



Article

Empirically Investigating Extraneous Influences on the “APCO” Model—Childhood Brand Nostalgia and the Positivity Bias

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Abstract: Pokémon Go is one of the most successful mobile games of all time. Millions played and still play this mobile augmented reality (AR) application, although severe privacy issues are pervasive in the app due to its use of several sensors such as location data and camera. In general, individuals regularly use online services and mobile apps although they might know that the use is associated with high privacy risks. This seemingly contradictory behavior of users is analyzed from a variety of different perspectives in the information systems domain. One of these perspectives evaluates privacy-related decision making processes based on concepts from behavioral economics. We follow this line of work by empirically testing one exemplary extraneous factor within the “enhanced APCO model” (antecedents–privacy concerns–outcome). Specific empirical tests on such biases are rare in the literature which is why we propose and empirically analyze the extraneous influence of a positivity bias. In our case, we hypothesize that the bias is induced by childhood brand nostalgia towards the Pokémon franchise. We analyze our proposition in the context of an online survey with 418 active players of the game. Our results indicate that childhood brand nostalgia influences the privacy calculus by exerting a large effect on the benefits within the trade-off and, therefore, causing a higher use frequency. Our work shows two important implications. First, the behavioral economics perspective on privacy provides additional insights relative to previous research. However, the effects of several other biases and heuristics have to be tested in future work. Second, relying on nostalgia represents an important, but also double-edged, instrument for practitioners to market new services and applications.

Keywords: APCO; nostalgia; positivity bias; privacy concerns; bounded rationality; mobile augmented reality applications; Pokémon Go

1. Introduction

The privacy calculus states that individuals engage in deliberate trade-offs between benefits (e.g., using a technology or disclosing information) and costs (e.g., privacy risks) when making privacy-related decisions [1]. However, recent research suggests that the deliberate privacy-related decision making process is influenced by irrational factors like heuristics or biases [2].

Empirical studies indicate that consumers respond positively to known brands [3] because individuals’ earliest experiences have an important influence on current and future preferences across the consumer life cycle [4]. Furthermore, prior research indicates that nostalgia positively influences technology acceptance of nostalgic games such as Pokémon Go [5]. Thus, this study proposes that nostalgic feelings from a user’s childhood may positively bias her or his rationale in the privacy calculus and alleviate possible privacy concerns while increasing perceived benefits

of the technology: The user's view on the privacy calculus is through the rose-colored glasses (Merriam-Webster defines the expression 'rose-colored glasses' as having "favorably disposed opinions [of something or somebody]" [6].) of nostalgia. By introducing and empirically testing this example of a positivity bias, this work partially tests the proposed "enhanced APCO" (antecedents–privacy concerns–outcome) model [2] as a first step towards understanding extraneous factors in privacy-related decision-making processes.

For evaluating the role of this extraneous factor, an online survey with active players of the smartphone game Pokémon Go is conducted. Pokémon Go is a mobile augmented reality (MAR) game developed by Niantic for mobile devices. It is based on the Pokémon franchise, especially the video games from Nintendo which first appeared in the 90s. Pokémon Go is used as a case for testing the proposition since the Pokémon brand is very strong and well known among people. Besides specific privacy concerns associated with Pokémon Go [7,8], research indicates that there are major privacy issues with MAR apps in general [9,10] and that individuals are concerned about their privacy when using AR [11–13]. We gathered 418 complete questionnaires from active players of the game in an online survey. The players are between 18 and 35 years old to evaluate the research model. The data set is restricted like this as players older than 35 years cannot be influenced by childhood brand nostalgia for Pokémon.

Privacy concerns are considered as the central construct of the study whereas the operationalization *Concerns for Information Privacy (CFIP)* [14] as a second-order construct [15] is used. It is one of the most reliable scales for measuring individuals' concerns towards organizational privacy practices [16]. Based on this construct, this research develops an enhanced APCO model [2] to address the following research question:

What influence has a positivity bias induced by childhood brand nostalgia for Pokémon on the privacy calculus of individuals related to the use behavior of Pokémon Go?

Specific privacy concerns towards a company are not used as an operationalisation since the questioned individuals might not associate the companies with the respective application in focus. In this case, the game Pokémon Go was developed by *Niantic* (in collaboration with *Nintendo* via *The Pokémon Company*) while the brand Pokémon was earlier closer connected to Nintendo. Thus, it would have been necessary to control for the knowledge about *Niantic*, *Nintendo* as well as other possible entities the participants saw in the role of handling their data.

This work contributes to the literature by proposing and empirically analyzing childhood brand nostalgia as a positivity bias which influences users privacy-related decision making towards using technologies and neglecting privacy issues.

The remainder of the paper is as follows: Section 2 describes the literature review on the antecedents of CFIP as well as a brief overview of nostalgia. Research hypotheses, research model and the data collection process are discussed in Section 3. An assessment of the reliability and validity of the results follows in Section 4. Section 5 contains the interpretation of the results, limitations and future research opportunities. Section 6 summarizes the contributions.

2. Related Work and Research Model

We discuss all relevant components for empirically testing a possible effect of the positivity bias on the APCO model in this section. First, we briefly present the APCO model with a special focus on the extraneous factors discussed by [2]. We match the authors' theoretical thoughts with our actual model used to test one component of their theory—the positivity bias represented by childhood brand nostalgia. Second, we provide an overview of past literature on the antecedents of our conceptualization of privacy concerns—CFIP. This is crucial since these antecedents are important control variables for isolating the specific effect of childhood brand nostalgia on CFIP. Third, we discuss the concept of nostalgia and the specific conceptualization that we chose for our research study. Furthermore, we outline why nostalgia is a concrete example of a positivity bias.

2.1. Model Development

The authors of [15] test the nomological validity of the second-order CFIP construct for the first time by using a model of antecedents–privacy concerns–outcomes (APCO). They use computer anxiety as an antecedent to test the nomological validity of CFIP. Later research proposes a more general APCO model [16]. The authors mention CFIP as one of the possible operationalizations of the privacy concerns concept in the APCO model. In the APCO model, privacy concerns represent only one part in the decision making process known as the privacy calculus [1]. The privacy calculus represents a deliberate trade-off made by individuals weighing up benefits and costs. However, this deliberate process reflected in the APCO model is questioned by prior work on which we built our empirical analysis [2]. This prior work points out the role of biases for privacy-related decision making processes. There is also related research pointing out that individuals follow their “gut feeling” when it comes to privacy-related decisions in practice [17]. Following these results, the biases in our model might be always existent for players of Pokémon Go. Figure 1 illustrates a simplified version of the enhanced APCO model proposed by [2]. We simplified and adapted the model to show how the positivity bias influences the respective concepts in the APCO model and to map the high level concepts as risks or benefits to the actually used constructs in our analysis.

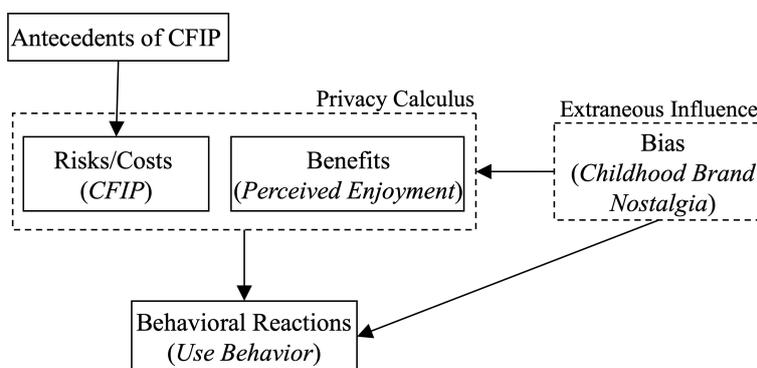


Figure 1. Simplified and adapted representation of the “enhanced APCO” model following Dinev et al., 2015.

The effect of extraneous factors like the positivity bias depends on the level of cognitive effort that an individual puts into the decision-making process [2]. This process is comparable to the relationship and mechanisms of “system 1” and “system 2” [18]. The positivity bias induced by childhood brand nostalgia is assumed to have the largest effect on the privacy calculus and the outcome variable (use behavior) in scenarios where Pokémon Go players put in the lowest levels of effort when deciding to play the game. However, the sample consists of active players of the game who regularly use the game, indicating a relatively low cognitive effort that is put in the decision to play the game. Thus, we argue that childhood brand nostalgia can influence the privacy calculus towards using the game more frequently.

2.2. Antecedents of Cfp in Prior Research

Our systematic literature review can be classified as follows [19]. It focuses on research outcomes in order to identify relevant constructs impacting privacy concerns. The goal is to integrate these findings since we compare past results to our empirical findings at a later stage in our article. We conducted a forward search based on the article by [15] since they were the first ones using CFIP as a second-order construct in an APCO model. We only consider papers evaluating antecedents of privacy concerns in the forward search. Afterwards, we checked for duplicates due to the search in multiple databases. We then excluded papers if they were not in English or not peer-reviewed. We searched in the following databases (number of found forward citations): Google Scholar (593), INFORMS PubsOnline (203), Web of Science (166), ACM Digital Library (91), CiteSeerX (83), and Business Source

Premier (69). Four hundred and sixty-two papers remained to be analyzed after the cleanup. We briefly discuss the most relevant antecedents which are also included in our research model (Figure 2).

Inconclusive effects of demographics on privacy concerns: The influence of age on privacy concerns is inconclusive. There is research finding no effect of age on privacy concerns [20,21] as well as research identifying age as a significant factor for explaining privacy concerns [16,22–26]. There is also disagreement on whether the effect of age on privacy concerns is positive or negative. Our review suggests a positive effect, i.e., older people are more concerned about their privacy. Gender is one of the most evaluated antecedents of privacy concerns. As for age, the results are inconclusive with respect to the question of whether there is an effect at all as well as whether women [26,27] or men [24] are more concerned. Education is assumed to have a statistically significant effect on privacy concerns. However, the effect sign of education is either negative [23] or positive [24]. Smartphone experience is not widely employed as an antecedent. Yet, we found the similar antecedent *internet experience* and prior research indicates that a higher level alleviates privacy concerns [21,28,29]. Contradicting research observes no statistically significant effect [23].

Risk aversion leads to higher privacy concerns: The construct *risk propensity* [30] used in our model is comparable to *risk taking* [31], which is evaluated in one article within the context of multiple personality characteristics. Among others, the authors find that risk taking is shown to have a negative and significant effect on privacy concerns. At this point, it is relevant to note that risk taking is defined in the opposite way compared to risk propensity. Thus, we would hypothesize a positive relationship between risk propensity and privacy concerns, i.e., the more risk-averse a person is, the more privacy concerns she/he has.

Negative privacy experiences cause higher privacy concerns: Privacy experiences are reflected in our model by the construct *privacy victim experience* [32]. This concept is one of the most evaluated privacy-related antecedents. It questions whether the respondents were ever privacy victims, and how often those incidents happened. Most findings suggest that prior privacy experiences have a positive and significant effect on privacy concerns [16,27,33–37].

2.3. Nostalgia Induces a Positivity Bias

Nostalgia as an object of scientific investigations mainly originates from the field of psychology [38,39] and marketing [40,41]. During the course of the last century, the meaning of nostalgia changed from being seen as a negative individual affliction to a positive one. The notion of nostalgia shifted through the course of the last century from a negatively associated affliction to a concept associated with positive emotions [38–40]. Literature states that nostalgic emotions are triggered by personal experiences in the past which usually include an “important social element” ([39], p. 976). This means that social relationships with other important persons are highly influential for creating nostalgia. In addition, prior literature suggests that not only persons can induce nostalgia but also certain events or relevant locations [39]. Furthermore, consumption decisions can be affected by nostalgia [42]. The appearance of “retro games” such as Snake or Pinball on mobile devices suggests that nostalgic feelings can also be induced through certain game designs. Thus, it is possible that Pokémon Go players associate nostalgic feelings with the brand Pokémon. After its release in Germany in 1999, the different forms of Pokémon (e.g., Gameboy, card games or TV series) were mainly experienced by children [43]. Therefore, when choosing a fitting operationalization of nostalgia, we need to account for the fact that it can represent a franchise or brand and that the individuals were children at the time of creating nostalgic feelings. Thus, we adapt the “childhood brand nostalgia” (CBN) construct [41] for operationalizing nostalgia. This construct satisfies the criteria outlined before and the respective literature shows its validity and reliability. To the best of our knowledge, a comparable construct does not exist in the literature. CBN is defined 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” ([41], p. 362).

For our object of study, Pokémon Go, we argue that nostalgia stemming from users’ childhood about the brand Pokémon induces a strong positivity bias (“rose-colored glasses”) which alleviates negative factors and emotions and heightens positive ones. The authors of [2] define the positivity bias in the context of privacy as follows: “[...] one can expect positivity bias to impact privacy concerns. Consider, for example, that a person might, on one hand, claim that ‘Internet companies do not care about my privacy, and I hate to disclose information’ but, at the same time, frequently disclose information on Facebook and Twitter” (p. 648). Following the same logic, we argue that although individuals might have serious privacy concerns about the processing of their personal information by online companies, they do not connect these risks with the company (Niantic) which runs Pokémon Go. Thus, individuals are more prone to disclose potentially highly sensitive information to this game (e.g., objects in their personal environments when using the augmented reality feature of the game, location data, etc.).

3. Methodology

This section contains the hypotheses development and the subsequent research model used to analyze our research question. Furthermore, we provide details on our survey instrument and the data collection.

3.1. Research Hypotheses and Model

It is worth mentioning that privacy concerns are in general measured at an individual level. However, not all antecedents which we found in the literature survey are measured at the individual level. Some (e.g., culture/climate) are at the organizational or national level [16]. For our selection of the antecedents, we focused on those on an individual level. We develop our research hypotheses in this section. The resulting research model is shown in Figure 2.

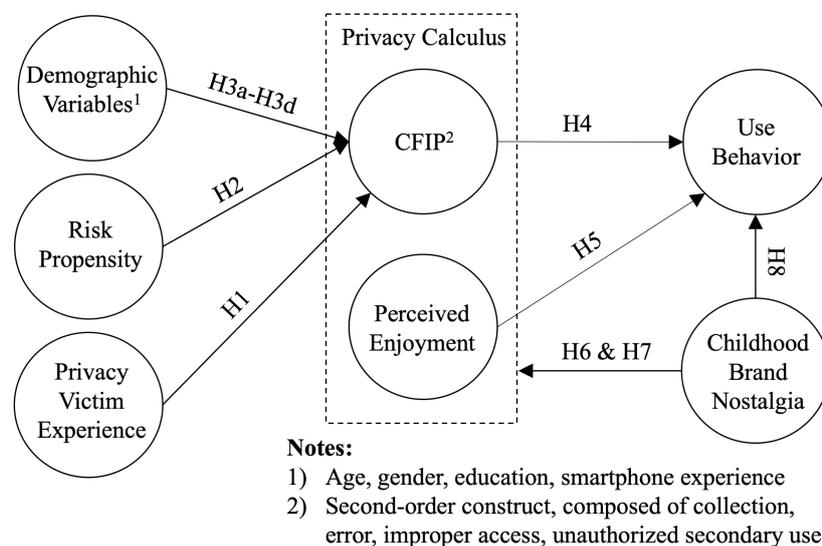


Figure 2. Research model.

Literature on the effect of prior privacy experiences is unanimous. Privacy is in general a very abstract issue which can lead to an indifference of individuals related to the issue. This is reflected in the quote “I’ve got nothing to hide” [44]. However, if individuals experienced privacy breaches in their past, they know about the possible risks and are more concerned about their privacy [32]:

1. Prior privacy victim experiences (VIC) have a positive effect on CFIP.

A higher the level of risk propensity indicates a higher risk-aversion. Thus, the more risk-averse individuals are, the more concerned they are supposed to be about their privacy. This hypothesis is supported by our finding in the literature review [31]:

2. *Risk propensity (RP) has a positive effect on CFIP.*

The results for the effects of the demographic antecedents on CFIP are inconclusive. Past literature indicates that older individuals are more concerned about their privacy than younger ones [26]. We hypothesize that this relation also applies to the case of smartphone games like Pokémon Go. With respect to gender, we follow the rationale in the literature that females are possibly more cautious regarding privacy issues [26,27]. Furthermore, we argue that more educated players of Pokémon Go are more aware about possible organizational practices with respect to their data and more able to understand associated privacy risks which leads to increasing concerns. Thus, we are in line with the literature indicating a positive effect of education on privacy concerns [24]. As elaborated in Section 2, smartphone experience is not investigated yet to the best of our knowledge. The concept of internet experience from the literature is primarily related to personal computers. We argue that the two antecedents are not comparable with respect to the possibility of defending oneself against attacks. For example, it is nearly impossible to prevent third-party tracking of smartphone applications. However, users with more experience are supposed to have witnessed more privacy-related breaches and attacks on smartphones. Thus, we argue that more years of smartphone experience increase the concerns for information privacy. In summary, we hypothesize:

3. (a) *Age has a positive effect on CFIP.*
- (b) *Female players of Pokémon Go show higher levels of CFIP.*
- (c) *Education has a positive effect on CFIP.*
- (d) *Smartphone experience has a positive effect on CFIP.*

Literature on CFIP as an independent variable influencing outcomes variables like behavioral intention to use a technology, actual use behavior or willingness to disclose is conclusive with respect to the assumed negative effect. Individuals' privacy concerns are supposed to have a negative effect on the outcome variable, partially mediated by other variables like trust [16]. In our case, the outcome variable (USE) is directly influenced by CFIP. It is important to notice that we also asked for the behavioral intention of playing Pokémon Go, but chose to develop our model with actual use behavior as outcome variable. This decision was made due to findings from the literature indicating that the link between intention and use is not always given in the context of privacy and security [45]. Thus, we hypothesize:

4. *CFIP have a negative effect on the use behavior of Pokémon Go (USE).*

There is research showing that the link between privacy concerns and behavior is not as straightforward as it seems. Research finds that individuals state that they have high privacy concerns, but do not behave accordingly (e.g., by using an untrustworthy technology or disclosing sensitive personal information on social network sites). This finding is called the privacy paradox [46]. A possible explanation for this paradox was developed by researchers stating that individuals engage in a deliberate trade-off between benefits (of using a technology or disclosing information) and costs (potential privacy risks) when making privacy-related decisions (privacy calculus) [1]. To account for this possibility, we include the notion of the privacy calculus in our model by adding a variable reflecting benefits of playing Pokémon Go. Perceived enjoyment reflects the fun players have when playing the game and prior research in the context of Pokémon Go shows that it has a significant effect on intentions to play the game [47]. We hypothesize:

5. *Perceived enjoyment (PE) has a positive effect on the use behavior of Pokémon Go (USE).*

In summary, we hypothesize that players deliberately weigh up the fun against the privacy risks (operationalized by their stated privacy concerns) when making their use decision. However, recent research suggests that the reliance on this deliberate process reflected in the privacy calculus alone should be questioned [2]. This is due to the fact that we cannot assume individuals to always put in a high level of effort when making daily choices. In contrast, individuals oftentimes rely on a variety of heuristics [48] and peripheral cues [49] which enable them to make thousands of decisions per day in the first place. Prior literature proposes that certain biases can influence the privacy calculus (i.e., the variables representing the benefits and costs) as well as the outcome variable. One type of bias is the so-called “positivity bias” which is the phenomenon “[...] that people tend to evaluate individuals positively and favorably, even in the case of negative evaluations of the group or entity to whom that individual belongs” ([2], p. 648). By applying this idea to technologies and applications, we argue that CBN is such a bias and induces players looking through the ‘rose-colored glasses’ of nostalgia which causes them to be less concerned about their privacy in the context of the survey. This is due to the fact that CFIP deals about organizational privacy practices which individuals link to the used technology or application in focus. In our case, Pokémon Go is by the organization *Niantic*. In addition, this bias increases the fun of players by triggering positive emotions as well as mitigating possible weaknesses. In sum, we expect that the privacy calculus is positively biased by CBN towards playing Pokémon Go and hypothesize:

6. *CBN has a negative effect on CFIP.*
7. *CBN has a positive effect on players’ perceived enjoyment of playing Pokémon Go (PE).*

Lastly, we argue that CBN positively influences USE directly since players with more nostalgic feelings are more dedicated to a game which triggers these memories and emotions. Thus, we hypothesize that:

8. *CBN has a positive effect on the use behavior of Pokémon Go (USE).*

3.2. Questionnaire and Data

The constructs for our research model are adapted from existing research (cf. Appendix A). Since we conducted the study in Germany, the items had to be translated. We first translated the English questionnaire into German with the help of a certified translator (translations are standardized following the DIN EN 15038 norm). A second independent certified translator retranslated the German version back into English to ensure the equivalence of the translation. Finally, five experts compared the two English versions for equivalence. Such an iterative process of translating questionnaire constructs was done in prior studies [50]. Preliminary reliability and validity of the constructs was tested with students of a Master’s course.

Since we investigate the role of CBN as a positivity bias affecting the use of Pokémon Go, we only sampled active players of the game. We conducted the study with a certified sample provider (certified following the ISO 26362 norm) in order to ensure quality of our data. 9338 participants from the online panel started the online survey. 683 participants remained after asking whether they are older than 18 years, play Pokémon Go and after deleting participants who incorrectly answered a test question. Two additional participants were deleted since they stated to “never” play the game. We asked the participants about their current level in Pokémon Go in addition to the test questions. We did this since the game ends at level 40 and we could test the knowledge of the participants about the game. Some participants stated to have a level higher than 40 and we consequently deleted them as well, assuming that they actually do not play the game or did not read the questions carefully. Based on these screen-outs, we only considered participants aged 35 years or younger, as older players are—per definition of the used operationalization of nostalgia—too old to be influenced by childhood brand nostalgia for Pokémon. The final sample used for the data analysis consists of 418 active players (cf. Appendix B, Table A1 for the descriptive statistics).

4. Results

Our research goal is to predict the target construct “use behavior of Pokémon Go”. Thus, we use partial least squares structural equation modeling (PLS-SEM) for our analysis [51]. We tested the model using SmartPLS version 3.2.8 [52]. As computational settings, the path weighting scheme with a maximum of 300 iterations and a stop criterion of 10^{-7} were chosen. Furthermore, 5000 bootstrap subsamples and no sign changes were used as the method for handling sign changes during the iterations of the bootstrapping procedure. Interpreting the results of the structural model requires an analysis of the reliability and validity of the measurement model. We present these tests in the consequent part.

4.1. Assessment of the Measurement Model

For a reflectively measured model as in our case, it is required to assess the internal consistency reliability (ICR), convergent validity and discriminant validity [51]. The values for Cronbach’s α and composite reliability should be between 0.7 and 0.95 for research that builds upon accepted models. Cronbach’s α is seen as a lower bound and results of the composite reliability are seen as an upper bound in the assessment. The values for Cronbach’s α and the composite reliability are all within the suggested range of 0.7 up to 0.95 (cf. Appendix B, Table A2).

Convergent validity (based on the assessment of outer loadings and the AVE) is given since all loadings are higher than 0.7, except for RP2 with a value of 0.692. However, the AVE of this construct is above the suggested threshold of 0.5. Thus, we kept this item. The AVE values of the other constructs are also well above 0.5, demonstrating convergent validity. Discriminant validity is also given since all outer loadings of our analyzed constructs are larger than their cross-loadings with other constructs and the square roots of the AVEs of the single construct are larger than the correlation with the respective other constructs (Fornell-Larcker criterion) (Appendix B, Table A3).

Our data was gathered with a self-reported survey at one point in time in one questionnaire. Thus, a test for the common method bias (CMB) is required. We performed an unrotated principal component factor analysis to conduct the Harman’s single-factor test [53]. It indicates that eight factors have eigenvalues larger than 1 which account for 70.14% of the total variance. The first factor explains 25.12% of the total variance. These values indicate that the CMB is not an issue in our data.

4.2. Assessment of the Structural Model

To assess the structural model, we test for possible collinearity problems (two predictor variables with high correlations) and analyze the path coefficients, as well as the R^2 -level. We evaluate the inner variance inflation factor (VIF) to check for collinearity which would be present if a VIF was above 5. The highest VIF in our model is 1.203, indicating that collinearity is not present. Table 1 shows the results of the path estimates and the R^2 -values of the endogenous variables CFIP, PE and USE. The R^2 -values for all variables are relatively low. This is not surprising since all variables are only influenced by a relatively low number of exogenous constructs. The path coefficients indicate to what extent the construct are correlated or even causally related to each other. Asterisks show statistical significance which ranges from three asterisks for p-values smaller than 0.001 to one asterisk for p-values smaller than 0.05. We will analyze and interpret our findings in the next section.

Table 1. Results of the structural model. Three, two and one asterisks show statistical significance at the 0.1%, 1% and 5% significance level, respectively (VIC: Prior privacy victim experiences, RP: Risk propensity, GDR: Gender, EDU: Education, EXP: Smartphone experience, CBN: Childhood brand nostalgia, CFIP: Concerns for information privacy, PE: Perceived enjoyment, USE: Use behavior).

Independent Var.	Path Coeff.
H1: VIC	0.071
H2: RP	0.182 ***
H3a: AGE	0.094
H3b: GDR	0.106 *
H3c: EDU	−0.020
H3d: EXP	0.105 *
H6: CBN	0.159 **
(a) Dependent Variable: CFIP	
Independent Var.	Path Coeff.
H7: CBN	0.343 ***
(b) Dependent Variable: PE	
Independent Var.	Path Coeff.
H4: CFIP	−0.013
H5: PE	0.254 ***
H8: CBN	−0.024
(c) Dependent Variable: USE	
Dependent Var.	Adj. R ²
CFIP	0.073
PE	0.116
USE	0.053
(d) Adj. R ² Values	

5. Discussion

Our results show differences compared to what we hypothesized based on theory as well as what we found in the literature. We will discuss each hypothesis following the numbering in Figure 2.

Negative privacy experiences do not affect privacy concerns (effect size of 0.071). This finding is in contrast to the majority of findings from the literature (H1 not confirmed). **Risk-aversion of Pokémon Go players increases privacy concerns** (0.182), indicating that risk-averse players tend to be more concerned (H2 confirmed). We find no statistical significant effect for age on CFIP. This might be due to our restricted sample including only players between 18 and 35 years. We ran the model again with the remaining data set consisting only of players older than 35 years (N = 263). We find that age has a statistically significant positive effect on CFIP (0.254), indicating that **age only matters for older players**. Therefore, we cannot confirm H3a, but acknowledge that age might have an effect on CFIP for older players. **Female (0.106) and more experienced (0.105) players have higher concerns** confirming Hypotheses 3b and 3d. In contrast, **education does not affect privacy concerns** (−0.020). This result is not in line with prior literature. Thus, the results regarding the impact of education remain inconclusive and H3c cannot be confirmed.

CFIP plays no role in the privacy calculus for active players Hypotheses 4 and 5, which reflect the privacy calculus towards USE, can only be partially confirmed. Hypothesis 4 cannot be confirmed. This result indicates that privacy concerns with respect to organizational practices do not play a role in the players use decision. One explanation is that players in our sample already decided that they play Pokémon Go (since we only asked active players). Thus, it might be possible that they already ran through the process of weighing up benefits and costs before they decided to download the application. From a research point of view, the limitation of asking only active users of a technology is hard to

address since it is nearly impossible to find users who did not download and play the game due to certain factors. However, this reference group would be needed to address this limitation properly. In contrast to H4, we can confirm the positive effect of perceived enjoyment on USE (H5), indicating that fun is a major driver of use behavior (effect size of 0.254).

Nostalgia positively affects privacy concerns and enjoyment Hypothesis 6 and 7 represent the effect of CBN on the two variables of the privacy calculus (CFIP and PE). Our results indicate that only hypothesis 7 can be confirmed, i.e., CBN towards Pokémon Go positively influences the fun players have when playing the game (effect size of 0.343). Thus, CBN enhances the benefits in the privacy calculus. However, we observe a puzzling result with respect to hypothesis 6. CBN has a positive effect on CFIP (0.159) which is in contrast to our expectations that the positive bias caused by CBN alleviates the privacy concerns. There are four possible explanations for this result. First, it could be the case of an omitted variable bias (unknown important variable influencing CFIP and USE is missing) which could cause this relationship to be significant and positive. Secondly, CBN as a construct is relatively new and not widely tested in other contexts [41]. We could also observe relatively high values for the ICR for our sample, indicating that the four items of CBN are content-wise too similar to each other. Thus, we cannot rule out that this is a possible cause for the result. Thirdly, CFIP is not a context-specific operationalization of privacy concerns. It asks about privacy concerns related to data handling practices of organizations in general. In contrast, CBN is a context-specific construct focused on Pokémon Go. From a logical point of view, it is easier to hypothesize relationships between general constructs like CFIP as an independent variable and context-specific constructs like the actual use behavior of an application as a dependent variable (DV). This is due to the fact that one cannot surely assume that individuals associate the research object named in the context-specific construct with the questions of the general construct (if this is the DV). Therefore, it would have been good to have a context-specific construct for privacy concerns in our study [54]. We discussed this problem in Section 1 when we reasoned why we are using CFIP and that players might mix up the corresponding companies. Thus, the problem could still exist when players mix up companies or do not associate the questions with the correct context even when asking for context-specific privacy concern constructs. Fourthly, we only questioned active players of the game who already made the decision to play the game. Thus, only an additional sample with individuals who do not play the game or specifically decided against it due to privacy concerns could yield the necessary insights to overcome this issue. Lastly, prior results indicate that individuals rely solely on their gut feeling in situations with low cognitive effort. Thus, a trade-off as described in the privacy calculus does not occur. In these situations, factors become relevant for the privacy-related decision-making process which objectively play no role for privacy and even the individuals themselves were unsure why they chose these factors as decisive factors [17]. Thus, CBN might be such an objectively irrelevant factor which still plays an important role for spontaneous (gut feeling) decisions and, therefore, eliminating the deliberate privacy calculus process at all. In sum, although hypothesis 6 cannot be confirmed, we still argue that it is possible that the privacy calculus is positively influenced by the positivity bias generated through nostalgia. Lastly, our results show that **PE mediates the effect of nostalgia on use behavior** (H8 cannot be confirmed). Table 2 shows a summary of all hypotheses of our research model.

Table 2. Summary of the results.

	Hypothesis	Result
H1:	VIC has a positive effect on CFIP	✗
H2:	RP has a positive effect on CFIP	✓
H3a:	Age has a positive effect on CFIP	✗
H3b:	Females are more concerned about their privacy (CFIP)	✓
H3c:	EDU has a positive effect on CFIP	✗
H3d:	EXP has a positive effect on CFIP	✓
H4:	CFIP have a negative effect on the use behavior of Pokémon Go	✗
H5:	PE has a positive effect on the use behavior of Pokémon Go	✓
H6:	CBN has a negative effect on CFIP	✗
H7:	CBN has a positive effect on PE	✓
H8:	CBN has a positive effect on the use behavior of Pokémon Go	✗

5.1. Limitations

Our study has certain limitations. First, 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 even if the translation follows a careful process. Secondly, the results might be biased and possibly do not hold for other countries or cultural regions since the sample only contains German-speaking participants. Thirdly, as mentioned before, our study only focussed on active players of the game. In a next step, it would be beneficial to conduct a similar study with non-players and compare the respective results. Lastly, there are potential self-reporting biases (e.g., social desirability). We addressed this issue by gathering the data fully anonymized.

5.2. Future Work

It would be highly interesting for future research to investigate different nostalgic games with a similar research model in order to evaluate whether Pokémon Go was an outlier or whether such effects can be repeatedly found. Furthermore, research on other concepts from behavioral economics would be beneficial to understand privacy-related decision making in more detail. Based on the discussion of hypotheses 6 and 7, future research should consider not only whether privacy concerns and the related variables are measured on an individual, group or organizational level [16]. Based on our results, it is at least equally important to consider the context in which you ask individuals about privacy. Therefore, theories like contextual integrity [55] could serve as a good starting point to develop a research model that is able to provide deeper insights to address our second research question. In line with this, it would have been valuable to have a context-specific construct for privacy concerns with respect to Pokémon Go in our study. However, it is very difficult to know whether entities are associated by individuals with the respective application or technology. Therefore, this problem presents a challenging task but could reveal more insights in the decision making process of individuals.

6. Contributions

In summary, this work contributes to the literature in two ways. First, it adds empirical evidence on the relationships between six selected antecedents of privacy concerns known from the literature in the context of mobile games.

Second, the research provides empirical evidence for a bias (nostalgia) which is able to impact the deliberate decision-making process reflected in the privacy calculus [2]. Mobile and non-mobile applications, especially games, which build on old franchises or did exist years before and are now revived (retro games), are currently succeeding in the market. This shows the importance of the chosen concept, nostalgia, as a potential bias. The results indicate that childhood nostalgia towards Pokémon Go triggers users to wear some kind of ‘rose-colored glasses’ in a way that the privacy calculus is positively influenced towards a more frequent use behavior.

Author Contributions: Conceptualization, D.H. and S.P.; methodology, D.H. and S.P.; validation, D.H.; investigation, D.H. and S.P.; data curation, D.H.; writing—original draft preparation, D.H. and S.P.; writing—review and editing, D.H. and S.P. All authors have read and agreed to the published version of the manuscript.

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Appendix A. Questionnaire

All items are measured with a seven-point Likert scale (“strongly disagree” to “strongly agree”), if not stated otherwise.

Childhood Brand Nostalgia (CBN) [41]

Please answer the following questions about Pokémon.

1. I have fond memories of this brand from my childhood.
2. This brand features in happy memories of when I was younger.
3. I still feel positive about this brand today because it reminds me of my childhood.
4. This brand is one of my favorite brands from my childhood.

Perceived Enjoyment (PE) [50,56]

1. Playing Pokémon Go is fun.
2. Playing Pokémon Go is enjoyable.
3. Playing Pokémon Go is very entertaining.

Use Behavior (USE) (Frequency scale adapted from [57])

Please choose your usage frequency of playing.

- | | |
|--------------------------|--------------------------|
| 1. Never | 6. Once a day |
| 2. Once a month | 7. Several times a day |
| 3. Several times a month | 8. Once an hour |
| 4. Once a week | 9. Several times an hour |
| 5. Several times a week | 10. All the time |

Demographics

1. Age: How old are you?
2. Gender: What is your gender? (1 = female, 0 = male)
3. Education: What is the highest degree or level of school you have completed? In case you are currently enrolled, please provide the highest degree received. (ranging from no qualification (1) to doctorate (7))
4. Smartphone experience: How many years of experience do you have with smartphones? (0 years (1) to >10 years (11))

Concerns for Information Privacy (CFIP) [14,58]

The sub-dimensions of CFIP (collection, error, improper access and unauthorized secondary use) were unalteredly taken from the original paper.

Risk Propensity (RP) [30] and Privacy Victim Experience (VIC) [32]

The items of the two constructs were unalteredly taken from the original articles.

Appendix B. Descriptive Statistics and Measurement Model Assessment

Table A1. Descriptive statistics (N = 418).

Variable	Median	Mean	Std. Dev.	Min.	Max.
AGE	27	26.766	4.626	18	35
GDR	1	0.612	0.488	0	1
EDU	4	4.091	1.117	2	7
EXP	6	6.007	2.209	0	10
VIC	3	2.694	1.375	1	7
RP	4.667	4.499	1.238	1	7
COLL	5.25	5.257	1.139	1.25	7
ERR	5.25	5.151	1.126	1	7
IA	6	5.872	1.097	2.333	7
USU	6.25	5.958	1.050	3.25	7
CBN	5.5	5.138	1.486	1	7
PE	6	5.649	0.979	1	7
USE	6	5.617	1.622	2	10

Table A2. ICR, factor loadings and AVE.

Construct	Item	Cr.'s α	CR	FL	AVE
Collection	COLL1	0.834	0.890	0.833	0.668
	COLL2			0.792	
	COLL3			0.827	
	COLL4			0.817	
Error	ERR1	0.857	0.903	0.806	0.700
	ERR2			0.865	
	ERR3			0.826	
	ERR4			0.847	
Improper Access	IA1	0.871	0.921	0.903	0.795
	IA2			0.876	
	IA3			0.895	
Unauthorized Secondary Use	USU1	0.892	0.925	0.864	0.755
	USU2			0.874	
	USU3			0.867	
	USU4			0.871	
Risk Propensity	RP1	0.800	0.873	0.936	0.700
	RP2			0.692	
	RP3			0.863	
Perceived Enjoyment	PE1	0.927	0.954	0.942	0.873
	PE2			0.940	
	PE3			0.921	
Childhood Brand Nostalgia	CBN1	0.950	0.964	0.948	0.870
	CBN2			0.937	
	CBN3			0.942	
	CBN4			0.904	

Cr.'s α : Cronbach's Alpha; CR: Composite Reliability; FL: Factor Loading.

Table A3. Discriminant validity with AVEs and construct Correlations (\sqrt{AVE} -values are on the diagonal; construct correlations are off-diagonal elements).

Const.	CBN	COLL	ERR	IA	PE	RP	USU
CBN	0.933						
COLL	0.043	0.817					
ERR	0.131	0.435	0.836				
IA	0.124	0.591	0.461	0.892			
PE	0.343	0.139	0.106	0.291	0.934		
RP	0.040	0.259	0.152	0.135	0.110	0.837	
USU	0.127	0.539	0.386	0.836	0.309	0.111	0.869

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