UGA or TAM: Which Approach Explains Digital Voice Assistant Acceptance Better?

Karolina Ewers and Daniel Baier

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/are 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 participants). The results are promising: Both approaches (UGA and TAM) are valid tools. Pastime, expediency, and enjoyment demonstrate to be important drivers for using DVAs.

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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 trigger 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 understand, whether and why their customers accept or reject them. Since this topic has not yet been sufficiently researched for DVAs, 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 compare the results (Section 3). The paper ends with conclusions and an outlook on future studies (Section 4).

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 fundamentally examines 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 the 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).

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

Technology (sample size)	Found gratifications	Reference
Mobile phones (n=834)	Appropriateness, social connectedness, calming	Leung and Wei (2000)
Internet (n=498)	Information search, distraction, personal status	Song et al. (2004)
Social networks (n=167)	Social benefit, information exchange, entertainment	Ancu and Cosma (2009)
Instant messaging (n=150)	Pastime, information search, contact maintenance	Ku et al. (2013)
Online/mob. games (n=237)	Individual (enjoyment, interaction with others)	Wei and Lu (2014)
Social networks (n=3,172)	Entertainment, information exchange, self-portrayal	Alhabash et al. (2014)
Social networks (n=368)	Interest, information exchange, social influence	Malik et al. (2016)
Chatbots (n=146)	Productivity, pastime, social advantages	Brandtzaeg and Føldstad (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 information), technological (appeal of medium)	Gan and Li (2018)

Contrary to previous criticisms (see, e.g., Knobloch, 2003), UGA can be used in the context of modern communication technologies. In the field of Internet-based media, UGA already found its application. In this context, researchers 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.

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 is currently 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. The basic attitude of the user, the socalled “Attitude Towards Using“ construct decides whether the new technology will in fact be used by its user in the near future. According to Davis (1985), “Attitude Towards 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 the consumer’s perspective. Moreover, they have a direct impact on “Attitude Towards 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 Towards Using“ – are related to “Behavioral Intention to Use“, which finally influences “Actual System Use“.

Table 2: Application of the technology acceptance model (TAM).

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-Frim-pong (2017)
Smart home (n=304)	Security technologies are perceived as “useful“ whereas the convenience apps are perceived as “pleasant“	Chen et al (2018)

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).

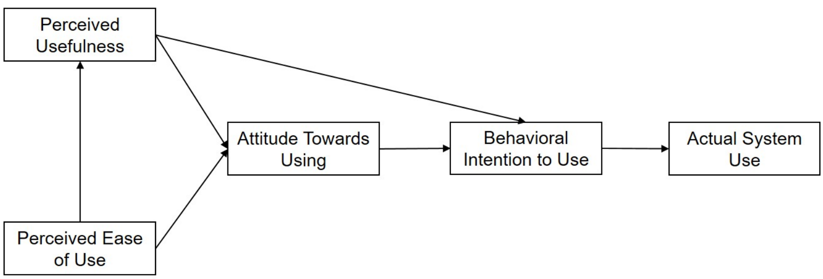

Figure 1: TAM structural model for DVA acceptance measurement.

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 factors 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 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.

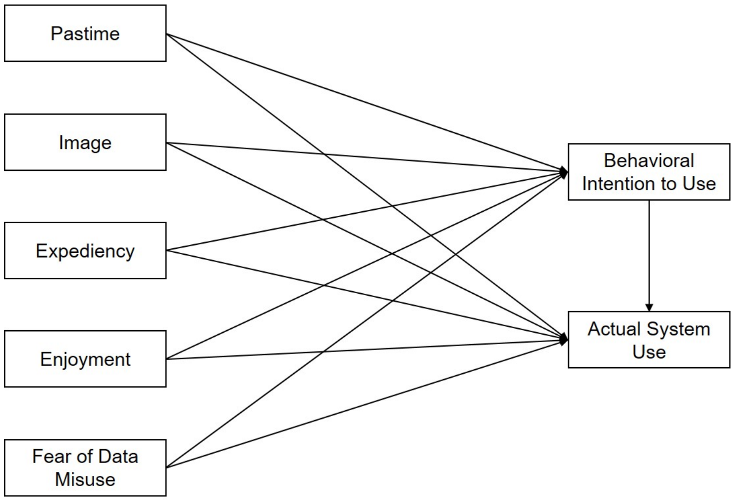

Figure 2: UGA structural model for DVA acceptance measurement.

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 an 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 completely 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 completely 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 in the near future. Even though companies try to appeal to all age groups with their products and services, 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.

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

Construct (no. of items)	R^2	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)

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

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 provided in the current literature and are considered valid. Furthermore, the average variance extracted and Cronbach's alpha are used to validate the construct reliability. All values statisying 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. Outer loadings of the two models also show no abnormalities and can therefore be considered as sufficient.

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

Construct (no. of items)	R^2	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 Towards Using (3)	.656	.652	.862	.864	.619	2.62 (1.027)	Venkatesh and Davis (2000),Porter, 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)

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

The existence of reliability is a precondition for validity. Therefore, validity can now be checked by looking at the means of the discriminant validity and the collinearity. For that the Fornell-Larcker Criterion (Fornell and Larcker, 1981) and the Heterotrait-Monotrait Ratio (HTMT) (Hair et al., 2017) will be investigated. The Fornell-Larcker Criterion examines the construct 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 the 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.

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

f^2	BIU	ASU
Pastime (PA)	.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)		

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

f^2	PU	ATU	BIU	ASU
Perceived Ease of Use (PEOU)	.207	.019		
Perceived Usefulness (PU)		1.424	.048	
Attitude Towards Using (ATU)			.460	
Behavior Intention to Use (BIU)				1.781
Actual System Use (ASU)				

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

In order to be able to interpret the structural equation model accordingly, an examination of R^2, R^2 Adjusted and f^2 is indispensable (Chin and Marcoulides, 1998). All these values can be seen in Tables 5 and 6. Furthermore, the 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.

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 criterion for comparison. In such cases the Bayesian Information Criterion for model selection (BIC) is 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.

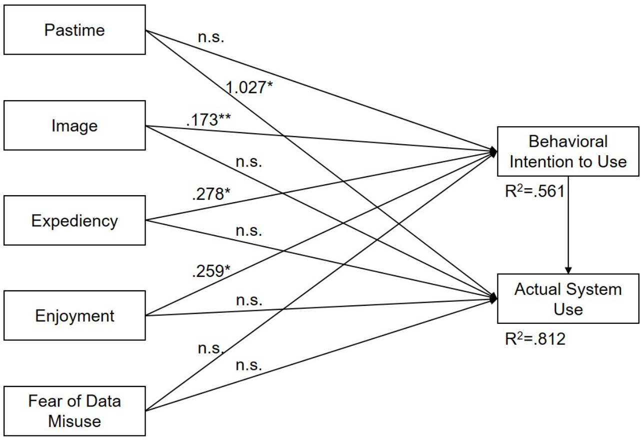

Figure 3: UGA structural model with standardized path coefficients; * (**) denotes significant at the p=0.01 (0.001) level; n.s.=not significant.

After the completion of all the evaluations presented above, the findings shown in Figure 3 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“.
4. “Fear of Data Misuse“ has no influence on neither “Behavioral Intention to Use“ nor “Actual System Use“.

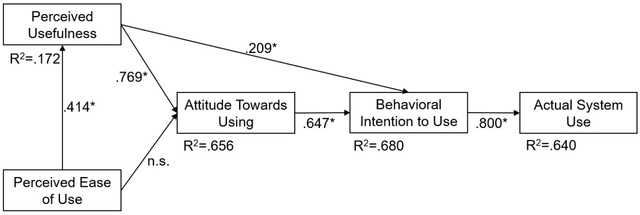

Figure 4: TAM structural model with standardized path coefficients; * denotes significant at the p=0.01 level; n.s.=not significant.

Relating to TAM, all constructs show a significant correlation between each other, (see Figure **??**. 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 the constructs mentioned above and “Actual System Use“ are relevant or even, whether “Actual System Use“ needs to be integrated in this model at all.

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 everyday life easier and that they are 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 Towards 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 Explains Digital Voice Assistant Acceptance Better? “), 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 the 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, BIc 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 investigated. Comparing these two models from a prediction-only perspective, UGA seems to be better (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.

With regard to 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 rather be 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.

4 Conclusions 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, navigating a car, or traveling, especially when a manual input is not possible. Furthermore, in some of the comments on the survey, the software was 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, an 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 recent, 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 everyday life much easier.

Future studies are encouraged to interview a larger, more 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 specific 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).

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