to use a DVA. The following hypothesis is therefore made in this context:

- Behavioral Intention to Use a DVA has a positive effect on the Actual Use (ASU) of a DVA (H4).

Gan and Li (2018) attach great explanatory value to hedonistic gratuities in order to find reasons for usage behavior or usage intentions (Gan and Li 2018). Enjoyment (EN) is one of these hedonistic gratifications (Rauschnabel et al. 2017). In our study, enjoyment means the degree to which using a DVA is enjoyable and is perceived by its users as pleasant. Enjoyment has so far proven to be a significant bonus in a wide variety of studies on UGA in order to further expand the intended use of instant messaging (Gan and Li 2018), Mobile / Online Games (Li et al. 2015; Rauschnabel et al. 2017) and social networks (Papacharissi and Mendelson 2010; Valenzuela et al. 2009). Therefore, we hypothesized the following:

- Enjoyment has a positive effect on Perceived Usefulness of a DVA (H5).

In addition, utilitarian gratifications can be crucial for the use of a DVA. For this reason, two gratuities: Social Status (SS) and Social Influence (SI) are also included in the research model. Social status (SS) can be defined as the extent to which the use of a DVA helps to convey a certain self-image of a person (Gan and Li 2018). Through this self-image, a person should be perceived and seen by fellows, but also by strangers in a certain, deliberated way. Previous studies have shown that people use technology and media to convey a certain self-image to the outside world (Leung and Zhang 2016; Rauschnabel et al. 2017; Song et al. 2004). Therefore, the arguments lead to the following hypothesis:

- Social status has a positive effect on Perceived Usefulness of a DVA (H6).

Another gratification that could speak for the use of DVAs is Social Influence. Based on Rauschnabel et al. (2017) social influence can be understood as to the extent to which DVAs' users believe that the usage of DVAs is expected by other people (Rauschnabel et al. 2017). Rauschnabel and Ro (2016) and Venkatesh et al. (2012) believe that social influence is decisive for the intended use. The following causal relationship can therefore be proposed:

- Social Influence has a positive effect on Perceived Usefulness of a DVA (H7).

Although media and technologies are becoming more and more personal and omnipresent, concerns of consumers are steadily increasing (Junglas et al. 2008). In addition to already

mentioned motives, which have a positive influence on the use of the DVA, risks and concerns about the use of DVAs should not be neglected. Rauschnabel et al. (2017) take up consumers' concerns in their study on the intended use of Pokemon Go and integrate two constructs: Physical Risks and Privacy Concerns. A significant connection between privacy concerns and the attitude to use Pokemon Go could not be found, but a slight influence of physical risks on the attitude could be confirmed (Rauschnabel et al. 2017). Contrary to Rauschnabel et al. (2017), it is assumed with regard to DVAs that there is a causal relationship between the two types of risks and the BIU and ASU. Physical risks include all those dangers and risks that may arise from the use of a DVA, e.g. a distraction in traffic. Due to Malhotra et al. (2004) privacy concerns reflect consumer fears. They fear that the use of a technology or a medium will result in their personal and private data loss or even data breaches (Malhotra et al. 2004). Following hypotheses can therefore be derived for the two constructs:

- Physical risks have a negative impact on Behavioral Intention to Use a DVA (H8a).
- Physical risks have a negative impact on Actual Use (ASU) of a DVA (H8b).
- Privacy concerns have a negative impact on Behavioral Intention to Use a DVA (H9a).
- Privacy concerns have a negative impact on Actual Use (ASU) of a DVA (H9b).

Against the background of derived hypotheses and theoretical principles, the research model can be depicted as demonstrated in *Fig. 1.* In the following, we apply the approach for measuring DVA acceptance to estimate the technology acceptance by digital natives (Millennials) using Apple's Siri. *Fig. 1* shows our theory-based construct model. Further, *Tab. 3*, presents all hypotheses and corresponding references in the literature.

Hypotheses		Literature
H1	PU has a positive impact on BIU.	Davis et al. 1989; Venkatesh 2000
H2	PEOU has a positive impact on PU.	Davis et al. 1989; Venkatesh 2000; Venkatesh and Davis 2000
H3	PEOU has a positive impact on BIU.	Davis 1989; Davis et al. 1989
H4	BIU has a positive impact on ASU.	Wu and Wang 2005
H5	EN has a positive impact on PU.	Gan and Li 2018; Rauschnabel et al. 2017; Li et al. 2015; Papacharissi and Mendelson 2010, Valenzuela et al. 2009
H6	SS has a positive impact on PU.	Gan and Li 2018; Leung and Zhang 2016; Rauschnabel et al. 2017; Song et al. 2004
H7	SI has a positive impact on PU.	Rauschnabel et al. 2017; Rauschnabel and Ro 2016; Venkatesh et al. 2012
H8a	PR has a negative impact on BIU.	Junglas et al. 2008; Rauschnabel et al. 2017
H8b	PR has a negative impact on ASU.	
H9a	PC has a negative impact on BIU.	Rauschnabel et al. 2017; Malhotra et al. 2004
H9b	PC has a negative impact on ASU.	

Notes: PU = Perceived Usefulness; PEOU = Perceived Ease of Use; BIU = Behavioral Intention to Use; ASU = Actual System Use; EN = Enjoyment; SS = Social Status; SI = Social Impact; PR = Physical Risks; PC = Privacy Concerns

Tab. 3: Hypotheses and their derivation

4.4 Empirical study, questionnaire design, data collection and analysis

In order to operationalize the DVA acceptance measurement approach, Apple's Siri and Millennials were in the focus of the empirical study. Siri was selected as being wide-spread among German Millennials (aged between 17 and 35) which have different values, traits, behaviors and a bigger purchasing power compared to previous generations (Eastman et al. 2013; Eastman et al. 2014). Millennials can be classified as the first "high-tech"-generation (Lissitsa and Kol 2016). They grew up with smartphones in the age of mobile technologies and do not only impress with their technical knowhow, but also with their affinity for digital novelties (Karakas et al. 2015). Also, Millennials – especially in Germany – are the first generation with a high percentage of studying at universities (e.g., in Berlin 85%, in Bavaria 52%).

An online questionnaire was developed that mainly contained closed-form questions: For the TAM-constructs as well as the UGA-gratuities (as discussed in *Fig. 1* and *Tab. 3*) well-known items from the literature were adapted to the DVA/Siri context (see. *Tab. 4*). Respondents were asked to state their agreement to these items on 5-point Likert scales. The answer options ranged from 1 ("disagree"), to 3 (a neutral middle category), to 5 ("fully agree"). Due to the odd number of answer options, survey participants could take a neutral position at any time and were not forced to choose one side.

In addition to closed questions, the questionnaire also contained three open questions, which could be used to obtain additional information on the acceptance of DVAs. By combining open and closed questions, it was possible to have a comprehensive look at the topic based on quantitative (closed questions) and qualitative (open questions) data. The survey started on December 21, 2018 and ended on February 5, 2019. The interviewed sample were bachelor and master students from the University of Bayreuth, Germany.

In total, 340 people between the age of 17 and 35 participated in the survey. Corresponding to a completion rate of 83.2%, 283 survey participants finished the questionnaire. For further empirical investigation, a sample of n=283 is used. The gender distribution in the study sample is 63.9% women and 35.7% men. One person did not give an indication of the gender. 27 survey participants (9.5%) are assigned to the age group 17 to 20 years. 142 persons (50.2%) were 21 to 25 years old and 99 persons (35.0%) were between 26 and 30 years. The remaining 15 survey participants were older than 31 years and younger than 35 years.

For the study, variance-based PLS-SEM and the software SmartPLS 3 to analyze and evaluate the collected data were chosen (Sarstedt et al. 2016; Hair et al. 2016; Hair et al. 2012). In comparison to CB-SEM (e.g. AMOS), PLS-SEM (here: SmartPLS) will be used for relatively

Construct	Items	References
Perceived Usefulness (PU)	With the help of Siri, I can make my life more effective. (PU1) Siri is a great support in my everyday work. (PU2) The information I receive fully answers my questions. (PU3) The answers that Siri provides are very relevant to me. (PU4) I feel that using Siri makes my job easier. (PU5)	Venkatesh 2000; Venkatesh and Davis 1996; Davis 1989.
Perceived Ease of Use (PEOU)	The operation of Siri is easy to understand. (PEOU1) The use of Siri is intuitive and flexible. (PEOU2) Siri is user-friendly and can be used by anyone. (PEOU3)	Venkatesh 2000; Venkatesh and Davis 1996; Davis 1989.
Attitude Towards Using (ATU)	I have a positive attitude towards Siri. (ATU1) It makes sense to use Siri in certain situations. (ATU2) I like to call on Siri for information and advice. (ATU3) I enjoy using Siri at university / work. (ATU4)	Venkatesh and Davis 2000.
Behavioral Intention to Use (BIU)	I intend to use Siri in the future. (BIU1) I intend to use Siri more often in the future. (BIU2) I will recommend the use of Siri to other people. (BIU3) If I have to choose a DVA in the future, I select Siri. (BIU4)	Venkatesh et al. 2012; Moon and Kim 2001; Venkatesh 2000.
Actual System Use (ASU)	I use Siri very often (six times or more a week). (ASU1) I use Siri frequently (one to five times a week). (ASU2) I use Siri occasionally (up to once a week). (ASU3)	Moon and Kim 2001.
Enjoyment (EN)	Using Siri gives me pleasure. (EN1) I enjoy using Siri in the workplace. (EN2) Using Siri at the university is a pleasure. (EN3)	Gan and Li 2018; Rauschnabel et al. 2017; Li et al. 2015; Papacharissi and Mendelson 2010; Valenzuela et al. 2009.
Social Status (SS)	Using Siri improves my image. (SS1) Using Siri has a positive effect on my self-confidence. (SS2) I use Siri to show other people that I am following trends. (SS3)	Leung and Zhang 2016; Rauschnabel et al. 2017; Song et al. 2004.
Social Influence (SI)	In the university there are some students who use Siri. (SI1) At my workplace, Siri is used by a few colleagues. (SI2) People, whose opinion I appreciate, recommend Siri. (SI3)	Rauschnabel et al. 2017; Rauschnabel and Ro 2016; Venkatesh et al. 2012.
Physical Risks (PR)	Siri has distraction potential and represents a risk to me. (PR1) I am afraid that by using Siri is risky in everyday life. (PR2) I think using Siri can be dangerous in some situations. (PR3)	Rauschnabel et al. 2017.
Privacy Concerns (PC)	I'm concerned that Apple gets too much information. (PC1) I'm worried that Apple is abusing my data. (PC2) Unauthorized third parties could use my data. (PC3) I'm afraid of being manipulated by the use of Siri. (PC4)	BVDW e.V. 2017; PwC 2017; Rauschnabel et al. 2017; van Eeuwen 2017.

Tab. 4: Operationalization of all constructs used in the study

small sample sizes (here: n=283) (Hair et al. 2016; Hair et al. 2017) and when the analytical focus lies on prediction and identification of relationships between constructs (Hair et al. 2019; Chin 1998; Hair et al. 2011). Moreover, PLS-SEM is a predictive method (to predict outcomes using the chosen model) with the aim of theory development (Hair et al. 2016; Sharma et al. 2019; Shmueli et al. 2016) and it fits perfectly for the aim of this study.

Obtained data depicts reality, if not distorted too much by measurement errors (Hair et al. 2017, p. 6). Therefore, it is necessary to examine the reliability and the validity of the measurement models (Gerpott and Paukert 2011). *Tab. 5* summarizes quality assessment of the measurement models underlying the research model. Following quality criteria are used to assess the measurement models: indicator reliability, internal consistency reliability (measured by Cronbach's alpha (CA ≥ 0.7) and composite reliability (CR ≥ 0.6)), convergence va-

lidity (measured by average variance (AVE ≥ 0.5) and discriminant validity (measured by Fornell-Larcker criterion; correlations (values below the diagonal) should all be smaller than the values on the main diagonal) (Hair et al. 2011). Each of these quality criteria defines a calculated key figure (see *Tab. 5 and 6*).

Constructs	n	Mean (SD)	FL	CR	AVE	CA
PU				0.940	0.758	0.940
PU1	283	2.93 (1.24)	0.910			
PU2	283	2.39 (1.35)	0.919			
PU3	283	2.99 (1.21)	0.795			
PU4	283	2.98 (1.21)	0.862			
PU5	283	2.64 (1.35)	0.862			
PEOU				0.775	0.538	0.775
PEOU1	283	4.40 (0.68)	0.648			
PEOU2	283	4.11 (0.82)	0.847			
PEOU3	283	4.17 (0.87)	0.690			
BIU				0.928	0.765	0.925
BIU1	283	2.95 (1.38)	0.893			
BIU2	283	2.74 (1.37)	0.891			
BIU3	283	2.51 (1.38)	0.966			
BIU4	283	2.94 (1.41)	0.731			
ASU				0.860	0.672	0.855
ASU1	283	1.91 (1.42)	0.870			
ASU2	283	2.08 (1.56)	0.830			
ASU3	283	2.81 (1.72)	0.755			

Constructs	n	Mean (SD)	FL	CR	AVE	CA
EN				0.875	0.701	0.870
EN1	283	3.17 (1.14)	0.751			
EN2	283	2.35 (1.18)	0.884			
EN3	283	2.43 (1.16)	0.871			
SS				0.940	0.840	0.940
SS1	283	1.97 (1.15)	0.948			
SS2	283	1.88 (1.18)	0.932			
SS3	283	1.78 (1.20)	0.867			
SI				0.801	0.577	0.799
SI1	283	3.16 (1.06)	0.638			
SI2	283	2.57 (1.23)	0.778			
SI3	283	2.28 (1.32)	0.847			
PR				0.887	0.725	0.883
PR1	283	2.86 (1.33)	0.851			
PR2	283	2.64 (1.38)	0.950			
PR3	283	3.06 (1.34)	0.740			
PC				0.908	0.731	0.911
PC1	283	4.16 (1.08)	0.602			
PC2	283	3.83 (1.21)	0.670			
PC3	283	3.75 (1.26)	0.741			
PC4	283	3.33 (1.42)	1.251			

Tab. 5: Quality assessment of the constructs

In order to be able to fully test the reliability and the validity of the measurement models, discriminant validity must be analyzed in addition to indicator reliability, internal consistency reliability and convergence validity (Hair et al. 2011). Discriminant validity is used to ensure the empirical autonomy of the construct (Hair et al. 2017, p. 99). It is examined on the basis of the Fornell-Larcker-Criterion (Hair et al. 2016; Henseler et al. 2009; Lee et al. 2011) and will be here fulfilled (*Tab. 6*). The current measurement model provides evidence of reliability and validity. Therefore, the analysis shifts to the structural model (Shmueli et al. 2019; Hair et al. 2012).

To assess the quality of the structural model, relationships between the constructs, predictive capability and prognostic relevance are used as evaluation criteria (Hair et al. 2011). *Tab. 5* provides an overview of the results regarding to the quality of the structural model. The evaluation criteria used to assess the structural model's quality is in line with the approach of Ringle et al. (2012). This approach is also used by Götz et al. (2010), Hair et al. (2013) and Henseler et al. (2009). Relationships between the constructs, as well as the predictive power and predictive relevance of the model, are considered for assessing the quality of the model (Hair et al. 2011). *Fig. 2* depicts most important findings of the structural model. Overall the quality of the measurement model and structural model has been assessed. The measure-

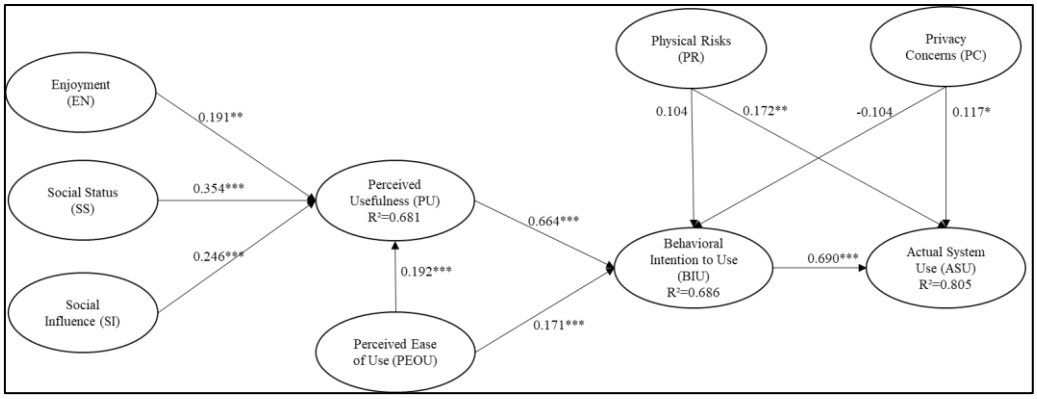
ment model provided evidence of reliability and validity, whereas the structural model met different criteria for the assessment of a structural model.

	ASU	BIU	EN	PC	PEOU	PR	PU	SI	SS
ASU	**0.820**								
BIU	0.861	**0.875**							
EN	0.657	0.739	**0.837**						
PC	0.341	0.150	0.136	**0.855**					
PEOU	0.477	0.529	0.385	0.068	**0.734**				
PR	0.580	0.427	0.413	0.611	0.137	**0.851**			
PU	0.848	0.808	0.711	0.277	0.485	0.539	**0.871**		
SI	0.753	0.711	0.752	0.378	0.321	0.689	0.731	**0.760**	
SS	0.677	0.697	0.741	0.270	0.333	0.548	0.736	0.721	**0.917**

Notes: PU = Perceived Usefulness; PEOU = Perceived Ease of Use; BIU = Behavioral Intention to Use; ASU = Actual System Use; EN = Enjoyment; SS = Social Status; SI = Social Impact; PR = Physical Risks; PC = Privacy Concerns

Tab. 6: Fornell-Larcker-Criterion

Moreover, in order to gain additional impressions about the empirically collected data, concerning age and gender effects, a correlation analysis based on descriptive statistics was conducted. The analysis is intended to reveal group-related relationships between the moderating variables – age and gender – and the respective constructs from the research model. Against this background, correlation coefficients were calculated on the basis of the demographic data. Therefore, we used a multi-group analysis, which in this case shows that the pre-defined data groups have no significant differences in their group-specific parameter estimates (Henseler et al., 2009; Hair et al. 2016). This statement is in line with the fact, that Millennials (with no difference either between men and women or between younger (17-25 years old) and older (26-35 years old)) act in a similar way (Hartman & McCambridge 2011).



Notes: *p < .05; **p < .01; ***p < .001

Fig. 2: Structural model - results of the quality assessment

An evaluation of the open-ended question about the current use in everyday life shows that Siri represents a frequently used source of information for many of the respondents (n=211). Survey participants use Siri, for example, to get informed about the weather forecast, to query general information or to search for information in the Internet. Some of the respondents also consider Siri to be very helpful for making and receiving phone calls or messages by using only the voice input. Siri will also be used for navigation while driving. However, a quarter of the respondents stated that they do not see any use for Siri in their everyday life and do not use the DVA at all. This view is also shared by two-thirds of the respondents, who answered the question about the current use of Siri in everyday student life. In 103 out of 157 cases, Siri is not used at the university. Nonetheless, Millennials use their DVAs to quickly acquire information and search in the Internet. Finally, concerning Siri's potential applications in the future, 132 answers of the survey participants have been collected. Many interviewees consider the collection of different kind of information with the help of Siri to be an interesting application possibility in the future. In contrast, a quarter of respondents do not see any future applications for Siri in their everyday lives.

4.5 Discussion and implications

Although there are some studies about DVAs (Coskun-Setirek and Mardikyan 2017; Joo and Sang 2013), there is no such study, which examines the acceptance of DVAs in such broad spectrum as we do. We develop a new, literature-based approach for measuring the DVA acceptance and apply it to the acceptance of a DVA – Siri.

By closely looking at the predictive power and the predictive relevance, it can be stated, that the approach suits for the acceptance measurement very well. Following Luo et al. (2011), the criterion of predictive power is used first. Variables explain here 68.6% of the variance of Behavioral Intention to Use DVAs and 80.5% of the Actual Use of DVAs. Overall, the forecasting performance of the model is moderate (Hair et al. 2011; Chin 1998). In terms of predictive relevance, values for Q^2 of 0.463 for Behavioral Intention to Use DVAs and 0.482 for Actual Use of DVAs have been determined for the approach for measuring DVA acceptance. The empirically collected data can be well reconstructed by the model and the PLS parameters (Chin 1998, p. 317). The research model therefore does not only show moderate predictive power, but it can also be considered as relevant for the prediction of the Millennials' acceptance for using DVAs. By searching for suitable gratifications, we wanted to learn more about reasons for using or not using DVAs in daily life by digital natives. Overall, the level of information content and the adjustment effort (Luo et al. 2011) was high. We not only used original TAM-constructs but also incorporated in our model five up-to-date gratifications tailored for a such new technology like DVAs. This procedure was more effortful than using

existing constructs for TAM but, on the other hand, in this way, we found out, what has an influence on Millennials using DVAs.

On the basis of the empirical results from the previous chapters, the research question set up at the beginning of the study can be answered. Overall, nine hypotheses (H1, H2, H3, H4, H5, H6, H7, H8b, H9b) can be accepted. With regard to the research question about the factors which positively or negatively influence the acceptance of DVAs, the following results can be compiled for the approach for measuring DVA acceptance: The results of this study suggest that enjoyment, social status and social influence play an important role in consumers' decision to use DVAs. Consumers, who enjoy talking to their mobile devices, are indeed more likely to use DVAs. Moreover, when some colleagues, friends or students use a DVA, it will be very likely, that theirs friends will also do so. On the other hand, some consumers are concerned about companies who can easily get too much personal information about the consumers and eventually misuse them by e.g. giving them to some unauthorized third parties. Even though DVAs are an interesting and (in some life situations, e.g. navigate a car, receive quick answers, set the timer) very useful device (189 responds), still many respondents (103 people) do not use DVAs in public, e.g. at the university. They rather do so at home, where nobody will laugh at them because of talking to their smartphones. The findings of the open questions show, that many of the respondents see no current use of Siri and will not use DVAs in the future. Similar results emerge from the consideration of the mean values for Behavioral Intention to Use DVAs (BIU) and Actual Use of DVAs (ASU): Means for BIU, 2.95, as well as those for ASU, 2.81, both below the scale mean, do not indicate acceptance of Siri in the target group. Some of the interviewees give reason for that, e.g. they do not want to control their devices by using their voice. Moreover, privacy concerns, fear of being intercepted and unexplained legal situation of DVAs are further reasons for not using such devices. Among digital natives, privacy concerns are indeed an issue (Mean=4.16; SD=1.08), but not to the extent as they would adversely affect the acceptance or the usage of Siri.

Our findings go in line with several other studies, which (at least in some way) look for reasons/gratuities for acceptance of modern technology devices. Joo and Sang (2013) found out that smartphone use is mainly affected by motivations based on goal-oriented and instrumental use. Their findings can be clearly reflected in our gratuities: enjoyment, social status and social influence, which are also goal-oriented. Moreover, Kim and Shin (2015) found out that e.g. mobility and availability of modern devices (there: smartwatches) are crucial for their acceptance. This also goes in line with our findings. We assume that DVAs are available everywhere we go – not only at home but also en route. Both studies take for granted immediate access to information as a "technology's primary utilitarian purpose" (Kim and Shin 2015). Otherwise than by Coskun-Setirek and Mardikyan (2017), who pointed out that job

relevance and output quality positively influence Actual Usage of Voice Activated Personal Assistants (like e.g. DVA Siri), we found out, that people, who use DVAs do so because they want to be entertained and look for an enjoyable activity. The difference here clearly lies in the choice of a study sample. While we focused on Millennials, only 43,7% of the study sample from Coskun-Setirek and Mardikyan (2017) were students in such age. It shows, that different age groups have varying needs and requirement for using DVAs.

Moreover, our study has important theoretical and practical implications. No previous study examined factors that had either a positive or a negative impact on the acceptance of DVAs under digital natives (Millennials). By doing so, we filled a research gap in the area of technology acceptance. The findings suggest, that enjoyment, social status and social impact are the main drivers while choosing to use DVAs. On the other side, privacy concerns negatively influence the acceptance of DVAs. For theoreticians, it provides a new context for the application of DVAs as an innovative, modern AI-technology. Our model has proven, that also such a founded method like TAM, can still be used for modern technologies. But our findings are especially useful for practitioners. In our study we show, that not only the functions of DVAs themselves are relevant for the customers but especially motivations like enjoyability, social impact and social status decide, whether DVAs will be used or not. By saying this, we strongly recommend putting more emphasis by accordingly targeting marketing campaigns of DVAs to familiarize their potential under the customers. It is also recommendable to strongly address customers' concerns (e.g. privacy concerns). Doing so can add a lot of value in the development and distribution of DVAs.

Besides (service-)robots (Wirtz et al. 2018; Ivanov & Webster 2019b; Jörling et al. 2019; Rosenthal-von der Pütten 2018) also voice-based technologies are constantly evolving and experiencing a constant change (Tuzovic and Paluch 2018). Personal DVAs are now integrated in any smartphone or smart speaker. In the meantime, the retail, automotive and healthcare sectors are also relying on voice controls to offer their customers voice-based technologies and services (see e.g. Lee et al. 2015). Time will tell how businesses can meet the needs of consumers with voice-based services and which attitude consumers will adopt towards integrating DVAs in their daily life.

4.6 Limitations and further research

Although the study presents helpful and crucial contributions to the literature, some caveats must be discussed. The main limitations of the study are educational level and geographic coverage of the respondents. First of all, it should be noted that students of the University of Bayreuth between the age of 17 and 35 were defined as the target group of our study and interviewed. Therefore, the results of the empirical study cannot be transferred to other stu-

dents at other universities in Germany or even in the world. In order to measure the general acceptance of all Millennials or the total population in Germany, further studies would have to be carried out.

Moreover, it would be interesting to know, if cultural differences play a role in the acceptance of DVAs. Conducting a transnational study in this context might be advisable. Not only cultural differences, but also the transience of time play an important role by examining new technologies. As we can see, in our study, Actual Use of DVA was generally low. One probable reason for that can be the fact, that every new technology firstly needs some time to adapt and to be used by the mass. We therefore recommend to repeat this study in some years.

Furthermore, it cannot be ensured that gratifications chosen within UGA are only possible gratifications that influence the usage and the intention to use DVAs. Therefore, future research may focus on examining whether and, if so, which other factors influence the usage of DVAs.

It could also be interesting to reflect upon the other side of the coin and think about motives for not using DVA. This approach might illustrate the future potential of DVAs and also uncover reasons against their usage.

Ultimately, research can use other technology acceptance models to look closer for the factors that have an impact on the adoption of DVAs.

4.7 References

Apple (2019), “Verfügbarkeit von iOS Features“, https://www.apple.com/de/ios/feature-availability/#siri.

Bagozzi, R. P. (2007), “The Legacy of the Technology Acceptance Model and a Proposal for a Paradigm Shift”, Journal of the Association for Information Systems, 8 (4), 244-254.

Benbasat, I. and H. Barki (2007), “Quo vadis, TAM?”, Journal of the Association for Information Systems, 8 (4), 211-218.

Bitkom e.V. (2018), “Die Zukunft der Consumer Technology: 2018“.

Brandtzaeg, P. B. and Følstad A. (2017), “Why People Use Chatbots” in Internet Science: 4th International Conference, INSCI 2017, Thessaloniki, Greece, November 22-24, 2017, Proceedings. Lecture Notes in Computer Science, Vol. 10673., (Eds.) I. Kompatsiaris, J. Cave, Anna Satsiou, Georg Carle, Antonella Passani, Efstratios Kontopoulos, Sotiris Diplaris und Donald McMillan, Cham: Springer International Publishing, 377–392.

Bundesverband Digitale Wirtschaft (BVDW) e.V. (2017), “Digital Trends: Umfrage zu digitalen Sprachassistenten“.

Čaić, M., G. Odekerken-Schröder and D. Mahr (2018), “Service robots: value co-creation and co-destruction” in elderly care networks, Journal of Service Management, 29(2), 178-205.

Chin, W. W. (1998), „The Partial Least Squares Approach for Structural Equation Modeling” in Modern Methods for Business Research, (Hrsg.) Marcoulides, G.; Mahwah, A.: Lawrence Erlbaum Associates, 295-336.

Coskun-Setirek, A. and S. Mardikyan (2017), “Understanding the Adoption of Activated Personal Assistants”, International Journal of E-Services and Mobile Applications, 9 (3), 1-21.

Davis, F. D. (1986), ”A Technology Acceptance Model for Empirically Testing New End-User Information Systems: Theory and Results”, doctoral dissertation, Sloan School of Management, Massachusetts Institute of Technology, Cambridge, MA 02142.

Davis, F. D. (1989), “Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology”, Management Information Systems Quarterly, 13 (3), 319-340.

Davis, F. D., R. P. Bagozzi and P. R. Warshaw (1989), “User Acceptance of Computer Technology: A Comparison of Two Theoretical Models”, Management Science, 35 (8), 982-1003.

Dunne, A., M.-A. Lawlor and J. Rowley (2010), “Young People's Use of Online Social Networking Sites: A Uses and Gratifications Perspective”, Journal of Research in Interactive Marketing, 4 (1), 46-58.

Eastman, J. K., R. Iyer, S. Liao-Troth, D. F. Williams and M. Griffin, (2014), “The Role of Involvement on Millennials’ Mobile Technology Behaviors: The Moderating Impact of Status Consumption, Innovation, and Opinion Leadership”, Journal of Marketing Theory and Practice, 22 (4), 455-470.

Eastman, J. K., R. Iyer and S. P. Thomas (2013), “The impact of status consumption on shopping styles: an exploratory look at the millennial generation”, Journal of Marketing Management, 23 (1), 57-73.

Easwara Moorthy, A. and K.-P. L. Vu (2015), “Privacy Concerns for Use of Voice Activated Personal Assistant in the Public Space”, International Journal of Human-Computer Interaction, 31 (4), 307-335.

Elmorshidy, A. (2013), “Applying The Technology Acceptance And Service Quality Models To Live Customer Support Chat For E-Commerce Websites”, Journal of Applied Business Research, 29 (2), 589-596.

Fornell, C. and D. F. Larcker (1981), “Evaluating Structural Equation Models with Unobservable Variables and Measurement Error”, Journal of Marketing Research, 18 (1), 39-50.

Gan, C. and H. Li (2018), “Understanding the effects of gratifications on the continuance intention to use WeChat in China: A perspective on uses and gratifications, Computers” in Human Behavior, 78 (2018), 306–315.

Gerpott, T. J. and M. Paukert (2011), “Reliabilität empirischer Konstruktmessungen“, WiST – Wirtschaftswissenschaftliches Studium, 40 (2), 58-65.

Götz, O., K. Liehr-Gobbers and M. Krafft (2010), “Evaluation of Structural Equation Models Using the Partial Least Squares (PLS) Approach” in Handbook of partial least squares: Concepts, methods and applications, Vol. 1. (Eds.) Vinzi, V. E., Chin, W. W., Henseler, J. and Wang, H., Berlin: Springer Verlag, 691-711.

Griol, D., J. I. Carbó Rubiera and J. M. Molina López (2013), “An automatic dialog simulation technique to develop and evaluate interactive conversational agents”, Applied Artificial Intelligence, 27 (9), 759-780.

Hair, J. F. Jr., G. T. M. Hult, C. M. Ringle and M. Sarstedt (2016), “A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)”, Vol. 2., Los Angeles: Sage Publications, Inc.

Hair, J. F. Jr., G. T. M. Hult, C. M. Ringle, M. Sarstedt, N. F. Richter and S. Hauff (2017), “Partial Least Squares Strukturgleichungsmodellierung (PLS-SEM)”, Vol. 1., München: Verlag Franz Vahlen.

Hair, J. F. Jr., C. M. Ringle and M. Sarstedt (2011), “PLS-SEM: Indeed a Silver Bullet”, Journal of Marketing Theory and Practice, 19 (2), 139-152.

Hair, J. F. Jr., C. M. Ringle and M. Sarstedt (2013), “Partial Least Squares Structural Equation Modeling: Rigorous Applications, Better Results and Higher Acceptance”, Long Range Planning, 46 (1-2), 1-12.

Hair, J. F. Jr., J. J. Risher, M. Sarstedt and C. M. Ringle (2019), “When to use and how to report the results of PLS-SEM”, European Business Review, Forthcoming.

Hair, J. F. Jr., M. Sarstedt, C. M. Ringle and J. A. Mena (2012), “An assessment of the use of partial least squares structural equation modeling in marketing research”, Journal of the Academy of Marketing Science, 40 (3), 414-433.

Hartman, J. L. and J. McCambridge (2011), “Optimizing Millennials’ Communication Styles”, Business and Professional Communication Quarterly, 74 (1), 22-44.

Henseler, J., C. M. Ringle and R. R. Sinkovics (2009), ”The use of partial least squares path modeling in international marketing” in New Challenges to International Marketing (Advances in International Marketing), Vol. 20. (Eds.) Sinkovics, R. R. and Ghauri, P. N., Bingley: Emerald Group Publishing Limited, 277-319.

Ivanov S. and C. Webster (2019a), “Perceived Appropriateness and Intention to Use Service Robots in Tourism”. In: Pesonen J., Neidhardt J. (eds) Information and Communication Technologies in Tourism 2019, Proceedings of the International Conference in Nicosia, Cyprus, 30.01-01.02.2019, 237-248.

Ivanov, S. and C. Webster (2019b), “What should robots do? A comparative analysis of industry professionals, educators and tourists”. In: Pesonen, J. and Neidhardt, J. (Eds.) Information and Communication Technologies in Tourism 2019, Proceedings of the International Conference in Nicosia, Cyprus, 30.01- 01.02.2019, pp. 249-262.

Joo, J. and Y. Sang (2013), “Exploring Koreans’ smartphone usage: An integrated model of the technology acceptance model and uses and gratifications theory”, Computers in Human Behavior, 29 (6), 2512-2518.

Jörling, M., R. Böhm and S. Paluch (2019). “Service Robots: Drivers of Perceived Responsibility for Service Outcomes”, Journal of Service Research, 22 (4), 404-420.

Junglas, I. A., N. A. Johnson and C. Spitzmüller (2008), “Personality traits and concern for privacy: an empirical study in the context of location-based services”, European Journal of Information Systems, 17 (4), 387-402.

Karakas, F., A. Manisaligil and E. Sarigollu (2015), “Management learning at the speed of life: Designing reflective, creative, and collaborative spaces for millennials”, International Journal of Management Education, 13 (3), 237-248.

Katz, E. (1959), “Mass Communications Research and the Study of Popular Culture: An Editorial Note on a Possible Future for This Journal”, Studies in Public Communication, 2 (1-6).

Katz, E., J. G. Blumler and M. Gurevitch (1974), “Uses and Gratifications Research”, The Public Opinion Quarterly, 37 (4), 509-523.

Kim, H.-W., H. C. Chan and S. Gupta (2007), „Value-based Adoption of Mobile Internet: An empirical investigation”, Decision Support Systems, 43 (1), 111-126.

Kim, K. J. and D.-H. Shin (2015), ”An acceptance model for smart watches: Implications for the adoption of future wearable technology”, Internet Research, 25 (4), 527-541.

Ko, E., E. Y.,Kim and E. K. Lee (2007), ”Modeling consumer adoption of mobile shopping for fashion products in Korea”, Psychology and Marketing, 26 (7), 669-687.

Lee, C., B. Reimer, B. Mehler and J. F. Coughlin (2015), “User Acceptance of Voice Interfaces in the Automobile”. Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 59(1), 1641-1645.

Lee, L., S. Petter, D. Fayard and S. Robinson (2011), “On the use of partial least squares path modeling in accounting research”, International Journal of Accounting Information Systems, 12 (4), 305-328.

Lee, S., R., Ratan and T. Park (2019), “The Voice Makes the Car: Enhancing Autonomous Vehicle Perceptions and Adoption Intention through Voice Agent Gender and Style”, Multimodal Technologies and Interaction, 3 (1), 20-31.

Leung, L. and R. Wei (2000), “More than just talk on the move: uses and gratifications of the cellular phone”, Journalism and Mass Communication Quarterly, 77 (2), 308-320.

Leung, L. and R. Zhang (2016), “Predicting tablet use: A study of gratifications-sought, leisure boredom, and multitasking”, Telematics and Informatics, 33 (2), 331-341.

Li, H., Y. Liu, X. Xu, J. Heikkilä and H. van der Heijden (2015), “Modeling hedonic is continuance through the uses and gratifications theory: An empirical study in online games”, Computers in Human Behavior, 48 (2015), 261–272.

Lissitsa, S. and O. Kol (2016), “Generation X vs. Generation Y – A decade of online shopping”, Journal of Retailing and Consumer Services, 31 (2016), 304-312.

Lowry, P. B., J. Gaskin, N. Twyman, B. Hammer and T. L. Roberts (2013), “Taking “Fun and Games” Seriously: Proposing the Hedonic-Motivation System Adoption Model (HMSAM)”, Journal of the Association for Information Systems, 14 (11), 617-671.

Luo, M. M., S. Chea and J.-S. Chen (2011), “Web-based information service adoption: A comparison of the motivational model and the uses and gratifications theory”, Decision Support Systems, 51 (1), 21-30.

Malhotra, N. K., S. S. Kim and J. Agarwal (2004), “Internet Users‘ Information Privacy Concerns (IUIPC): The Construct, the Scale, and a Causal Model”, Information Systems Research, 15 (4), 336-355.

Malik, A., A. Dhir and M. Nieminen (2016), “Uses and Gratifications of digital photo sharing on Facebook”, Telematics and Informatics, 33 (1), 129–138.

Moon, J. W. and Y. G. Kim (2001), ”Extending the TAM for a World-Wide-Web context”, Information and Management, 38 (4), 217-230.

Nabi, R. L., C. R. Stitt, J. Halford and K. L. Finnerty (2006), “Emotional and Cognitive Predictors of the Enjoyment of Reality-Based and Fictional Television Programming: An Elaboration of the Uses and Gratifications Perspective”, Media Psychology, 8 (4), 421-447.

Onobhayedo, P. A. (2017), “Implementing Web Technologies as Organizational Communication Media: A Study of Employee Adoption Likelihood”, Journal of Business Theory and Practice, 5 (2), 120-140.

Papacharissi, Z. and A. Mendelson (2010), “Toward a new(er) sociability: uses, gratifications and social capital on Facebook” in Media Perspectives for the 21st Century, Vol. 1. (Eds.) Papathanassopoulus, S., London: Routledge, 212-230.

Parasuraman, A. (2000), “Technology Readiness Index (TRI). A Multiple-Item Scale to Measure Readiness to Embrace New Technologies”, Journal of Service Research, 2 (4), 307-320.

Park, E. and K. J. Kim (2014), “An Integrated Adoption Model of Mobile Cloud Services: Exploration of Key Determinants and Extension of Technology Acceptance Model”, Telematics and Informatics, 31 (3), 376-385.

Park, E., H. Kim and J. Y. Ohm (2014), “Understanding driver adoption of car navigation systems using the extended technology acceptance model”, Behaviour and Information Technology, 34 (7), 741-751.

Park, N. (2010), “Adoption and Use of Computer-Based Voice Over Internet Protocol Phone Service: Toward an Integrated Model”, Journal of Communication, 60 (1), 40-72.

Park, N., K. M. Lee and P. H. Cheong (2007), “University Instructors’ Acceptance of Electronic Courseware: An Application of the Technology Acceptance Model”, Journal of Computer-Mediated Communication, 13 (1), 163-186.

PwC (2017), “Digitale Assistenten - Bevölkerungsbefragung 2017“.

Quan-Haase, A. and A. L. Young (2010), “Uses and Gratifications of Social Media: A Comparison of Facebook and Instant Messaging”, Bulletin of Science, Technology and Society, 30 (5), 350-361.

Rauschnabel, P. A., J. He and Y. K. Ro (2018), “Antecedents to the adoption of augmented reality smart glasses: A closer look at privacy risks”, Journal of Business Research, 92 (2018), 374-384.

Rauschnabel, P. A. and Y. K. Ro (2016), “Augmented reality smart glasses: an investigation of technology acceptance drivers”, International Journal of Technology Marketing, 11 (2), 123-148.

Rauschnabel, P. A., A. Rossmann and M. C. tom Dieck (2017), “An adoption framework for mobile augmented reality games: The case of Pokémon Go”, Computers in Human Behavior, 76 (2017), 276-286.

Ringle, C. M., M. Sarstedt and D. W. Straub (2012), “A Critical Look at the Use of PLS-SEM in MIS Quarterly”, Management Information Systems Quarterly, 36 (1), 3-14.

Rosenthal-von der Pütten, A. M., N. C. Krämer and J. Herrmann (2018), “The effects of humanlike and robot-specific affective nonverbal behavior on perception, emotion, and behavior”, International Journal of Social Robotics, 10, 569-582.

Rubin, A. M. (2002), “The uses-and-gratifications perspective of media effects” in Media effects: Advances in theory and research, Vol. 2. (Eds.) Bryant, J. und Zillmann, D.: LEA’s communication series, Mahwah: Lawrence Erlbaum Associates, 525-548.

Ruggiero, T. E. (2000), “Uses and Gratifications Theory in the 21st Century”, Mass Communication and Society, 3 (1), 3-37.

Sarstedt, M., J. F. Hair, C. M. Ringle, K. O. Thiele and S. P. Gudergan (2016), “Estimation issues with PLS and CBSEM: Where the bias lies!”, Journal of Business Research, 69(10), 3998-4010.

Schweiger, W. (2007), “Theorien der Mediennutzung: Eine Einführung“, Wiesbaden: VS Verlag für Sozialwissenschaften.

Sharma, P. N., G. Shmueli, M. Sarstedt, N. Danks and S. Ray (2019), “Prediction-oriented model selection in partial least squares path modeling”, Decision Sciences, Forthcoming.

Sheldon, P., P. A. Rauschnabel, M. G. Antony and S. Car (2017), “A cross-cultural comparison of Croatian and American social network sites: Exploring cultural differences in motives for Instagram use”, Computers in Human Behavior, 75 (2017), 643-651.

Shmueli, G., S. Ray, J. M. Velasquez Estrada and S. B. Chatla (2016), “The elephant in the room: evaluating the predictive performance of PLS models”, Journal of Business Research, 69(10), 4552-4564.

Shmueli, G., M. Sarstedt, J.-H. Cheah, H. Ting, S. Vaithilingam and C. M. Ringle (2019), “Predictive model assessment in PLS-SEM: guidelines for using PLSpredict”, European Journal of Marketing, Forthcoming.

Simon, S. J. and D. Paper (2007), “User Acceptance of Voice Recognition Technology: An Empirical Extension of the Technology Acceptance Model”, Journal of Organizational and End User Computing, 19(1), 24-50.

Song, I., R. LaRose, M. S. Eastin and C. A. Lin (2004), “Internet Gratifications and Internet Addiction: On the Uses and Abuses of New Media”, CyberPsychology and Behavior, 7 (4), 384–394.

Srite, M. and E. Karahanna (2006), “The Role of Espoused National Cultural Values in Technology Acceptance”, Management Information Systems Quarterly, 30 (3), 679-704.

Statista (2017), “Welchen Nutzen sehen Sie bei der zunehmenden Verbreitung von Sprachassistenten?“, https://de.statista.com/statistik/daten/studie/739315/umfrage/umfrage-zum-nutzen-von-digitalen-sprachassistenten/.

Taherdoost, H. (2018), “A review of technology acceptance and adoption models and theories”, Procedia Manufacturing, 22, 960-967.

Tuzovic and Paluch (2018), “Conversational Commerce. A New Era for Service Business Development?” in Forum Dienstleistungsmanagement. Service Business Development, Bruhn and Hadwich (Eds.), Springer, Wiesbaden.

Valenzuela, S., N. Park and K. F. Kee (2009), “Is There Social Capital in a Social Network Site?: Facebook Use and College Students' Life Satisfaction, Trust, and Participation”, Journal of Computer-Mediated Communication, 14 (4), 875-901.

Van der Heijden, H. (2004), “User Acceptance of Hedonic Information Systems”, Management Information Systems Quarterly, 28 (4), 695-704.

Van Eeuwen, M. (2017), “Mobile conversational commerce: messenger chatbots as the next interface between businesses and consumers”, https://essay.utwente.nl/71706/1/van%20Eeuwen_MA_BMS.pdf.

Venkatesh, V. (2000), “Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model”, Information Systems Research, 11(4), 342-365.

Venkatesh, V. and H. Bala (2008), “Technology Acceptance Model 3 and a Research Agenda on Interventions”, Decision Sciences, 39 (2), 273-315.

Venkatesh, V. and F. D. Davis (1996), “A Model of the Antecedents of Perceived Ease of Use: Development and Test”, Decision Sciences, 27 (3), 451-481.

Venkatesh, V. and F. D. Davis (2000), “A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies”, Management Science, 46 (2), 186-204.

Venkatesh, V. and M. G. Morris (2000), “Why Don't Men Ever Stop to Ask for Directions? Gender, Social Influence, and Their Role in Technology Acceptance and Usage Behavior”, Management Information Systems Quarterly, 24 (1), 115-139.

Venkatesh, V., M. G. Morris, G. B. Davis and F. D. Davis (2003), “User Acceptance of Information Technology: Toward a Unified View”, Management Information Systems Quarterly, 27 (3), 425-478.

Venkatesh, V., J. Y. L. Thong and X. Xu (2012), “Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology”, Management Information Systems Quarterly, 36 (1), 157-178.

Weizenbaum, J. (1966), “ELIZA – A Computer Program for the Study of Natural Language Communication between Man and Machine”, Communications of the ACM, 9 (1), 36-45.

Wirtz, J., P. Patterson, W. Kunz, T. Gruber, V. N. Lu, S. Paluch and A. Martins (2018), „Brave New World: Service Robots in the Frontline”, Journal of Service Management, 29(5), 907-931.

Wu, J.-H. and S.-C. Wang (2005), “What drives mobile commerce? An empirical evaluation of the revised technology acceptance model”, Information and Management, 42 (5), 719-729.

Wünderlich, N.V. and S. Paluch (2017), “A Nice and Friendly Chat with a Bot: User Perceptions of AI-Based Service Agents”. ICIS 2017.

Xu, C., S. Ryan, V. Prybutok and C. Wen (2012), “It is not for fun: An examination of social network site usage”, Information and Management, 49 (5), 210-217.

5 Research paper #4: How about older people and Digital Voice Assistants? – An empirical investigation of Amazon's Alexa based on UTAUT2

Author: Ewers, K.

Submitted in: Journal of Service Management Research

Abstract: Spoken language is an elementary foundation of human communication. It has even the potential to change the future of human-computer interaction radically. In this context, Digital Voice Assistants (DVAs) are likely to revolutionize such interaction (Tsai et al. 2015). Still, people in mid-age currently use them (< 55-year-old) rather than by older ones (55+ years old) (Panch et al. 2018).

The study aims to close the existing research gap and determine which factors play an essential role in accepting DVAs by older people. For this purpose, the study uses Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Venkatesh et al. 2012). Furthermore, based on open questions, possible gaps are identified, and main age-specific influencing factors are nearly discussed.

With the help of a structured questionnaire, we interviewed 223 people aged 55 and over in Bayreuth (population: 74.657), a mid-sized German city in Upper Franconia, Bavaria. Statistics indicate that the model has a good predictive capability ($R^2 = 0.507$). Results show that, Performance Expectancy, Social Influence, Facilitating Conditions, and Hedonic Motivation positively influence the intention to use DVAs, depending on age and gender. Furthermore, open questions show that topics such as Privacy and Data Protection, Technophobia and Technology-related self-efficacy can be possible barriers in the acceptance process.

Results indicate that especially older women are influenced by the opinion and behavior of their loved ones in their decisions. Future research should examine the factors and their determinants in more detail and show what role family members or related persons play in the decision-making process. It should also be considered what primary conditions (e.g., customer support) need to be created for older people to decide to use DVAs. Furthermore, the analysis shows noticeable differences between people aged 55 to 64 years and people aged 65 years and older. As a result, older people cannot be seen as a largely homogenous group. Future studies should keep it in mind and work out other vital differences on the basis of larger samples.

Keywords: Digital Voice Assistants, UTAUT2, older people, technology acceptance, TAM

5.1 Introduction

Demographic change and its effects on politics and the economy can be seen as central social challenges of the 21st century (England and Azzopardi-Muscat 2017; Goldstein and Kluge 2016). For example, an increasing number of older people means higher spending on health and social services and, at the same time, lower tax revenues from people of working age (Choudrie et al. 2018; Vassli and Farshchian 2018). The aging of our society brings difficulties, but it can also mean new opportunities for the economy in new business models and customer groups (Kohlbacher et al. 2015).

Constant development and improvement of information and communication technologies (Luo and Bu 2016) can significantly contribute to the fact that older people can live their lives as independently as possible (Ma et al. 2015; Merkel et al. 2017; Nikou 2015; Guner and Acarturk 2018). An example of this are DVAs, which are characterized by a voice-based user interface and make the interaction with technical devices as natural as possible (Hoy 2018). The global market for DVAs is growing year by year and is expected to exceed $ 3.5 trillion by 2021 (Gartner 2017).

Although technology acceptance has been an integral part of scientific research for many years, there is still relatively little in-depth research into technology acceptance among older people compared to other age groups (Kim et al. 2016; Mostaghel 2016; Sovie et al. 2017; Vantiv 2018; Guner and Acarturk 2018). The few studies available relating to DVAs are of a qualitative nature and use interviews, focus groups, and observations in particular (Hellwig et al. 2018; Mizak et al. 2017; Wulf et al. 2014). There is, therefore, a lack of quantitative studies that include various factors in an empirical model.

The paper aims to close the existing research gap and determine which factors play an essential role in the acceptance of DVAs by older people. Therefore, we use the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), a technology acceptance model from 2012 (Venkatesh et al. 2012). Furthermore, possible gaps in the model should be closed by open questions.

The paper is structured as follows: In sections 2 and 3, technology acceptance and technology acceptance by older people will be discussed. Section 4 describes in detail UTAUT2 – a model for measuring technology acceptance. In the next step (section 5 and 6) a research model, hypotheses and a questionnaire will be presented, followed by the results (based on the structural equation model and open questions) in section 7. The paper will be closed with a discussion (section 8), limitations (section 9) as well as a conclusion including some theoretical and managerial implications (section 10).

5.2 Technology Acceptance

Product launches, especially such in technology and services, often fail because users do not accept them, even if they offer added value from a purely technical point of view or have the potential to improve the quality of consumers' life (Choudrie and Vyas 2014; Kotzé et al. 2016; Heidenreich and Handrich 2015; Heidenreich and Kraemer 2016). Individual acceptance is, therefore, a central factor that decides whether or not to succeed. To understand and investigate the complex process of acceptance and its influencing factors, it first must be clarified what will be in general understood under acceptance and in particular for the investigation in this study under technology acceptance.

The term "acceptance" is used in an interdisciplinary manner and has different meanings and components depending on the research area and context. Acceptance will be examined, among other things, in sociology, psychology, business administration, and there in particular in consumer behavior, innovation, and information system research (Lee and Coughlin 2015; Macedo 2017). The essence of almost all attempts to define the term in the field of technology-oriented acceptance research is that a subject (e.g. a person or a group) accepts or rejects an object (e.g. a technological product or service) within certain framework conditions (e.g. age, income or social environment) (Schäfer and Keppler 2013). It is basically about understanding a consumer's complex decision-making processes and explaining why technology is used or why not. The acceptance process begins before the actual contact with the technology and is characterized by dynamism and change (Jockisch 2010).

Basic principles of the technology acceptance research have their origin in the Theory of Reasoned Action (TRA) – a socio-psychological theory by Fishbein and Ajzen, which tries to make human behavior explainable and predictable (Fishbein and Ajzen 1975). At its core, TRA tries to explain human behavior and make it possible to make predictions about behavior (Fishbein and Ajzen 1975). A rationally-acting person, who consciously chooses behavior based on all available information, has power and control over it. Although numerous studies of individual technology acceptance were investigated in the years after that, research especially gained tremendous popularity with introducing the Technology Acceptance Model (TAM) (Davis et al. 1989; Davis 1989; Venkatesh et al. 2007). Figure 1 gives an overview of the well-known models of technology acceptance research and their time of recognition.

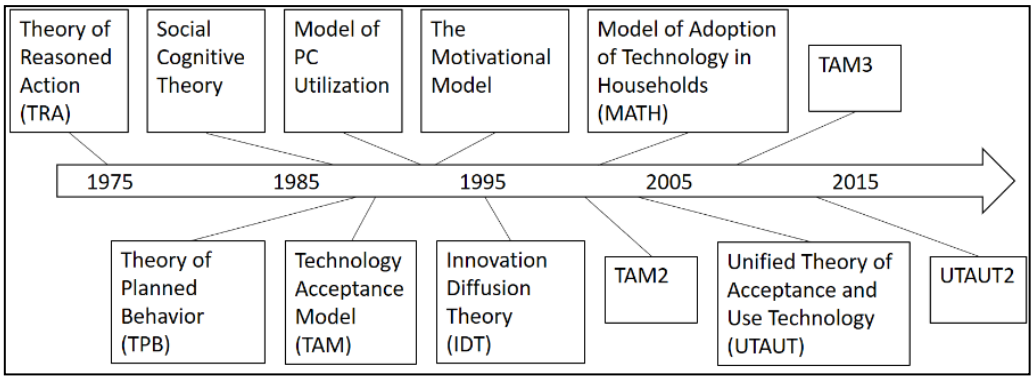


Figure 1: Technology acceptance models over time (1975 – 2015)
Source: Own depiction

5.3 Technology acceptance by older people

Demographic change has the world firmly under control. Already today, older people are increasingly shaping the image of society in most countries. The proportion of people over 65 was 727 million worldwide in 2020 (United Nations 2020). The reason for this is the so-called baby boomer generation. It describes the baby boomers after World War II. However, a uniform definition of "older people" cannot be found in the literature. The reasons for this lie in the various socio-economic factors that lead to this phenomenon. In the USA, people born after 1945 are included in this group, while in Germany, the year 1955 is defined as the beginning of the baby boomer generation (Knickmann and Snell 2002). As a result, the generation aged 55 and over is most frequently represented within the population. For this reason, people older than 55 years are considered for this study.

Older people often encounter difficulties using information and communication technologies and use them less frequently than younger people (Kim et al. 2016, 147). The image of the tech-savvy group of seniors seems to be changing. While around five years ago, there were comparatively few people over the age of 60 on the Internet, the Silver Surfer generation recorded an increase of about 15% (Janson 2019). It is necessary to examine which factors are responsible for accepting or rejecting new technologies to make them more accessible to older people.

Older people need to live independently for as long as possible. Unfortunately, studies show that the risk of social isolation increases with age (Federal Ministry for Family Affairs, Senior Citizens, Women and Youth (BMFSFJ) 2016; Hellwig et al. 2018). Reports show that smart devices are almost assigned human characteristics as conversation partners (Ashley 2019). DVAs rather offer a gateway to the outside world (Hellwig et al. 2018). Due to DVAs, Emails can be read aloud, or emergency calls can be made (Hellwig et al. 2018). DVAs can also be used as translators between e.g., nurses and senior citizens if they do not speak the same

language. Small mistakes, such as incorrect interpretation of the language, are accepted and do not deter its users from using DVAs (Basu 2019). Data protection concerns also seem to play a subordinate role within the age group. Here the compromise is made to gain more comfort against personal data through DVA (Tech-enhanced Life 2017).

Various reports and application scenarios for seniors have one thing in common: Either the DVAs are installed by relatives or organizations and set up ready for use (Schwarz 2018). Seniors themselves do not have to deal with the technical conditions of the facility. It is due to the discrepancy between installation and use – while the usage is easy to learn for everyone, a rudimentary technical understanding must prevail to integrate DVAs into the home network. The integration can only occur via WLAN and must be carried out for many DVAs using a smartphone or a computer – a challenge for many at an advanced age, which can deter use. But as soon as the seniors are familiarized with the functioning of DVAs, initial skepticism changes to curiosity (VoCo 2018). The table in Appendix (see Appendix 1) provides an overview of current studies on technology acceptance of older people based on the models: TAM, UTAUT, and UTAUT2 over the last years.

5.4 UTAUT2 – Acceptance measurement

In addition to the TAM and its expanded forms, many other technology acceptance models were developed, such as the Motivation Model (Davis et al. 1992) or the Model of Adoption of Technology in Households (Brown and Venkatesh 2005; Venkatesh and Brown 2001), so that researchers could use a variety of possible models (Venkatesh et al. 2003). Individual constructs were often selected from various models as preferred, or a specific model was selected based on seemingly arbitrary criteria (Brown and Venkatesh 2005). Venkatesh et al. (2003) reviewed existing acceptance models, worked out commonalities and differences, and designed a merged and universal model for predicting individual technology acceptance based on empirical studies. It resulted in building a Unified Theory of Acceptance and Use of Technology (UTAUT), which consists of eight different models and theories (Venkatesh et al. 2003). Finally, a synthesis was created from building blocks of these models and the four constructs: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions, were included in the final model. The first three determinants have a direct impact on the intention to use new technology. Facilitating conditions is a direct determinant of both- Behavioral Intention and Use Behavior (Venkatesh et al. 2003). In addition, Gender, Age, Experience, and Voluntariness of Use moderate the impact of the constructs (Venkatesh et al. 2003).

Since UTAUT was primarily created for the organizational and not for the consumer context, Venkatesh et al. modified the model and created the UTAUT2, which we used in our study

(Venkatesh et al. 2012). The authors identified three other key factors that play an important role, especially in consumer acceptance. The first newly added construct, Hedonic Motivation, describes the fun or the joy of using technology. The second construct, Price Value, is balancing a consumer by monetary costs against usage benefits. Both determinants have a direct influence on Behavioral Intention. The third and final construct, Habit, is defined as the degree to which an individual tends to perform behavior automatically based on learning processes. This construct has a direct effect on the Behavioral Intention as well as on the Use Behavior.

5.5 Research model and hypotheses

In our study, we use a modified UTAUT2 by Venkatesh et al. (2012), which we adjusted to the context of DVAs. It was specially developed for the consumer context and combined the essential factors in a holistic model by synthesizing existing technology acceptance models (Venkatesh et al. 2003). In addition, UTAUT2 already proved its robustness in predicting the acceptance of digital technologies (Alalwan et al. 2018; Owusu Kwateng et al. 2019; Tak and Panwar 2017).

In its original form, UTAUT2 consists of seven constructs that influence Behavioral Intention and Use Behavior (Venkatesh et al. 2012). Relationships between the constructs are moderated by age, gender, and experience. Based on the findings, currently, only a small number of older people use DVAs. The model is built up to Behavioral Intention. The focus lies on the current non-users, i.e., the potential future users (Brown and Venkatesh 2005; Slade et al. 2015). For this reason, the construct Habit is omitted, since analogous to the procedure of Venkatesh et al. (2012), it can be argued that only current users can answer questions about habits. The construct Experience is also not included, since Venkatesh et al. (2012) carried out two staggered surveys in their study and were able to map different levels of experience. Table 2 presents all derived hypotheses, while Figure 2 shows a research model used in our study.

In addition to these main effects, Age and Gender moderate all the relationships (Venkatesh et al. 2003; Venkatesh et al. 2012). The hypotheses H1a, H2a, H3a, H4a, H5a, and H6a each refer to the moderator Age, whereas the hypotheses H1b, H2b, H3b, H4b, H5b, and H6b postulate the moderating effect of Gender on the respective relationship.

	Hypothese	Source
H1	**Performance Expectancy** has a positive impact on Behavioral Intention of older people to use digital voice assistants in the future.	Venkatesh et al. 2012; Arenas-Gaitán et al. 2015; Choudrie et al. 2018; Cimperman et al. 2016; Hoque and Sorwar 2017; Lai 2018
H2	**Effort Expectancy** has a positive impact on Behavioral Intention of older people to use digital voice assistants in the future.	Venkatesh et al. 2012; Arenas-Gaitán et al. 2015; Choudrie et al. 2018; Hoque and Sorwar 2017; Macedo 2017; Moura et al. 2017
H3	**Social Influence** has a positive impact on Behavioral Intention of older people to use digital voice assistants in the future.	Venkatesh et al. 2012; Arenas-Gaitán et al. 2015; Choudrie et al. 2018; Cimperman et al. 2016; Diño and Guzman 2015; Gao et al. 2015; Hoque and Sorwar 2017; Lai 2018; Macedo 2017
H4	**Facilitating Conditions** have a positive impact on Behavioral Intention of older people to use digital voice assistants in the future.	Venkatesh et al. 2012; Choudrie et al. 2018; Cimperman et al. 2016; Macedo 2017; Suta et al. 2018
H5	**Hedonic Motivation** has a positive impact on Behavioral Intention of older people to use digital voice assistants in the future.	Venkatesh et al. 2012; Choudrie et al. 2018; Gao et al. 2015; Macedo 2017
H6	**Price Value** has a positive impact on Behavioral intention of older people to use digital voice assistants in the future.	Venkatesh et al. 2012; Arenas-Gaitán et al. 2015; Macedo 2017

Table 2: Research hypotheses

Source: Own depiction

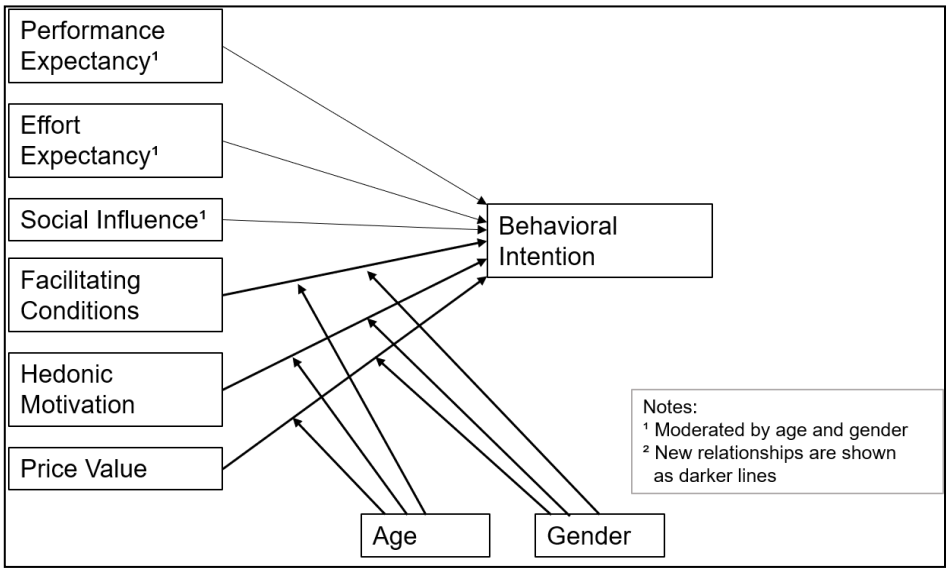


Figure 2: Research model – modified UTAUT2

Source: Own depiction based on Venkatesh et al. (2012)

5.6 Questionnaire and data collection

At first, items and questions (see table 3) were taken from existing examinations and adjusted to the research context of DVAs. This method corresponds to the approach of many studies in quantitative technology acceptance research (Alalwan et al. 2018; Choudrie et al. 2018; Macedo 2017; Oliveira et al. 2016; Slade et al. 2015; Tak and Panwar 2017). Since the items come from English-language studies, but the sample consists exclusively of German-speaking test subjects, the statements were translated into German and then checked by

native speakers. This made it possible to ensure that the translation process did not falsify the content. To measure the attitudes of the test persons to the individual statements, the items were based on Owusu Kwateng et al. (2019) operationalized on a five-point Likert scale with symmetry around a mean value. To examine the comprehensibility and completeness of the developed questionnaire and avoid errors, a pretest was carried out with five test persons. The persons were selected according to their suitability concerning the target group, and the pretest was carried out under the same conditions as the main study.

Specifically, the questionnaire was divided into three sections. The first part included the greeting and a general introduction to the topic of the survey. In addition to data protection issues, the test respondents were introduced to the functionality of Digital Voice Assistants both in text form and with the help of a product video. In the second part, the constructs operationalized in the previous section were queried using the multi-item scales. In the third and last part of the questionnaire, respondents were asked to provide general information on their gender, year of birth, the highest level of education, current professional situation, personal monthly net income, and whether or not they had an Internet connection (WLAN). The questionnaire ended with three open questions. Here, respondents had the opportunity to provide comments, remarks, or feedback on the use of Alexa or Digital Voice Assistants in general and on the survey.

The choice of a survey as the study design, opposed to observation, makes sense in this study because it asks the respondents' opinions or attitudes towards a certain issue and not of observing a specific behavior. When it comes to whether the data is collected orally, in writing, by telephone, or via online input, the decision should always be made with the target group in mind (Kuß et al. 2014). Since in the present case, it can be assumed that most older people are not familiar with completing online surveys, as, for example, with students, the choice fell on an oral survey. Although this is significantly more time-consuming than the other methods, and there is a risk of influencing by the interviewer, the advantages of a high response rate as well as the completeness and quality of the data outweigh this (Kuß et al. 2014). Furthermore, there is the possibility to respond directly to queries from the participants. Since it was impossible to reach all older people in Germany, only part of the population was surveyed using a sample. A non-random and conscious selection was used in the selection process, as was the case in similar studies (Guner and Acarturk 2018; Lai 2018). The data were collected between February 27th and April 30th, 2019, using a paper questionnaire. The participants were recruited personally in Bayreuth, a medium-sized town in the Upper Franconian administrative region with 74.657 inhabitants in southeast Germany. Participation in the survey was completely voluntary. After consenting to participate, each test person was informed about the general procedure of the survey and data protection issues at the beginning. Afterward, the functioning of Digital Voice Assistants was explained to each

test person both verbally and in a video using Alexa as an example. Only after querying the individual constructs were sensitive data such as age and income queried. Based on current studies on technology acceptance among older people, surveyed women and men were 55 years old and over (Guner and Acarturk 2018; Lai 2018; Ma et al. 2016; Macedo 2017).

In the course of the study period, a total of 225 people took part in the survey, of which two questionnaires had to be removed from the sample afterward because they were too young. On average, a personal interview lasted around 30 minutes. At the end of the study period, the data collected was transferred to the Qualtrics survey platform, enabling automatic export to the SPSS statistics software. After the data cleansing, a final data set of 223 participants remained. Concerning the gender ratio, the overall sample shows a balanced ratio of 99 male (44.39%) and 124 female participants (55.61%). The mean age is 65.7 years (SD = 8.6), the minimum: 55 years, and the maximum: 91 years.

Construct (Source)	Name	Item
Performance Expectancy (Venkatesh et al. 2012)	PE_1	I find that digital voice assistants are useful in my everyday life.
	PE_2	Using digital voice assistants increases my chances of achieving things that are important to me.
	PE_3	There are many things that I can do faster with the help of digital voice assistants than without them.
	PE_4	The use of digital voice assistants increases my productivity.
Effort Expectancy (Venkatesh et al. 2012)	EE_1	I believe that it is easy to learn how to use digital voice assistants.
	EE_2	My interaction with digital voice assistants is clear and understandable.
	EE_3	I find it easy to use digital voice assistants.
	EE_4	I have no difficulty in becoming skilled with digital language assistants.
Social Influence (Venkatesh et al. 2012)	SI_1	People who are important to me find that I should use digital voice assistants.
	SI_2	People who influence my behavior believe that I should use digital voice assistants.
	SI_3	I use digital voice assistants because many people around me use them.
	SI_4	People whose opinions I value want me to use digital voice assistants.
Facilitating Conditions (Venkatesh et al. 2012)	FC_1	I have the necessary resources to use digital voice assistants.
	FC_2	Digital voice assistants are compatible with other technologies that I use.
	FC_3	I can receive help from other people if I have difficulty using digital voice assistants.
Hedonic Motivation (Venkatesh et al. 2012)	HM_1	Using digital voice assistants is fun.
	HM_2	Using digital voice assistants is pleasant.
	HM_3	Using digital voice assistants is very entertaining.
Price Value (Venkatesh et al. 2012)	PV_1	The price of digital voice assistants seems reasonable to me.
	PV_2	Digital voice assistants are worth the money.
	PV_3	Concerning the current price, digital voice assistants offer a good price-performance ratio.
Behavioral Intention (Niehaves and Plattfaut 2014)	PV_1	I intend to use digital voice assistants (also) in the future.
	PV_2	I predict that I will (also) use digital voice assistants in the future.
	PV_3	I plan to use digital voice assistants in the future.

Table 3: Constructs and Items of the research model

Source: Own depiction

The proportion of respondents decreases with increasing age, which roughly corresponds to the population. While 72 respondents are between 55 and 64 years old (32.29%), there are 88 people in the age group between 65 and 74 (39.46%). Another 63 respondents are over 75 years old (28.25%). As expected for the age group, almost half (45%) of the respondents have an apprenticeship / vocational training as the highest educational qualification, 26.7% with a university degree, and 11.7% with a (technical) A-Level. As expected, with a view to the current professional situation, pensioners form the largest group with 47.5%, followed by employees with 30%. Only a few respondents are looking for work or are homemakers. Concerning monthly net income, the majority of respondents can fall back on a medium to high income. The largest percentage of respondents (31.7%) earn € 1,001 to € 2,000 per month, followed by 28.3% who have € 2,001 to € 3,000 per month and 15.8% with a net income between € 3,001 and € 5,000. Only a small number of the surveyed people earn less than € 500. Another interesting finding when looking at the descriptive results, which primarily concerns the use of Digital Voice Assistants specially developed for the home environment, is that the majority of the test subjects (87.5%) have an Internet connection (WLAN) at home. It is a basic requirement for using DVAs. Concerning other characteristics such as income or educational qualifications, we found no other notable differences.

Since gender plays an important role in the subsequent multivariate analysis of non-users, the two groups' most important gender-specific descriptive results are also briefly explained. Looking at the level of education, it becomes clear that far more men than women have a university or technical college degree (34.7% compared to 13.0%). Among women, respondents with an apprenticeship / vocational training make up the strongest group. There are also differences in disposable monthly net income in that women earn less than men on average. For example, while 33.3% of women have less than € 1,000 a month at their disposal, only 4.1% of the male respondents. The opposite is true for earnings of over € 3,000. While only 13.0% of the female respondents can fall back on more than € 3,000 per month, the figure is 30.7% for men.

As part of the descriptive results, the analysis finally answers the question for which tasks the respondents would use a Digital Voice Assistant. Specifically, the test subjects had the opportunity to choose from a series of preselected answer categories. They could imagine using a DVA (multiple answers were possible). The most common answer was playing music/radio mentioned with an approval rate of 61.2%, followed by retrieving various information in search engines with 60.2%. The lowest agreement, with 42.7%, was for sending and listening to messages. 16.5% of those questioned would not use DVAs for any of the tasks mentioned. It has been shown that smart home applications such as controlling lights and operating appliances in the household are less popular than basic tasks such as playing music or querying information in search engines. It also becomes clear that tasks that require

the entry of personal data, such as managing calendar entries and appointments and sending and listening to messages, are less popular. Since the present work is a complex research model consisting of several causal relationships between latent variables, structural equation modeling (SEM) is chosen as a second-generation multivariate analysis method for the statistical examination of the connections (Chin 1998; Hair et al. 2014).

5.7. Results

5.7.1. Results based on the structural equation model

Since our study deals with two complex research models consisting of several causal relationships between latent variables, structural equation modeling (SEM) is chosen as a second-generation multivariate analysis method for the statistical examination of the models presented in this study (Chin 1998; Hair et al. 2014; Rigdon 2016). Based on Venkatesh et al. (2012), the method of partial least squares structural equation modeling (PLS-SEM) is chosen because, in addition to the numerous causal relationships, there are several moderating effects in the model, and this method can estimate such a complex model (Hair et al. 2014; Venkatesh et al. 2012). PLS-SEM is also appropriate because it is a relatively small sample, and it delivers significantly better and more robust results than the covariance-based structural equation modeling (CBS-SEM), which is also often used in the context of the SEM (Choudrie et al. 2018; Hair et al. 2014).

Before the relationships in the structural model can be tested and interpreted for their relevance and significance, the measurement models must first be checked for their reliability and validity, as described in the previous chapter (Fornell and Larcker 1981; Hair et al. 2014).

The first step is to check whether the measuring instrument is free from random errors and always delivers the same results when measurements are repeated under the same conditions (Campbell and Fiske 1959). Since the measurement models are reflective specified, the internal consistency of the multi-item scales at construct level can be tested with the help of the statistical test criteria Cronbach's alpha and composite reliability (Hair et al. 2014). In the present research model, all Cronbach's alpha values exceed the recommended limit of 0.7 (Nunnally and Bernstein 1994), and all composite reliability values exceed the recommended threshold of 0.6 (Bagozzi and Yi 1988). In this way, a high degree of internal consistency reliability can be guaranteed for each construct. A summary of the results can be found in Table 4. After considering Cronbach's alpha and the composite reliability, the reliability of each indicator is also checked with the help of the outer loadings (Hair et al. 2011; Hair et al. 2017). All but one of the indicators meet this criterion.

In a second step, the validity of the measurement model is examined (Straub 1989). The convergence and discriminant validity of the individual constructs are listed above (Hair et al. 2014; Macedo 2017). This can be seen from the average variance extracted (AVE). As can be seen in Table 4, this applies to all AVE values, which means that the respective construct is able, on average, to explain more than half of the variance of its indicators (Chin 1998). Consequently, each construct can be assigned a high degree of convergence validity.

To be able to check the discriminant validity in the next step, three methodological approaches are selected, which are explained in detail below and applied to the measurement model (Hair et al. 2019). First, the loadings and cross-loadings of the individual indicators on the constructs are compared (Hair et al. 2014). In both samples, the loadings are higher than the cross loadings in all cases, and thus discriminant validity can be proven based on the cross loadings. Another method of evaluating discriminant validity is based on the Fornell-Larcker criterion. According to this, a construct should share more variance with its indicators than other constructs (Owusu Kwateng et al. 2019). As shown in table 5, the presence of discriminant validity can also be confirmed by this quality criterion.

Since both the application of the cross-loading and the Fornell-Larcker criterion show weaknesses in the assessment of discriminant validity under certain conditions, according to Henseler et al., a third test criterion can be used - the heterotrait-monotrait criterion (HTMT), which measures the ratio of the average heterotrait-heteromethod correlations to the average monotrait-heteromethod correlations (Henseler et al. 2015). Table 6 shows that this is the case for the measurement models.

In conclusion, it can be stated that both the reliability and the validity of the measurement models can be confirmed since all the values used for testing achieve good to very good results. Furthermore, the values of the VIF in both investigation models are below the limit value of 5. Thus, the collinearity between the exogenous constructs in the structural model can be excluded. Next, the relationships in the structural model are checked (Hair et al. 2014).

For the present model, the estimates reveal moderate relationships. The bootstrapping method is used to check whether the respective path coefficient is statistically significant (Owusu Kwateng et al. 2019). It shows that Performance Expectancy, Social Influence, Facilitating Conditions, and Hedonic Motivation significantly influence the Behavioral Intention to use DVAs. Thus, four of the six hypotheses can be confirmed in the investigation models (H1, H3, H4, and H5). No significant influence can be demonstrated for Effort Expectancy and Price Value. Since the coefficient can be statistically significant, but the level of the influence can only be small, in a further step, the relative importance and the relationship between them are determined for all significant relationships (Hair et al. 2014). In both samples,

only small to medium influences on the constructs can be spoken of. Within the sample, Facilitating Conditions had the greatest effect on Behavioral Intention with β=0.386. Further most important constructs are: Social Influence (β=0.257), followed by Performance Expectancy (β=0.256) and Hedonic Motivation with β=0.225.

Construct/ Item	Loading	Cronb. Alpha	Comp. Reliability	AVE
Performance Expectancy		0.896	0.927	0.762
PE1	0.881			
PE2	0.884			
PE3	0.842			
PE4	0.884			
Effort Expectancy		0.842	0.892	0.674
EE1	0.806			
EE2	0.833			
EE3	0.787			
EE4	0.857			
Social Influence		0.909	0.936	0.786
SI1	0.902			
SI2	0.915			
SI3	0.815			
SI4	0.911			
Facilitating Conditions		0.779	0.870	0.690
FC1	0.856			
FC2	0.866			
FC3	0.767			
Hedonic Motivation		0.909	0.943	0.846
HM1	0.933			
HM2	0.939			
HM3	0.887			
Price Value		0.876	0.923	0.799
PV1	0.870			
PV2	0.910			
PV3	0.902			
Behavioral Intention		0.954	0.970	0.916
BI1	0.965			
BI2	0.960			
BI3	0.946			

Table 4: Reliability and validity of the constructs

	BI	EE	FC	HM	PE	PV	SI
BI	0.957						
EE	0.309	0.821					
FC	0.393	0.516	0.831				
HM	0.500	0.379	0.112	0.920			
PE	0.519	0.362	0.060	0.580	0.873		
PV	0.382	0.286	0.291	0.438	0.341	0.894	
SI	0.512	0.212	0.085	0.433	0.546	0.268	0.887

Table 5: Discriminant validity – Fornell-Larcker Criterion

	BI	EE	FC	HM	PE	PV	SI
BI							
EE	0.329						
FC	0.445	0.645					
HM	0.536	0.422	0.133				
PE	0.560	0.405	0.148	0.645			
PV	0.409	0.334	0.367	0.476	0.376		
SI	0.546	0.241	0.113	0.475	0.603	0.287	

Table 6: Discriminant validity – HTMT Criterion

After examining the path coefficients' significance, relevance, and relation, the structural model is examined for various quality criteria to assess the model's predictability (Hair et al. 2014). First, the coefficient of determination R^2 is considered a fundamental and widely used criterion in evaluating structural models (Chin 1998). The research model shows a moderate forecasting ability with an R^2=0.507. The adjusted R^2 is R^2adj=0.493. In contrast to the R^2, which enables a prediction within the sample, the Q^2 offers a measure of the out-of-sample prognosis capability (Sarstedt et al. 2014). Looking at the blindfolding procedure results for the established research models, Q^2=0.451. As a result, the model has a high level of prognostic relevance for the endogenous construct of intended use.

The analysis of the moderation effect of gender (divided in men and women) and age (divided in two age groups: 55-64 years and 65+ years) show that the Performance Expectancy is much more important for the younger of the two age groups (Venkatesh et al. 2003). While the time is important for working people and Digital Voice Assistants can help increase productivity, these practical benefits are not relevant for older people. For those over 65, Social Influence and Facilitating Conditions are more important. These results are consistent with the findings of Venkatesh et al. (2012). For older people, the availability of supportive framework conditions, such as aids or technical support, as well as the opinion of someone close to them, is important.

To show the gender-specific differences, the total sample is divided into groups analogously to age. The results show that Social Influence plays a more important role for women than for men, as the path coefficients are 0.354 (female) and 0.290 (male). These results are in line with Venkatesh et al. 2003. Accordingly, women tend to include the opinion of other people in their decision-making process using technology (Venkatesh et al. 2000).

The results show that eight hypotheses can be confirmed (H1, H3, H4, H5, H1a, H3a, H4a and H3b. Performance Expectancy, Social Influence, Facilitating Conditions and Hedonic Motivation significantly influence Behavioral Intention to use DVAs, whereas no statistical significance could be found for the Effort Expectancy and Price Value. The relationship between Performance Expectancy and Behavioral Intention to Use is moderated by age, in such a way that this effect is stronger for the age group of 55 to 64-year-olds. Social Influence is moderated by age and gender so that the relationship is stronger for women over 65 years. Ultimately, the relationship between the Facilitating Conditions and Behavioral Intention to Use is moderated by age so that a stronger effect can be attested for people aged 65 and over. In our study, Performance Expectancy has a greater influence on Behavioral Intention for men, while Social Impact dominates for women. Concerning age, the effect of Facilitating Conditions on Behavioral Intention is greater for those over 70 than in the younger study group.

5.7.2 Results based on open questions

In contrast to the closed questions, no predefined answer alternatives are provided for the open questions. However, these results provide more profound insights into the participants' ideas, needs, and fears and can be added to the quantitative analysis. It makes it possible to uncover potential deficits in the model and to understand relationships better. Since answers to these questions were not necessary, data only exist for some of the respondents. To be able to evaluate the open-ended responses, the data are first viewed, and a category scheme is developed from this (Berekoven et al. 2009). Specifically, the test subjects had the

opportunity to express their opinion on three questions at the end of the survey. The first two questions relate to the use of Alexa or Digital Voice Assistants in general. Since the participants answered either one or the other question, the results are summarized for better clarity. The third question deals with the feedback on the survey and provides additional important insights into the design of the questionnaire.

By far, the most frequently cited answers relate to the privacy and data protection category. In connection with digital technologies, data protection issues play an important role for consumers (Arpaci et al. 2015; Weinberg et al. 2015). Mani and Chouk (2017) were able to show in their study that privacy concerns increase consumers' resistance to smart technologies. Miltgen et al. (2016) conducted a negative effect of data protection concerns on the intended use of innovative technologies, mediated by trust and risk perception. When looking at the individual answers, it becomes clear that the test persons do not want their data to be collected and stored by large corporations. The fear of data abuse by third parties and surveillance by corporations is also great.

The second most frequently mentioned category, technophobia relates to a person's negative or fearful behavior towards technological products. Similar to privacy and data protection, this construct harms the acceptance process and can be seen as a factor that inhibits acceptance (Sinkovics et al. 2002). When analyzing the answers, it becomes apparent that two aspects of technophobia play an important role - the fear that Digital Voice Assistants will replace human communication and those technologies will instead dominate daily interaction (Sinkovics et al. 2002).

In addition, the following categories were occasionally mentioned: state of health ("Voice assistants can harm memory performance and independence, especially in old age"), technology-related self-efficacy (conviction of a person being able to use technologies independently (cf. Compeau and Higgins 1995) and resistance to change. The repeated mention of usefulness and safety when driving a car should also be emphasized. It shows that, in particular, the ability to manage several things simultaneously and save time in everyday tasks has a positive influence on the intended use.

5.8 Discussion

Results of the structural equation modeling show that in contrast to the majority of previous studies (Cimperman et al. 2016; Diño and Guzman 2015; Gao et al. 2015; Hoque and Sorwar 2017; Macedo 2017; Venkatesh et al. 2012). Facilitating Conditions and Social Influence have the greatest effect on Behavioral Intention. This finding is in line with the results of Lai (2018) and emphasizes the importance of close people (family and friends) in the ac-

ceptance process, especially of older people and women. A qualitative study based on open questions by Luijkx et al. (2015) showed that spouses, children and grandchildren in particular play an important role in the decision-making process. It must be remembered that everyone has different goals and that the opinions of the grandchildren are often particularly important.

Facilitating Conditions have the strongest influence on Behavioral Intention, which is also in line with the results of Lai (2018). Macedo (2017) was also able to show this factor as one of the strongest predictors of Behavioral Intention. This shows how important is the availability of necessary resources and support for older people. In addition, there is the intensifying effect of age in the present model, so that this effect is stronger the older the respondent is. It is important that older people in particular find adequate support and receive help in using Digital Voice Assistants.

While Performance Expectancy turned out to be the most important predictor of intended use in previous studies (Diño and Guzman 2015; Hoque and Sorwar 2017; Macedo 2017; Suta et al. 2018) turns out to be the third strongest predictor in the present research model. Older people see the more Digital Voice Assistants as beneficial for their everyday lives, the more willing they are to use the devices in the future. However, caution should be exercised in the general assumption of what older people find useful. There is a difference in living conditions and related needs between employed and retired people. It can be seen in the moderating effect of age so that the influence of the expected benefit is stronger for the younger age group of 55 to 64-year-olds. This reinforcing effect of age is also in line with the findings of Venkatesh et al. (2003). In particular, temporal aspects and productivity play a completely different or subordinate role in the advanced age. Several times in the survey, test persons aged 65 and over said that time and efficiency are not relevant factors in their everyday lives.

In contrast to most of the previous studies (Arenas-Gaitán et al. 2015; Choudrie et al. 2018; Cimperman et al. 2016; Diño and Guzman 2015; Hoque and Sorwar 2017; Macedo 2017), but in line with the results of Lai (2018), Effort Expectancy has no significant influence on Behavioral Intention. A possible explanation can be seen in the fact that the test subjects (current non-users) rated the use as very easy. Still, this assessment is based purely on the imagination and not on actual practical experience. The results might be different if the test subjects had already had experience with the devices.

In the same way, as for the expected effort, no statistical significance can be determined for Price Value in the context of the present study. This finding is in line with the results of Macedo (2017) but in contrast to the studies by Arenas-Gaitán et al. (2015) and Venkatesh et al. (2012). In the case of Arenas-Gaitán et al. (2015) the difference can be explained because the studies were not based on the same multi-item scale, and therefore, different con-

structs were measured. In relation to the study by Venkatesh et al. (2012), the lack of influence of the Price Value in this study could be attributed to the fact that the test subjects had great difficulty assessing the price of Digital Voice Assistants because they are non-users. In Venkatesh et al. (2012), only users of the technology were involved. Furthermore, a lack of significance can be attributed to the fact that many of the test subjects were surprised at the low price of Digital Voice Assistants in the survey course. A comparison was often made with high-priced smartphones, and the price for Digital Voice Assistants was therefore classified as very low.

During the evaluation of the open questions, it became clear that two categories in particular function as relevant barriers due to the frequency they are mentioned. On the one hand, there are privacy and data protection issues, which were mentioned by far the most frequently. Another barrier is the negative and fear-shaped behavior of the test persons concerning technical products, which was summarized under the category technophobia. Since these constructs are not included in UTAUT2, they should be checked for their statistical significance in further studies.

5.9 Limitations

This study is the first to examine the acceptance of DVAs among the older generation at a point in time when the spread of the technology within the target group can be regarded as low so that a discussion of the restrictions and limitations is essential for the classification of the results.

It must be noted that there is no standardized definition for “older people”; different age limits are used as selection criteria (Mostaghel 2016). With increasing life expectancy due to medical progress and the gradual increase in retirement age, the limits of when a person is considered old are shifting upwards. Therefore, results with other studies should be compared with caution.

Since no studies were available in this context, our study was designed using a generic model (UTAUT2), adjusted to the examined age group. In further studies, the role of DVAs should be worked out in a stronger and more targeted manner. Ideally, own models for explaining the Behavioral Intention should be developed.

For the sample, a survey was carried out in two districts: Upper Franconia (southern Germany) and Oder-Spree (north-east Germany). The study is therefore tied to specific geographical conditions. The gender distribution roughly corresponds to that of the population. However, this cannot be transferred to the entire German population. The exclusion of West German citizens, in particular, can distort the results because they came into contact with

technologies earlier than, e.g., the East German population. As a result, the generalizability of the study should be carefully considered. Conducting the survey in other parts of Germany may lead to different results.

Concerning the research model, it must also be stated that this work focuses exclusively on the intended use (Nutzungsabsicht), which is referred to in the literature as the so-called “pre-implementation stage” (Luijkx et al. 2015). However, the results of Wu and Du (2012) show that the Behavioral Intention cannot predict the actual system use precisely, and therefore, the main focus should always be on the Use Behavior in combination with the Behavioral Intention. In our study, the focus on the intention to use DVAs can be traced back to the small number of current users (14.2%) compared to the non-users (85.8%). The results of this work must also be interpreted with caution since the non-users often had difficulties putting themselves in the position of a user and consequently found it difficult to answer the questions about the constructs.

Moreover, the study was based on a relatively small sample due to the extensive interview of the test persons. Although misunderstandings could be minimized by answering additional questions, this behavior can also cause distortions in understanding the topic. Studies with more resources should reduce the influence of an interviewer through other types of surveys.

A final limitation regarding the generalizability of the results is the concentration of the study on a special technology – DVAs. A transfer to other digital technologies, or generally – information and communication technologies, is therefore questionable.

5.10 Conclusion and implications

The research goal of our study was to investigate the acceptance of Digital Voice Assistants by older people. To work out the most important influencing factors on the behavioral intention to use DVA, both a quantitative approach based on UTAUT2 and a qualitative approach in the form of open questions were chosen for both samples. This combination of the two methods allowed a deeper understanding of the complex processes than the pure focus on quantitative results within the structural model framework. The statistical analysis results of the structural model show that the model has moderate predictive capabilities (R^2=0.507, R^2adj=0.493). As part of the statistical examination of the significance and relevance of the causal relationships in the structural model, statistical significance ($p < 0.05$) could be demonstrated for four of the six relationships. The most important influencing factors in predicting behavioral intention are: Performance Expectancy (β=0.256, t=3.680, p=0.000), Social Influence (β=0.257, t=4.088, p=0.000), Facilitating Conditions (β=0.386, t=6.888, p=0.000) and Hedonic Motivation (β=0.225, t=3.533, p=0.000). The hypotheses H1, H3, H4,

and H5 can thus be confirmed. No statistically significant relationships can be found for Effort Expectancy and Price Value, which leads to a refutation of the hypotheses H2 and H6.

Regarding the moderating effects of age and gender on these relationships, four of the twelve postulated hypotheses can be confirmed with the help of multi-group analyses (H1a, H3a, H4a, and H3b). The analysis shows that the effect of Performance Expectancy on Intended Use is stronger for the age group of 55 to 64-year-olds. In contrast, Social Influence and Facilitating Conditions strongly affect the Intended Use in the older age group. Gender can only be confirmed within the framework of Social Influence. The statistical results show that other people's opinion plays a more important role for women than for men. As part of the evaluation of the open questions, issues such as privacy and data protection, technophobia, technology-related self-efficacy, and resistance to change can act as barriers in the acceptance process.

An important contribution of this work is the demonstration of the importance of social influence and the facilitating conditions in the decision-making process of older people for or against the use of a Digital Voice Assistant. These factors play a more important role than the usefulness for everyday life and the fun of using DVAs. Older women, in particular, are influenced in their decision-making by the opinion and behavior of their friends and family members. Future research should start here, examine the factors and their determinants more closely, and show the role, for example, of family members or loved ones in the decision-making process. It should also be questioned which basic framework conditions must be created so that older people decide to use a DVA. The analysis also shows differences between people of working age (55 to 64 years) and those of retirement age (65 years and older). As a result, older people cannot be seen as a largely homogeneous group. Future studies can start here and work out other important differences based on larger samples. Another relevant finding from this study relates to the issues of privacy and data protection. The results of the qualitative analysis indicate a necessary revision of UTAUT2. Individual studies have shown significant relationships between privacy, security, and trust in behavioral intention and user behavior. Future studies can achieve better results by including such previously neglected constructs. Above all, attention should be paid to the effect relationships emanating from the individual constructs and whether they act, for example, as moderators or determinants of the behavioral use or use behavior.

The knowledge about the acceptance process among older people, which was gained through empirical research from this study, can also provide important clues for managerial practice. People mustn't be left alone when setting up the devices and through the whole use period. Long-term support is particularly important because even after a successful setup, older people repeatedly encounter difficulties when trying to set up new devices on their own.

Technical support can be provided, for example, by family members or professional technical advisors. Business models of this type already exist on the market (Consena 2019). Another possibility or extension of such individual consultation would be to hold workshops and training units in groups. In this way, both technical support can be guaranteed, and loneliness in old age can be prevented through group dynamics. The intensive exchange with people of the same age or people of different age groups can also generate new ideas for using DVAs in everyday life. Another finding of the present study is that when developing new technologies and applications, a stronger focus must be placed on the needs of older people, as their everyday lives differ from that of younger age groups. Another option is to focus more on age-related needs in marketing and advertising (Lai 2018). However, when choosing suitable communication measures, care must be taken to avoid stereotyping and ultimately stigmatizing older people, as this can lead to rejection and even resistance.

5.11 Appendix

Appendix 1: Technology acceptance by older people – state of the art; **Source:** Own depiction

Source (Year); Country	Technology	Model	Sample size	Age	Key results
Suta et al. (2018); Thailand	Multimedia platform	UTAUT	30	60+	Significantly strong correlations could be demonstrated between almost all examined relationships and Behavioral Intention. Performance Expectancy had the greatest influence, followed by Social Influence, Effort Expectancy, Voluntariness of Use and Facilitating Conditions. No significant correlation could be proven for Experience.
Guner and Acarturk (2018); Turkey	Information and communicationss technologies (ICT)	TAM (expanded)	232	60+	Perceived Ease of Use and User Friendliness positively influenced the setting, which positively affected Behavioral Intention. Furthermore, it emerged based on open questions that older people are willing to learn how to use ICT and would like to use them, but they encounter some obstacles in the process. In addition, almost all participants noted that it was very important for them to be part of the community and that communication, especially with younger family members, was often neglected.
Lai (2018); Taiwan	Mobile Computing Devices	UTAUT	238	55+	It turned out that Social Influence exerted the strongest influence on Behavioral Intention. This could be attributed to the fact that the opinion of children and grandchildren has an exalted rank in the decision-making process of older people. Performance Expectancy turned out to be the second most important predictor. In contrast to earlier studies, it is astonishing that no influence of Effort Expectancy on Behavioral Intention could be found. Despite the lack of significance of this relationship, a moderating effect of Gender could be shown. The influence was stronger for men than for women. Finally, it could be proven that Behavioral Intention and Facilitating Condition are important predictors for Actual Use.
Choudrie et al. (2018); England	Smartphone	IDT UTAUT TAM3	984	50+	Perceived Pleasure showed the greatest influence on Behavioral Intention, followed by Performance Expectancy. Significant results could also be demonstrated for Facilitating Conditions and Effort Expectancy. Behavioral Intention had a strong effect on Actual Use.
Moura et al. (2017); Brazil	Internet	UTAUT2 (expanded)	211	60+	Effort Expectancy was found to be a strong predictor of Attitude. In addition, it could be shown that the higher the Perceived Joy and Trust in the Technology, the more positive the attitude towards it. Habit directly influenced both attitudes and Usage Behavior. From this, it could be concluded that once an older person has adopted technology, it is very likely that it will be used frequently and become part of everyday life.
Hoque and Sorwar (2017); Bangladesh	Mobile Health	UTAUT (expanded)	274	60+	Significant influences on Behavioral Intention could be demonstrated in descending order for Performance Expectancy, Resistance to Change, Fear of Technology, Effort Expectancy, and Social Influence. Facilitating Conditions turned out to be irrelevant, as they had no significant influence neither on Behavioral Intention nor on Use Behavior. Behavioral Intention proved to be a strong predictor of Use Behavior.

Source (Year); Country	Technology	Model	Sample size	Age	Key results
Macedo (2017); Portugal	Information and communicationss technologies (ICT)	UTAUT2	278	55+	Behavioral Intention was strongly influenced by Performance Expectancy, followed by Facilitating Conditions. Less strong but nevertheless significant influences could be found for Social Influence, Hedonic Motivation, and Effort Expectancy. Surprisingly, Price Value could not be confirmed as a predictor. Habit and Intention to Use demonstrated high predictive power concerning Use Behavior. Neither Gender nor Age influenced Use Behavior, whereas Experience and Level of Education influenced it.
Ma, Chan and Chen (2016); China	Smartphone	TAM UTAUT (expanded)	120	55+	Cost Tolerance turned out to be the most important predictor of Behavioral Intention. The more the person believed that the technology offered added value, the higher was the acceptance. Furthermore, it turned out that older people with higher self-confidence were more likely to have a higher Perceived Usefulness and Perceived Ease of Use. Use Behavior, in general, differed depending on demographic characteristics. Accordingly, the lower the age and the higher the educational qualification, the more likely is the acceptance of older people. They also received more support from their families rather than others.
Cimperman et al. (2016); Slovenia	Home Telehealth Services	UTAUT (expanded)	400	50+	Effort Expectancy became the strongest predictor of Behavioral Intention, followed by Performance Expectancy, Perceived Security Risk, and the Facilitating Conditions. One possible explanation was that in this age group, due to the decline in cognitive processes, the effort to use a technology seemed more important than the ultimately resulting benefit from its use. Social Influence could not be confirmed as a predictor.
Diño and Guzman (2015); The Philippines	Telehealth,	UTAUT	82	60+	The investigated constructs: Performance Expectancy, Effort Expectancy, and Social Influence could be identified in descending order as predictors of Behavioral Intention. An increased effect for Gender as a moderating variable could not be proved for any of the three correlations.
Gao et al. (2015); China	Smartphone	UTAUT IDT	121	45+	Hedonic Motivation became the most important influencing factor of Behavioral Intention, followed by Social Influence. Also significant but less important were Performance Expectancy and Effort Expectancy. There could be found no causal relationship between Behavioral Intention and both constructs: Facilitating Conditions and Price Value.
Arenas-Gaitán et al. (2015); Spain	Internet Banking	UTAUT2	415	55+	Behavioral Intention was positively influenced in descending order by the four constructs: Habit, Performance Expectancy, Price Value, and Effort Expectancy. Use Behavior was positively influenced by Behavioral Intention and Habit. A difference between men and women could not be proven.
Veer et al. (2015); The Netherlands	E-Health	UTAUT	1014	57+	Behavioral Intention strongly influenced behavioral Intention and Effort Expectancy. Self-efficacy had a weak impact on Behavioral Intention. No correlation could be found for Social Influence. Basically, all participants were open to e-health, whereby participants with a lower level of education as well as women and older participants were less inclined to use e-health in the future.

5.12 References

Alalwan, A. A., Y. K. Dwivedi, N. P. Rana and R. Algharabat (2018), „Examining factors influencing Jordanian customers' intentions and adoption of internet banking: Extending UTAUT2 with risk", Journal of Retailing and Consumer Services, 40, 125–138.

Arenas-Gaitán, J., B. Peral-Peral and M. A. Ramón-Jerónimo (2015), „Elderly and Internet Banking: An Application of UTAUT2", Journal of Internet Banking and Commerce, 20 (1), 1–23.

Arpaci, I., K. Kilicer and S. Bardakci (2015), „Effects of security and privacy concerns on educational use of cloud services", Computers in Human Behavior, 45, 93–98.

Ashley, C. (2019), „A companion for our times: Home care system for the elderly to aid independent living", https://www.accenture.com/us-en/blogs/blogs-christopher-ashley-home-care-amazon-alexa-app

Bagozzi, R. P. and Y. Yi (1988), „On the Evaluation of Structure Equation Models", Journal of the Academy of Marketing Science, 16 (1), 74–94.

Basu, T. (2019), „Alexa wird deine beste Freundin, wenn du alt bist", https://www.heise.de/tr/artikel/Alexa-wird-deine-beste-Freundin-wenn-du-alt-bist-4557467.html

Berekoven, L., W. Eckert and P. Ellenrieder (2009), „Marktforschung: Methodische Grundlagen und praktische Anwendung", Wiesbaden: Gabler Verlag.

Brown, S. A. and V. Venkatesh (2005), „Model of Adoption of Technology in Households: A Baseline Model Test and Extension Incorporating Household Life Cycle", MIS Quarterly, 29 (3), 399–426.

Campbell, D. T. and D. W. Fiske (1959), „Convergent and discriminant validation by the multitrait-multimethod matrix", Psychological Bulletin, 56 (2), 81–105.

Chin, W. W. (1998), „The partial least squares approach to structural equation modeling", Modern methods for business research, 295 (2), 295–336.

Choudrie, J., S. Pheeraphuttranghkoon and S. Davari (2018), „The Digital Divide and Older Adult Population Adoption, Use and Diffusion of Mobile Phones: a Quantitative Study", Information Systems Frontiers, 1–23.

Choudrie, J. and A. Vyas (2014), „Silver surfers adopting and using Facebook? A quantitative study of Hertfordshire, UK applied to organizational and social change", Technological Forecasting and Social Change, 89, 293–305.

Cimperman, M., M. Makovec Brenčič and P. Trkman (2016), „Analyzing older users' home telehealth services acceptance behavior applying an Extended UTAUT model", International Journal of Medical Informatics, 90, 22–31.

Compeau, D. R. and C. A. Higgins (1995), „Computer Self-Efficacy: Development of a Measure and Initial Test", MIS Quarterly, 19 (2), 189–211.

Consena (2019), „Smarter Service für Senioren", http://www.consena.de/

Davis, D. D., R. P. Bagozzi and P. R. Warshaw (1989), „User Acceptance of Computer Technology: A Comparison of Two Theoretical Models", Management Science, 35 (8), 982–1003.

Davis, F. D. (1989), „Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology", MIS Quarterly, 13 (3), 319–340.

Davis, F. D., R. P. Bagozzi and P. R. Warshaw (1992), „Extrinsic and Intrinsic Motivation to Use Computers in the Workplace", Journal of Applied Social Psychology, 22 (14), 1111–1132.

Diño, M. J. S. and A. B. de Guzman (2015), „Using Partial Least Squares (PLS) in Predicting Behavioral Intention for Telehealth Use among Filipino Elderly", Educational Gerontology, 41 (1), 53–68.

England, K. and N. Azzopardi-Muscat (2017), „Demographic trends and public health in Europe", European Journal of Public Health, 27 (4), 9–13.

Federal Ministry for Family Affairs, Senior Citizens, Women and Youth, BMFSFJ (2016), „Ältere Menschen in Deutschland und der EU", https://www.bmfsfj.de/blob/93214/95d5fc19e3791f90f8d582d61b1 3a95e/aeltere-menschen-deutschland-eu-data.pdf

Fishbein, M. and I. Ajzen (1975), „Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research", Reading, MA: Addison-Wesley.

Fornell, C. and D. F. Larcker (1981), „Evaluating Structural Equation Models with Unobservable Variables and Measurement Error", Journal of Marketing Research, 18 (1), 39–50.

Gao, S., Y. Yang and J. Krogstie (2015), „The Adoption of Smartphones Among Older Adults in China", in Information and Knowledge Management in Complex Systems. IFIP Advances in In-formation and Communication Technology, (Hrsg.) K. Liu, K. Nakata, W. Li and D. Galarreta, Cham: Springer Inter-national Publishing, 112–122.

Gartner (2017), „Gartner Says Worldwide Spending on VPA-Enabled Wireless Speakers Will Top $3.5 Billion by 2021", https://www.gartner.com/en/newsroom/press-releases/2017-08-

24-gartner-says-worldwide-spending-on-vpa-enabled-wireless-speakers-will-top-3-billion-by-2021

Guner, H. and C. Acarturk (2018), „The use and acceptance of ICT by senior citizens: a comparison of technology acceptance model (TAM) for elderly and young adults", Universal Access in the Information Society, 1–20.

Hair, J. F., C. M. Ringle and M. Sarstedt (2011), „PLS-SEM: Indeed a Silver Bullet", Journal of Marketing Theory and Practice, 19 (2), 139–151.

Hair, J. F., M. Sarstedt, L. Hopkins and V. G. Kuppelwieser (2014), „Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research", European Business Review, 26 (2), 106–121.

Hair, J. F., S. Hauff, G. T. M. Hult, N. F. Richter, C. M. Ringle and M. Sarstedt (2017), „Partial Least Squares Strukturgleichungsmodellierung: Eine anwendungsorientierte Einführung", München: Verlag Franz Vahlen.

Hair, J. F., M. Sarstedt and C. M. Ringle (2019), „Rethinking some of the rethinking of partial least squares", European Journal of Marketing, 53 (4), 566–584.

Heidenreich, S. and M. Handrich (2015), „What about Passive Innovation Resistance? Investigating Adoption-Related Behavior from a Resistance Perspective", Journal of Product Innovation Management, 32 (6), 878–903.

Heidenreich, S. and T. Kraemer (2016), „Innovations-Doomed to Fail? Investigating Strategies to Overcome Passive Innovation Resistance", Journal of Product Innovation Management, 33 (3), 277–297.

Hellwig, A., S. Meister, W. Deiters and C. Schneider (2018), „Sprachassistenten in der ambulanten Pflege: Ein Leitfaden für den Einsatz von Voice User Interfaces am Beispiel der kommerziellen Sprachassistenzsysteme Amazon Echo und Google Home für Senioren und Pflegekräfte", in Zukunft der Pflege: Tagungsband der 1. Clusterkonferenz 2018, (Hrsg.) S. Boll, A. Hein, W. Heuten and K. Wolf-Ostermann, 72–77.

Henseler, J., C. M. Ringle and M. Sarstedt (2015), „A new criterion for assessing discriminant validity in variance-based structural equation modeling", Journal of the Academy of Marketing Science, 43 (1), 115–135.

Hoque, R. and G. Sorwar (2017), „Understanding factors influencing the adoption of mHealth by the elderly: An extension of the UTAUT model", International Journal of Medical Informatics, 101, 75–84.

Hoy, M. B. (2018), „Alexa, Siri, Cortana, and More: An Introduction to Voice Assistants", Medical Reference Services Quarterly, 37 (1), 81–88.

Janson, M. (2019), „Die Alten zieht's ins Internet", https://de.statista.com/infografik/12799/immer-mehr-internetnutzer-ueber-60-jahre/

Jockisch, M. (2010), „Das Technologieakzeptanzmodell: Die verhaltenswissenschaftliche Modellierung von Beziehungsstrukturen mit latenten Konstrukten am Beispiel von Benutzerakzeptanz", in "Das ist gar kein Modell!": Unterschiedliche Modelle und Modellierungen in Betriebswirtschaftslehre und Ingenieurwissenschaften, (Hrsg.) G. Bandow and H. H. Holzmüller, Wiesbaden: Gabler, 233–254.

Kim, S., K. Z. Gajos, M. Muller and B. J. Grosz (2016), „Acceptance of Mobile Technology by Older Adults: A Preliminary Study", in Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services - MobileHCI '16, (Hrsg.) F. Paternò and K. Väänänen, New York: ACM Press, 147–157.

Knickmann, J. R., and E. K. Snell (2002), „The 2030 Problem: Caring for Aging Baby Boomers", Health Service Research 37, Nr. 4, 849-884.

Kohlbacher, F., C. Herstatt and N. Levsen (2015), „Golden opportunities for silver innovation: How demographic changes give rise to entrepreneurial opportunities to meet the needs of older people", Technovation, 39-40, 73–82.

Kotzé, T. G., O. Anderson and K. Summerfield (2016), „Technophobia: Gender differences in the adoption of high-technology consumer products", South African Journal of Business Management, 47 (1), 21–28.

Kuß, A., R. Wildner and H. Kreis (2014), „Marktforschung: Grundlagen der Datenerhebung und Datenanalyse", Wiesbaden: Springer Gabler.

Lai, H.-J. (2018), „Investigating older adults' decisions to use mobile devices for learning, based on the unified theory of acceptance and use of technology", Interactive Learning Environments, 13 (2), 1–12.

Lee, C. and J. F. Coughlin (2015), „PERSPECTIVE: Older Adults' Adoption of Technology: An Integrated Approach to Identifying Determinants and Barriers", Journal of Product Innovation Management, 32 (5), 747–759.

Luijkx, K., S. Peek and E. Wouters (2015), „"Grand-ma, You Should Do It - It's Cool" Older Adults and the Role of Family Members in Their Acceptance of Technology", International journal of environmental research and public health, 12 (12), 15470–15485.

Luo, Y. and J. Bu (2016), „How valuable is information and communication technology? A study of emerging economy enterprises", Journal of World Business, 51 (2), 200–211.

Ma, Q., A. H. S. Chan and K. Chen (2016), „Personal and other fac-tors affecting acceptance of smartphone technology by older Chinese adults", Applied Ergonomics, 54, 62–71.

Ma, Q., K. Chen, A. H. S. Chan and P.-L. Teh (2015), „Acceptance of ICTs by Older Adults: A Review of Recent Studies", in Human Aspects of IT for the Aged Population. Design for Aging. Lecture Notes in Computer Science, (Hrsg.) J. Zhou and G. Salvendy, Cham: Springer International Publishing, 239–249.

Macedo, I. M. (2017), „Predicting the acceptance and use of information and communication technology by older adults: An empirical examination of the revised UTAUT2", Computers in Human Behavior, 75, 935–948.

Mani, Z. and I. Chouk (2017), „Drivers of consumers' resistance to smart products", Journal of Marketing Management, 33 (1-2), 76–97.

Merkel, S., P. Enste, J. Hilbert, K. Chen, A. H.-S. Chan and S. Kwon (2017), „Technology Acceptance and Aging", in Gerontechnology: Research, Practice, and Principles in the Field of Technology and Aging, (Hrsg.) Sunkyo Kwon, New York: Springer Publishing Company, 335–349.

Miltgen, C. L., J. Henseler, C. Gelhard and A. Popovič (2016), „Introducing new products that affect consumer privacy: A mediation model", Journal of Business Research, 69 (10), 4659–4666.

Mizak, A., M. Park, D. Park and K. Olson (2017), „Amazon Alexa Pilot Analysis Report", http://fpciw.org/wp-content/uploads/sites/15/2017/12/FINAL-DRAFT-Amazon-Alexa-Analysis-Report.pdf

Mostaghel, R. (2016), „Innovation and technology for the elderly: Systematic literature review", Journal of Business Research, 69 (11), 4896–4900.

Moura, A. C. D., M. D. S. Gosling, J. M. M. Christino and S. B. Macedo (2017), „Acceptance and use of technology by older adults for choosing a tourism destination: a study using UTAUT2", Revista Brasileira de Pesquisa em Turismo, 11 (2), 239–269.

Niehaves, B. and R. Plattfaut (2014), „Internet adoption by the elderly: employing IS technology acceptance theories for understanding the age-related digital divide", European Journal of Information Systems, 23 (6), 708–726.

Nikou, S. (2015), „Mobile technology and forgotten consumers: the young-elderly", International Journal of Consumer Studies, 39 (4), 294–304.

Nunnally, J. C. and I. R. Bernstein (1994), "Psychometric Theory", New York: McGraw Hill.

Oliveira, T., M. Thomas, G. Baptista and F. Campos (2016), „Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology", Computers in Human Behavior, 61, 404–414.

Owusu Kwateng, K., K. A. Osei Atiemo and C. Appiah (2019), „Acceptance and use of mobile banking: an application of UTAUT2", Journal of Enterprise Information Management, 32 (1), 118–151.

Panch, T., P. Szolovits and R. Atun (2018), „Artificial intelligence, machine learning and health systems", Journal of global health, 8 (2), 1–8.

Rigdon, E. E. (2016), „Choosing PLS path modeling as analytical method in European management research: A realist perspective", European Management Journal, 34 (6), 598–605.

Schäfer, M. and D. Keppler (2013), „Modelle der technikorientierten Akzeptanzforschung: Überblick und Reflexion am Beispiel eines Forschungsprojekts zur Implementierung innovativer technischer Energieeffizienz-Maßnahmen", https://depositonce.tu-berlin.de/bitstream/11303/4758/1/schaefer_keppler.pdf

Schwarz, G. (2018), „Leben mit Alexa – eine Zwischenbilanz (2018-01)", https://www.seniorenfreundlich.de/smartspeaker-praxis-senioren.html

Sinkovics, R. R., B. Stöttinger, B. B. Schlegelmilch and S. Ram (2002), „Reluctance to use technology-related products: Development of a technophobia scale", Thunderbird International Business Review, 44 (4), 477–494.

Slade, E. L., Y. K. Dwivedi, N. C. Piercy and M. D. Williams (2015), „Modeling Consumers' Adoption Intentions of Remote Mobile Payments in the United Kingdom: Extending UTAUT with Innovativeness, Risk, and Trust", Psychology & Marketing, 32 (8), 860–873.

Sovie, D., J. Curran, M. Schoelwer and A. Björnsjö (2017), „Dynamic Digital Consumers: Ever-Changing Expectations And Technology Intrigue", https://www.accenture.com/us-en/_acnmedia/PDF-39/Accenture-PoV-Dynamic-Consumers.pdf

Straub, D. W. (1989), „Validating Instruments in MIS Research", MIS Quarterly, 13 (2), 147–169.

Suta, P., N. Limdumrongnukoon, P. Chalardkitsirikul, T. Suntiyotin, P. Mongkolnam and J. H. Chan (2018), „Analysis of Factors Affecting Multimedia Delivery for El-derly People", Engineering Journal, 22 (1), 49–64.

Tak, P. and S. Panwar (2017), „Using UTAUT 2 model to predict mobile app based shopping: evidences from India", Journal of Indian Business Research, 9 (3), 248–264.

Tech-enhanced Life (2017), "Amazon Echo and Alexa for the Elderly", https://www.techenhancedlife.com/explorers/amazon-echo-and-alexa-elderly

Tsai, H.-Y. S., R. Shillair, S. R. Cotten, V. Winstead and E. Yost (2015), „Getting Grandma Online: Are Tablets the Answer for Increasing Digital Inclusion for Older Adults in the U.S.?", Educational Gerontology, 41 (10), 695–709.

United Nations (2020) „World Population Ageing 2020", https://www.un.org/development/desa/pd/sites/www.un.org.development.desa.pd/files/files/documents/2020/Sep/un_pop_2020_pf_ageing_10_key_messages.pdf

Vantiv (2018), „Digital Assistants Consumer Survey Results", https://www.vantiv.com/content/dam/vantiv/documents/digital-assistants-consumer-survey-results_18-1830-1.pdf

Vassli, L. T. and B. A. Farshchian (2018), „Acceptance of Health-Related ICT among Elderly People Living in the Community: A Systematic Review of Qualitative Evidence", International Journal of Hu-man–Computer Interaction, 34 (2), 99–116.

Veer, A. J. E. de, J. M. Peeters, A. E. M. Brabers, F. G. Schellevis, J. J. D. J. M. Rademakers and A. L. Francke (2015), „Determinants of the intention to use e-Health by community dwelling older people", BMC Health Services Research, 15 (1), 1–9.

Venkatesh, V. and S. A. Brown (2001), „A Longitudinal Investigation of Personal Computers in Homes: Adoption Determinants and Emerging Challenges", MIS Quarterly, 25 (1), 71–102.

Venkatesh, V., F. D. Davis and M. G. Morris (2007), „Dead Or Alive? The Development, Trajectory And Future Of Technology Adoption Research.", Journal of the Association for Information Systems, 8 (4), 267–286.

Venkatesh, V., M. G. Morris, G. B. Davis and F. D. Davis (2003), „User Acceptance of Information Technology: Toward a Unified View", MIS Quarterly, 27 (3), 425–478.

Venkatesh, V., J. Y. L. Thong and X. Xu (2012), „Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology", MIS Quarterly, 36 (1), 157–178.

VoCo (2018), „Everything You Need to Know About Alexa for Seniors", https://medium.com/@sayvoco/everything-you-need-to-know-about-alexa-for-seniors-1717d3c35f14

Weinberg, B. D., G. R. Milne, Y. G. Andonova and F. M. Hajjat (2015), „Internet of Things: Convenience vs. privacy and secre-cy", Business Horizons, 58 (6), 615–624.

Wu, J. and H. Du (2012), „Toward a better understanding of behavioral intention and system usage constructs", European Journal of Information Systems, 21 (6), 680–698.

Wulf, L., M. Garschall, J. Himmelsbach and M. Tscheligi (2014), „Hands free – Care free: Elderly People taking Advantage of Speech-only Interaction", in Proceedings of the 8th Nordic Conference on Human-Computer Interaction Fun, Fast, Foundational - NordiCHI '14, (Hrsg.) V. Roto, T. Olsson, K. Väänänen-Vainio-Mattila, J. Häkkilä, E. Hvannberg and O. Juhlin, New York: ACM Press, 203–206.

6 Conclusion

New technologies and innovations increasingly shape today's world. Digital Voice Assistants represent one of the most important changes in the interaction with technologies. However, there has not yet been sufficient scientific research into the current acceptance level in private use. What drives individuals to use a particular technology? Research into usage of DVAs and user acceptance represent a central field of investigation in the IT context and is also the main subject of this thesis. Factors that influence the acceptance of technology are diverse and depend, among other things, on the age and interests of the examined target group. Analyzing the predictors in the group of Millennials, Pastime is the most important aspect that influences the acceptance of DVAs. Furthermore, Enjoyment, Image (Social Status), Expediency and Social Influence also play an important role in accepting DVAs. Nonetheless, privacy concerns and the fear of being intercepted negatively influence Millennials' use of DVAs. While with Millennials, Enjoyment, Entertainment, and Image are decisive for accepting a new medium such as DVAs, within the age group of the older people: Performance Expectancy, Facilitating Conditions and Hedonic Motivation are the most important predictors for the acceptance of DVAs. However, it should be noted that there are noticeable differences between people aged 55 to 64 years and people over the age of 65 years. For this reason, older people cannot be seen as a largely homogenous group.

The analysis of the open questions has shown that DVAs will be already used by those two examined age groups and they are helpful while quickly looking for some information, navigating a car, or traveling, especially when manual input is not possible. Customers mainly use their DVAs for time-saving and to increase their image among friends and family. Many users also turn to DVAs when they feel alone and are looking for a conversation with somebody. Within the age group of older people, the results of the moderation effects show that especially older women are strongly influenced by the opinion and behavior of family and friends. Family members or related persons play an important role in the decision-making process.

While various research models have been developed over the years, the modified TAM and the modified UTAUT2 have proven to be reliable theories for testing the acceptance of new media. Both underlying models were adapted to include the research context worked out in the theoretical part, i.e., constructs, specially adapted to the research area Conversational User Interface. The degree of technological novelty played an essential role in the development of the model. Since the two models have a moderate to high effect on Behavioral Intention to Use, it cannot be clearly stated that one model fits noticeably better in the context of DVAs than the other. Suppose one considers other variables (Q^2, f^2, etc.) and the accuracy of fit of the gratifications. In that case, it can be concluded that UTAUT2 fits better into the

context of the acceptance of DVAs by consumers. UTAUT2 established itself as a model within research, either as a basis for constructive theories or for checking acceptance relationships (Tamilmani et al. 2017). The model was also used for different target groups, such as tourists, end consumers or students in various technological contexts (Tamilmani et al. 2019; Tamilmani et al. 2018). UTAUT2 is also used in new technologies such as mobile banking or augmented reality to measure acceptance and was able to achieve comparatively similar values for the explanatory variance concerning the intended use, as in the initial study by Venkatesh et al. (2003) (Chaouali et al. 2016; Harborth and Pape 2017). However, many studies forego usage behavior in new technologies and are limited only to the intended use (Tamilmani et al. 2019). Slade et al. (2015) justify this in their project with time and resource restrictions at the study time (Slade et al. 2015). Completely new target variables, such as purchase intention, are also possible (Degirmenci and Breitner 2017). Nevertheless, the analysis of this thesis confirmed the predictive power of the modified TAM and the modified UTAUT2. With these findings, this thesis joins the research into user acceptance and use by the expanded TAM and UTAUT2 and provides another example with a new context for these.

For future investigations, a more precise breakdown into different types of gratifications (e.g., hedonic, utilitarian or barriers) is recommended. Based on the proposals by Venkatesh et al. (2016), detailed predictions can be made about the individual components of the respective technology. However, it must always be borne in mind that the results obtained based on the studies presented cannot be transferred one-to-one to other DVAs. The evaluation of the technology users also depends on subtleties that are difficult to measure through a survey. Moreover, future investigations could begin to identify optimal procedures and prove them empirically.

Appendix

Appendix A: Individual contributions to the included research papers

In the following, I will in detail describe the contribution of all four papers presented in this thesis.

Research paper #1, which is presented in chapter 2, was authored by two authors. The idea for the topic came from Prof. D. Baier. He also contributed through conceptual and methodological advice and multiple revisions of the paper. As the corresponding author, I was responsible for carrying out the literature review, developing the research design, conducting the interviews, analyzing the data, writing the article, and managing the revision process.

Research paper #2 presented in chapter 3 and research paper #4 (chapter 5) were exclusively written by myself.

Research paper #3, which is presented in chapter 4, was authored by three researchers. Nadine Höhn developed the survey and was responsible for the collection of the data. Prof. D. Baier was contributed through constant conceptual and empirical advice and both revision processes of the paper. I was the corresponding author of this paper and was responsible for conceptualizing the study, carrying out the literature review, analyzing the data, writing the article, and managing the revision process.

I would like to thank both co-authors – for your technical knowledge, professionality, help and great ideas.

References

Ajzen, I. (1985), “From Intentions to Actions: A Theory of Planned Behavior “, in Action Control - From Cognition to Behavior, (Hrsg.) J. Kuhl and J. Beckmann, Berlin, Heidelberg, Springer Verlag: 11-39.

Alalwan, A. A., Y. K. Dwivedi, N. P. Rana and R. Algharabat (2018), “Examining factors influencing Jordanian customers’ intentions and adoption of internet banking: Extending UTAUT2 with risk”, Journal of Retailing and Consumer Services, 40, 125–138.

Alhabash, S., Y. Chiang and K. Huang (2014), “TAM & U&G in Taiwan: Differences in the uses and gratifications of Facebook as a function of motivational reactivity”, Computers in Human Behavior, 35, 423–430.

Ancu, M. and R. Cozma (2009), “MySpace Politics: Uses and Gratifications of Befriending Candidates”, Journal of Broadcasting & Electronic Media, 53 (4), 567–583.

Apple (2019), „Verfügbarkeit von iOS Features“, https://www.apple.com/de/ios/feature-availability/#siri.

Arenas-Gaitán, J., B. Peral-Peral and M. A. Ramón-Jerónimo (2015), „Elderly and Internet Banking: An Application of UTAUT2”, Journal of Internet Banking and Commerce, 20 (1), 1–23.

Arpaci, I., K. Kilicer and S. Bardakci (2015), “Effects of security and privacy concerns on educational use of cloud services”, Computers in Human Behavior, 45, 93–98.

Ashley, C. (2019), “A companion for our times: Home care system for the elderly to aid independent living”, https://www.accenture.com/us-en/blogs/blogs-christopher-ashley-home-care-amazon-alexa-app

Bagozzi, R. P. and Y. Yi (1988), “On the Evaluation of Structure Equation Models”, Journal of the Academy of Marketing Science, 16 (1), 74–94.

Bagozzi, R. P. (2007), “The Legacy of the Technology Acceptance Model and a Proposal for a Paradigm Shift”, Journal of the Association for Information Systems, 8 (4), 244-254.

Baier, D., A. Rese and M. Röglinger (2018), “Conversational user interfaces for online shops? A categorization of use cases”, International Conference on Information Systems 2018, ICIS 2018.

Bass, F. M. (1969), “A new product growth model for consumer durables”, Management Science, 15, 215–227.

Basu, T. (2019), „Alexa wird deine beste Freundin, wenn du alt bist“, https://www.heise.de/tr/artikel/Alexa-wird-deine-beste-Freundin-wenn-du-alt-bist-4557467.html

Beaudry, A. and A. Pinsonneault (2010), “The Other Side of Acceptance: Studying the Direct and Indirect Effects of Emotions on Information Technology Use”, MIS Quarterly, 34 (4), 689-710.

Benbasat, I. and H. Barki (2007), “Quo vadis, TAM?”, Journal of the Association for Information Systems, 8 (4), 211-218.

Bendel, O. (2019), „Smart Home“ https://wirtschaftslexikon.gabler.de/definition/smart-home-54137/version-368820

Berekoven, L., W. Eckert and P. Ellenrieder (2009), „Marktforschung: Methodische Grundlagen und praktische Anwendung“, Wiesbaden: Gabler Verlag.

Bitkom (2017), „Das Smartphone gehorcht aufs Wort”, https://www.bitkom.org/Presse/Presseinformation/Das-Smartphone-gehorcht-aufs-Wort.html.

Bitkom (2018), „Zukunft der Consumer Technology - 2018: Marktentwicklung, Trends, Mediennutzung, Technologien, Geschäftsmodelle”.

BMWi – Bundesministerium für Wirtschaft und Energie (2018), „Altmaier: „Künstliche Intelligenz maßgeblich für Wachstum im produzierenden Gewerbe“”, https://www.bmwi.de/Redaktion/DE/Pressemitteilungen/2018/20180719-altmaier-kuenstliche-intelligenz-massgeblich-fuer-wachstum-im-produzierenden-gewerbe.html.

Brandtzaeg, P. B. and A. Følstad (2017), “Why People Use Chatbots”, in Internet Science: 4th International Conference, INSCI 2017, Thessaloniki, Greece, November 22-24, 2017, Proceedings. Lecture Notes in Computer Science, 10673. Aufl., (Hrsg.) Y. Kompatsiaris, J. Cave, Anna Satsiou, G. Carle, A. Passani, E. Kontopoulos, S. Diplaris and D. McMillan, Cham: Springer International Publishing, 377–392.

Brown, S. A. and V. Venkatesh (2005), “Model of Adoption of Technology in Households: A Baseline Model Test and Extension Incorporating Household Life Cycle”, MIS Quarterly, 29 (3), 399–426.

Bundesverband Digitale Wirtschaft (BVDW) e.V. (2017), „Digital Trends: Umfrage zu digitalen Sprachassistenten“.

BVDW e.V. (2017), “Digital Trends: Umfrage zu digitalen Sprachassistenten“, Bericht, Bundesverband Digitale Wirtschaft (BVDW) e.V., Düsseldorf, 40212.

Čaić, M., G. Odekerken-Schröder and D. Mahr (2018), “Service robots: value co-creation and co-destruction in elderly care networks”, Journal of Service Management, 29(2), 178-205.

Campbell, D. T. and D. W. Fiske (1959), “Convergent and discriminant validation by the multitrait-multimethod matrix”, Psychological Bulletin, 56 (2), 81–105.

Capgemini Digital Transformation Institute (2017), “Conversational Commerce: Why consumers are embracing voice assistants in their lives”.

Chaouali, W., I. B. Yahia and N. Souiden (2016), “The interplay of counter-conformity motivation, social influence, and trust in customers' intention to adopt Internet banking services: The case of an emerging country”, Journal of Retailing and Consumer Services 28, Nr. C, 209-218.

Chen, R., Z. Tian, H. Liu, F. Zhao, S. Zhang, H. Liu (2018), “Construction of a voice-driven life assistant system for visually impaired people”, 2018 International Conference on Artificial Intelligence and Big Data, IEEE Press, Piscataway, NJ, pp 87–92, DOI 10.1109/ICAIBD.2018.8396172

Chen, J.-Y., Y.-P. Ma, T. S. Jeng and C.-C. Chang (2011), “An assessment of user needs for intelligent living space”, Intelligent Buildings International, 2 (1), 20–40.

Chen, R., Z. Tian, H. Liu, F. Zhao and S. Zhang (2018), “Construction of a voice-driven life assistant system for visually impaired people”, in 2018 International Conference on Artificial Intelligence and Big Data: ICAIBD 2018, May 26-28, 2018, Chengdu, China, Piscataway, NJ: IEEE Press, 87–92.

Chin, W. W. (1998), “The partial least squares approach to structural equation modeling”, Modern methods for business research, 295 (2), 295–336.

Choudrie, J. and A. Vyas (2014), “Silver surfers adopting and using Facebook? A quantitative study of Hertfordshire, UK applied to organizational and social change”, Technological Forecasting and Social Change, 89, 293–305.

Choudrie, J., S. Pheeraphuttranghkoon and S. Davari (2018), “The Digital Divide and Older Adult Population Adoption, Use and Diffusion of Mobile Phones: a Quantitative Study”, Information Systems Frontiers, 1–23.

Chu, A. and R. Chu (2011), “The intranet’s role in newcomer socialization in the hotel industry in Taiwan - technology acceptance model analysis”, The International Journal of Human Resource Management, 22 (5), 1163–1179.

Chung, H., M. Iorga, J. Voas and S. Lee (2017), “Alexa, Can I Trust You?”, Computer, 50 (9), 100–104.

Chung, M., E. Ko, H. Joung and S.J. Kim (2018), “Chatbot e-service and customer satisfaction regarding luxury brands”, Journal of Business Research, Elsevier, vol. 117(C), 587-595.

Cimperman, M., M. Makovec Brenčič and P. Trkman (2016), “Analyzing older users’ home telehealth services acceptance behavior applying an Extended UTAUT model”, International Journal of Medical Informatics, 90, 22–31.

Cleff, T. (2015), „Deskriptive Statistik und Explorative Datenanalyse“, Wiesbaden, Gabler Verlag.

Cohen, J. (1992), “A Power Primer”, Psychological Bulletin, 112 (1), 155–159.

Compeau, D. R. and C. A. Higgins (1995a), “Computer Self-Efficacy: Development of a Measure and Initial Test”, MIS Quarterly, 19 (2), 189–211.

Compeau, D. R. and C. A. Higgins (1995b), “Application of Social Cognitive Theory to Training for Computer Skills”, Information Systems Research, 6 (2), 118-143.

Consena (2019), „Smarter Service für Senioren”, http://www.consena.de/

Coskun-Setirek, A. and S. Mardikyan (2017), “Understanding the Adoption of Activated Personal Assistants”, International Journal of E-Services and Mobile Applications, 9 (3), 1-21.

Curras-Perez, R., C. Ruiz-Mafe and S. Sanz-Blas (2014), “Determinant of user behavior and recommendation in social networks: An integrative approach from the uses and gratifications perspective”, Industrial Management & Data Systems, 114 (9), 1477–1498.

Dale, R. (2016), “The return of the chatbots”, Natural Language Engineering, 22 (5), 811-817.

Davis F.D. (1985), “A technology acceptance model for empirically testing new end-user information systems: Theory and results”. Ph.D. thesis, Massachusetts Institute of Technology

Davis, D. D., R. P. Bagozzi and P. R. Warshaw (1989), “User Acceptance of Computer Technology: A Comparison of Two Theoretical Models”, Management Science, 35 (8), 982–1003.

Davis, F. D. (1989), “Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology”, MIS Quarterly, 13 (3), 319–340.

Davis, F. D., R. P. Bagozzi and P. R. Warshaw (1992), “Extrinsic and Intrinsic Motivation to Use Computers in the Workplace”, Journal of Applied Social Psychology, 22 (14), 1111-1132.

Davis, F. D. (1986), “A Technology Acceptance Model for Empirically Testing New End-User Information Systems: Theory and Results”, doctoral dissertation, Sloan School of Management, Massachusetts Institute of Technology, Cambridge, MA 02142.

Deal, J. J., D. G. Altman and S. G. Rogelberg (2010), “Millennials at Work: What We Know and What We Need to Do (If Anything)”, Journal of Business and Psychology, 25, 191-199.

DeFleur, M. L. (2016), “Mass communication theories: Explaining origins, processes, and effects”, London, New York: Routledge Taylor & Francis Group.

Degirmenci, K. and M. H. Breitner (2017), “Consumer purchase intentions for electric vehicles: Is green more important than price and range?”, Transportation Research Part D 51, March 2017, 250-260.

Deloitte (2018), “Beyond Touch – Voice Commerce 2030: Wie Voice-assisted Interfaces den Handel in Europa revolutionieren werden (Deloitte Monitor)", https://www.thinkwithgoogle .com/_qs/documents/8031/Beyond_Touch__Voice_Commerce_2030.pdf

Destatis (2019a), „Altersstruktur der Bevölkerung in Deutschland zum 31. Dezember 2018", https://www-genesis.destatis.de/genesis//online/data?operation=previous&levelindex=3&step =1&titel=Statistik+%28Tabellen%29&levelid=1581610369505&levelid=1581610348449

Destatis (2019b), „Anzahl der Studierenden an deutschen Hochschulen", https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Bildung-Forschung-Kultur/Hochschulen/Tabellen/studierende-insgesamt-bundeslaender.html;jsessionid=5B0C6762799B6DE860938E6D5032EFF9.internet731

Digital Trends (2018) “Google assistant: The complete history of the voice of android”. URL https://www.digitaltrends.com/mobile/google-assistant/

Dijkstra, T. K., and J. Henseler (2015), “Consistent Partial Least Squares Path Modeling”, MIS Quarterly, 39 (2), 297–316.

Diño, M. J. S. and A. B. de Guzman (2015), “Using Partial Least Squares (PLS) in Predicting Behavioral Intention for Telehealth Use among Filipino Elderly”, Educational Gerontology, 41 (1), 53–68.

Drosdowski, G. (1997), „Das Herkunftswörterbuch: Etymologie der deutschen Sprache", Mannheim.

Dunne, A., M.-A. Lawlor and J. Rowley (2010), “Young People’s Use of Online Social Networking Sites: A Uses and Gratifications Perspective”, Journal of Research in Interactive Marketing, 4 (1), 46-58.

Eastman, J. K., R. Iyer, S. Liao-Troth, D. F. Williams and M. Griffin (2014), “The Role of Involvement on Millennials’ Mobile Technology Behaviors: The Moderating Impact of Status Consumption, Innovation, and Opinion Leadership”, Journal of Marketing Theory and Practice, 22 (4), 455-470.

Eastman, J. K., R. Iyer and S. P. Thomas (2013), “The impact of status consumption on shopping styles: an exploratory look at the millennial generation”, Journal of Marketing Management, 23 (1), 57-73.

Easwara, M. A. and K.-P. L. Vu (2015), “Privacy Concerns for the use of Voice Activated Personal Assistant in the Public Space”, International Journal of Human-Computer Interaction, 31 (4), 307–335.

Elmorshidy, A. (2013), “Applying the Technology Acceptance and Service Quality Models to Live Customer Support Chat for E-Commerce Websites”, The Journal of Applied Business Research, 29 (2), 589–595.

Elmorshidy, A., M. M. Mostafa, I. El-Moughrabi and H. Al-Mezen (2015), “Factors Influencing Live Customer Support Chat Services: An Empirical Investigation in Kuwait”, Journal of Theoretical and Applied Electronic Commerce Research, 10 (3), 63–76.

England, K. and N. Azzopardi-Muscat (2017), “Demographic trends and public health in Europe”, European Journal of Public Health, 27 (4), 9–13.

EY (2018), „Intelligente Sprachassistenten: Ergebnisse der Kundenbedürfnisanalyse”.

Federal Ministry for Family Affairs, Senior Citizens, Women and Youth, BMFSFJ (2016), „Ältere Menschen in Deutschland und der EU”, https://www.bmfsfj.de/blob/93214/95d5fc19e3791f90f8d582d61b1 3a95e/aeltere-menschen-deutschland-eu-data.pdf

Fishbein, M. and I. Ajzen (1975), “Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research”, Reading, Mass: Addison-Wesley.

Fornell, C. and D. F. Larcker (1981), “Evaluating Structural Equation Models with Unobservable Variables and Measurement Error”, Journal of Marketing Research, 18 (1), 39.

Gaggioli, A. (2018), “Virtual Personal Assistants: An Emerging Trend in Artificial Intelligence”, Cyberpsychology, behavior and social networking, 21 (12), 803–804.

Gan, C. and H. Li (2018), “Understanding the effects of gratifications on the continuance intention to use WeChat in China: A perspective on uses and gratifications”, Computers in Human Behavior, 78, 306–315.

Gao, S., Y. Yang and J. Krogstie (2015), “The Adoption of Smartphones Among Older Adults in China”, in Information and Knowledge Management in Complex Systems. IFIP Advances in Information and Communication Technology, (Hrsg.) K. Liu, K. Nakata, W. Li and D. Galarreta, Cham: Springer International Publishing, 112–122.

Gao, T., F. Sultan and A. J. Rohn (2010), “Factors influencing Chinese youth consumers’ acceptance of mobile marketing”, Journal of Consumer Marketing, 574–583.

Gartner (2017), “Gartner Says Worldwide Spending on VPA-Enabled Wireless Speakers Will Top $3.5 Billion by 2021”, https://www.gartner.com/en/newsroom/press-releases/2017-08-24-gartner-says-worldwide-spen ding-on-vpa-enabled-wireless-speakers-will-top-3-billion-by-2021

Gefen, D., E. Karahanna and D. W. Straub (2003), “Trust and TAM in online shopping: An integrated model”, Management Information Systems Quarterly, 27 (1), 51–90.

Gerpott, T.J. and M. Paukert (2011), „Reliabilität empirischer Konstruktmessungen", WiST – Wirtschaftswissenschaftliches Studium, 40 (2), 58-65.

Govindarajo, N. and D. Kumar (2013), “Does “Y” Generation Managers Attributes is Associated with Technology Adoption Behavior?". Information Management and Business Review, 5 (6), 292–299.

Götz, O., K. Liehr-Gobbers and M. Krafft (2010), “Evaluation of Structural Equation Models Using the Partial Least Squares (PLS) Approach” in Handbook of partial least squares: Concepts, methods and applications, Vol. 1. (Eds.) Vinzi, V. E., Chin, W. W., Henseler, J. & Wang, H., Berlin: Springer Verlag, 691-711.

Greenberg, B. S. (1974), “Gratifications of television viewing and their correlates for British children”, in The uses of mass communications: Current perspectives on gratifications research, (Hrsg.) J. G. Blumler and E. Katz, Beverly Hills, CA: Sage, 71–92.

Griol, D., J. I. Carbó Rubiera and J. M. Molina López (2013), “An automatic dialog simulation technique to develop and evaluate interactive conversational agents”, Applied Artificial Intelligence, 27 (9), 759-780.

Guner, H. and C. Acarturk (2018), “The use and acceptance of ICT by senior citizens: a comparison of technology acceptance model (TAM) for elderly and young adults”, Universal Access in the Information Society, 1–20.

Guzman, A. L. (2017), “Making AI safe for humans: A conversation with Siri”, in Socialbots and their friends: Digital media and the automation of sociality, (Hrsg.) R. W. Gehl und M. Bakardjieva, New York, NY: Routledge, 69–85.

Haas, M. (2018), “Smartphone-Markt: Konjunktur und Trends“, Präsentation, Bitkom, 2018, https://www.bitkom.org/sites/default/files/2019-02/Bitkom-Pressekonferenz%20Smartphone-Markt%2020%2002%202019%20Pr%C3%A4sentation_final.pdf

Hair, J. F., G. T. M. Hult, C. M. Ringle, M. Sarstedt, N. F. Richter and S. Hauff (2017), „Partial Least Squares Strukturgleichungsmodellierung (PLS-SEM): Eine anwendungsorientierte Einführung",1st ed. Franz Vahlen, München.

Hair, J. F., M. Sarstedt, C. M. Ringle (2019), “Rethinking some of the rethinking of partial least squares”, European Journal of Marketing 53(4):566–584.

Hair, J. F., C. M. Ringle and M. Sarstedt (2011), “PLS-SEM: Indeed a Silver Bullet”, Journal of Marketing Theory and Practice, 19 (2), 139–151.

Hair, J. F., M. Sarstedt, C. M. Ringle and J. A. Mena (2012), “An assessment of the use of partial least squares structural equation modeling in marketing research”, Journal of the Academy of Marketing Science, 40 (3), 414-433.

Hair, J. F., M. Sarstedt, L. Hopkins and V. G. Kuppelwieser (2014), “Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research”, European Business Review, 26 (2), 106–121.

Hair, J.F. Jr., G. T. M. Hult, C. M. Ringle and M. Sarstedt (2016), “A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)”, Vol. 2., Los Angeles: Sage Publications, Inc.

Hair, J.F. Jr., G. T. M. Hult, C. M. Ringle, M. Sarstedt, N. F. Richter and S. Hauff (2017), „Partial Least Squares Strukturgleichungsmodellierung (PLS-SEM)”, Vol. 1., München: Verlag Franz Vahlen.

Hair, J.F. Jr., C. M. Ringle and M. Sarstedt (2013), “Partial Least Squares Structural Equation Modeling: Rigorous Applications, Better Results and Higher Acceptance”, Long Range Planning, 46 (1-2), 1-12.

Hair, J.F. Jr., J. J. Risher, M. Sarstedt and C. M. Ringle (2019), “When to use and how to report the results of PLS-SEM”, European Business Review, Forthcoming.

Han, S. and H. Yang (2018), “Understanding adoption of intelligent personal assistants: a parasocial relationship perspective”, Industrial Management & Data Systems, 118 (3), 618-636.

Harborth, D. and S. Pape (2017), “Exploring the Hype: Investigating Technology Acceptance Factors of Pokémon Go”, IEEE International Symposium on Mixed and Augmented Reality, 2017: 155-168.

Hartman, J.L. and J. McCambridge (2011), “Optimizing Millennials’ Communication Styles”, Business and Professional Communication Quarterly, 74 (1), 22-44.

Heidenreich, S. and M. Handrich (2015), “What about Passive Innovation Resistance? Investigating Adoption-Related Behavior from a Resistance Perspective”, Journal of Product Innovation Management, 32 (6), 878–903.

Heidenreich, S. and T. Kraemer (2016), “Innovations-Doomed to Fail? Investigating Strategies to Overcome Passive Innovation Resistance”, Journal of Product Innovation Management, 33 (3), 277–297.

Hellwig, A., S. Meister, W. Deiters and C. Schneider (2018), „Sprachassistenten in der ambulanten Pflege: Ein Leitfaden für den Einsatz von Voice User Interfaces am Beispiel der kommerziellen Sprachassistenzsysteme Amazon Echo und Google Home für Senioren und Pflegekräfte”, in Zukunft der Pflege: Tagungsband der 1. Clusterkonferenz 2018, (Hrsg.) S. Boll, A. Hein, W. Heuten and K. Wolf-Ostermann, 72–77.

Henseler, J., C. M. Ringle and M. Sarstedt (2015), „A new criterion for assessing discriminant validity in variance-based structural equation modeling”, Journal of the Academy of Marketing Science, 43 (1), 115-135.

Henseler, J., C. M. Ringle and M. Sarstedt (2015), “A new criterion for assessing discriminant validity in variance-based structural equation modeling”, Journal of the Academy of Marketing Science, 43 (1), 115–135.

Henseler, J., C M. Ringle and R. R. Sinkovics (2009), “The use of partial least squares path modeling in international marketing”, New Challenges to International Marketing (Advances in International Marketing), Vol. 20. (Eds.) Sinkovics, R. R. & Ghauri, P. N., Bingley: Emerald Group Publishing Limited, 277-319.

Herrero, S. T., L. Nicholls and Y. Strengers (2018), “Smart home technologies in everyday life: do they address key energy challenges in households?”, Current Opinion in Environmental Sustainability, 31, 65-70.

Himme, A. (2007), „Gütekriterien der Messung: Reliabilität, Validität und Generalisierbarkeit" in Methodik der empirischen Forschung, (Hrsg.) S. Albers, Wiesbaden, Gabler Verlag, 485-500.

Hoque, R. and G. Sorwar (2017), “Understanding factors influencing the adoption of mHealth by the elderly: An extension of the UTAUT model”, International Journal of Medical Informatics, 101, 75–84.

Hoy, M. B. (2018), “Alexa, Siri, Cortana, and More: An Introduction to Voice Assistants”, Medical Reference Services Quarterly, 37 (1), 81–88.

Hu, P. J., P. Y. K. Chau, O. R. L. Sheng and K. Y. Tam (1999), “Examining the Technology Acceptance Model Using Physician Acceptance of Telemedicine Technology”, Journal of Management Information Systems, 16 (2), 91–112.

Huber, F., A. Herrmann, F. Meyer, J. Vogel and K. Vollhardt (2007), Kausalmodellierung mit Partial Least Squares, Wiesbaden: Gabler Verlag.

Ivanov S. and C. Webster (2019a), “Perceived Appropriateness and Intention to Use Service Robots in Tourism”. In: Pesonen J., Neidhardt J. (eds) Information and Communication Technologies in Tourism 2019, Proceedings of the International Conference in Nicosia, Cyprus, 30.01-01.02.2019, 237-248.

Ivanov, S. and C. Webster (2019b), “What should robots do? A comparative analysis of industry professionals, educators and tourists”, In: Pesonen, J. & Neidhardt, J. (Eds.) Information and Communication Technologies in Tourism 2019, Proceedings of the International Conference in Nicosia, Cyprus, 30.01- 01.02.2019, pp. 249-262.

Jahn, S. (2007), „Strukturgleichungsmodellierung mit LISREL, AMOS und SmartPLS: Eine Einführung (An Introduction to Structural Equation Modeling with LISREL, AMOS and SmartPLS)" SSRN Electronic Journal, 26 (2), 1-46.

Janson, M. (2019), „Die Alten zieht's ins Internet", https://de.statista.com/infografik /12799/immer-mehr-internetnutzer-ueber-60-jahre/

Jiang, J., A. H. Awadallah, R. Jones, U. Ozertem, I. Zitouni, R. G. Kulkarni and O. Z. Khan (2015), “Automatic Online Evaluation of Intelligent Assistants”, in Proceedings of the 24th International Conference on World Wide Web, (Hrsg.) World Wide Web Conference, Florence, Italy, 506–516.

Jockisch, M. (2010), „Das Technologieakzeptanzmodell: Die verhaltenswissenschaftliche Modellierung von Beziehungsstrukturen mit latenten Konstrukten am Beispiel von Benutzerakzeptanz”, in "Das ist gar kein Modell!": Unterschiedliche Modelle und Modellierungen in Betriebswirtschaftslehre und Ingenieurwissenschaften, (Hrsg.) G. Bandow and H. H. Holzmüller, Wiesbaden: Gabler, 233–254.

Jones, V. K. (2018), “Voice-activated Change: Marketing in the age of artificial intelligence and virtual assistants”, Journal of brand strategy, 7 (3), 239-251.

Joo, J. and Y. Sang (2013), “Exploring Koreans’ smartphone usage: An integrated model of the technology acceptance model and uses and gratifications theory”, Computers in Human Behavior, 29 (6), 2512–2518.

Jörling, M., Böhm, R. and S. Paluch (2019), “Service Robots: Drivers of Perceived Responsibility for Service Outcomes”, Journal of Service Research, 22 (4), 404-420.

Junglas, I. A., N. A. Johnson and C. Spitzmüller (2008), “Personality traits and concern for privacy: an empirical study in the context of location-based services”, European Journal of Information Systems, 17 (4), 387-402.

Karakas, F., A. Manisaligil and E. Sarigollu (2015), “Management learning at the speed of life: Designing reflective, creative, and collaborative spaces for millennials”, International Journal of Management Education, 13 (3), 237-248.

Katz, E. (1974), “The uses of mass communications: Current perspectives on gratifications research”, Sage annual reviews of communication research, vol 3. Sage Publ, Beverly Hills, California.

Katz, E. (1959), “Mass Communications Research and the Study of Popular Culture: An Editorial Note on a Possible Future for This Journal”, Departmental Papers (ASC).

Katz, E., J. G. Blumler and M. Gurevitch (1974), “Uses and Gratifications Research”, The Public Opinion Quarterly, 37 (4), 509-523.

Katz, E., J. G. Blumler and M. Gurevitch, (Hrsg.) (1974), “Utilization of Mass Communication by the Individual”, The uses of mass communications: Current perspectives on gratifications research, Beverly Hills, Calif. Sage Publ., 1974, 19-32.

Kayak (2017), “Mobile Travel Report”, https://www.kayak.co.uk/news/mobile-travel-report-2017/.

Kaye, B. K. (1998), “Uses and gratifications of the World Wide Web: From couch potato to web potato”, New Jersey Journal of Communication, 6 (1), 21–40.

Kepuska, V. and G. Bohouta (2018), “Next-generation of virtual personal assistants (Microsoft Cortana, Apple Siri, Amazon Alexa and Google Home)”, in Proceedings of the 8th annual Computing and Communication Workshop and Conference, (Hrsg.) IEEE, Las Vegas, NV, 99–103.

Kim, H.-W., H. C. Chan and S. Gupta (2007), “Value-based Adoption of Mobile Internet: An empirical investigation”, Decision Support Systems, 43 (1), 111-126.

Kim, K.J. and D.-H. Shin (2015), “An acceptance model for smart watches: Implications for the adoption of future wearable technology”, Internet Research, 25 (4), 527-541.

Kim, S., K. Z. Gajos, M. Muller and B. J. Grosz (2016), “Acceptance of Mobile Technology by Older Adults: A Preliminary Study”, in Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services - MobileHCI ’16, (Hrsg.) F. Paternò and K. Väänänen, New York: ACM Press, 147–157.

Klauser, F. (2006), “Wissenschaftliche Grundlagen zur Erforschung der Akzeptanz Computer- und Netzbasierter Lernangebote. Berufs- und Wirtschaftspädagogische Grundlagenforschung. Lehr-Lern-Prozesse und Kompetenzdiagnostik“, Frankfurt: Peter Lang.

Klopfenstein, L. C., S. Delpriori, S. Malatini and A. Bogliolo (2017), “The Rise of Bots”, Proceedings of the Conference on Designing Interactive Systems, (Hrsg.) DIS, Edinburgh, UK, 555–565.

Knickmann, J. R. and E. K. Snell (2002), “The 2030 Problem: Caring for Aging Baby Boomers “, Health Service Research 37, Nr. 4, 849-884.

Knobloch, S. (2003), “Mood adjustment via mass communication”, Journal of Communication, 53, 233–250.

Ko, E., E. Y. Kim and E. K. Lee (2007), “Modeling consumer adoption of mobile shopping for fashion products in Korea”, Psychology & Marketing, 26 (7), 669-687.

Kohlbacher, F., C. Herstatt and N. Levsen (2015), “Golden opportunities for silver innovation: How demographic changes give rise to entrepreneurial opportunities to meet the needs of older people”, Technovation, 39-40, 73–82.

Kotzé, T. G., O. Anderson and K. Summerfield (2016), “Technophobia: Gender differences in the adoption of high-technology consumer products”, South African Journal of Business Management, 47 (1), 21–28.

Ku, Y. C., T. H. Chu and C. H. Tseng (2013), “Gratifications for using CMC technologies: A comparison among SNS, IM, and e-mail”, Computers in Human Behavior, 29 (1), 226–234.

Kuß, A., R. Wildner and H. Kreis (2014), „Marktforschung: Grundlagen der Datenerhebung und Datenanalyse“, Wiesbaden: Springer Gabler.

Lai, H.-J. (2018), “Investigating older adults’ decisions to use mobile devices for learning, based on the unified theory of acceptance and use of technology”, Interactive Learning Environments, 13 (2), 1–12.

Lee, C. and J. F. Coughlin (2015), “PERSPECTIVE: Older Adults’ Adoption of Technology: An Integrated Approach to Identifying Determinants and Barriers”, Journal of Product Innovation Management, 32 (5), 747–759.

Lee, C., B. Reimer, B. Mehler and J. F. Coughlin (2015), “User Acceptance of Voice Interfaces in the Automobile”. Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 59(1), 1641-1645.

Lee, L., S. Petter, D. Fayard and S. Robinson (2011), “On the use of partial least squares path modeling in accounting research”, International Journal of Accounting Information Systems, 12 (4), 305-328.

Lee, S., R. Ratan and T. Park (2019), “The Voice Makes the Car: Enhancing Autonomous Vehicle Perceptions and Adoption Intention through Voice Agent Gender and Style”, Multimodal Technologies and Interaction, 3 (1), 20-31.

Legris, P., J. Ingham and P. Collerette (2003), “Why do people use information technology? A critical review of the technology acceptance model”, Information & Management, 40 (3), 191–204.

Leung, L. and R. Zhang (2016), “Predicting tablet use: A study of gratifications-sought, leisure boredom, and multitasking”, Telematics and Informatics, 33 (2), 331-341.

Leung, L. and R. Wei (2000), “More Than Just Talk on the Move: Uses and Gratifications of the Cellular Phone”, Journalism & Mass Communication Quarterly, 77 (2), 308–320.

Li, H., Y. Liu, X. Xu, J. Heikkilä and H. van der Heijden (2015), “Modeling hedonic is continuance through the uses and gratifications theory: An empirical study in online games”, Computers in Human Behavior (48), 261–272.

Likert, R. (1932), “A technique for the measurement of attitudes”, Archives of Psychology, 22 (140), 55.

Lin, H.-F. and C.-H. Chen (2017), “Combining the Technology Acceptance Model and Uses and Gratifications Theory to examine the usage behavior of an Augmented Reality Tour-sharing Application”, Symmetry, 7 (9), 1–22.

Lissitsa, S. and O. Kol (2016), “Generation X vs. Generation Y – A decade of online shopping”, Journal of Retailing and Consumer Services, 31 (2016), 304-312.

Lometti, G. E., B. Reeves and C. R. Bybee (1977), “Investigating the Assumptions of Uses and Gratifications Research”, Communication Research, 4 (3), 321–338.

Lowry, P.B., J. Gaskin, N. Twyman, B. Hammer and T. L. Roberts (2013), “Taking “Fun and Games” Seriously: Proposing the Hedonic-Motivation System Adoption Model (HMSAM)”, Journal of the Association for Information Systems, 14 (11), 617-671.

Luger, E. and A. Sellen (2016), “Like Having a Really Bad PA: The Gulf between User Expectation and Experience of Conversational Agents” in Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI ’16), San Jose, USA, 7-12 May, 2016, Proceedings, 5286–5297.

Luijkx, K., S. Peek and E. Wouters (2015), “Grandma, You Should Do It - It’s Cool” Older Adults and the Role of Family Members in Their Acceptance of Technology”, International Journal of Environmental Research and Public Health, 12 (12), 15470–15485.

Luo, M.M., S. Chea and J.-S. Chen (2011), “Web-based information service adoption: A comparison of the motivational model and the uses and gratifications theory”, Decision Support Systems, 51 (1), 21-30.

Luo, Y. and J. Bu (2016), “How valuable is information and communication technology? A study of emerging economy enterprises”, Journal of World Business, 51 (2), 200–211.

Ma, Q., A. H. S. Chan and K. Chen (2016), “Personal and other factors affecting acceptance of smartphone technology by older Chinese adults”, Applied Ergonomics, 54, 62–71.

Ma, Q., K. Chen, A. H. S. Chan and P.-L. Teh (2015), “Acceptance of ICTs by Older Adults: A Review of Recent Studies”, in Human Aspects of IT for the Aged Population. Design for Aging. Lecture Notes in Computer Science, (Hrsg.) J. Zhou and G. Salvendy, Cham: Springer International Publishing, 239–249.

Macedo, I. M. (2017), “Predicting the acceptance and use of information and communication technology by older adults: An empirical examination of the revised UTAUT2”, Computers in Human Behavior, 75, 935–948.

Macronomy (2018), „Digitale Sprachassistenten – Nutzung von Alexa, Siri und Co. nimmt zu”, https://www.marconomy.de/digitale-sprachassistenten-nutzung-von-alexa-siri-und-co-nimmt-zu-a-722632/.

Malhotra, N.K., S. S. Kim and J. Agarwal (2004), “Internet Users’ Information Privacy Concerns (IUIPC): The Construct, the Scale, and a Causal Model”, Information Systems Research, 15 (4), 336-355.

Malik, A., A. Dhir and M. Nieminen (2016), “Uses and Gratifications of digital photo sharing on Facebook”, Telematics and Informatics, 33 (1), 129–138.

Mani, Z. and I. Chouk (2017), “Drivers of consumers’ resistance to smart products”, Journal of Marketing Management, 33 (1-2), 76–97.

Mari, A. (2019, October), “Voice Commerce: Understanding shopping-related voice assistants and their effect on brands” In IMMAA Annual Conference. Northwestern University in Qatar, Doha (Qatar).

McLean, G. and K. Osei-Frimpong (2017), “Examining satisfaction with the experience during a live chat service encounter-implications for website providers”, Computers in Human Behavior, 76, 494–508.

McQuail, D., J. G. Blumler and J. R. Brown (1972), “The television audience: a revised perspective”, in Sociology of Mass Communications, (Hrsg.) D. McQuail, Middlesex: Penguin, 135–165.

McTear, M. F., Z. Callejas and D. Griol (2016), “The Conversational Interface - Talking o Smart devices”, Cham, Springer International Publishing.

McTear, M. F. (2017), „The Rise of the Conversational Interface: A New Kid on the Block?", in Future and Emerging Trends in Language Technology. Machine Learning and Big Data, (Hrsg.) J. F. Quesada, F.-J. Martín Mateos, and T. López Soto, 10341, Cham, Springer International Publishing, 38-49.

Merkel, S., P. Enste, J. Hilbert, K. Chen, A. H.-S. Chan and S. Kwon (2017), “Technology Acceptance and Aging”, in Gerontechnology: Research, Practice, and Principles in the Field of Technology and Aging, (Hrsg.) Sunkyo Kwon, New York: Springer Publishing Company, 335–349.

Miltgen, C. L., J. Henseler, C. Gelhard and A. Popovič (2016), “Introducing new products that affect consumer privacy: A mediation model”, Journal of Business Research, 69 (10), 4659–4666.

MindMeld 2016. “Intelligent Voice Assistants - Q1 2016 User Adoption Survey”.

Mizak, A., M. Park, D. Park and K. Olson (2017), “Amazon Alexa Pilot Analysis Report”, http://fpciw.org/wp-content/uploads/sites/15/2017/12/FINAL-DRAFT-Amazon-Alexa-Analysis-Report.pdf

Moon, J-W and Y. G. Kim (2001), “Extending the TAM for a World-Wide-Web context”, Information & Management, 38 (4), 217–230.

Mostaghel, R. (2016), “Innovation and technology for the elderly: Systematic literature review”, Journal of Business Research, 69 (11), 4896–4900.

Moura, A. C. D., M. D. S. Gosling, J. M. M. Christino and S. B. Macedo (2017), “Acceptance and use of technology by older adults for choosing a tourism destination: a study using UTAUT2”, Revista Brasileira de Pesquisa em Turismo, 11 (2), 239–269.

Myers, K. K. and K. Sadaghiani (2010), “Millennials in the Workplace: A Communication Perspective on Millennials’ Organizational relationships and Performance”, Journal of Business and Psychology, Vol. 25 No.2, Special Issue June 2010, 225-238.

Nabi, R. L., C. R. Stitt, J. Halford and K. L. Finnerty (2006), “Emotional and Cognitive Predictors of the Enjoyment of Reality-Based and Fictional Television Programming: An Elaboration of the Uses and Gratifications Perspective”, Media Psychology, 8 (4), 421-447.

Nasirian, F., M. Ahmadian and O. K. D. Lee (2017), “AI-based voice assistant systems: Evaluating from the interaction and trust perspectives”, Twenty-third Americas Conference on Information Systems, Boston, 2017.

Niehaves, B. and R. Plattfaut (2014), “Internet adoption by the elderly: employing IS technology acceptance theories for understanding the age-related digital divide”, European Journal of Information Systems, 23 (6), 708–726.

Nikou, S. (2015), “Mobile technology and forgotten consumers: the young-elderly”, International Journal of Consumer Studies, 39 (4), 294–304.

Nunnally, J. C. and I. R. Bernstein (1994), “Psychometric Theory”, New York: McGraw Hill.

Olbrich, R., D. Battenfeld and C.-C. Buhr (2012), „Marktforschung: Ein einführendes Lehr- und Übungsbuch", Berlin, Heidelberg: Springer Berlin Heidelberg.

Oliveira, T., M. Thomas, G. Baptista and F. Campos (2016), “Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology”, Computers in Human Behavior, 61, 404–414.

Onobhayedo, P.A. (2017), “Implementing Web Technologies as Organizational Communication Media: A Study of Employee Adoption Likelihood”, Journal of Business Theory and Practice, 5 (2), 120-140.

Owusu Kwateng, K., K. A. Osei Atiemo and C. Appiah (2019), “Acceptance and use of mobile banking: an application of UTAUT2”, Journal of Enterprise Information Management, 32 (1), 118–151.

Pakalski, I. (2018), “Apples Homepod liegt beim Marktanteil hinter Alexa und Co“, https://www.golem.de/news/smarte-lautsprecher-apples-homepod-liegt-beim-marktanteil-hinter-alexa-und-co-1805-134455.html

Panch, T., P. Szolovits and R. Atun (2018), “Artificial intelligence, machine learning and health systems”, Journal of global health, 8 (2), 1–8.

Papacharissi, Z. and A. Mendelson (2010), “Toward a new(er) sociability: uses, gratifications and social capital on Facebook” in Media Perspectives for the 21st Century, Vol. 1. (Eds.) Papathanassopoulus, S., London: Routledge, 212-230.

Papacharissi, Z. and A. M. Rubin (2000), “Predictors of Internet Use”, Journal of Broadcasting & Electronic Media, 44 (2), 175–196.

Parasuraman, A. (2000), “Technology Readiness Index (TRI). A Multiple-Item Scale to Measure Readiness to Embrace New Technologies”, Journal of Service Research, 2 (4), 307-320.

Park, E. and K. J. Kim (2014), “An Integrated Adoption Model of Mobile Cloud Services: Exploration of Key Determinants and Extension of Technology Acceptance Model”, Telematics and Informatics, 31 (3), 376-385.

Park, E., Kim, H. and J. Y. Ohm (2014), “Understanding driver adoption of car navigation systems using the extended technology acceptance model”, Behaviour & Information Technology, 34 (7), 741-751.

Park, N. (2010), “Adoption and Use of Computer-Based Voice Over Internet Protocol Phone Service: Toward an Integrated Model”, Journal of Communication, 60 (1), 40-72.

Park, N., K. M. Lee and P. H. Cheong (2007), “University Instructors’ Acceptance of Electronic Courseware: An Application of the Technology Acceptance Model”, Journal of Computer-Mediated Communication, 13 (1), 163-186.

Park, S. Y. (2009), “An Analysis of the Technology Acceptance Model in Understanding University Students’ Behavioral Intention to Use e-Learning”, Educational Technology & Society, 3 (12), 150–162.

PEW Research Center (2017), “American Trends Panel”.

Porter, C. E. and N. Donthu (2006), “Using the technology acceptance model to explain how attitudes determine Internet usage: The role of perceived access barriers and demographics”, Journal of Business Research, 59 (9), 999–1007.

PwC (2017), „Digitale Assistenten - Bevölkerungsbefragung 2017“.

PwC (2018), “Consumer Intelligence Series: Prepare for the voice revolution”.

PwC United States (2018), “Prepare for the voice revolution”, https://www.pwc.com/us/en/services/consulting/library/consumer-intelligence-series/voice-assistants.html.

Quan-Haase, A. and A. L. Young (2010), “Uses and Gratifications of Social Media: A Comparison of Facebook and Instant Messaging”, Bulletin of Science, Technology & Society, 30 (5), 350-361.

Rase, Y., A. Ormaza Cuadra and C. de Moerloose (2018), “The use of personal voice assistants in the context of retail digitalization: An empirical study of consumers’ attitude and privacy concerns” (Doctoral dissertation, Master’s thesis). Louvain School of Management, Université catholique de Louvain, Louvain-la-Neuve.

Rauschnabel, P. A. (2018), “A Conceptual Uses & Gratification Frame-work on the Use of Augmented Reality Smart Glasses”, in Augmented Reality and Virtual Reality: Empowering

Human, Place and Business. Progress in IS, (Hrsg.) T. Jung and M. C. Tom Dieck, Cham: Springer International Publishing, 211–227.

Rauschnabel, P. A. and Y. K. Ro (2016), “Augmented reality smart glasses: an investigation of technology acceptance drivers”, International Journal of Technology Marketing, 11 (2), 123–148.

Rauschnabel, P. A., A. Rossmann and M. C. Tom Dieck (2017), “An adoption framework for mobile augmented reality games: The case of Pokemon Go”, Computers in Human Behavior (76), 276–286.

Rauschnabel, P.A., J. He and Y. K. Ro (2018), “Antecedents to the adoption of augmented reality smart glasses: A closer look at privacy risks”, Journal of Business Research, 92 (2018), 374-384.

Rese, A., S. Schreiber and D. Baier (2014), “Technology acceptance modeling of augmented reality at the point of sale: Can surveys be replaced by an analysis of online reviews?”, Journal of Retailing and Consumer Services, 1–8.

Rigdon E. E., M. Sarstedt, C. M. Ringle (2017) “On comparing results from CB-SEM and PLS-SEM: Five perspectives and five recommendations”. Marketing ZFP 39(3), 4–16.

Rigdon, E. E. (2016), “Choosing PLS path modeling as analytical method in European management research: A realist perspective”, European Management Journal, 34 (6), 598–605.

Ringle, C. M. and M. Sarstedt (2016), “Gain more insight from your PLS-SEM results: The importance-performance map analysis”, Industrial Management & Data Systems, 116 (9), 1865–1886.

Ringle, C. M., M. Sarstedt and D. W. Straub (2012), “A Critical Look at the Use of PLS-SEM in MIS Quarterly”, MIS Quarterly, 36 (1), iii.

Rogers, E. M. (1995), “Diffusion of Innovations”, New York: Free Press.

Rosenthal-von der Pütten, A.M., N. C. Krämer and J. Herrmann (2018), “The effects of humanlike and robot-specific affective nonverbal behavior on perception, emotion, and behavior”, International Journal of Social Robotics, 10, 569-582.

Rubin, A.M. (2002), “The uses-and-gratifications perspective of media effects” in Media effects: Advances in theory and research, Vol. 2. (Eds.) Bryant, J. und Zillmann, D.: LEA’s communication series, Mahwah: Lawrence Erlbaum Associates, 525-548.

Ruggiero, T.E. (2000), “Uses and Gratifications Theory in the 21st Century”, Mass Communication and Society, 3 (1), 3-37.

Sarikaya, R. (2017), “The Technology Behind Personal Digital Assistants: An overview of the system architecture and key components”, IEEE Signal Processing Magazine, 34 (1), 67–81.

Sarstedt, M., J. F. Hair, C. M. Ringle, K.O. Thiele and S. P. Gudergan (2016), “Estimation issues with PLS and CBSEM: Where the bias lies!”, Journal of Business Research, 69(10), 3998-4010.

Sayago, S., B. B. Neves and B. R. Cowan (2019), “Voice assistants and older people: some open issues”, In Proceedings of the 1st International Conference on Conversational User Interfaces (7), ACM.

Schäfer, M. and D. Keppler (2013), „Modelle der technikorientierten Akzeptanzforschung: Überblick und Reflexion am Beispiel eines Forschungsprojekts zur Implementierung innovativer technischer Energieeffizienz-Maßnahmen”, https://depositonce.tu-berlin.de/bitstream/11303/4758/1/schaefer_keppler.pdf

Schwarz, G. (2018), „Leben mit Alexa – eine Zwischenbilanz (2018-01)“, https://www.seniorenfreundlich.de/smartspeaker-praxis-senioren.html

Schweiger, W. (2007), „Theorien der Mediennutzung: Eine Einführung“, Wiesbaden: VS Verlag für Sozialwissenschaften.

Shankar, V. (2018), “How Artificial Intelligence (AI) is reshaping retail”. Journal of Retailing, 94(4), VI-XI.

Sharma, P. N., G. Shmueli, M. Sarstedt, N. Danks and S. Ray (2019), “Prediction-oriented model selection in partial least squares path modeling”, Decision Sciences, 52 (3), 567-607.

Sheldon, P., P. A. Rauschnabel, M. G. Antony and S. Car (2017), “A cross-cultural comparison of Croatian and American social network sites: Exploring cultural differences in motives for Instagram use”, Computers in Human Behavior, 75 (2017), 643-651.

Shmueli, G., S. Ray, J. M. Velasquez Estrada and S. B. Chatla (2016), “The elephant in the room: evaluating the predictive performance of PLS models”, Journal of Business Research, 69(10), 4552-4564.

Shmueli, G., M. Sarstedt, J.-H. Cheah, H. Ting, S. Vaithilingam and C. M. Ringle (2019), “Predictive model assessment in PLS-SEM: guidelines for using PLSpredict”, European Journal of Marketing, 53 (11), 2322-2347.

Simon, S. J. and D. Paper (2007), “User Acceptance of Voice Recognition Technology: An Empirical Extension of the Technology Acceptance Model”, Journal of Organizational and End User Computing, 19(1), 24-50.

Sinkovics, R. R., B. Stöttinger, B. B. Schlegelmilch and S. Ram (2002), “Reluctance to use technology-related products: Development of a technophobia scale”, Thunderbird International Business Review, 44 (4), 477–494.

Slade, E. L., Y. K. Dwivedi, N. C. Piercy and M. D. Williams (2015), “Modeling Consumers’ Adoption Intentions of Remote Mobile Payments in the United Kingdom: Extending UTAUT with Innovativeness, Risk, and Trust”, Psychology & Marketing, 32 (8), 860–873.

Snell, J. (2018), “Siri: What Apple needs to do to improve its voice-activated digital assistant”, Macworld, 95–99.

Song, I., R. LaRose, M. S. Eastin and C. A. Lin (2004), “Internet Gratifications and Internet Addiction: On the Uses and Abuses of New Media”, Cyberpsychology & behavior, 7 (4), 384–394.

Sovie, D., J. Curran, M. Schoelwer and A. Björnsjö (2017), “Dynamic Digital Consumers: Ever-Changing Expectations And Technology Intrigue”, https://www.accenture.com/us-en/_acnmedia/PDF-39/Accenture-PoV-Dynamic-Consumers.pdf

Srite, M. and E. Karahanna (2006), “The Role of Espoused National Cultural Values in Technology Acceptance, Management Information Systems Quarterly, 30 (3), 679-704.

Stafford, T. F., M. R. Stafford and L. L. Schkade (2004), “Determining Uses and Gratifications for the Internet”, Decision Sciences, 35 (2).

Stalz-John, D. (2019), „How to define AI? – Using the Turing Test to measure human-like intelligence in machines.", Codecentric, https://blog.codecentric.de/en/2019/06/ai-%E2%80%A8turing-testhuman-like-intelligence-machines/

Statista (2017a), „In immer mehr Bereichen des Lebens spielen digitale Sprachassistenten eine Rolle. Welche dieser Sprachassistenten kennen Sie?”, https://de.statista.com/statistik/daten/studie/739040/umfrage/umfrage-zur-bekanntheit-ausgewaehlter-sprachassistenten-in-deutschland/.

Statista (2017b), „Prognose zum Volumen der jährlich generierten digitalen Datenmenge weltweit in den Jahren 2016 und 2025”, https://de.statista.com/statistik/daten/studie/267974/umfrage/prognose-zum-weltweit-generierten-datenvolumen/.

Statista (2017c), „Welchen Nutzen sehen Sie bei der zunehmenden Verbreitung von Sprachassistenten?“, https://de.statista.com/statistik/daten/studie/739315/umfrage/umfrage-zum-nutzen-von-digitalen-sprachassistenten/.

Statista (2017d) „Umfrage zur Nutzung von stimmengesteuerten virtuellen Assistenten von Millennials—Anzahl der Millennials in Deutschland, die stimmengesteuerte virtuelle Assisten-

ten wie Siri, Hey Google, Cortana oder Alexa nutzen im Jahr 2017", https://de.statista.com/statistik/studie/id/45289/dokument/millennials-in-deutschland/

Statista (2019) „Prognose zum Umsatz mit intelligenten Lautsprechern weltweit in den Jahren 2017 bis 2022 (in Milliarden US-Dollar) (Statista Dossier Smart Speaker)", https://de.statista.com/statistik/daten/studie/751700/umfrage/prognose-zum-umsatz-mit-intelligenten-lautsprechern-weltweit/

Stavropoulos, V., D. Kuss, M. Griffiths and F. Motti-Stefanidi (2016), “A Longitudinal Study of Adolescent Internet Addiction”, Journal of Adolescent Research, 31 (4), 442–473.

Stone, M. (1974), “Cross-validation and multinomial prediction”, Biometrika, 61 (3), 509–515.

Straub, D. W. (1989), “Validating Instruments in MIS Research”, MIS Quarterly, 13 (2), 147-169.

Sundar, S. S. and A. M. Limperos (2013), “Uses and Grats 2.0: New Gratifications for New Media”, Journal of Broadcasting & Electronic Media, 57 (4), 504–525.

Suta, P., N. Limdumrongnukoon, P. Chalardkitsirikul, T. Suntiyotin, P. Mongkolnam and J. H. Chan (2018), “Analysis of Factors Affecting Multimedia Delivery for Elderly People”, Engineering Journal, 22 (1), 49–64.

Taherdoost, H. (2018), “A review of technology acceptance and adoption models and theories”, Procedia Manufacturing, 22, 960-967.

Tak, P. and S. Panwar (2017), “Using UTAUT 2 model to predict mobile app-based shopping: evidences from India”, Journal of Indian Business Research, 9 (3), 248–264.

Taken Smith, K. (2012), “Longitudinal study of digital marketing strategies targeting Millennials”, Journal of Consumer Marketing, 29 (2), 86–92.

Tamilmani, K., N. P. Rana and Y. K. Dwivedi (2017), “A Systematic Review of Citations of UTAUT2 Article and Its Usage Trends”, Digital Nations–Smart Cities, Innovation, and Sustainability: 16th Conference on e-Business, e-Services, and e-Society, Delhi, India, 21-23 November, 2017, Proceedings, 38-49.

Tamilmani, K., N. P. Rana and Y. K. Dwivedi (2019), “Use of ‘Habit’ Is not a Habit in Understanding Individual Technology Adoption: A Review of UTAUT2 Based Empirical Studies”, Smart Working, Living and Organising, (Hrsg.) A. Elbanna, Y. K. Dwivedi, D. Bunker, and D. Wastell, 533, Springer International Publishing, 277-294.

Tamilmani, K., N. Rana, Y. Dwivedi, G.P. Sahu, and S. Roderick (2018), “Exploring the Role of 'Price Value' for Understanding Consumer Adoption of Technology: A Review and Meta-analysis of UTAUT2 based Empirical Studies”, Pacific Asia Conference on Information Sys-

tems (PACIS 2018), 1-10. Yokohama: Hirano, Masaaki; Myers, Michael; Kijima, Kyoichi, 2018.

Taylor, S. and P. Todd (1995), “Assessing IT Usage: The Role of Prior Experience”, Management Information Systems Quarterly, 19(4), 561–570.

Tech-enhanced Life (2017), “Amazon Echo and Alexa for the Elderly”, https://www.techenhancedlife.com/explorers/amazon-echo-and-alexa-elderly

Thomas, J. A. (2015), “Deontology, consequentialism and moral realism”, Journal of Philosophy 19(1), 1-24.

Thompson, R. L., C. A. Higgins and J. M. Howell (1991), “Personal Computing: Toward a Conceptual Model of Utilization”, Management Information Systems Quarterly, 15(1), 125-143.

Tsai, H.-Y. S., R. Shillair, S. R. Cotten, V. Winstead and E. Yost (2015), “Getting Grandma Online: Are Tablets the Answer for Increasing Digital Inclusion for Older Adults in the US?”, Educational Gerontology, 41 (10), 695–709.

Tuzovic, S. and S. Paluch (2018), „Conversational Commerce. A New Era for Service Business Development?" in Forum Dienstleistungsmanagement. Service Business Development, Bruhn & Hadwich (Eds.), Springer, Wiesbaden.

Tuzovic, S. and Paluch, S. (2018), “Alexa–What’s on my shopping list? Investigating consumer perceptions of voice-controlled services”, In SERVSIG Conference Proceedings 2018 Paris: Opportunities for services in a challenging world. SERVSIG, France, 107-110.

United Nations (2017), “World Population Prospects: The 2017 Revision, Key Findings and Advance Tables. Working Paper No. ESA/P/WP/248.”, https://esa.un.org/unpd/wpp/Publications/Files/WPP2017_KeyFindings.pdf

United Nations (2020), “World Population Ageing 2020”, https://www.un.org/development/desa/pd/sites/www.un.org.development.desa.pd/files/files/documents/2020/Sep/un_pop_2020_pf_ageing_10_key_messages.pdf

Valenzuela, S., N. Park and K. F. Kee (2009), “Is There Social Capital in a Social Network Site?: Facebook Use and College Students’ Life Satisfaction, Trust, and Participation”, Journal of Computer-Mediated Communication, 14 (4), 875-901.

Van der Heijden, H. (2004), “User Acceptance of Hedonic Information Systems”, MIS Quarterly, 28 (4), 695–704.

Van Eeuwen, M. (2017), “Mobile conversational commerce: messenger chatbots as the next interface between businesses and consumers”, https://essay.utwente.nl/71706/1/van%20Eeuwen_MA_BMS.pdf.

Vantiv LLC (2018), “Digital Assistants Consumer Survey Results”, https://www.vantiv.com/content/dam/vantiv/documents/digital-assistants-consumer-survey-results_18-1830-1.pdf

Vassli, L. T. and B. A. Farshchian (2018), “Acceptance of Health-Related ICT among Elderly People Living in the Community: A Systematic Review of Qualitative Evidence”, International Journal of Hu-man–Computer Interaction, 34 (2), 99–116.

Veer, A. J. E. de, J. M. Peeters, A. E. M. Brabers, F. G. Schellevis, J. J. D. J. M. Rademakers and A. L. Francke (2015), “Determinants of the intention to use e-Health by community-dwelling older people”, BMC Health Services Research, 15 (1), 1–9.

Venkatesh, V., F. D. Davis (2000), “A theoretical extension of the technology acceptance model: Four longitudinal field studies”, Management Science 46(2):186–204, DOI 10.1287/mnsc.46.2.186.11926

Venkatesh, V. and H. Bala (2008), “Technology Acceptance Model 3 and a Research Agenda on Interventions”, Decision Sciences, 39 (2), 273-315.

Venkatesh, V. and F. D. Davis (1996), “A Model of the Antecedents of Perceived Ease of Use: Development and Test”, Decision Sciences, 27 (3), 451-481.

Venkatesh, V. and M. G. Morris (2000), “Why Don’t Men Ever Stop to Ask for Directions? Gender, Social Influence, and Their Role in Technology Acceptance and Usage Behavior”, Management Information Systems Quarterly, 24 (1), 115-139.

Venkatesh, V. (2000), “Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model”, Information Systems Research, 11(4), 342-365.

Venkatesh, V. and F. D. Davis (2000), “A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies”, Management Science, 46 (2), 186–204.

Venkatesh, V. and S. A. Brown (2001), “A Longitudinal Investigation of Personal Computers in Homes: Adoption Determinants and Emerging Challenges”, MIS Quarterly, 25 (1), 71–102.

Venkatesh, V., F. D. Davis and M. G. Morris (2007), “Dead Or Alive? The Development, Trajectory And Future Of Technology Adoption Research.”, Journal of the Association for Information Systems, 8 (4), 267–286.

Venkatesh, V., J. Y. L. Thong and X. Xu (2012), “Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology”, MIS Quarterly, 36 (1), 157–178.

Venkatesh, V., J. Y. L. Thong and X. Xu. (2016), „Unified Theory of Acceptance and Use of Technology: A Synthesis and the Road Ahead", Journal of the Association for Information Systems, 17 (5), 328–376.

Venkatesh, V., M. G. Morris, G. B. Davis and F. D. Davis (2003), “User Acceptance of Information Technology: Toward a Unified View”, MIS Quarterly, 27 (3), 425–478.

Viswanathan, V. and V. Jain (2013), “A dual-system approach to understanding “generation Y” decision making”, Journal of Consumer Marketing, 30/6, 484-492.

VoCo (2018), “Everything You Need to Know About Alexa for Seniors”, https://medium.com/@sayvoco/everything-you-need-to-know-about-alexa-for-seniors-1717d3c35f14

Wagner, K., F. Nimmermann and H. Schramm-Klein (2019), “Is It Human? The Role of Anthropomorphism as a Driver for the Successful Acceptance of Digital Voice Assistants”, In Proceedings of the 52nd Hawaii International Conference on System Sciences.

Wei, P. S. and H. P. Lu (2014), “Why do people play mobile social games? An examination of network externalities and of uses and gratifications”, Internet Research, 24 (3), 313–331

Weiber, R. and D. Mühlhaus (2014), „Strukturgleichungsmodellierung", Berlin, Heidelberg: Springer Berlin Heidelberg.

Weinberg, B. D., G. R. Milne, Y. G. Andonova and F. M. Hajjat (2015), “Internet of Things: Convenience vs. privacy and secrecy”, Business Horizons, 58 (6), 615–624.

Weizenbaum, J. (1966), “ELIZA – A Computer Program for the Study of Natural Language Communication between Man and Machine”, Communications of the ACM, 9 (1), 36-45.

Whiting, A. and D. Williams (2013), “Why people use social media: a uses and gratifications approach”, Qualitative Market Research: An International Journal, 16 (4), 362–369.

Wirtz, J., P. Patterson, W. Kunz, T. Gruber, V. N. Lu, S. Paluch and A. Martins (2018), “Brave New World: Service Robots in the Frontline”, Journal of Service Management, 29(5), 907-931.

Wold, H. (1975), “Path Models with Latent Variables: The NIPALS Approach”, Quantitative Sociology, Academic Press, 307–357.

Wu, J. H. and S. C. Wang (2005), “What drives mobile commerce?”, Information & Management 42(5), 719– 729.

Wu, J. and H. Du (2012), “Toward a better understanding of behavioral intention and system usage constructs”, European Journal of Information Systems, 21 (6), 680–698.

Wu, J.-H. and S.-C. Wang (2005), “What drives mobile commerce? An empirical evaluation of the revised technology acceptance model”, Information & Management (42), 719–729.

Wulf, L., M. Garschall, J. Himmelsbach and M. Tscheligi (2014), „Hands free – Care free: Elderly People taking Advantage of Speech-only Interaction”, in Proceedings of the 8th Nordic Conference on Human-Computer Interaction Fun, Fast, Foundational - NordiCHI '14, (Hrsg.) V. Roto, T. Olsson, K. Väänänen-Vainio-Mattila, J. Häkkilä, E. Hvannberg and O. Juhlin, New York: ACM Press, 203–206.

Wünderlich, N.V. and S. Paluch (2017), “A Nice and Friendly Chat with a Bot: User Perceptions of AI-Based Service Agents”, ICIS 2017.

Xu, C., S. Ryan, V. Prybutok and C. Wen (2012), “It is not for fun: An examination of social network site usage”, Information & Management, 49 (5), 210-217.

Yang, H. und H. Lee (2019), “Understanding user behavior of virtual personal assistant devices”, Information Systems and e-Business Management, 17, 65–87.

YouGov (2017), „Kommunikation per Chatbot: Sind Ihre Kunden bereit für das nächste Level des Kundenservice?”, https://campaign.yougov.com/DE_2017_08_Reports_Chatbots.html?utm_source=press&utm_medium=media&utm_campaign=report_chatbot.

Young, A. M. and Mary D. Hinesly (2012), “Identifying Millennials’ key influencers from early childhood: Insights into current consumer preferences”, Journal of Consumer Marketing, 29 (2), 146–155.