Exploring the Hype: Investigating Technology Acceptance Factors of Pokémon Go

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Abstract

We investigate the technology acceptance factors of the AR smartphone game Pokémon Go with a PLS-SEM approach based on the UTAUT2 model by Venkatesh et al. [1]. Therefore, we conducted an online study in Germany with 683 users of the game. Many other studies rely on the users' imagination of the application's functionality or laboratory environments. In contrast, we asked a relatively large user base already interacting in the natural environment with the application.

Not surprisingly, the strongest predictor of behavioral intention to play Pokémon Go is hedonic motivation, i.e. fun and pleasure due to playing the game. Additionally, we find medium-sized effects of effort expectancy on behavioral intention, and of habit on behavioral intention and use behavior. These results imply that AR applications – besides needing to be easily integrable in the users' daily life – should be designed in an intuitive and easily understandable way. We contribute to the understanding of the phenomenon of Pokémon Go by investigating established acceptance factors that potentially fostered the massive adoption of the game.

Index Terms: H.1.2 [Information Systems]: Models and Principles—Systems and Information TheoryInformation theory; H.1.2 [Information Systems]: Models and Principles—User/Machine SystemsHuman factors H.5.1 [Information Interfaces and Presentation]: Multimedia Information Systems—Artificial, augmented, and virtual realities H.5.1 [Information Interfaces and Presentation]: Multimedia Information Systems—Evaluation/methodology K.8.0 [Personal Computing]: General—Games

1 Introduction

Although the idea of augmented reality (AR) stems back to 1968 [2], the development of AR hard- and software received a boost in the past decade. Already in 2005, Swan and Gabbard [3] postulated the need to further developed AR systems from a technology-centric medium to a user-centric medium and demanded user-based experimentation. A decade later, Dey et al. [4] report on ten years of user studies published in AR papers. They state that most of these studies are formal user studies, with little field testing and almost no heuristic evaluations, and sample populations which are dominated by mostly young, educated, and male participants. Non surprisingly, many of the existing studies on augmented reality focus on the behavior of users interacting with the technology, especially in laboratory environments. However, for products tested in laboratory environments which could not be explored in real life, users have to estimate if and how they would make use of the examined product. This may lead to an enthusiastic overestimation of the product's value and usage in daily life. For example, Howe et al. [5] find out that the installation of Pokémon Go leads to a significant increase of the users' daily steps, but this effect is not sustainable over time.

In many other studies, the product is not widely spread across the general population. Thus, researchers have to rely on the users' imagination of the functionalities (e.g. for research on head-mounted displays (HMD) see Segura and Thiesse [6]). Research on hypothetical products and applications is important since it can provide new information about the practical realization of a product. However, similar to studies in laboratory environments, it is possible that users systematically overestimate their perceptions towards the technology. This is especially problematic, since they never experienced an actual interaction, but rather get a presentation of the technology based on a video or textual description.

The advantage of our study is that we asked a relatively large user base about their perceptions of Pokémon Go. All of them made their own decision to play and install Pokémon Go and actually interact in the natural environment with the application.

Only few research has been done on how users accept and use AR technology in their daily life [7]. A branch of information systems theory is focused on technology acceptance models (TAM) with the UTAUT2 model from Venkatesh et al. being state of the art [1]. In order to investigate the reasons why people want to use AR, behavioral intention (BI), and why they are actually using it, actual use (USE), we investigate the most relevant factors for technology adoption for Pokémon Go.

Pokémon Go [8] is a location-based augmented reality game developed by Niantic for mobile devices. It is often referred to as the unofficial successor of Ingress [9], [10] which was also developed by Niantic. Although there seems to be no homogeneous opinion of whether Pokémon Go matches all criteria of AR, there is broad agreement that it can be seen as a first step towards AR [11]–[16].

To investigate the driving factors of technology adoption, one needs to have a sufficiently large user base to examine. Therefore, in contrast to other applications such as serious augmented games (e.g. [17]), the hype of Pokémon Go is an excellent basis for investigations. After only one month, Pokémon Go had already set five new all-time highs related to revenue grossed and number of downloads in mobile games [18]–[20]. Additionally, it has been shown that people already spend more time on average with Pokémon Go than with social media apps [21]. Thus, we aim to investigate how this success could have been achieved and its most relevant factors. Better understanding this subject could help to bring more AR technology into the market and spread it among average consumers.

The remainder of this paper is structured as follows: Related work is discussed in Section 2. The used methodology, our hypotheses, the questionnaire, the data collection and the sample are described in Section 3. Our results are presented in Section 4 and discussed in Section 5. Finally, we conclude with Section 6. The questions of our questionnaire can be found in the appendix A.

2 Theoretical Background

This section presents the theoretical background for this work. First, we briefly discuss the AR smartphone game Pokémon Go

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(PG) and AR in general. Second, we outline the technology acceptance research on which our research model is based and discuss existing technology acceptance research on AR.

2.1 Pokémon Go and Augmented Reality

Pokémon Go is already subject of a few user studies which investigate the consequences of playing the game on users. Examples include research on the change of social interactions due to transmedia storytelling in PG [21] or changes in physical activity [22]. Further studies highlight potential harms and benefits [23] and change of movement and preference of places [24] due to location-based games both using the example of PG. More general studies discuss the effects on learning by location-based games [25] and the user acceptance of location-aware mobile guides [26]. Nonetheless, up to now, no articles have investigated technology acceptance factors of PG. Due to the strong diffusion among millions of users worldwide, it becomes possible to conduct large-scale studies with the goal to understand users' perceptions of AR more appropriately.
AR in general, is defined in a variety of ways. A comprehensive definition is provided by Azuma et al., stating that "[...] an AR system [...] combines real and virtual objects in a real environment; runs interactively, and in real time; and registers (aligns) real and virtual objects with each other" [27, p. 34]. Following this general definition of AR, we briefly provide an overview of past research areas dealing with AR on handheld devices, since PG is a smartphone application.

Several papers investigate the perception of users when interacting with AR applications on smartphones, which is particularly important to increase the user experience (e.g. [28]–[30]). Further research deals with touch screen use, when interacting with mobile AR applications, which is also highly relevant for the development of mobile AR [31]. Different mobile AR applications, like navigation on smartphones [32] or projection-based AR on smartphones [33] have important implications with regard to the interaction of users. Another research area focuses on human perception and psychology in augmented reality [34], e.g. the social acceptability of gestures in public use when interacting with a mobile [35] and user attitudes towards data glasses usage [36].

2.2 Technology Acceptance Research

The field of technology adoption and use has been the subject to a multitude of previous research, yielding several competing concepts, theories, and models. Some of the most prominent models will be briefly introduced in order to create a common understanding for the following analysis.

The Theory of Reasoned Action (TRA) falls back on empirical research conducted by the social psychologists Fishbein and Ajzen from 1975 [37]. According to TRA, a behavior is determined by a person's intention to perform this particular behavior. The behavioral intention (BI), in turn, is influenced by his subjective norms (SN) and attitude toward the given behavior (A). BI can also be viewed as a function of certain beliefs. On the one hand, A is related to a person's beliefs about and evaluation of the behavior's consequences. On the other hand, the subjective norms concerning a given behavior are affected by normative beliefs and normative pressure. This refers to a person's motivation to comply with people saying whether he should perform the behavior or not. Feedback loops can arise at various stages of the process, as the performance of a given behavior can have an impact on beliefs, which in turn influences BI and hence the behavior itself [37].

The Theory of Planned Behavior (TPB) by Ajzen [38] is built on the TRA. Specifically, the overall structural process remains unchanged, i.e. BI is influenced by several components, and in turn influences the performance of a behavior. Nevertheless, it was created as an extension of the TRA integrating the addition of perceived behavioral control (PBC). In practical terms, this denotation refers to a person's perception regarding the ease or difficulty of performing a given behavior in a given situation. Consequently, PBC is assumed to depend on the extent to which required resources and opportunities are available. PBC can have an impact on behavior in two ways. First, indirectly through its influence on BI and its relationship with A and SN. Second, together with BI, PBC can be used directly for predicting behavioral achievement [38].

Based on the TRA and TPB, the technology acceptance model (TAM) was developed in 1985 by Davis [39]. The model specifically focuses on the user acceptance of information systems. Similar to TRA, TAM hypothesizes that system use is determined by BI to use. However, it differs from the former model, as BI is jointly influenced by a person's overall attitude toward using the technology (A) and its perceived usefulness (U). Subjective perceptions regarding the system's ease of use are theorized to be fundamental determinants of system use, too. They directly influence A and U. Again, U refers to the extent to which a system would enhance a person's job performance within an organizational context. Perceived ease of use (E) is the degree of effort needed to use the system. Furthermore, external variables affect one's attitude and behavior indirectly through their impact on U and E [39]–[41].

In 2003 Venkatesh et al. [42] synthesized the findings of the eight previous models (TRA, TAM, TPB, a model combining TAM and TPB, the Motivational Model, the Model of PC Utilization, the Innovation Diffusion Theory and the Social Cognitive Theory) into a unified model called the Unified Theory of Acceptance and Use of Technology (UTAUT). Though the theory maintains the overall structure proposed in TRA, it also establishes several changes. First, technology use behavior is not only determined by BI but also by the newly added construct of facilitating conditions (FC). Moreover, UTAUT introduces three novel determinants of behavioral intention. These are performance expectancy (PE), effort expectancy (EE), and social influence (SI). In addition, the determinants of BI and actual use behavior (USE) are influenced by up to four moderators, i.e. gender, age, experience, and voluntariness of use.

While UTAUT focuses on an organizational setting, its extension, known as UTAUT2, takes the consumer context into consideration [1]. Consequently, the moderator "voluntariness of use" proposed by UTAUT has been eliminated since consumers cannot be forced to accept and use a technology. Besides the four constructs already formulated in UTAUT, hedonic motivation (HM), price value (PV), and habit (HT) are incorporated as three additional constructs. Individual differences, particularly age, gender, and experience, are identified as moderators of these constructs with regard to their effects on BI and USE. UTAUT2 further extends the initial theory by adding a link between FC and BI.

TAM, in particular, has been the subject of various studies and extensions. There are several quantitative user studies [43]–[48], as well as qualitative user studies [49], [50] in the literature that investigate AR. This is also shown by the results of Dey et al. [4], who show an increase in the number of published AR user studies. Most of these papers have in common that the sample is biased towards younger males with a high level of education. This sample characteristic does not apply to our case. Furthermore, to the best of our knowledge, none of the papers that are based on technology acceptance models used the UTAUT2 model as a theoretical starting point. Thus, our work adapts this recent model for the first time to AR. Finally, sample sizes are relatively small in the past literature due to the missing diffusion of AR technologies in mass markets. Since we have chosen PG as an object of research, we are able to present results based on a large sample with 683 active players of PG. Although there are other important methods to assess the interaction of users with technologies like usability studies [51], technology acceptance research is needed to foster the understanding of how AR could find its way in everyone's daily life.

3 METHODOLOGY

We base our research on the UTAUT2 model. The original research on this model investigates the acceptance of mobile internet technologies [1]. Thus, the context of the model fits well to the mobile AR application PG. In addition, we argue that the model provides the theoretical justification to assume that the results are at least generalizable within the boundaries of mobile AR applications. For analyzing the cause-effect relationships between the latent (unobserved) variables, we use structural equation modelling (SEM). There are two main approaches for SEM, namely covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM) [52]. Since our research goal is to predict the target constructs BI and USE of playing PG and maximize the explained variance of those dependent variables, we use PLS-SEM for our analysis [52], [53]. In the following subsections, we discuss the hypotheses based on the UTAUT2 model [1], the questionnaire composition, the data collection process, as well as the demographics.

3.1 Research Hypotheses

As Figure 4 shows, the structural model contains several relationships between exogenous and endogenous variables. We develop our research hypotheses for these relationships based on the original hypotheses of the UTAUT2 model [1]. In the original UTAUT paper [42], performance expectancy is defined in an utilitarian way. As the paper deals with acceptance factors in an organizational context, the focus on job performance enhancement due to technology makes sense. In the consumer context, this focus shifts towards a more general definition of performance apart from the pure job perspective. Still, this construct deals with the extrinsic motivation of people to use a technology [1]. This is important to recognize since hedonic motivation is included in the model as the theoretical complement. For the case of Pokémon Go, we argue that playing a smartphone game is equal to using a hedonic information system. Therefore, playing PG is more likely to be intrinsically rather than extrinsically motivated [54].

H1: Performance expectancy (PE) has a positive, but smaller effect on behavioral intention (BI) compared to the effect of hedonic motivation on BI.

Effort expectancy measures the ease of use of playing PG. The rationale behind this construct is straightforward as it is assumed that technologies which are easy to use are more likely to be adopted. This rationale also holds for a smartphone game like PG, as an easy interaction experience increases the acceptance of the application.

H2: Effort expectancy (EE) has a positive effect on behavioral intention (BI).

Social influence is a complex construct with several dimensions. Based on the items of the construct, one can say that it is about the perception of users regarding the opinions of others on their use behavior of a certain technology. "Others" are in this case either important, influencing or esteemed people related to the user in some way [42]. Social influence is also interesting for the case of PG since there are two imaginable opposing effects. On the one hand, a kind of peer pressure is possibly exerted, especially on younger users. On the other hand, it is possible that especially older users are ashamed of playing this game. Still, we hypothesize that social influence has a positive effect, as we think that the combination of the mentioned peer pressure and the wide public interest supersedes possible opposing effects.

H3: Social influence (SI) has a positive effect on behavioral intention (BI).

Facilitating conditions in the consumer context are defined as fostering factors for the intention to use a technology and actual use behavior [1]. In the case of PG, this can either be represented by appropriate hardware (e.g. battery packs for smartphones) or by having access to interesting information about the game.

H4: Facilitating conditions (FC) have a positive effect on behavioral intention (BI) as well as use behavior (USE).

Hedonic motivation represents a user's intrinsic motivation to use an information system. The items operationalize the construct with adjectives like fun, enjoyable und entertaining (cf. Appendix A). For PG, this construct is assumed to have the strongest effect on the behavioral intention to play it. This assumption is supported by previous research on hedonic information systems [54], [55].

H5: Hedonic motivation (HM) has a positive effect on behavioral intention (BI).

The price value construct follows the rationale that users face a trade-off between the perceived benefits of a technology and its monetary costs for each purchase decision [56]. If the benefits predominate, the price value construct is positive, and has a positive effect on the intention to use [1]. PG is based on a freemium pricing model. Thus, the game is playable without facing any costs. Therefore, we hypothesize that

H6: Price value (PV) has a positive effect on behavioral intention (BI).

The habit construct is based on the perception of a user about his or her routine behavior [57]. Since it is proposed that habit has an effect on use directly, as well as mediated by behavioral intention [57], we take on this hypothesis as in the original UTAUT2 model [1]. Since smartphone games are an inherent part of the regular smartphone use for many people [58] and can possibly also be addictive in certain cases [59], habit is assumed to have a positive effect on BI and USE.

H7: Habit (HT) has a positive effect on behavioral intention (BI) as well as use behavior (USE).

Research on the relationship between BI and USE goes back to Fishbein and Ajzen [37]. There is a large amount of research on this topic and the link between the two constructs is found to exist [60]. Thus, we assume that the positive effect of BI on USE is also apparent in the case of PG.

H8: Behavioral intention (BI) has a positive effect on use behavior (USE).

3.2 Questionnaire

The questionnaire constructs are adapted from the original UTAUT2 paper [1]. All items can be found in Appendix A. Since we conducted the study with a German panel, all items had to be translated into German. As we wanted to ensure content validity of the translation, we followed a rigorous translation process [1]. First, we translated the English questionnaire into German with the help of a certified translator (translators are standardized following the DIN EN 15038 norm). The German version was then given to a second independent certified translator who retranslated the questionnaire to English. This step was done to ensure the equivalence of the translation. Third, a group of five academic colleagues checked the two English versions with regard to this equivalence. All items were found to be equivalent, except for one. For this case, we contacted the translator of the German version and discussed and solved the issue personally. In a last step, the German version of the questionnaire was administered to students of a Master's course to check preliminary reliability and validity.

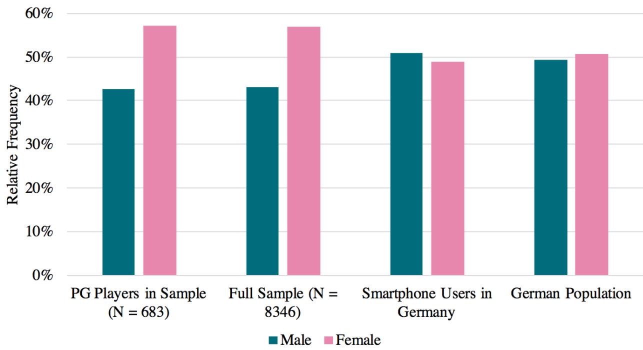

Figure 1: Distribution of Gender

3.3 Data Collection and Selection

Since we want to investigate why people play PG, our sample consists only of active players of the game. Although PG is the most successful smartphone application in the history, this is a challenging sampling task. Therefore, we decided to conduct the study with the help of a sample provider and focus on one country. Thereby, we could ensure two things. First, we could eliminate the country-specific differences in perceptions and control them. Second, the focus on one country allowed us to gather this relatively large data set. To ensure quality of our data, we chose a certified provider (certified following the ISO 26362 norm). We installed the survey on a university server and managed it with the survey software LimeSurvey (version 2.63.1) [61]. This link was distributed by the panel provider to 9338 participants. Of those 9338 approached participants, only 683 remained after asking whether they play PG, whether they are older than 18 years old and, whether they answered a test question in the middle of the survey correctly. Besides that test question, we asked the PG players about their current level. We designed this question intentionally as a free field question with numeric entries only. As PG ends at level 40, we could test the knowledge of the participants and establish an additional screen-out mechanism. We sorted out all participants who stated to have a level higher than 40, since they were actually not playing, they did not answer the questions carefully or they did not take the questionnaire seriously enough.

3.4 Demographics

A thorough analysis of the demographic characteristics of the used sample is presented in this section. When possible, we compared the sample characteristics with data of the German population and German smartphone users. Additionally, we incorporated the information that was provided by all survey participants who were screened out at later stages of the questionnaire or terminated the survey before finishing (full sample). Due to different termination points in the questionnaire, the numbers for the full sample slightly differ for the various demographics.

Figure 1 shows the distribution of gender. PG players in our sample are mainly women. This is not representative with respect to the German population, even though there are also more women than men in Germany[62]. The ratios for PG players and the full sample are similar. Thus, the differences in the ratios can be explained to a certain degree by the demographic nature of the participants approached by the sample provider. In addition, we provided the ratio of smartphone users in Germany [63]. This ratio slightly indicates more men than women.

Figure 2 presents the age distribution of PG players, compared to the full sample, German smartphone users [64], and the whole German population [65]. The age distribution of PG players is positively skewed, meaning that more younger users are in the sample. The distributions of the full sample, of the German smartphone users, and of the German population are very similar. Due to the fact that the full sample has a similar age distribution to the whole German population, it is highly probable that the age of PG players in Germany is distributed based on the shown distribution. For relatively older users, the data are not comparable, since it can be assumed that relatively few people older than 65 play PG.

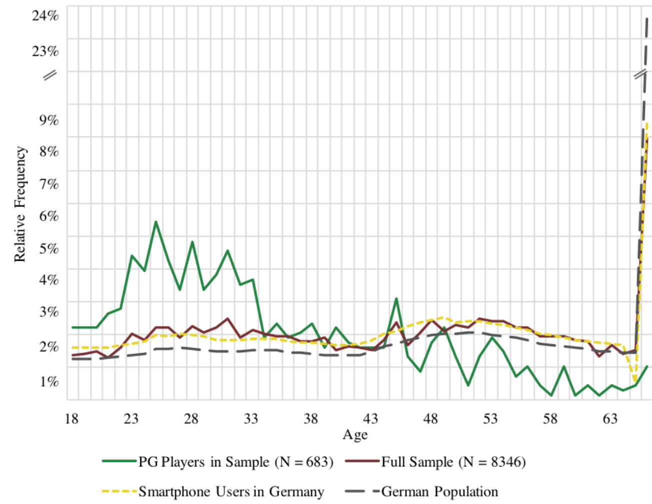

Figure 2: Distribution of Age

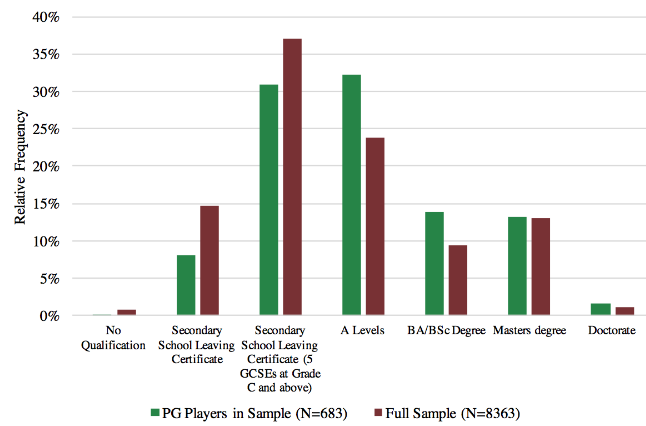

Figure 3: Distribution of Educational Degrees

For the distribution of educational degrees, we could not find comparable statistics for Germany. Thus, we only compared the distribution of PG players in our sample with the distribution of the full sample. Figure 3 shows the distributions. It can be seen that our sample consists not only of university students, but also incorporates both lower and higher eductional levels. In this regard, our sample is not biased towards higher educational degrees. The comparison to the full sample shows that PG players have almost the same education levels with only slight differences, which are not systematic.

Several user studies on AR only include students as participants or young males with a high level of education, which limits the validity of the results to a certain degree [4]. Our sample overcomes this drawback to a large extent. In summary, we argue that the results of our analysis are representative for Germany to a great extent.

4 RESULTS

This section presents the results of our work. We tested the model using SmartPLS version 3.2.6 [66]. Before looking at the result of the structural model and discussing its implications, we discuss the measurement model, and check for the reliability and validity of our results. This is a precondition of being able to interpret the results of the structural model. Furthermore, it is recommended to report the computational settings [67]. For the PLS algorithm, we choose the path weighting scheme with a maximum of 300 iterations and a stop criterion of 10^{-7}. For the bootstrapping procedure, we use 5000 bootstrap subsamples and no sign changes as the method for handling sign changes during the iterations of the bootstrapping procedure.

4.1 Assessment of the Measurement Model

As the model is measured solely reflectively, we need to evaluate the internal consistency reliability, convergent validity and discriminant validity to assess the measurement model properly [52].

Internal Consistency Reliability Internal consistency reliability (ICR) measurements indicate how well certain indicators of a construct measure the same latent phenomenon. Two standard approaches for assessing ICR are Cronbach's α and the composite reliability. The values of both measures should be between 0.7 and 0.95 for research that builds upon accepted models. Values of Cronbach's α are seen as a lower bound and values of the composite reliability as an upper bound of the assessment [53].

Table 1 includes the ICR of the used variables in the last two rows. It can be seen that all values are above the lower threshold of 0.7 and for Cronbach's α no value is above 0.95. As the composite reliability is a less conservative measure, the values for HM, PE and SI are above 0.95. Values above that upper threshold indicate that the indicators measure the same dimension of the latent variable, which is not optimal with regard to the validity [53]. But since Cronbach's α is within the suggested range and we use accepted constructs, we consider the ICR as acceptable.

Convergent Validity Convergent validity determines the degree to which indicators of a certain reflective construct are explained by that construct. This is assessed by calculating the outer loadings of the indicators of the constructs (indicator reliability) and by looking at the average variance extracted (AVE) [52]. Loadings above 0.7 imply that the indicators have much in common, which is desirable for reflective measurement models [53]. Table 1 shows the outer loadings in bold on the diagonal. All loadings are higher than 0.7 except for the indicators 3 and 4 of the FC constructs, which are dropped consequently. Convergent validity for the construct is assessed by the AVE. AVE is equal to the sum of the squared loadings divided by the number of indicators. A threshold of 0.5 is acceptable, indicating that the construct explains at least half of the variance of the indicators [53]. The diagonal values of Table 2 present the AVE of our constructs. All values are well above 0.5, demonstrating convergent validity.

Discriminant Validity Discriminant validity measures the degree of uniqueness of a construct compared to other constructs. Comparable to the convergent validity assessment, two approaches are used for investigated discriminant validity. The first approach, assessing cross-loadings, is dealing with single indicators. All outer loadings of a certain construct should be larger than its cross-loadings with other constructs [52]. Table 1 illustrates the cross-loadings as off-diagonal elements. All cross-loadings are smaller than the outer loadings, fulfilling the first assessment approach of discriminant validity. The second approach is on the construct level and compares the square root of the constructs' AVE with the correlations with other constructs. The square root of the AVE of a single construct should be larger than the correlation with other constructs (Fornell-Larcker criterion) [53]. Table 2 contains the square root of the AVE on the diagonal in parentheses. All values are larger than the correlations with other constructs, indicating discriminant validity. Since there are problems in determining the discriminant validity with both approaches, researchers propose the heterotrait-monotrait ratio (HTMT) for assessing discriminant validity as a superior approach to the others [68]. HTMT divides between-trait correlations by within-trait correlations, therefore providing a measure of what the true correlation of two constructs would be if the measurement is flawless [53]. Values close to 1 for HTMT indicate a lack of discriminant validity. A conservative threshold is 0.85 [68]. Table 3 contains the values for HTMT and no value is above the suggested threshold of 0.85.

To evaluate whether the HTMT statistics are significantly different from 1, a bootstrapping procedure with 5,000 subsamples is conducted to get the confidence interval in which the true HTMT value lies with a 95% chance. The HTMT measure requires that no confidence interval contains the value 1, which is fulfilled (cf. Table 4). Thus, discriminant validity is established for our model.

Common Method Bias The common method bias (CMB) can occur if data is gathered with a self-reported survey at one point in time in one questionnaire [69]. Since this is the case in our research design, the need to test for CMB.
An unrotated principal component factor analysis is performed with the software package STATA 14.0 to conduct the Harman's single-factor test to address the issue of CMB [70]. The assumptions of the test are that CMB is not an issue if there is no single factor that results from the factor analysis or that the first factor does not account for the majority of the total variance [70]. The test shows that six factors have eigenvalues larger than 1 which account for 73.38% of the total variance. The first factor explains 33.34% of the total variance. Based on results of previous literature [71], [72], we argue that CMB is not likely to be an issue in the data set.

4.2 Assessment and Results of the Structural Model

To assess the structural model, we follow the steps proposed by Hair et al. [53] which include an assessment of possible collinearity problems, of path coefficients, of the level of R^2, of the effect size f^2, of the predictive relevance Q^2, and the effect size q^2. We want to briefly address these evaluation steps to ensure the predictive power of the model with regard to the target constructs.

Collinearity Collinearity is present if two predictor variables are highly correlated with each other. To address this issue, we assess the inner variance inflation factor (inner VIF). All VIF values above 5 indicate that collinearity between constructs is present. For our model, the highest VIF is 2.007. Thus collinearity is apparently not an issue.

Significance and Relevance of Model Relationships Figure 4 presents the results of the path estimations and the adjusted R^2 of the two endogenous variables, BI and USE. We used the adjusted R^2 as it is a more conservative measure for the explained variance of a dependent variable by avoiding a bias towards more complex models [53]. The R^2 is 0.55 for BI and 0.25 for USE. Thus, our models explains 55% of the variance in BI and 25% of the variance in USE.
There are different proposals for interpreting the size of this value. We choose to use the very conservative threshold proposed by Hair et al. [52], where R^2 values are weak with values around 0.25, moderate with 0.50 and substantial with 0.75. Based on this classification, the R^2 value for BI is moderate, and weak for USE. The path coefficients are presented on the arrows connecting the exogenous and endogenous constructs in Figure 4. Statistical significance is indicated by asterisks, ranging from three asterisks for p-values smaller than 0.001 to one asterisk for p-values smaller than 0.05. The p-value indicates the probability that a path estimate is incorrectly assumed to be significant. Thus, the lower the p-value, the

Table 1: Loadings and Cross-Loadings of the Reflective Items and Internal Consistency Reliability

Constructs	BI	EE	FC	HT	HM	PE	PV	SI
BI1	**0.932**	0.53	0.481	0.333	0.643	0.235	0.379	0.149
BI2	**0.862**	0.373	0.339	0.466	0.504	0.418	0.324	0.318
BI3	**0.948**	0.516	0.474	0.371	0.657	0.288	0.377	0.19
EE1	0.461	**0.902**	0.555	0.111	0.459	-0.026	0.357	-0.012
EE2	0.467	**0.896**	0.586	0.17	0.494	0.044	0.395	0.033
EE3	0.477	**0.917**	0.547	0.15	0.469	0.008	0.369	0.01
EE4	0.474	**0.897**	0.583	0.177	0.417	0.036	0.392	0.03
FC1	0.409	0.524	**0.903**	0.139	0.393	0.07	0.267	0.059
FC2	0.456	0.62	**0.924**	0.119	0.442	0.037	0.336	0.039
HT1	0.451	0.273	0.228	**0.868**	0.33	0.39	0.304	0.307
HT2	0.228	0.015	0.02	**0.812**	0.114	0.571	0.19	0.438
HT3	0.262	-0.011	-0.011	**0.841**	0.124	0.62	0.177	0.47
HT4	0.413	0.182	0.147	**0.888**	0.321	0.572	0.282	0.357
HM1	0.643	0.5	0.454	0.274	**0.946**	0.235	0.397	0.132
HM2	0.626	0.482	0.443	0.27	**0.948**	0.233	0.416	0.15
HM3	0.599	0.455	0.396	0.274	**0.933**	0.244	0.405	0.158
PE1	0.344	0.04	0.086	0.568	0.273	**0.909**	0.293	0.517
PE2	0.286	-0.002	0.047	0.573	0.204	**0.948**	0.255	0.546
PE3	0.299	-0.013	0.036	0.565	0.195	**0.946**	0.236	0.544
PE4	0.326	0.034	0.04	0.554	0.257	**0.928**	0.261	0.501
PV1	0.298	0.378	0.274	0.205	0.359	0.152	**0.838**	0.129
PV2	0.352	0.326	0.281	0.296	0.388	0.328	**0.894**	0.258
PV3	0.392	0.413	0.326	0.276	0.4	0.257	**0.93**	0.22
SI1	0.237	0.037	0.071	0.421	0.162	0.549	0.23	**0.963**
SI2	0.209	0.009	0.043	0.394	0.129	0.515	0.203	**0.942**
SI3	0.225	0.001	0.035	0.438	0.151	0.547	0.229	**0.952**
Cronbach's α	0.901	0.924	0.734	0.880	0.937	0.950	0.866	0.949
Composite Reliability	0.939	0.946	0.910	0.914	0.960	0.964	0.918	0.967

Table 2: Discriminant Validity with AVEs and Construct Correlations

	BI	EE	FC	HM	HT	PE	PV	SI	USE
BI (0.836)	0.914								
EE (0.815)	0.52	0.903							
FC (0.835)	0.475	0.629	0.914						
HM (0.889)	0.661	0.509	0.458	0.943					
HT (0.726)	0.423	0.169	0.14	0.289	0.852				
PE (0.87)	0.339	0.017	0.057	0.252	0.606	0.933			
PV (0.789)	0.395	0.419	0.332	0.431	0.294	0.282	0.888		
SI (0.907)	0.235	0.017	0.053	0.155	0.439	0.565	0.232	0.952	
USE	0.421	0.317	0.272	0.264	0.412	0.163	0.202	0.116	1

Note: AVEs in parentheses in the first column. Values for $\sqrt{AVE}$ are shown on the diagonal and construct correlations are off-diagonal elements.

higher is the probability that the given relationship exists. The relevance of the path coefficients is expressed by the relative size of the coefficient compared to the other explanatory variables [53].

The relationship of PE and BI is statistically significant to the 1% significance level, whereas the path coefficient is relatively small with 0.098. The same holds for the relationship between FC and BI and FC and USE. All relationships are significant at the 1% level and the coefficients are 0.127 and 0.116, respectively. This can be interpreted as a rather weak effect. The coefficient for the relationship between EE and BI is statistically significant at the 0.1% level and medium-sized with a coefficient of 0.191 compared to the other coefficients. The same holds for the relationship of HT and BI. Interestingly, SI as well as PV have no relevant effect on BI and are not statistically significant. Habit seems to have a relatively strong impact on USE, larger than the impact of BI on USE (0.293 compared to 0.243). Both coefficients are statistically significant at the 0.1% significance level. HM is statistically significance at the 0.1% level and the strongest predictor of the behavioral intention to play PG is HM.

Effect Sizes f^2 The f^2 effect size measures the impact of a construct on the endogenous variable by omitting it from the analysis and assessing the resulting change in the R^2 value [53]. The values are assessed based on thresholds by Cohen [73], who defines effects as small, medium and large for values of 0.02, 0.15 and 0.35, respectively. Table 5 shows the results of the f^2 evaluation. Values in italics indicate small effects and values in bold indicate medium effects. All other values have no substantial effect. The results correspond to those of the previous analysis of the path coefficients, where HM is the most important predictor.

Predictive Relevance Q^2 The Q^2 measure indicates the out-of-sample predictive relevance of the structural model with regard to the endogenous latent variables based on a blindfolding procedure [53]. We used an omission distance d=7. Recommended values for d are between five and ten [52]. Furthermore, we report the Q^2 values of the cross-validated redundancy approach, since this approach is based on both the results of the measurement model as well as of the structural model [53]. Detailed information about the calculation cannot be provided at this point due to space limitations.

Table 3: Heterotrait-Monotrait Ratio (HTMT)

	BI	EE	FC	HM	HT	PE	PV	SI	USE
BI									
EE	0.567								
FC	0.553	0.727							
HM	0.715	0.546	0.526						
HT	0.448	0.166	0.149	0.286					
PE	0.368	0.038	0.065	0.264	0.686				
PV	0.442	0.468	0.394	0.478	0.315	0.303			
SI	0.259	0.026	0.060	0.164	0.501	0.594	0.251		
USE	0.444	0.330	0.302	0.273	0.414	0.167	0.219	0.119	

Table 4: Confidence Intervals of HTMT

			Original	Mean	Bias	2.5%	97.5%
EE	→	BI	0.567	0.566	−0.001	0.482	0.635
FC	→	BI	0.553	0.554	0.000	0.462	0.637
FC	→	EE	0.727	0.727	0.001	0.653	0.790
HM	→	BI	0.715	0.715	0.000	0.656	0.769
HM	→	EE	0.546	0.546	0.000	0.452	0.630
HM	→	FC	0.526	0.527	0.001	0.425	0.621
HT	→	BI	0.448	0.446	−0.002	0.370	0.523
HT	→	EE	0.166	0.175	0.009	0.121	0.211
HT	→	FC	0.149	0.159	0.010	0.101	0.200
HT	→	HM	0.286	0.284	−0.001	0.210	0.363
PE	→	BI	0.368	0.368	−0.001	0.299	0.436
PE	→	EE	0.038	0.053	0.015	0.018	0.050
PE	→	FC	0.065	0.073	0.007	0.025	0.140
PE	→	HM	0.264	0.263	−0.001	0.193	0.332
PE	→	HT	0.686	0.685	−0.001	0.631	0.738
PV	→	BI	0.442	0.442	0.000	0.356	0.521
PV	→	EE	0.468	0.468	−0.001	0.382	0.546
PV	→	FC	0.394	0.394	0.001	0.311	0.474
PV	→	HM	0.478	0.477	−0.001	0.406	0.549
PV	→	HT	0.315	0.315	−0.001	0.229	0.393
PV	→	PE	0.303	0.302	−0.001	0.224	0.376
SI	→	BI	0.259	0.258	0.000	0.178	0.333
SI	→	EE	0.026	0.046	0.020	0.007	0.033
SI	→	FC	0.060	0.068	0.008	0.020	0.138
SI	→	HM	0.164	0.164	0.000	0.086	0.236
SI	→	HT	0.501	0.500	−0.001	0.427	0.575
SI	→	PE	0.594	0.594	0.000	0.529	0.655
SI	→	PV	0.251	0.251	0.000	0.166	0.329
USE	→	BI	0.444	0.443	−0.001	0.366	0.514
USE	→	EE	0.330	0.328	−0.001	0.243	0.414
USE	→	FC	0.302	0.302	0.000	0.216	0.386
USE	→	HM	0.273	0.271	−0.001	0.181	0.360
USE	→	HT	0.414	0.414	−0.001	0.336	0.488
USE	→	PE	0.167	0.166	−0.001	0.082	0.243
USE	→	PV	0.219	0.218	−0.001	0.137	0.299
USE	→	SI	0.119	0.119	0.000	0.041	0.197

For further information see Chin [74]. For our model, Q^2 is calculated for BI and USE. Values above 0 indicate that the model has the property of predictive relevance. In our case, the Q^2 value is equal to 0.434 for BI and to 0.242 for USE. Since they are substantially larger than 0, predictive relevance of the model is established.

Effect Sizes q^2 The assessment of q^2 follows the same logic as the one of f^2. It is based on the Q^2 values of the endogenous variables and calculates the individual predictive power of the exogenous variables by omitting them and comparing the change in Q^2. The effect sizes q^2 have to be calculated with the formula [53]:

$$q^2_{X\rightarrow Y} = \frac{Q^2_{included} - Q^2_{excluded}}{1 - Q^2_{included}}$$

Table 5: Values for the f^2 and q^2 Effect Size Assessment

Variables	f^2		q^2	
Exogenous \ Endogenous	BI	USE	BI	USE
BI	-	*0.051*	-	*0.047*
EE	*0.041*	-	*0.023*	-
FC	*0.021*	0.014	0.012	0.008
HM	**0.252**	-	**0.155**	-
HT	*0.042*	*0.094*	*0.023*	*0.091*
PE	0.011	-	0.005	-
PV	0.000	-	-0.002	-
SI	0.001	-	0	-

All individual values for q^2 are calculated with an omission distance d of seven. The results are shown in Table 5. The thresholds for the f^2 interpretation can be applied here, too [73]. Values in italics indicate small effects and values in bold indicate medium effects. All other values have no substantial effect. Only HM has a medium-sized effect, implying the highest predictive power of all included exogenous variables. Besides that, all results are in line with the previously observed results.

4.3 Multi-Group Analysis of Moderators

After presenting the results of the structural model and assessing the research hypotheses, we want to explore differences of effects between demographic groups. This is achievable with a multi-group analysis (MGA), by splitting the sample in two groups, calculating the differences in path coefficients and testing whether the differences are statistically significant. Age and smartphone experience are divided in two groups based on an equal distribution. This grouping method is called "median split" and is a common method for moderator analyses [75]. Besides that, an equal distribution of the data set ensures a sufficient sample size. Age is divided in two groups. Group "age_{b32}" includes 341 records and captures all participants with an age below 32 years, excluding participants age 32. Group "age_{a31}" has 342 records and captures all participants with an age above 31 years, excluding participants age 31. Smartphone experience is divided in groups "exp_{a5}" and "exp_{b6}" with participants having smartphone experience above 5 years and below 6 years, respectively. Table 6 shows the results of the MGA for the demographic characteristics, gender, age and experience.

It can be seen that only the relationship between HT and USE differs significantly for gender and age with regard to the path coefficient difference and the related statistical significant. The corresponding results are in bold print. The results for the gender MGA indicate that the effect of habit on actual use behavior is stronger for women than for men. For the case of age, we can observe a stronger effect for users younger than 32 years. In summary, it can be said that our sample seems to be very homogenous with regard to the impact of demographic differences on the structural model.

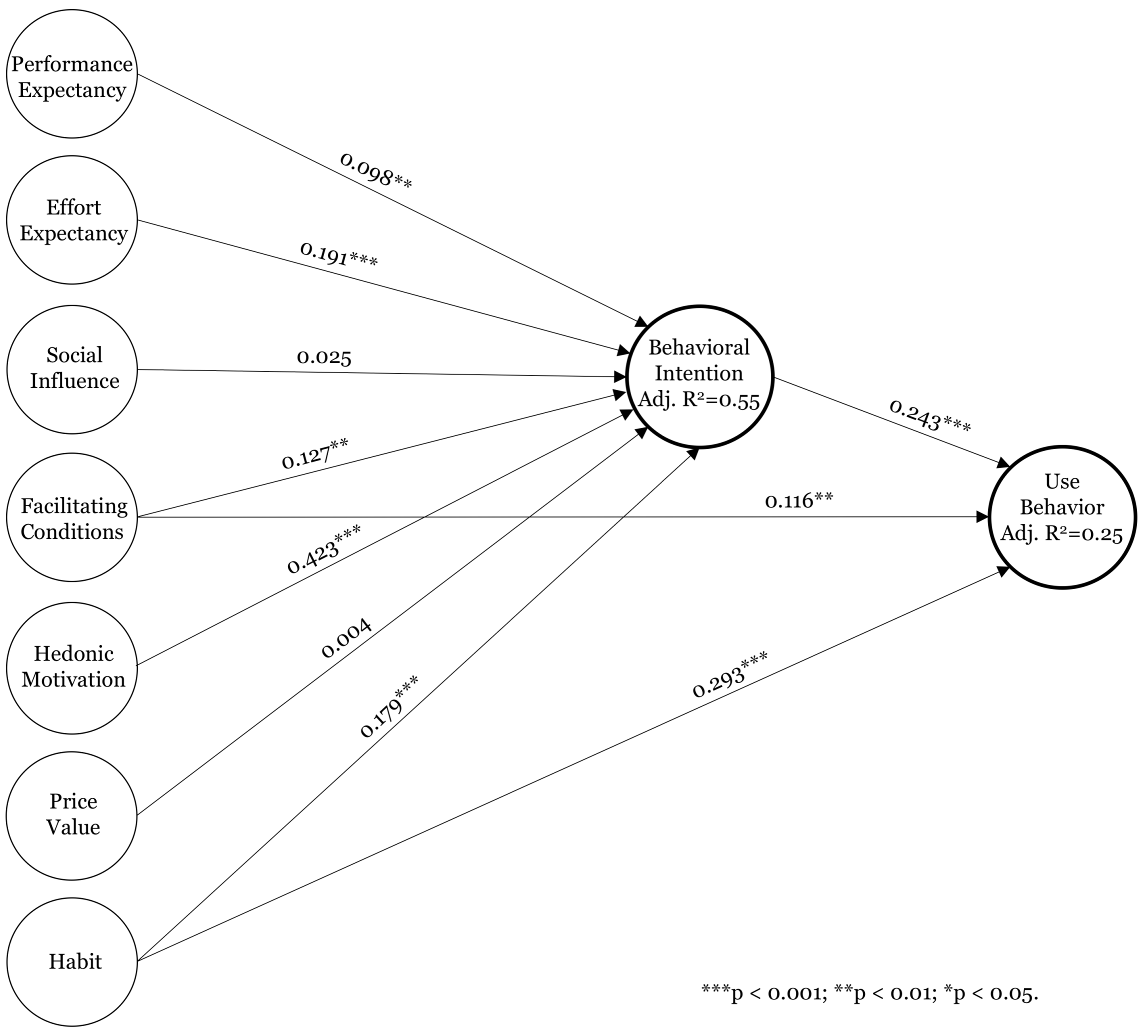

Figure 4: Path Estimates and Adjusted R2 values of the Structural Model

5 Discussion

This section presents the interpretation of the structural model results as well as the limitations of our research. Based on this, we derive recommendations for future research.

5.1 Interpretation and Implications of the Results

The overall explained variance of BI is better than in the original UTAUT2 research setting (55% compared to 44%) and is comparable to the results of similar studies that are based on modified UTAUT2 models (c.f. [6]) or on TAM models (c.f. [44]). The adjusted R^2 for USE is smaller than in the original UTAUT2 setting (25% compared to 35%). Thus, it can be said that the adapted UTAUT2 research model explains BI to a satisfiable degree but the explained variance of USE can be improved. Compared to the results of the original research on UTAUT2 [1], SI and PV are neither statistically significant nor relevant. This is a surprising result since the UTAUT2 model has a similar technology as a focus, namely mobile internet applications. On the other hand, our results correspond to the literature on hedonic information systems [54], where HM is by far the strongest predictor outweighing PE, and EE has a larger effect on BI than PE. The following subsection contains a detailed discussion of the derived hypotheses.

Discussion of Research Hypotheses Hypothesis 1 (PE $\rightarrow$ BI and PE $\rightarrow$ BI $<$ HM $\rightarrow$ BI) can be confirmed as the effect size of PE on BI is four times smaller than the effect size of HM on BI. Still it is statistically significant and relevant. Following the rationale of hedonic information systems [54], this result corresponds to our theoretical assumption about the motives of users to play PG.

Hypothesis 2 (EE $\rightarrow$ BI) can also be confirmed. Although many games have steep learning curves, it seems to be particular important for mobile smartphone games to be relatively easy to use. This has important implications for application designers, especially for new features introduced through the implementation of AR. Those features should be self-explanatory in order to increase technology acceptance.

Hypothesis 3 (SI $\rightarrow$ BI) cannot be confirmed as SI has no statistically significant effect on BI. As we mentioned in the hypothesis development, there are several opposing effects possible, which influence the impact of SI on BI. We cannot disentangle those effects based on the data at hand and this issue has to remain open for future work.

Hypothesis 4 (FE $\rightarrow$ BI and FE $\rightarrow$ USE) can be confirmed since both effects between FC and BI as well as FC and USE are statistically significant and substantial in size. This has several implications. First, a technology should be completed by some kind of

Table 6: Results of the PLS Multi-Group Analysis for Moderators Gender, Age, Experience

Moderator			Gender		Age		Experience	
Relations \ Test Stat.			Path Coefficient (|female - male|)	p-Value (female vs male)	Path Coefficient ($\|age_{b32}$ - $age_{a31}\|$)	p-Value (age_{b32} vs age_{a31})	Path Coefficient ($\|exp_{a5}$ - $exp_{b6}\|$)	p-Value (exp_{a5} vs exp_{b6})
PE	→	BI	0.002	0.511	0.068	0.174	0.083	0.125
EE	→	BI	0.093	0.156	0.110	0.127	0.097	0.146
SI	→	BI	0.013	0.416	0.080	0.090	0.124	0.980
FC	→	BI	0.030	0.624	0.052	0.712	0.053	0.722
HM	→	BI	0.017	0.416	0.027	0.618	0.042	0.689
PV	→	BI	0.103	0.917	0.024	0.370	0.001	0.498
HT	→	BI	0.028	0.354	0.060	0.778	0.046	0.273
FC	→	USE	0.072	0.189	0.047	0.716	0.052	0.259
HT	→	USE	**0.175**	**0.010**	**0.164**	**0.015**	0.019	0.600
BI	→	USE	0.013	0.562	0.015	0.435	0.032	0.357

community (e.g. online forums). Second, users should have easy access to tutorials or help pages. Third, the AR technology should be compatible with existing technologies. Especially the last point could be one reason for the massive success of smartphone-based AR applications and comparably slow adoption of HMDs which form a whole new product category.

Hypothesis 5 (HM → BI) can be confirmed. Based on all analyses of the structural model, it can clearly be stated that HM is the strongest predictor of BI. Following the reasoning for hypothesis 1, this result is expected and shows that the developers of PG succeeded in creating a highly enjoyable AR application.

Contradicting hypothesis 6 (PV → BI), PV has no positive impact on BI. A possible explanation is that users do not face the same cognitive trade-off for PG with its freemium pricing model compared to other consumer technologies with a fixed price. Therefore, a better perceived value has no effect on the behavioral intention when there are potentially no costs involved. Still, pricing issues are highly relevant for the market entry of technologies and should be carefully considered.

Hypothesis 7 (HT → BI and HT → USE) can be fully confirmed, as both relationships of HT and BI, as well as HT and USE are statistically significant and relevant. Specifically, HT is the strongest predictor of USE compared to BI and FC, which is in contrast to the results of the original UTAUT2 setting [1]. Obviously, users of PG perceive the reccuring and potentially addictive nature of the game as very intense, which strongly influences their intention and actual use of the game. The implication is that technologies should be designed in a way that they can be easily integrated in the daily life of the user. The significance of HT in the case of PG has certainly to do with the smartphone on which the game runs, since it has become an integral component of people's everyday life.
Hypothesis 8 (BI → USE) can be confirmed. As predicted by previous literature [60], BI has a medium-sized effect on USE compared to the other constructs. A theoretical implication is that research on AR technologies, which can only question BI due to the use of hypothetical technologies, is important for the understanding of users' perceptions about technologies and their future actual use behavior.

5.2 Limitations

Since our study is one of the first ones investigating acceptance factors of AR technologies, the goal is to use predictors which are established in the literature on technology acceptance. This follows the principle of conducting general research as a starting point and, by that, enable more specific research in the future. This approach has the limitations that we are not investigating AR-specific characteristics and the perceptions and attitudes of users towards them. But, besides the mentioned approach above, we used these variables since there are no AR-specific constructs for user studies developed up to now. Second, our sample contains more younger users and more females. Thus, it is not representative for the German population. This skewness is also caused by the non-uniform distribution of players and non-players (cf. subsection 3.4). However, since there are no significant differences between age groups and gender groups (cf. Table 6), this limitation has most likely no significant impact on our results. Third, the original UTAUT2 article includes a model based several combinations of the exogenous variables with one to three moderators (product-indicator approach [76]). This results in a highly complex structural model with multiple exogenous variables [1]. This complexity requires a very large sample size in order to achieve meaningful and significant results. Despite the fact that current research on moderator analysis advises against the use of the product-indicator approach [53], we cannot rule out that we are missing some effects mostly concerning very specific subgroups of users. Fourth, the German translation might have been understood differently by the participants than originally intended by the English questionnaire. This is always a possible threat when adapting original constructs from a language to another. The last limitation concerns the country where our survey is conducted. Since the sample covers only a German sample, the results can possibly differ from surveys conducted in other countries or cultural regions. But, as we argued in Section 3.3, this focus has major advantages for this research.

5.3 Future Work

Based on the aforementioned limitation of missing AR-specific constructs, two highly interesting and relevant research questions for future work can be derived. First, specific work focusing on AR characteristics, like co-location of digital objects in the real environment, is needed. Second, constructs that capture the attitudes and perceptions of users with regard to AR functionalities have to be developed. This would enable more specific models and therefore we could observe whether users really value the specific technological advances coming along with AR or rather the traditional factors like ease of use or fun.

Furthermore, the constructs in the actual model should be investigated in more detail to disentagle different effects that influence the relationship towards the endogenous variables. For example, we observed that SI has no influence on BI. The opposing potential effects of this construct present a valuable research opportunity. For example, the question arises whether social influence is the same as peer pressure and how these phenomena differ in their influence on BI. This is also highly relevant for the case of HMDs, respectively data glasses and the acceptability of gestures since the social environment plays an important role in the success of such devices. This is not only important due to the superficial appearance but also because of certain features like integrated cameras in HMDs that can aggravate the people around the user.

The importance of intrinsic motivation is not only apparent in hedonic information systems like smartphone games. Trends like gamification are leading to an increasing relevance of the concepts involved in different fields of life that are not necessarily related to traditional games. Therefore, it is highly interesting to investigate what specific components of a technology activate and lever the intrinsic motivation of users and lead to the strong effect of HM on BI. For our specific case of PG, the simple question is *why is it so much fun to play?* Trying to provide answers to this question is a highly interesting research area with high practical relevance.

The results of hypotheses 2 and 4 (positive influence of EE on BI and of FC on BI and USE) suggest another interesting research question. The influence of a built-in tutorial in an application on the perceived ease of use and facilitating conditions could be investigated. This, in turn, could positively impact BI and USE. In addition, research could investigate the importance of ease of use and related variables furthermore by comparing perceptions with PG to other AR applications that appear to be intuitive and easy to use, too.

Following the results of habit, future work in the field of AR should investigate the impact of immersion and pervasiveness which are important perceptional characteristics of AR. The question about what role the increasing immersed experience will play with regard to habit formation of users also arises. For example, it is not clear whether immersion amplifies the perception of users in a way that the use of a AR technology is becoming natural or even addictive. Measuring these perceptions addresses the previously discussed issue of AR-specific constructs. Based on the limitations, it is recommended to increase sample sizes for user studies and try to get an even more representative sample with respect to the compared population. Furthermore, our research on PG could be conducted in other countries with different cultural values and along different points in time. It would be interesting to investigate whether differences in the perception about PG occur over time. In addition, this could help to understand whether PG is a one summer phenomenon and, if so, help to explain why.

6 Conclusion

In this research, we investigated the technology acceptance factors of the AR smartphone game Pokémon Go. We adapted the UTAUT2 model by Venkatesh et al. [1] and conducted an online study with German users of the game. Based on a sample with 683 PG players, we investigated the acceptance factors of behavioral intention to play PG and actual use behavior with a PLS-SEM approach. The strongest predictor of behavioral intention is hedonic motivation, i.e. fun and pleasure due to playing the game. In addition, effort expectancy has a medium-sized effect on behavioral intention and habit has a medium-sized effect on behavioral intention as well as use behavior.

The key findings of our research are the following. First, usability aspects play an important role in the acceptance of PG. Second, social influence by others seems to play no role in the decision of users to adopt the game. This unexpected result should be addressed in future research. Third, the habitual use of PG is a strong predictor and represents an important goal for practitioners who are developing AR applications. The probability of adoption increases, if it is easily possible for a user to integrate the application into his daily life. Fourth, the diffusion of AR can possibly be influenced by addressing the intrinsic motivation of users. Approaches like gamification could be a solution to habituate users to different AR technologies other than AR games. Thus, an application should not only be easy to use, but also fun to use. The last point addresses the need for constructs which are specifically developed to measure users' attitudes and perceptions of AR. These operationalisations are urgently needed for future user studies on AR.

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A Questionnaire

Performance Expectancy

PE1. I find Pokémon Go useful in my daily life.
PE2. Using Pokémon Go increases my chances of achieving things that are important to me.
PE3. Using Pokémon Go helps me accomplish things more quickly.
PE4. Using Pokémon Go increases my productivity.

Effort Expectancy

EE1. Learning how to play Pokémon Go is easy for me.
EE2. My interaction with Pokémon Go is clear and understandable.
EE3. I find Pokémon Go easy to play.
EE4. It is easy for me to become skillful at playing Pokémon Go.

Social Influence

SI1. People who are important to me think that I should play Pokémon Go.
SI2. People who influence my behavior think that I should play Pokémon Go.
SI3. People whose opinions that I value prefer that I play Pokémon Go.

Facilitating Conditions

FC1. I have the resources necessary to play Pokémon Go.
FC2. I have the knowledge necessary to play Pokémon Go.
FC3. Pokémon Go is compatible with other technologies and applications I use. (dropped)
FC4. I can get help from others when I have difficulties playing Pokémon Go. (dropped)

Hedonic Motivation

HM1. Playing Pokémon Go is fun.
HM2. Playing Pokémon Go is enjoyable.
HM3. Playing Pokémon Go is very entertaining.

Price Value

PV1. Pokémon Go is reasonably priced.
PV2. Pokémon Go is a good value for the money.
PV3. At the current price, Pokémon Go provides a good value.

Habit

HT1. Playing Pokémon Go has become a habit for me.
HT2. I am addicted to playing Pokémon Go.
HT3. I must play Pokémon Go.
HT4. Playing Pokémon Go has become natural to me.

Behavioral Intention

BI1. I intend to continue playing Pokémon Go in the future.
BI2. I will always try to play Pokémon Go in my daily life.
BI3. I plan to continue to play Pokémon Go frequently.

Use Behavior

Please choose your usage frequency for Pokémon Go:

- Never
- Once a month
- Several times a month
- Once a week
- Several times a week
- Once a day
- Several times a day
- Once an hour
- Several times an hour
- All the time

The frequency scale is adapted from [77]. All other items are measured with a seven-point Likert scale, ranging from "strongly disagree" to "strongly agree". Experience is measured based on the smartphone experience of a user, since Pokémon Go is only available mobile. Answer options range from "0 years" to "more than 10 years" experience with smartphones. Age is measured starting at age 18. Gender is coded as a binary with 1 for females and 0 for males.

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