How Nostalgic Feelings Impact Pokémon Go Players - Integrating Childhood Brand Nostalgia into the Technology Acceptance Theory

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The augmented reality smartphone game
commercial successes in the last years, posing the question concerning the factors contributing to 's succe . An apparent distinction t
strong brand . We derive a research model based on the established theory of technology acceptance, which includes an established construct for nostalgic feelings - *childhood brand nostalgia* - and theorize on how it is related to beliefs about technology characteristics and the intention to play the game. For this purpose, we adapt one of the most prominent technology acceptance models for the consumer context and for hedonic information systems, the UTAUT2 model.

Based on our model, we conduct a study with 418 active German players aged between 18 and 35. Our results indicate that the effect of *childhood brand nostalgia* on *behavioural intention* is fully mediated by the belief constructs. Thus, nostalgic feelings about Pokémon influence the intention of users through altering beliefs concerning Pokémon. We include nostalgic feelings in a technology acceptance model for the first time, therefore contributing to the theoretical advance in the IS domain. The results can be used to enhance the technology acceptance of newly designed products.

Keywords: Childhood brand ; hedonic informat ; augment
reality ; Poke ́mon Go; Technology acceptance model

1. Introduction

In July of 2016, the New York Times published an article titled "Pokémon Go, Millennials' First Nostalgia Blast" (Hardy, 2016). The augmented reality (AR) smartphone game Pokémon Go has broken several world records concerning revenue and download statistics (Swatman, 2016). Additionally, it has been shown that in 2016, on average, players spend more time with Pokémon Go than with social media apps

(Nedelcheva, 2016; Nelson, 2016). Pokémon Go is one of the most successful smartphone applications of all time and boosted interest in AR (Swatman, 2016). The big success, and the appearance of nostalgic feelings mentioned in articles as an important factor of the former (Baraniuk, 2016; BBC, 2016; Hardy, 2016), pose highly interesting research questions. We tackle these questions by deriving a theoretical research model for the role of nostalgic feelings in technology acceptance and testing it empirically. On the one hand, we deal with players' perceptions concerning Pokémon Go which cause them to play the game. Thus, we focus on technology acceptance and use theories. On the other hand, we use an established construct to operationalize a suitable form of nostalgic feelings for Pokémon Go, namely *childhood brand nostalgia* (Shields & Johnson, 2016). Previous literature from the field of psychology indicates that nostalgic feelings reframe certain beliefs in a positive manner (Batcho, 2013). In addition, previous research finds that such feelings induce the intention for a certain behaviour (Sedikides & Wildschut, 2016; Zhou, Wildschut, Sedikides, Shi, & Feng, 2012). Thus, we address the following research question with this work:

Does childhood brand nostalgia positively influence players' beliefs about technology characteristics and the behavioural intention to play Pokémon Go?

Pokémon Go (Niantic Labs, 2016) is a location-based augmented reality game for mobile devices. It is developed by Niantic Labs and available on iOS and Android (Niantic Labs, 2017). Various game mechanics are used to keep players motivated, such as player levels and virtual items. Pokémon Go is often referred to as the unofficial successor of the mobile game Ingress (Albao, 2014; Niantic Labs, 2012). They are based on the same location data, so it is not a coincidence that users face a similar gaming experience (Ravenscraft, 2016). Both games are quite popular with a vast number of reviews, blog entries, and user-made videos. However, Pokémon Go outperforms the success of Ingress by far considering downloads, active players and revenue (Perez, 2016; Swatman, 2016). The most relevant difference for this research is that Ingress is built on its own universe while Pokémon Go is built on Pokémon (Encyclopedia Britannica, 2017; The Pokémon Company, 2017b), a media franchise managed by "The Pokémon Company" (The Pokémon Company, 2017a). Pokémon started as a Game Boy (Wikipedia, 2017b) video game, but quickly expanded to trading cards, television shows, toys and comic books, and is among the best-selling video game franchises (Bainbridge, 2014; Wikipedia, 2017a). The principal part of the game is to catch and train fictional creatures called "Pokémon". Pokémon Go is a location-based game with the possibility to activate an augmented reality (AR) feature to combine the real environment with digitally placed Pokémon. The Pokémon appear at certain points in the real-world location of the player. The game is free to play and based on a freemium business model with in-app purchases (The Pokémon Company, 2017b). When it was released, Pokémon Go contained 151 Pokémon and was extended by 80 more in February 2017 (Pokémon GO Wiki, 2017). The number of available Pokémons is updated constantly and is currently 429 (Pokebattler, 2018).

Several articles investigate success factors and motivational aspects of Pokémon Go, like the intuitive interaction concepts employing a smartphone, the viral marketing, the powerful franchise behind Pokémon and proposed health benefits (Kaczmarek, Misiak, Behnke, Dziekan, & Guzik, 2017; Kogan, Hellyer, Duncan, & Schoenfeld-Tacher, 2017; Morschheuser, Riar, Hamari, & Maedche, 2017; Oleksy & Wnuk, 2017; Rauschnabel, Rossmann, & tom Dieck, 2017; Tabacchi, Caci, Cardaci, & Perticone, 2017; Yang & Liu, 2017; Zsila et al., 2017). However, childhood nostalgia related to the brand “Pokémon” is not investigated yet. To measure this concept, we use the recently developed *childhood brand nostalgia* (CBN) construct by Shields and Johnson (2016).

Since we want to investigate the role of nostalgia in the technology acceptance framework of a smartphone game, we do not base our study on a general technology acceptance model, but on a model for hedonic systems with constructs covering concepts like fun due to using the system. Therefore, we choose the extended unified theory of acceptance and use of technology (UTAUT2) as a base model for investigating CBN (Venkatesh et al., 2012).

To investigate the driving factors of technology acceptance and the role of nostalgia, a sufficiently large user base is needed. Therefore, in contrast to other AR technologies like head-mounted displays (HMD), the massive success of Pokémon Go allows us to investigate both the role of nostalgia towards the brand Pokémon in a technology acceptance model and the success factors of an AR technology based on a relatively large sample size. We use a data set containing 418 active players of Pokémon Go from Germany aged 18 to 35, collected in January 2017. We use this age restriction intentionally, since only players in this age range can possibly be the object of childhood brand nostalgia. We analyse the research model with partial least squares structural equation modelling (PLS-SEM).

The remainder of this paper is as follows. The theoretical background is discussed in Section 2. The methodology, research model and hypotheses as well as the questionnaire, data collection and demographics are described in Section 3. The results are presented in Section 4 and discussed in Section 5 together with the limitations and future work. Finally, we conclude with Section 6.

2. Theoretical Background

2.1 Nostalgia

The concept of nostalgia is primarily investigated in psychology (Cheung et al., 2013;

Sedikides & Wildschut, 2016; Sedikides et al., 2015; Wildschut, Sedikides, Arndt, & Routledge, 2006) and in the marketing field (Cheung et al., 2013; Fournier, 1998; Holak & Havlena, 1998; Holbrook, 1993; Holbrook & Schindler, 2003; Schindler & Holbrook, 2003; Shields & Johnson, 2016). The notion of nostalgia shifted through the course of the last century from a negatively associated affliction to a positive concept, inherently connected with positive emotions (Cheung et al., 2013; Holak & Havlena, 1998; Wildschut et al., 2006). The term nostalgia was mentioned for the first time in the year 1688 by physician Johannes Hofer describing a negative mental state and neurological disease of Swiss mercenaries who were fighting for different monarchs far away from home (Hofer, 1934). These earlier negative definitions of nostalgia were predominant until the 1970s and were generally describing individuals who are clinging to the past and, by that, are not able to live in the present and look positively into the future (Kleiner, 1977). This solely negative association was questioned by several researchers and differentiated based on a plethora of empirical research showing that nostalgia is related to psychological benefits (e.g. increasing self-esteem (Hepper, Ritchie, Sedikides, & Wildschut, 2012) or social connectedness (Wildschut et al., 2006)).

Nostalgia is triggered by elements personally experienced in the past. Wildschut et al. (2006) refer in their work to the "important social element" (p. 976) of nostalgia, indicating that nostalgic experiences are created by relationships with other important persons in the relevant period of time. But, as pointed out in literature, nostalgia is not necessarily oriented towards other persons, but can also be associated with events or relevant locations (Wildschut et al., 2006). For example, it was shown that nostalgia impacts consumption decisions (Holbrook & Schindler, 2003; Schindler & Holbrook, 2003). Related to our research, the current rise of "retro games" (e.g. Snake, Pinball or

Solitaire) on mobile devices indicates that the object of nostalgia can also be a game which people played years ago. Therefore, Pokémon as a brand may well be an object of the nostalgia of today's active players of Pokémon Go (cf. Section 2.2). Since Pokémon in its different game forms was mainly played by children (Bainbridge, 2014) after its release in Germany in 1999, the operationalization of nostalgia has to fulfil two important criteria. First, it has to account for the fact that Pokémon is a franchise or a brand, representing the object of the users' nostalgic feelings. Second, it has to account for the fact that players of Pokémon games (e.g. Gameboy, card games) or viewers of the TV series "Pokémon" (Pokémon Company International, 2019) were children when they were able to form this nostalgic relationship towards Pokémon. For purposes of validity and reliability, we decided against creating a construct ad hoc. Instead, we use the "*childhood brand nostalgia*" (CBN) construct by Shields and Johnson (2016) (cf. Table 9) to measure nostalgia in our research model, since it fulfils our predefined criteria and is tested with respect to validity and reliability. A comparable operationalization of the concept of nostalgia does not exist in the literature so far. The authors define *childhood brand nostalgia* as "[...] a positively valenced emotional attachment to a brand because of the brand's association with fond memories of the individual's non-recent lived past" (Shields & Johnson, 2016, p. 362). The developed emotion is defined as positively loaded.

2.2 Nostalgia in Information Technology Research

Nostalgia is not investigated in the current literature related to the adoption of information technologies to a large extent. There are several articles exploring the phenomenon of retro games which are based on individuals' nostalgic feelings (Heineman, 2014; Whalen, 2008). After the launch of Pokémon Go, several articles focused on the game as a prime example of retro games (Becker et al., 2016; Keogh, 2017; Loveday & Burgess, 2017; Oehlhorn & Maier, 2016).

Besides games, there are articles that mention nostalgia as a minor finding without elaborating on it in more detail or include it in a broader construct (Chungtae, Dongwook, & Soonhan, 2006). However, none of these articles systematically theorize how nostalgia is related to technology acceptance factors. Therefore, the need arises to understand the concept itself and its relationship with other variables in the context of the acceptance of information technologies. We perceive the inclusion of CBN in technology acceptance models as a fertile starting point to investigate nostalgia in this research context, since it can be assumed that it has a significant and relevant impact on users' decisions to adopt and use a technology. Because of the fact that no literature deals with this question, we set out to investigate the role of nostalgia in the technology acceptance process of a hedonic information system, Pokémon Go.

2.3 Research on Technology Acceptance

The field of technology adoption and use has been the subject of 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 and our choice for using UTAUT2 as the base model for the case of Pokémon Go.

The Theory of Reasoned Action (TRA) provides the theoretical starting point of the technology acceptance model (TAM). It falls back on empirical research conducted by the social psychologists Fishbein and Ajzen (Fishbein & Ajzen, 1975). According to TRA, a person’s behaviour is determined by that person’s intention to perform this particular behaviour. The *behavioural intention (BI)*, in turn, is influenced by his or her *subjective norms (SN)* and *attitude toward the given behaviour (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 consequences of the behaviour. On the other hand, the *subjective norms* concerning a given behaviour are affected by normative beliefs and normative pressure. Subjective norms refer to a person's motivation to comply with persons saying whether he or she should perform the behaviour or not. Feedback loops can arise at various stages of the process, as the performance of a given behaviour can have an impact on beliefs, which in turn influences BI and hence the behaviour itself.

The Theory of Planned Behavior (TPB) by Ajzen (Icek Ajzen, 1991) is based on the TRA. The overall structural process remains unchanged, i.e. BI is influenced by several components and in turn influences the performance of a behaviour. Nevertheless, it was created as an extension of the TRA integrating the addition of *perceived behavioural control (PBC)*. In practical terms, this denotation refers to a person's perception regarding the ease or difficulty of performing a given behaviour 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 behaviour in two ways. First, indirectly through its influence on BI and its relationship with A and SN. Secondly, together with BI, PBC can be used directly for predicting behavioural achievement. Based on the TRA and TPB, the technology acceptance model (TAM) was developed in 1985 by Davis (Davis, 1985). 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 towards the use* of the technology (A) and the *perceived usefulness* (U). Subjective perceptions regarding the system's ease of use are theorized to be fundamental determinants of the 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 behaviour indirectly through their impact on U and E (Davis, Bagozzi, & Warshaw, 1989). TAM has been the subject of various studies and extensions (Haugstvedt & Krogstie, 2012; H. C. Kim & Hyun, 2016; Olsson & Salo, 2011; Salinas Segura & Thiesse, 2015).

Venkatesh et al. (2003) 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 behaviour* is not only determined by BI but also by the newly added construct of *facilitating conditions* (FC). Moreover, UTAUT introduces three novel determinants of *behavioural intention*. These are *performance expectancy* (PE), *effort expectancy* (EE), and *social influence* (SI). In addition, the determinants of BI and *actual use behaviour* (USE) are influenced by up to four moderators being identified as gender, age, experience, and voluntariness of use.

While UTAUT focuses on an organizational setting, the original authors proposed an extension, known as UTAUT2, takes the consumer context into consideration (Venkatesh et al., 2012). The theory was originally applied to mobile internet consumers. 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. The UTAUT2 model is not the first technology acceptance model focusing on hedonic information systems. There exists a plethora of research dealing with information systems which primarily focus on the intrinsic motivation of users like getting fun, pleasure or enjoyment (Lin & Bhattacherjee, 2010; Lowry, Gaskin, Twyman, Hammer, & Roberts, 2013; Turel, Serenko, & Bontis, 2010; van der Heijden, 2004). However, our study is based on the UTAUT2 model due to the following reasons. First, as described earlier, the theory was specifically developed to explain and predict technology adoption in the consumer context, as is the case for the use decision of a game like Pokémon Go. Secondly, the theory also accounts specifically for hedonic information systems by incorporating the construct *hedonic motivation*. Thirdly, UTAUT2 is an integrative technology acceptance theory by including important explanatory variables of existing technology acceptance models (Venkatesh et al., 2003, 2012). Lastly, the model is widely employed and tested in previous literature and shows strong explanatory power with regard to behavioural intention and the use of technologies (Herrero, San Martín, & Garcia-De los Salmones, 2017; Liew, Vaithilingam, & Nair, 2014). Thus, we argue that these constructs are an appropriate basis for explaining the phenomenon at hand. In summary, the theory provides an appropriate framework, due to a comparable research context focusing on the consumer market and the importance of hedonic incentives with regard to Pokémon Go.

3. Methodology

We use structural equation modelling (SEM) to analyse the relationships between the latent variables of the research model. There are two main approaches for SEM, partial least squares SEM (PLS-SEM) and covariance-based SEM (CB-SEM) (Hair, Ringle, & Sarstedt, 2011). Since our research is highly exploratory with respect to the construct CBN and has the goal to predict the target construct *behavioural intention* of playing Pokémon Go and maximize the explained variance of this dependent variable, we use PLS-SEM for our analysis (Hair, Hult, Ringle, & Sarstedt, 2017; Hair et al., 2011; Lowry & Gaskin, 2014). In the following subsections, we develop our research model and the hypotheses based on the extended unified theory of acceptance and use of technology (UTAUT2) (Venkatesh et al., 2012). Furthermore, the questionnaire composition, the data collection and the demographics are described.

The literature review in Section 2.2 shows that nostalgia, and especially CBN, is not investigated within the context of such theories. Past research, which relies on different theoretical frameworks, also calls for work on Pokémon Go and mobile augmented reality that is based on technology acceptance theories (Rauschnabel et al., 2017).

3.1 Research Model and Hypotheses

The UTAUT2 model consists of seven exogenous variables that are theorized to have an effect on the *behavioural intention* to use a technology. Two of these exogenous variables and the *behavioural intention,* in turn, have an impact on the *actual use behaviour* (cf. Figure 2). Due to validity and reliability considerations, we wanted to stay as close as possible with the original item formulation when adapting the constructs to the case of Pokémon Go (see Appendix A).

Habit is the perception of a user concerning his or her routine behaviour (Limayem, Hirt, & Cheung, 2007). In our case, *habit* describes the extent to which users feel that playing Pokémon Go is natural or even necessary for their everyday life. It is theorized to have a direct effect on use, as well as a mediated effect via *behavioural intention*

(Venkatesh et al., 2012). Games are an inherent part of the regular use of smartphones for many people (GlobalWebIndex, n.d.) and can cause addiction in certain cases (Chóliz, Echeburúa, & Ferre, 2017). Therefore, we theorize that *habit* has a positive effect on the *behavioural intention* and *actual use behaviour* for the case of Pokémon Go.

H1a: Habit (HT) has a positive effect on behavioural intention (BI).

H1b: Habit (HT) has a positive effect on use behaviour (USE).

Originally, *performance expectancy* was considered a utilitarian concept, mainly included in technology acceptance models in the organizational context (Venkatesh et al., 2003). UTAUT2 deals with mobile internet services, and therefore, the items are changed towards a more general formulation on usefulness and accomplishment of important things. These features are also valid for Pokémon Go. Research indicates that Pokémon Go can improve health (Kaczmarek et al., 2017), social contacts (Kogan et al., 2017) and induce cooperation between people (Morschheuser et al., 2017). All of these outcomes are rather utilitarian in nature and go beyond having fun and pleasure as a direct result. The last item of the original construct is dropped as it focuses on productivity, which is not suitable for a game (cf. Appendix A).

H2: Performance expectancy (PE) has a positive effect on behavioural intention (BI).

Effort expectancy indicates the perceived ease of use of playing Pokémon Go. It is theorized that technologies which are easy to use are more likely to be adopted. We argue that this relationship holds for a smartphone game like Pokémon Go, too.

H3: Effort expectancy (EE) has a positive effect on behavioural intention (BI).

Social influence deals with the perception of users about opinions of others on their use behaviour of a certain technology. "Others" are either important, influencing or esteemed people that are in a relationship with the user in some way (Venkatesh et al., 2003). *Social influence* is also interesting for the case of Pokémon Go 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 imaginable that especially older users are ashamed of playing this game. Previous research on Pokémon Go indicates that there is no effect for a comparable construct (social norms) on the intentions to reuse (Rauschnabel et al., 2017). Still, we hypothesize that *social influence* has a positive effect, as we assume that the combination of the mentioned peer pressure and the wide public interest supersedes possible opposing effects.

H4: Social influence (SI) has a positive effect on behavioural intention (BI).

The construct *hedonic motivation* is the operationalization of the perceived enjoyment of users when using an information system (Venkatesh et al., 2012). Since Pokémon Go is a game with the main purpose of creating fun and pleasure for its users, this construct is assumed to have the strongest effect on the *behavioural intention* to play. This assumption is supported by previous research on hedonic information systems (Childers, Carr, Joann, & Carson, 2001; van der Heijden, 2004).

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

Price value measures the trade-off between the perceived benefits of a technology and its monetary costs for each purchase decision (Dodds, Monroe, & Grewal, 1991). If users perceive the benefits to outweigh the costs, the *price value* construct is positive, which implies a positive effect on the intention to use (Venkatesh et al., 2012).

Pokémon Go is based on a freemium pricing model, where monetary costs only occur if users decide to buy in-app goods (like gold coins that can be reused for acquiring extra features or new PokeBalls). Based on this, the game is playable without facing any costs per se. Thus, users can decide about monetary costs by themselves and therefore, we expect a positive effect on the *behavioural intention* to play.

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

Factors which support the use of information systems and therefore foster the *intention to use* a technology and the *actual use behaviour* are called *facilitating conditions* (FC). The effect is theorized to be positive for *intention to use* as well as *actual use* (Venkatesh et al., 2012). The effect is theorized to be positive for *intention to use* as well as *actual use*, because the authors argue that *facilitating conditions* behave like the *perceived behavioural control* construct in the theory of planned behaviour (TPB) (cf. Section 2.3). In the case of Pokémon Go, *facilitating conditions* can be resources like having access to interesting and helpful information about the game from friends.

H7a: Facilitating conditions (FC) have a positive effect on behavioural intention (BI).
H7b: Facilitating conditions (FC) have a positive effect on use behaviour (USE).

Hypotheses H1 to H7 match the original relationships from the UTAUT2 (Venkatesh et al., 2012). In a next step, *childhood brand nostalgia* has to be included in the theoretical framework of technology acceptance. A core purpose of the original technology acceptance (TAM) is to "[...] provide a basis for tracing the impact of external factors on internal beliefs, attitudes, and intentions" (Davis et al., 1989, p. 985). We did not choose TAM as a basis for our integration of CBN into technology acceptance theories since Pokémon Go is a hedonic information system, which we can capture more appropriately by using UTAUT2 by asking participants about their *hedonic motivation*. In addition, UTAUT2 provides other highly interesting concepts with regard to Pokémon Go and mobile AR applications in general, like *social influence* or *habit*. Nevertheless, this quote shows that external factors play a major role. In the original model, these external factors influence the *perceived usefulness* and the *perceived ease of use*, which are called "beliefs" in the context of TAM (Davis et al., 1989, p. 985). Following the understanding of beliefs in the TAM (Davis, 1985), we argue that beliefs are represented by the seven variables *habit*, *performance expectancy*, *effort expectancy*, *social influence*, *hedonic motivation*, *price value* and *facilitating conditions* in the case of UTAUT2.

By merging these insights, we theorize that CBN is an external factor which influences all beliefs of the players with regard to Pokémon Go. These beliefs, in turn, have an impact on the *behavioural intention* (cf. Figure 1). Thus, the relationship between CBN and BI is fully mediated by the beliefs.

Figure 1. Abstract research model

As pointed out in Section 2.2, CBN is associated with positive emotions. Previous literature from the field of psychology indicates that nostalgic feelings reframe certain beliefs in a positive manner (Batcho, 2013). In addition, previous research finds that nostalgic feelings induce the intention for a certain behaviour (Sedikides & Wildschut, 2016; Zhou et al., 2012). Therefore, we derive the following hypotheses:

H8: Childhood brand nostalgia (CBN) has a positive effect on habit (HT).

H9: Childhood brand nostalgia (CBN) has a positive effect on performance expectancy (PE).

H10: Childhood brand nostalgia (CBN) has a positive effect on effort expectancy (EE).

H11: Childhood brand nostalgia (CBN) has a positive effect on social influence (SI).

H12: Childhood brand nostalgia (CBN) has a positive effect on hedonic motivation (HM).

H13: Childhood brand nostalgia (CBN) has a positive effect on price value (PV).

H14: Childhood brand nostalgia (CBN) has a positive effect on facilitating conditions (FC).

The consequent research model is illustrated in Figure 2.

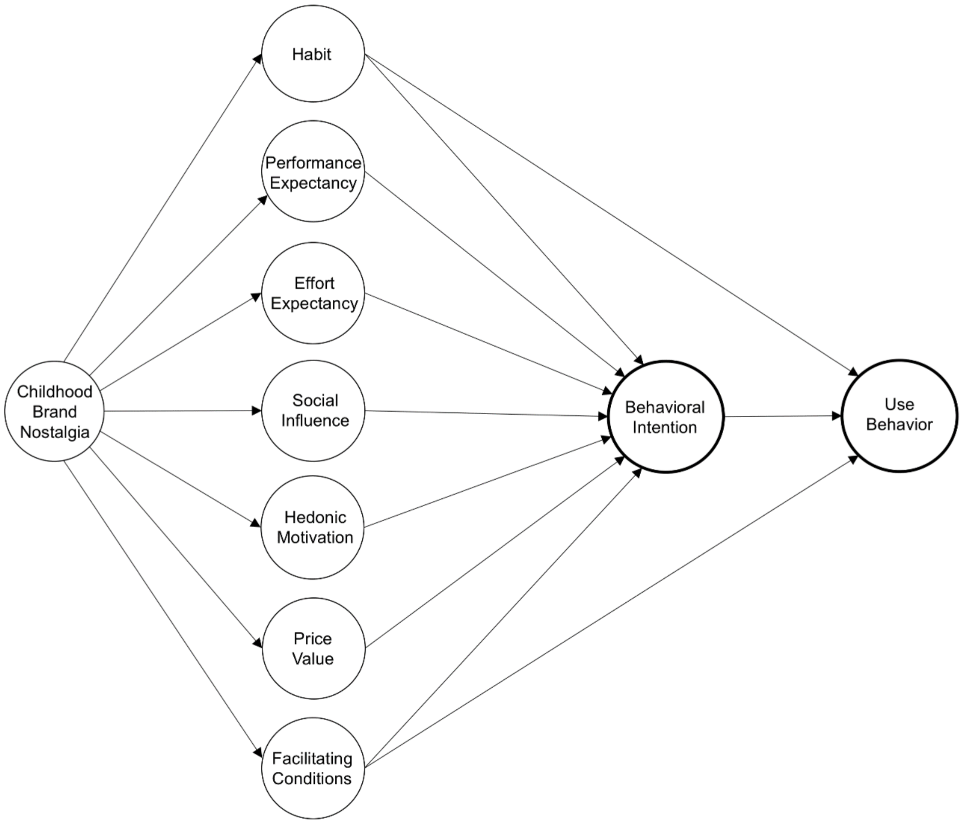

Figure 2. Detailed research model including *childhood brand nostalgia*

3.2 Questionnaire

The constructs of the questionnaire for adapting the TAM for hedonic information systems are taken from the paper by Venkatesh et al. (2012), while the CBN construct is taken from the paper by Shields and Johnson (2016). All items are measured based on a seven-point Likert scale and can be found in Table 9 (Appendix A). Since we conducted the study with a German panel, the items had to be translated into German language. As we wanted to ensure content validity of the translation, we followed a translation process used in comparable studies with non-English speaking study participants (Venkatesh et al., 2012). First, the English questionnaire was translated into German with the help of a certified translator (translations 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 experts checked the two English versions for 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 the last step, the German version of the questionnaire was administered to students of a Master's course to confirm preliminary reliability and validity of the measurement model.

3.3 Data Collection and Demographics

Since we want to investigate why people play Pokémon Go and what role CBN plays in this question, our sample consists of active players of the game. Although Pokémon Go is one of the most successful smartphone applications in history (Swatman, 2016), this is a challenging sampling task. Thus, we decided to conduct the study with the help of a sample provider. To ensure quality of our data, we chose a 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) (Schmitz, 2015). The link to this survey was then distributed by the panel provider to 9338 participants. Of those 9338 approached participants, only 683 remained after asking whether they play Pokémon Go, whether they are older than 18 years old and after filtering out participants who answered a test question in the middle of the survey incorrectly. In addition, two participants were sorted out because they stated to "never" play the game. Aside from the test questions, we asked the participants who stated that they play Pokémon Go about their current level. We designed this question intentionally as a free field question with numeric entries only. As Pokémon Go 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 either actually not playing or they did not answer the questions carefully. Based on this sample, we deleted every entry from participants older than 35 years, as these players are too old to be influenced by *childhood brand nostalgia* for Pokémon. The final sample used for the data analysis consists of 418 active players, of which 162 are male (38.76%) and 256 are female (61.24%). The number of participants aged 18 to 20 is 45 (10.76%), aged 21-25 is 131 (31.34%), aged 26-30 is 133 (31.82%) and aged 31-35 is 109 (26.08%). The most common educational degrees are the secondary school leaving certificate (5 GCSEs at Grade C and above) (107 participants - 25.60%) and the A levels degree (157 participants - 37.56%). Besides, 78 participants have a Bachelor's degree (18.66%) and 46 have a Master's degree (11.00%). 23 participants hold a secondary school leaving certificate (5.50%). The least occurring degree is the doctorate degree (7 participants - 1.67%).

4. Results

This section presents the results of our work. We tested the model using SmartPLS version 3.2.6 (Ringle, Wende, & Becker, 2015). Before evaluating the result of the structural model and discussing its implications, we discuss the measurement model and check for reliability and validity of our results. This is a precondition enabling the interpretation of the results of the structural model. Furthermore, it is recommended to report the computational settings (Hair, Sarstedt, Pieper, & Ringle, 2012). For the PLS algorithm, we choose the path weighting scheme with the recommended maximum of 300 iterations and a stopping criterion of 10^{-7} (Hair et al., 2017, p. 91). For the bootstrapping procedure, we choose 5000 as the number of bootstrap subsamples and no sign changes as the method for handling sign changes during the iterations of the bootstrapping procedure.

4.1 Measurement Model Assessment

As the model is measured solely reflectively, internal consistency reliability, convergent validity and discriminant validity have to be checked in order to assess the measurement model properly (Hair et al., 2011).

4.1.1 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. For both measures, it holds that values should be between 0.7 and 0.95 for research that builds upon accepted models, whereas values of Cronbach's α are seen as a lower bound and values of the composite reliability as an upper bound of the assessment (Hair et al., 2017). 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; for Cronbach's α, no value is above 0.95, except for CBN. As the composite reliability is a less conservative measure, the values for CBN, 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 (Hair et al., 2017). But since Cronbach's α is within the suggested range and we use accepted constructs, we consider the ICR as acceptable.

4.1.2 Convergent Validity

Convergent validity is assessed by calculating the outer loadings of the indicators of the constructs (indicator reliability) and by looking at the average variance extracted (AVE) (Hair et al., 2011). Loadings above 0.7 imply that the indicators have much in common, which is desirable for reflective measurement models (Hair et al., 2017). Table 1 shows the outer loadings in bold along the main diagonal. All loadings, except for FC3 and FC4, are higher than 0.7, indicating convergent validity of the indicators of the constructs in the model.

Table 1. Loadings and cross-loadings of the reflective items and ICR measures

Construct	BI	CBN	EE	FC	HT	HM	PE	PV	SI
BI1	0.919	0.341	0.518	0.508	0.257	0.595	0.180	0.332	0.109
BI2	0.850	0.278	0.355	0.360	0.424	0.450	0.364	0.269	0.273
BI3	0.937	0.330	0.522	0.507	0.296	0.608	0.247	0.332	0.164
CBN1	0.353	0.946	0.312	0.331	0.098	0.337	0.142	0.236	0.102
CBN2	0.318	0.934	0.298	0.301	0.093	0.339	0.161	0.233	0.156
CBN3	0.324	0.942	0.331	0.315	0.133	0.321	0.157	0.247	0.126
CBN4	0.315	0.909	0.278	0.299	0.137	0.279	0.195	0.224	0.125
EE1	0.449	0.276	0.901	0.529	0.044	0.438	-0.083	0.291	-0.053
EE2	0.441	0.289	0.892	0.535	0.070	0.473	-0.062	0.320	-0.045
EE3	0.469	0.307	0.912	0.545	0.073	0.461	-0.032	0.305	-0.020
EE4	0.499	0.299	0.882	0.578	0.133	0.411	-0.011	0.343	0.002
FC1	0.377	0.249	0.517	0.826	0.085	0.336	0.010	0.188	0.019
FC2	0.472	0.328	0.643	0.835	0.067	0.422	-0.019	0.303	-0.011
FC3	0.305	0.195	0.263	0.607	0.124	0.253	0.275	0.203	0.174
FC4	0.322	0.178	0.263	0.643	0.147	0.320	0.152	0.242	0.251
HT1	0.401	0.143	0.204	0.195	0.860	0.291	0.353	0.223	0.227
HT2	0.148	0.053	-0.076	0.041	0.791	0.055	0.525	0.119	0.377
HT3	0.160	0.016	-0.117	-0.040	0.808	0.017	0.548	0.083	0.373
HT4	0.359	0.139	0.130	0.144	0.890	0.258	0.542	0.228	0.322
HM1	0.607	0.309	0.503	0.462	0.235	0.942	0.171	0.376	0.113
HM2	0.576	0.345	0.465	0.438	0.207	0.940	0.155	0.378	0.117
HM3	0.534	0.304	0.420	0.388	0.192	0.921	0.165	0.346	0.119
PE1	0.318	0.198	0.002	0.128	0.530	0.220	0.932	0.281	0.467
PE2	0.226	0.133	-0.083	0.083	0.510	0.139	0.942	0.195	0.484
PE3	0.244	0.145	-0.082	0.081	0.524	0.112	0.929	0.177	0.484
PV1	0.271	0.180	0.316	0.229	0.154	0.336	0.099	0.838	0.048
PV2	0.277	0.237	0.244	0.271	0.209	0.329	0.296	0.871	0.174
PV3	0.354	0.240	0.362	0.335	0.199	0.369	0.226	0.923	0.171
SI1	0.197	0.135	0.002	0.139	0.339	0.129	0.483	0.156	0.967
SI2	0.177	0.113	-0.046	0.097	0.322	0.094	0.479	0.121	0.939
SI3	0.188	0.138	-0.047	0.093	0.370	0.129	0.492	0.161	0.941
Cronbach's $\propto$	0.886	0.950	0.919	0.715	0.867	0.927	0.928	0.851	0.945
Comp. Reliability	0.929	0.964	0.943	0.822	0.904	0.954	0.954	0.910	0.965

The values for ICR with FC3 and FC4 are above the threshold and convergent validity is also given. Based on this, there is no necessity to delete these items. Furthermore, we ensured content validity by retaining the items in the construct. Convergent validity for the construct as a whole is assessed by the average variance extracted (AVE). A threshold of 0.5 is acceptable, indicating that the construct explains at least half of the variance of the indicators (Hair et al., 2017). The first column of Table 2 presents the AVE of the constructs in parentheses. All values are above 0.5, demonstrating convergent validity.

4.1.3 Discriminant Validity

Discriminant validity is assessed by two approaches. The first approach, assessing cross-loadings, is on the level of indicators. All outer loadings of a certain construct should be larger than its cross-loadings with other constructs (Hair et al., 2011). 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.

Table 2. Convergent (AVEs) and discriminant validity (Fornell-Larcker approach)

Constructs (AVE)	BI	CBN	EE	FC	HM	HT	PE	PV	SI	USE
BI (0.815)	0.903									
CBN (0.870)	0.351	0.933								
EE (0.804)	0.519	0.327	0.897							
FC (0.541)	0.512	0.334	0.611	0.735						
HM (0.873)	0.614	0.342	0.497	0.461	0.934					
HT (0.702)	0.356	0.123	0.091	0.132	0.227	0.838				
PE (0.873)	0.288	0.175	-0.051	0.108	0.175	0.560	0.934			
PV (0.771)	0.346	0.252	0.352	0.321	0.393	0.215	0.240	0.878		
SI (0.901)	0.198	0.136	-0.031	0.116	0.124	0.363	0.511	0.155	0.949	
USE (1.000)	0.424	0.061	0.238	0.200	0.242	0.437	0.203	0.143	0.112	1.000

The square root of the AVE of a single construct should be larger than the correlation with other constructs (Fornell-Larcker criterion) (Hair et al., 2017). Table 2 contains the square root of the AVE on the main diagonal. 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 an improved approach (Henseler, Ringle, & Sarstedt, 2015). HTMT divides between-trait correlations with within-trait correlations, therefore providing a measure of what the true correlation between two constructs would be if the measurement is assumed to be flawless (Hair et al., 2017). Values close to 1 for HTMT indicate a lack of discriminant validity. A conservative threshold is 0.85 (Henseler et al., 2015). 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. No interval should contain the value 1 in order to establish that the two constructs are different from each other. No confidence interval in Table 10 contains the value 1 (cf. Appendix B). Thus, discriminant validity can be established for our model.

Table 3. Discriminant validity (HTMT approach)

Constructs	BI	CBN	EE	FC	HM	HT	PE	PV	SI	USE
BI										
CBN	0.382									
EE	0.570	0.349								
FC	0.627	0.392	0.707							
HM	0.673	0.364	0.537	0.555						
HT	0.366	0.118	0.174	0.210	0.204					
PE	0.315	0.182	0.073	0.202	0.181	0.648				
PV	0.393	0.278	0.395	0.403	0.441	0.223	0.257			
SI	0.220	0.143	0.045	0.194	0.132	0.424	0.546	0.165		
USE	0.451	0.062	0.247	0.216	0.251	0.441	0.209	0.157	0.115	

4.1.4 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 (Malhotra, Kim, & Patil, 2006). Since this is the case in our research design, the need to test for CMB arises. We perform an unrotated principal-component factor analysis with the software package STATA 14.0 (Harman’s single-factor test) to address the issue of CMB (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). The test shows that seven factors have eigenvalues larger than 1, which jointly account for 73.70% of the total variance. The first factor only explains 28.82% of the total variance. Based on results of previous literature, we argue that CMB is not likely to be an issue in the data set (Blome & Paulraj, 2013; Liang, Saraf, Hu, & Xue, 2007; Ruiz-Palomino, Martínez-Cañas, & Fontrodona, 2013).

4.2 Structural Model Assessment

To assess the structural model, we check for possible collinearity problems, path coefficients, the level of R^2, the effect size f^2, the predictive relevance Q^2 and the effect size q^2 (Hair et al., 2017). We address these evaluation steps to examine the predictive power of the model with regard to the target constructs.

4.2.1 Collinearity

All inner VIF values above 5 indicate that collinearity between constructs is present (Hair et al., 2017). For our model, the highest VIF is 1.915. This indicates that collinearity is no issue in the model.

4.2.2 Significance and Relevance of Relationships

Figure 3 presents the results of the path estimations and the R^2 of the endogenous variables. The R^2 values of the seven, originally exogenous, variables from the UTAUT2 model are not reported. The model explains 51% of the variance of users' *behavioural intention* to play Pokémon Go and 27% of the variance of users' *actual use behaviour*. There are different proposals for interpreting the size of this value. We choose to use the very conservative threshold proposed by Hair et al. (Hair et al., 2011), 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 3. Statistical significance is indicated by one, two or three asterisks, indicating that the p-values are smaller than 0.05, 0.01 and 0.001, respectively. The p-value indicates the probability that a path estimate is incorrectly assumed to be significant. Thus, the lower the p-value, the lower the probability that this result is spurious. The relevance of the path coefficients is expressed by the relative size of the coefficient compared to the other explanatory variables (Hair et al., 2017).

All relationships between *childhood brand nostalgia* and the seven mediators are statistically significant at the 5% level or higher. The effect sizes range from 0.123 (CBN on HT) to 0.342 (CBN to HM), indicating a small effect and a large effect, respectively. *Habit* has a statistically significant effect on BI and USE, whereas the effect on USE is approximately twice as strong. *Performance expectancy*, *effort expectancy*, *hedonic motivation* and the *facilitating conditions* of Pokémon Go exert statistically significant effects on BI. Effect sizes range from 0.119 (PE on BI) to 0.363 (HM on BI). *Facilitating conditions* have no impact on USE. In contrast to the stated hypotheses, *social influence* and *price value* have no significant influence on BI. *Behavioural intention* exerts a medium-sized statistically significant effect on USE.

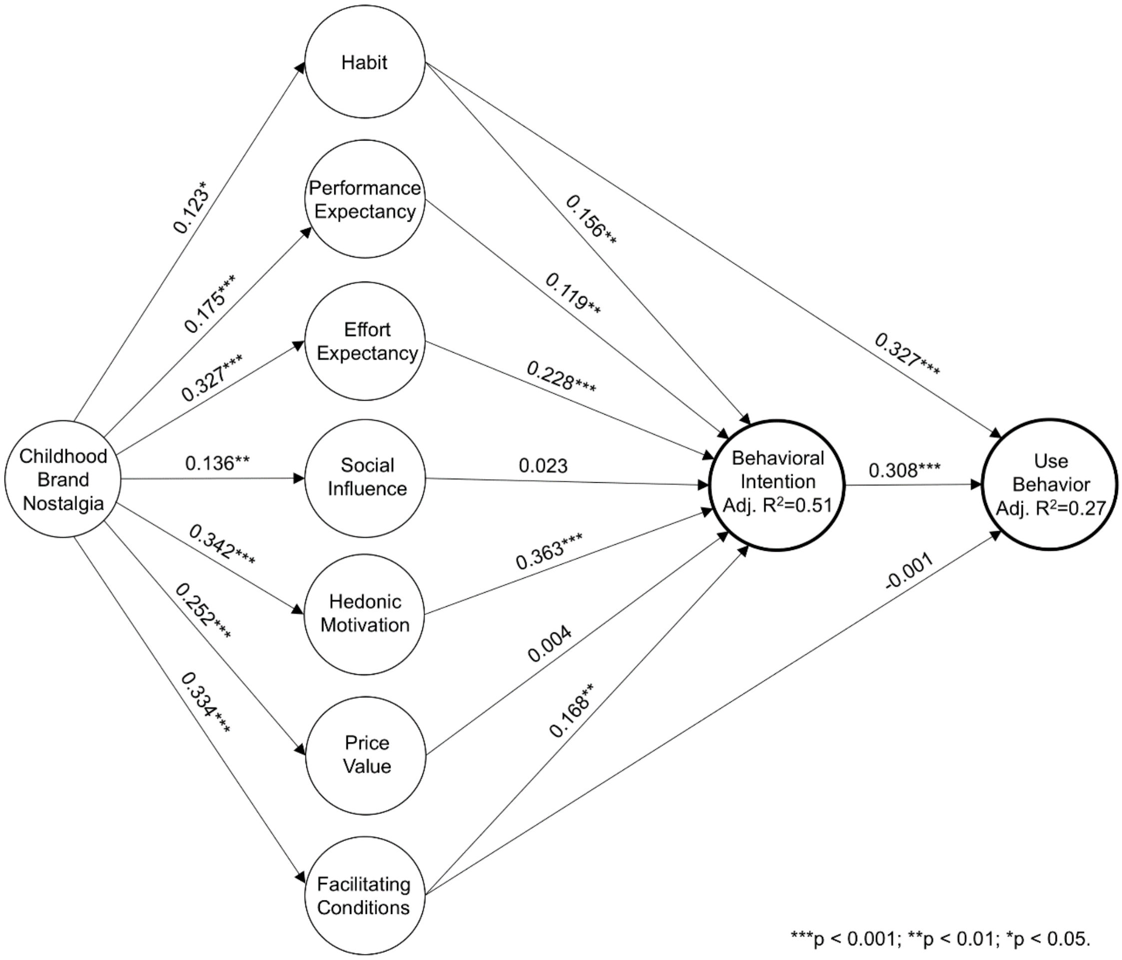

Figure 3. Path estimates and R2 values of the structural model

4.2.3 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 (Hair et al., 2017). The values are assessed based on thresholds by Cohen (1998), who defines effects as small, medium and large for values of 0.02, 0.15 and 0.35, respectively. Table 4 shows the results of the f^2 evaluation. Values in italics indicate small effects, while values in bold indicate medium effects. All other values indicate no substantial effect. The results correspond to those of the previous analysis of the path coefficients.

Table 4. Values for f^2

Variables	f^2								
Endogenous / Exogenous	BI	EE	FC	HM	HT	PE	PV	SI	USE
BI	-	-	-	-	-	-	-	-	*0.085*
CBN	-	*0.120*	*0.126*	*0.133*	0.015	0.032	*0.068*	0.019	-
EE	*0.057*	-	-	-	-	-	-	-	-
FC	*0.034*	-	-	-	-	-	-	-	0.000
HM	**0.180**	-	-	-	-	-	-	-	-
HT	*0.033*	-	-	-	-	-	-	-	*0.128*
PE	0.016	-	-	-	-	-	-	-	-
PV	0.000	-	-	-	-	-	-	-	-
SI	0.001	-	-	-	-	-	-	-	-

4.2.4 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 (Hair et al., 2017). We use seven as a value for the omission distance *d*. Recommended values for *d* are between five and ten (Hair et al., 2011). 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 and of the structural model (Hair et al., 2017). For further information, see Chin (1998). For our model, Q^2 is calculated for BI and USE. In addition, it is calculated for the seven mediators, since they represent endogenous variables with respect to CBN. As the goal of this model is the prediction of the intention and the consequent use behaviour, we only discuss these values. Values above zero indicate that the model has the property of predictive relevance. In our case, the Q^2 value for BI is equal to 0.399 and to 0.252 for USE. Since the values for BI and USE are substantially larger than zero, predictive relevance of the model is established.

4.2.5 Effect Sizes q^2

The assessment of q^2 follows the same logic as the f^2 assessment. It is based on the Q^2 measure 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 following formula (Hair et al. 2017, p. 207):

$$q^2_{X \to Y} = \frac{Q^2_{inclu\ d} - Q^2_{exclu\ d}}{1 - Q^2_{inclu\ d}}$$

All individual values for q^2 are calculated with an omission distance $d = 7$. The results are shown in Table 5. The thresholds for the f^2 interpretation can be applied here, too (Cohen, 1988). Values in italics indicate small effects and values in bold indicate medium effects. All other values indicate no substantial effect. All results of this analysis are in line with the previously observed results for the f^2 assessment. Since q^2 indicates predictive relevance of a single variable, we do not consider it for the relationships with CBN as the sole explanatory variable. As the Q^2 for the related explained variables would drop to 0 if CBN is excluded, the calculation of the q^2 effect does not make sense in this case.

Table 5. Values for q^2

Variables	q^2	
Endogenous / Exogenous	BI	USE
BI	-	**0.306**
EE	*0.045*	-
FC	*0.028*	-0.016
HM	**0.155**	-
HT	*0.033*	**0.345**
PE	0.015	-
PV	0.000	-
SI	0.003	-

4.2.6 Total Effects

The assessment of the total effects is of great interest for our research model since we can use it to investigate the influence of CBN on the target constructs BI und USE via the seven mediators. The values for the total effects and the corresponding p-values are shown in Table 6. The rows in bold represent the two effects that are composed of the primary effect and indirect effect via mediators. All other relationships are not mediated (e.g. CBN -> EE is a direct effect without any construct in between).

Table 6. Total effects of the structural model including the CBN construct

	Original Sample (O)	Sample Mean (M)	Std. Dev.	T Statistics (|O/STDEV|)	P-Values
CBN -> BI	**0.299**	**0.302**	**0.039**	**7.695**	**0.000**
CBN -> EE	0.327	0.330	0.049	6.652	0.000
CBN -> FC	0.334	0.337	0.050	6.702	0.000
CBN -> HM	0.342	0.345	0.050	6.852	0.000
CBN -> HT	0.123	0.125	0.051	2.400	0.016
CBN -> PE	0.175	0.175	0.047	3.745	0.000
CBN -> PV	0.252	0.253	0.052	4.831	0.000
CBN -> SI	0.136	0.136	0.051	2.669	0.008
CBN -> USE	**0.132**	**0.133**	**0.029**	**4.480**	**0.000**

4.3 PLS Multigroup Analysis of Gender

The analysis of the demographic distribution shows that approximately 60% of the participants are female. This imbalance in the sample makes it necessary to control for differences between the two groups. To achieve this, we employ the PLS multigroup analysis (PLS-MGA) (Henseler, Ringle, & Sinkovics, 2009). This procedure compares the results of the PLS-SEM analysis for females with that of males with regard to different path coefficients and checks whether those differences are statistically significant. As in Section 4, we choose the path weighting scheme with the recommended maximum of 300 iterations, a stopping criterion of 10^{-7} for the PLS calculations (Hair et al. 2017, p. 91) and 5000 as the number of bootstrap subsamples and no sign changes as the method for handling sign changes during the iterations of the bootstrapping procedure. For PLS-MGA, the differences of path coefficients between the two groups are statistically significant if the p-value is below 0.05 or above 0.95 (Hair et al., 2017). All significant differences are in bold font. The asterisks at the path coefficients indicate whether the different effects for the two subsamples are statistically significant at the 5% level (*), 1% level (**) or 0.1% level (***). The results are shown in Table 7. The results indicate that gender differences only exist for four relationships of the model. The effect of CBN on PE and on PV is significantly stronger for male players. The same holds for the effect of PV on BI. In contrast to these three relationships, the effect of HT on USE is stronger for females. Besides that, gender differences are not an issue in our research model.

Table 7. Results of the PLS multigroup analysis for gender

	Gender Differences			
Test Statistics / Relations	Path Coefficient (Female)	Path Coefficient (Male)	Path Coefficients-differences (| Female - Male |)	p-Value (Female vs Male)
BI -> USE	0.305***	0.305**	0.000	0.511
CBN -> EE	0.290***	0.384***	0.094	0.823
CBN -> FC	0.320***	0.358***	0.038	0.647
CBN -> HM	0.316***	0.381***	0.065	0.740
CBN -> HT	0.096	0.177*	0.081	0.777
CBN -> PE	0.117	0.276***	0.159	0.957
CBN -> PV	0.176**	0.372***	0.196	0.972
CBN -> SI	0.076	0.237**	0.161	0.946
EE -> BI	0.243***	0.203*	0.040	0.354
FC -> BI	0.187**	0.125	0.062	0.317
FC -> USE	0.034	-0.046	0.080	0.246
HM -> BI	0.397***	0.322***	0.075	0.237
HT -> BI	0.174**	0.107	0.067	0.248
HT -> USE	0.400***	0.200**	0.200	0.016
PE -> BI	0.103	0.128	0.025	0.612
PV -> BI	-0.060	0.133*	0.193	0.991
SI -> BI	0.019	0.035	0.016	0.585

5. Discussion

5.1 Interpretation of the Results

Figure 3 illustrates the results of the path estimations and the R^2 values. In combination with the insights of the total effects analysis, it is possible to interpret the results and assess the hypotheses. A summary of the research findings is illustrated in Table 8. Hypotheses 1 to 7 adapted from the original UTAUT2 for the case of Pokémon Go can be partly supported. Hypothesis 1a and hypothesis 1b can be confirmed. However, HT is the strongest driver of USE compared to the exogenous variables BI and FC. This is in contrast to the results of the original UTAUT2 setting (Venkatesh et al., 2012). A possible explanation is that users of Pokémon Go perceive the recurring and potentially addictive nature of the game as very intense, which strongly influences their *intention* and *actual use* of the game. This is in line with research from Xu (2014), who determines factors for continued use intention in online games and finds that habit is the second important driver of continuance intention. Earlier results from Gefen (2003) suggest that habit can also be an important driver if the continued use of an IT product among experienced users is investigated. A possible theoretical reason for this is that once a behaviour becomes a habit, it becomes automatic (Ouellette & Wood, 1998) and the intention to continue playing or to play again is not a conscious but automated decision without a preceding cognitive process (Aarts, Verplanken, & van Knippenberg, 1998). This idea was further developed and established as the habit/automaticity perspective (HAP) (Aarts & Dijksterhuis, 2000) and is in contrast to the instant activation perspective (IAP) (Ajzen & Fishbein, 2000), which considers automatic use as an expedited form of conscious use. However, in a comparison Kim, Malhotra, & Narasimhan (2005) find that heavier users become less evaluative and less intentional, supporting the argument that automaticity is stronger driven by habit.

The implication is that it might be beneficial to design technologies in a way that they can be easily integrated in the daily life of the user. This integration is intensified because of the important role of smartphones as an integral part of people's daily lives. As in previous research on hedonic information systems (van der Heijden, 2004), the effect of the utilitarian construct (PE) is relatively small compared to the effect of the *hedonic motivation* (HM), which is the strongest predictor of BI in our model. In addition, the effect of *performance expectancy* is twice the size of the effect of *effort expectancy* on *behavioural intention*.

Interestingly, hypothesis 4 cannot be supported. Thus, the opinion of others plays no role on the *behavioural intention* to play the game. This result is comparable to findings of previous research on Pokémon Go. For example, social norms - a construct highly related to SI - are also found to exert no statistically significant effect on the intention to reuse Pokémon Go (Rauschnabel et al., 2017). In an ethnographic study, Tokgöz and Polat (2018) argue that sociability stimulates the players to stay in the game and lack of it results in a monotone gaming experience causing the players to quit. They also find that a significant part of Turkish players quit the game after two or three months. Considering the gameplay of Pokémon Go where players cannot chat within the game and the collective play is rather limited, a lack of sociability within the game might result in a lower impact of SI. As mentioned in Section 3.1, several other opposing effects are also imaginable, which could influence the impact of SI on BI. Based on the data at hand, we cannot disentangle these effects and leave this highly interesting issue open for future work. A starting point could be a closer comparison with Ingress based on the observation from Tokgöz and Polat (2018) that sociability is integrated in Ingress' core game design.

Hypothesis 6 on the effect of *price value* on *behavioural intention* is also not supported by the results. A possible explanation is that this relatively old construct is not suitable for capturing the perceived price value for new pricing models, like the one used by Pokémon Go. Users do not face the same cognitive trade-off for the in-app purchases of Pokémon Go with its freemium pricing model compared to other consumer technologies with a fixed price, payable upfront. Therefore, a better perceived value possibly has no effect on the *behavioural intention* when there are no initial costs involved.

As hypothesized, the *facilitating conditions* of Pokémon Go have an effect on the users' *behavioural intention*. However, this is not the case for USE. Thus, hypothesis 7b must be rejected. This result is in contrast to the original results of UTAUT2 for the direct model calculation (without moderators) (Venkatesh et al., 2012). Nevertheless, *facilitating conditions* are assumed to become more important and relevant for older users of technologies. Thus, the effect of *facilitating conditions* could be not relevant, since we restricted our sample to a maximum age of 35 years. This user group might not depend as heavily on helpful resources and tips as older players. Additionally, Venkatesh et al. (2012) point out that users with more experience depend less on external support and given that Pokémon Go is considered to have an easy learning curve, this might hold for medium experienced users also.

Hypotheses 8 to 14 are all supported by our data analysis. Thus, *childhood brand nostalgia* has a statistically significant and relevant effect on all beliefs of the technology acceptance model. The effect sizes indicate that the strongest effects exist between *childhood brand nostalgia* and *effort expectancy*, *hedonic motivation* and *facilitating conditions*. Considering our abstract research model (Figure 1), our findings suggest that all effects of *childhood brand nostalgia* on *behavioural intention* are fully mediated by the beliefs. This result suggests that users' nostalgic feelings towards

Pokémon influence beliefs about technological characteristics positively. This, in turn, impacts the *behavioural intention* to play the game. Thus, our research contributes to the understanding of the recently developed construct *childhood brand nostalgia* and its role for the technology acceptance factors of hedonic information systems.

Table 8. Summary of research findings

Hypothesis	Hypothesis Statement	Support for Hypothesis
H1a	HT has a positive effect on BI	Yes
H1b	HT has a positive effect on USE	Yes
H2	PE has a positive effect on BI	Yes
H3	EE has a positive effect on BI	Yes
H4	SI has a positive effect on BI	No
H5	HM has a positive effect on BI	Yes
H6	PV has a positive effect on BI	No
H7a	FC have a positive effect on BI	Yes
H7b	FC have a positive effect on USE	No
H8	CBN has a positive effect on HT	Yes
H9	CBN has a positive effect on PE	Yes
H10	CBN has a positive effect on EE	Yes
H11	CBN has a positive effect on SI	Yes
H12	CBN has a positive effect on HM	Yes
H13	CBN has a positive effect on PV	Yes
H14	CBN has a positive effect on FC	Yes

5.2 Limitations

The limitations of our work relate primarily to the demographic distribution and the questionnaire translation. Although our sample is relatively large with a sample size of 418 participants, and diverse with regard to demographic characteristics, it is skewed with respect to the gender distribution, as our sample contains significantly more females than the general population. Thus, it is not fully representative for the German population. In addition, we do not know to what extent our sample is representative for the German population of Pokémon Go players in general. To the best of our knowledge, there are no reliable information with respect to this demographic distribution. Second, translating the constructs into German might cause differences in users' understanding of the constructs compared to the original English constructs. This threat cannot be ruled out when original constructs are adapted from a language to another one, even if the translation follows a careful process like the one we used. Third, our study only focused on active players of the game. In a next step, it would be beneficial to compare our results with the perceptions of non-players. Fourth, results can differ between countries and cultures. Since our sample contains only German players of Pokémon Go, the results can possibly differ from surveys conducted in other countries or cultural regions.

Lastly, quantitative studies based on self-reports in online questionnaires can potentially be biased due to misunderstandings of questionnaire items or wrong answers given by the participants. This could be caused by several different issues, like the social desirability bias or a specific mood in which participants are during filling out the survey.

5.3 Future Work

Since this is the first paper that investigates nostalgic feelings in the technology acceptance framework, future research is called to replicate our research approach and adapt it to other modifications of technology acceptance and use models. We argue that it would be beneficial to replicate this research not only with the same research object, i.e. Pokémon Go, but also with other relaunched smartphone applications which could potentially cause nostalgic feelings (e.g. Snake (dsd 164 Developer, 2014)). Testing whether *childhood brand nostalgia* measures what it is supposed to measure is also relevant for future studies. As an example, future work could replicate the research model with the research object Ingress instead of Pokémon Go. Since there is no comparable brand, franchise or predecessor for Ingress, it could be assessed whether

CBN really measures positive past memories and experiences. In such a setting, we would expect that CBN has no significant and relevant influence on any of the other variables in the model. In addition, gender differences with respect to nostalgic feelings could be investigated. The PLS-MGA shows that the effect of *childhood brand nostalgia* is partly stronger for males in our sample. This result provides an interesting opportunity for future research to aim for a deeper understanding of these differences. Theoretically, construct items can be formulated in different ways. For example, all constructs in this research are formulated rather positively. Thus, if participants tend to agree more, the effect on *behavioural intention* will be positive, i.e. their intention to play the game increases. On the other hand, constructs can operationalize a negative concept, e.g. privacy concerns (Smith, Milberg, & Burke, 1996). Here, items are formulated in such a way that participants who tend to agree more are more concerned, and therefore, a negative effect on *behavioural intention* will be noticed. Since we argue in Section 3.1 that nostalgic feelings reframe beliefs in a positive manner, the effect of positively formulated constructs should be reinforced and the effect of negatively formulated constructs should be weakened. The overall effect of *childhood brand nostalgia* would be the same with regard to *behavioural intention*. Nostalgic feelings would make people reframe positive beliefs more positively and negative beliefs less negatively and thus enhance the *behavioural intention*. Since all beliefs about technology in this research are positively directed, we could not test the above outlined hypothesis. Therefore, future research on nostalgic feelings should specifically consider it when including constructs about concerns or risks (see Rauschnabel et al. (2017) for an example of physical and privacy risks associated with Pokémon Go).

Another direction for future work is the assessment of *hedonic motivation*. It exerts by far the strongest effect on BI. The importance of intrinsic motivation is not only apparent in hedonic information systems like smartphone games. New approaches to motivate users to interact with information systems, like gamification, are experiencing an increasing relevance in different fields of life that are traditionally utilitarian (Fitz-Walter, Johnson, Wyeth, Tjondronegoro, & Scott-Parker, 2017; Hamari, 2017; Landers & Armstrong, 2017; Mekler, Brühlmann, Tuch, & Opwis, 2017; Schöbel, Söllner, & Leimeister, 2016; Wu & Chien, 2015). Therefore, it is highly interesting to investigate what specific components of a technology activate and lever the hedonic motivation of users and lead to the strong predictive relevance of HM on BI. This could be highly relevant for game designers and general application developers who utilize gamification approaches. Furthermore, our research on Pokémon Go could be conducted in other countries with different cultural norms and values. This could potentially yield different interesting results that further enhance our understanding of nostalgic feelings and its role in technology acceptance models, as well as of users' behaviour with respect to augmented reality technologies.

6. Conclusion

By adapting the UTAUT2 model by Venkatesh et al. (2012), we investigated the role of *childhood brand nostalgia* (CBN) in the acceptance of the augmented reality (AR) smartphone game Pokémon Go. CBN is a recently developed construct by Shields and Johnson (2016), who operationalize the concept for the first time in the literature. To assess the role of this mostly unexplored construct, we conducted an online study with active Pokémon Go players in Germany. Based on a sample of 418 players aged 18 to 35, we evaluated the model with a PLS-SEM approach. The strongest predictor of *behavioural intention* (BI) is *hedonic motivation* (HM), i.e. fun and pleasure derived from playing the game. The strongest predictor of *actual use* (USE) is the perceived regular use, i.e. the *habit* (HT) of playing the game and the *behavioural intention* (BI).

Our results indicate that our proposed abstract research model can be confirmed, namely that the effect of *childhood brand nostalgia* (CBN) is fully mediated by the beliefs (*habit, performance expectancy, effort expectancy, social influence, hedonic motivation, price value and facilitating conditions*).

In summary, our work provides several theoretical contributions. First, by conducting a literature review in the Information Technology research discipline, we show that nostalgia is a rather unexplored research topic. Based on these insights, we contribute to the literature by deriving a research model for including *childhood brand nostalgia* into technology acceptance and use theories (cf. Figure 1).

Consequently, we contribute to the understanding of acceptance factors of mobile AR technologies and the success of the smartphone game Pokémon Go by conducting a user study and using our abstract research model to frame the UTAUT2 model for the case of Pokémon Go and include *childhood brand nostalgia*. This is especially relevant since there is a lack of user studies on AR in the IS literature, as well as in related fields (Dey, Billinghurst, Lindeman, & Swan II, 2016; Harborth, 2017, 2019; Harborth, Hatamian, Tesfay, & Rannenberg, 2019; Swan II & Gabbard, 2005). In contrast to other studies, we built our research on technology acceptance theories for investigating Pokémon Go, thereby contributing to a deeper understanding of relevant concepts for Pokémon Go (e.g. Harborth & Pape, 2017; Kaczmarek et al., 2017; Rasche, Schlomann, & Mertens, 2017; Rauschnabel et al., 2017; Yang & Liu, 2017; Zsila et al., 2017).

The practical contributions are twofold. First, we could show that *childhood brand nostalgia* is a positive driver of beliefs about technologies, which in turn positively influence the *behavioural intention* to adopt and play the game. The causal chain indicates that re-using known brands and old franchises for developing new technologies can increase the probability of success for specific age groups, as respective users face positive nostalgic feelings which alter the beliefs about the technologies positively. This result has important implications for future technology design and marketing strategies. Second, since AR is gaining importance in the business and private context (Castellanos, 2016; Leswing, 2016), it is important for researchers to follow up on the developments and assess the perceptions, as well as the behaviour of the respective users with the AR technologies, in order to derive valuable insights for future AR development. We hope that this research demonstrates the importance of nostalgic feelings in the context of technology acceptance and will consequently stimulate further research in this domain.

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Appendices

Appendix A. Questionnaire

Table 9. Questionnaire Composition

Construct	Items	Source
Childhood Brand Nostalgia (CBN)	Please answer the following questions about Pokémon. CBN1. I have fond memories of this brand from my childhood. CBN2. This brand features in happy memories of when I was younger. CBN3. I still feel positive about this brand today because it reminds me of my childhood. CBN4. This brand is one of my favourite brands from my childhood.	CBN is adapted to the context of Pokémon Go from the paper by Shields & Johnson (2016a). Items are measured with a seven-point Likert scale, ranging from "strongly disagree" to "strongly agree".
Habit (HT)	HT1. Playing Pokémon a habit for me.	

Construct	Items	Source
	HT2. I am addicted to p l Go. HT3. I must play Po G . HT4. Playing Pokémon natural to me.	Constructs are adapted to the context of Pokémon Go from the paper by Venkatesh et al. (2012). Items are measured with a seven-point Likert scale, ranging from "strongly disagree" to "strongly agree". *The fourth item of the PE constructs is deleted due to missing content fit with regard to productivity and mobile games.
Performance Expectancy (PE)	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 G o productivity.*	
Effort Expectancy (EE)	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 (SI)	SI1. People who are i m think that I should . SI2. People who influe nc think that I should . SI3. People whose opini on prefer that I pl a .	
Hedonic Motivation (HM)	HM1. Playing Pokémon Go is fun. HM2. Playing Pokémon Go is enjoyable. HM3. Playing Pokémon Go is very entertaining.	
Price Value (PV)	PV1. Pokémon Go is reasonably priced. PV2. Pokémon Go is a g the money. PV3. At the curr e , Pokémo n provides a good value.	
Facilitating Conditions (FC)	FC1. I have the resources ne c play Poke . FC2. I have the knowled g play Poke . FC3. Pokémon Go is c om other technologies and applications I use. FC4. I can get help fro m have difficulties p la .	
Behavioural Intention (BI)	BI1. I intend to continue playing Pokémon Go in the future.	

Construct	Items	Source
	BI2. I will always try to play Pokémon Go in my daily life. BI3. I plan to continue to play Pokémon Go frequently.	
Use Behaviour (USE)	Please choose your u sa on Pokém : 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 Rosen et al. (2013).
Age is measured starting at age 18. Gender is coded as a binary with 1 for females and 0 for males.		

Appendix B. HTMT Confidence Intervals

Table 10. Confidence intervals for HTMT

	Original Sample (O)	Sample Mean (M)	Bias	2.5%	97.5%
CBN -> BI	0.382	0.384	0.001	0.264	0.489
EE -> BI	0.570	0.570	0.000	0.470	0.651
EE -> CBN	0.349	0.351	0.002	0.241	0.447
FC -> BI	0.627	0.627	-0.001	0.509	0.729
FC -> CBN	0.392	0.393	0.001	0.272	0.501
FC -> EE	0.707	0.708	0.001	0.615	0.783
HM -> BI	0.673	0.673	0.001	0.589	0.738
HM -> CBN	0.364	0.366	0.002	0.256	0.462
HM -> EE	0.537	0.538	0.001	0.411	0.648
HM -> FC	0.555	0.557	0.002	0.415	0.674
HT -> BI	0.366	0.367	0.001	0.269	0.472
HT -> CBN	0.118	0.131	0.013	0.057	0.203
HT -> EE	0.174	0.178	0.004	0.125	0.219
HT -> FC	0.210	0.218	0.009	0.135	0.292
HT -> HM	0.204	0.217	0.013	0.144	0.285
PE -> BI	0.315	0.315	0.000	0.216	0.407
PE -> CBN	0.182	0.181	0.000	0.080	0.275
PE -> EE	0.073	0.086	0.012	0.036	0.143

PE -> FC	0.202	0.220	0.018	0.121	0.259
PE -> HM	0.181	0.182	0.001	0.083	0.271
PE -> HT	0.648	0.647	-0.001	0.565	0.724
PV -> BI	0.393	0.394	0.001	0.285	0.488
PV -> CBN	0.278	0.277	0.000	0.165	0.389
PV -> EE	0.395	0.397	0.002	0.287	0.493
PV -> FC	0.403	0.403	0.001	0.301	0.499
PV -> HM	0.441	0.442	0.000	0.352	0.527
PV -> HT	0.223	0.227	0.005	0.129	0.328
PV -> PE	0.257	0.258	0.002	0.170	0.344
SI -> BI	0.220	0.220	0.000	0.120	0.315
SI -> CBN	0.143	0.143	0.000	0.044	0.244
SI -> EE	0.045	0.064	0.020	0.015	0.078
SI -> FC	0.194	0.215	0.021	0.110	0.248
SI -> HM	0.132	0.132	0.000	0.037	0.225
SI -> HT	0.424	0.422	-0.002	0.309	0.526
SI -> PE	0.546	0.545	-0.001	0.452	0.626
SI -> PV	0.165	0.170	0.004	0.080	0.267
USE -> BI	0.451	0.451	0.000	0.344	0.538
USE -> CBN	0.062	0.073	0.011	0.013	0.161
USE -> EE	0.247	0.247	0.000	0.129	0.351
USE -> FC	0.216	0.223	0.007	0.109	0.326
USE -> HM	0.251	0.251	0.000	0.123	0.365
USE -> HT	0.441	0.440	0.000	0.341	0.530
USE -> PE	0.209	0.209	0.000	0.104	0.305
USE -> PV	0.157	0.159	0.003	0.064	0.256
USE -> SI	0.115	0.116	0.000	0.022	0.214