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Loot Box Purchase Decisions in Digital Business Models: The Role of Certainty and Loss Experience

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Abstract

Game providers are increasingly employing and selling loot boxes, which can be considered virtual goods that consist of further virtual goods on a randomized basis. As such, game providers can foster profitability without impeding user experience. Drawing on prospect theory, we investigate ideas for the design of loot box menus to optimize revenue generation and user well-being. By conducting a contest-based online experiment with 159 participants, our analyses reveal that including certain (vs. uncertain) content in loot boxes can influence users' purchase behaviors and thus increase revenues. Moreover, this effect increases when participants previously experienced a loss. Thus, our findings demonstrate that game providers can profit from offering certain content in loot boxes.

1. Introduction

By engaging with games, people are said to train their cognitive and social abilities while being entertained and enjoying their selves. As a mass activity, gaming has become a pervasive part of pop culture and our daily lives. In recent years gaming has experienced massive growth and reached a global market of $137.9 billion in 2018 [31].

A recent development in global gaming markets is the success of mobile gaming. In 2018 for the first time more than half of the global gaming revenue came from mobile games. In contrast to traditional gaming business models they commonly employ a free-to-play (F2P) monetization strategy [6]. These business models typically feature a product or service for free (e.g., downloading an app and playing the game) [19]. Revenue is then primarily generated through in-game microtransactions where virtual goods, which enhance progress or experience within the game, are sold to players.

One particular successful way to monetize on F2P business models is to sell loot boxes (i.e., consumable virtual goods) which can be used to gain a randomized selection of further virtual goods usable in game, which substantially differ in value and may or may not exceed the price they are sold for [13, 24]. Global spending on these consumable virtual goods reached nearly $ 30 billion in 2018, which equals more than one fifth of the total gaming market, and is expected to grow by 70% until 2022 [19]. Loot boxes are not only the primary monetization strategy in F2P gaming (e.g., Fortnite: Battle Royale and League of Legends), they also have increasingly become prevalent in full priced games (e.g., Forza 7 and Overwatch) to enhance revenue generation.

F2P business models featuring loot boxes by default use game of chance elements to determine which particular virtual good is further obtained after opening a loot box. This game of chance elements is an inherent feature of loot boxes and seems not to be challenged by the majority of game developers. However, consumer behavior literature indicates that - depending on the context - game of chance elements can lead to sub-optimal user behavior.

Drawing on insights from prospect theory and behavioral economics, we provide ideas how these game of chance elements can be modified to increase user well-being and revenue generation from selling virtual goods in F2P business models.

By employing loot boxes which feature rewards (e.g., a specific virtual good) with a probabilistic uncertainty publishers leverage the motivating-uncertainty effect [27]. According to this effect a reward of an uncertain magnitude can be more motivating than a reward of a certain magnitude especially when affective experiences are involved. However, when facing gain options with focus on an events' outcome people are risk averse and prefer certain rewards [20, 30]. We additionally examined an effect altering the perception of uncertain rewards and consequently the preference for them. In this regard extant research has demonstrated previous loss

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experience (e.g., losing in a game of chance) to negatively influence subsequent risk seeking behavior (e.g., avoiding games of chance) [23].

Therefore, heeding Goes [8] call on design oriented and actionable research in the intersection of IS and behavioral economics, the objective of our study is to address the following research questions:

RQ1: How do certain vs. uncertain rewards in loot boxes affect user purchase behavior?

RQ2: How does previous loss experience moderate the effect of uncertain rewards in loot boxes on user purchase behavior?

To examine our research questions, we conducted a contest-based online experiment with 159 participants, featuring a self-developed game. Our study contributes to the current and ongoing debate on the role of loot boxes in digital business models.

Thus, we provide new insights into user's decision processes when choosing between different loot boxes to derive actionable and easily implementable implications for the design of loot box menus.

2. Background

Despite the huge commercial success of F2P business models, which usually incorporate an in-app-purchase (IAP) monetization strategy (e.g., selling in-game virtual goods in microtransactions), research on how these business models utilize virtual goods is limited [12]. Virtual goods are digital objects that only exist and are of use in a digital environment [22]. They can be distinguished into three categories, namely virtual goods with functional, hedonic or social attributes. Functional attributes have a direct impact on the game mechanic because they improve an avatars performance or unlocks new functionalities (e.g., enhanced weapons, amour, etc.). Hedonic and social attributes alter for instance the visual appearance of an avatar allowing for in-game social stratification but do not influence the player's performance [17]. In F2P business models the core service (playing the game) is provided for free and virtual goods, that enhance the game experience, can be purchased on a voluntary basis.

However, these priced virtual goods typically exhibit only moderate conversion rates of 5% [3]. Therefore, it is crucial to understand how to improve this conversion rate and increase revenue. This issue has been addressed by exploring how to engage in marketing activities to foster virtual good sales [15]. For instance, core product augmentation is a feature of games where inconvenient gameplay elements or visuals can be removed by purchasing a virtual good (e.g., automate repetitive and annoying tasks or deactivate in-game-advertising) making playing the game more enjoyable. However, due to the special characteristics of virtual goods prior to purchase any potential customers must play and enjoy the game per se without any augmentation. Furthermore, since satisfaction with how the virtual good is used is an important factor influencing purchase behavior, users should not have the feeling that game experience is deliberately obstructed to extract revenue [14]. Thus, it is essential to design F2P business models which promote virtual good purchases without impeding user experience [13]. However, despite acknowledging the importance of how virtual goods are visually designed and work within the specific digital environment where they are usable in, there has been little research on the effects of the marketing and sale of those goods, such as the conditions under which virtual goods can be purchased [14, 16].

Regardless, practitioners evolved F2P monetization design while impeding user experience to a lesser extent by leveraging insights which recently attracted much attention in consumer behavior literature. By selling loot boxes which can be used to gain a randomized selection of further virtual goods game publishers provide uncertain rewards. In contrast to other monetization strategies (e.g., removal of inconvenient gameplay elements), those rewards potentially affect the motivation of those users who purchase loot boxes without impairing the experience of other users.

Previous research relevant for F2P business models has revealed, that uncertainty can enhance motivation (measured via investment in effort, time and money) [27]. Another study on uncertain price promotion, found uncertain incentives to generate the same level of positive responses compared to certain incentives [9]. Additionally, Mazar, et al. [25] investigated how probabilistic vs. sure price promotions affected purchase decisions in retailing. In several experiments, consumers preferred a probabilistic free price promotion to the sure price promotion. However, for high probabilities ($p>=90\%$) no evidence for this preference was found. Taken together, insights from consumer behavior literature document that uncertainty regarding the conditions under which physical and digital goods are sold can enhance motivation and positively influence purchasing behavior.

Since uncertainty and probabilistic outcomes in particular are a defining characteristic of virtual goods used in the dominant type of microtransactions to monetize F2P business models, there is a need to investigate the under-researched question of how probabilistic uncertainty regarding the outcome of the purchase of virtual goods affects purchase decisions.

3. Research Framework and Hypotheses Development

Drawing upon insight from prospect theory and behavioral economics literature, we develop a research model that illuminates the effect of altering the eligible probabilities of receiving a virtual good on the user's choice between two loot boxes (H1). One loot box features a higher probability of receiving a virtual good but in exchange for a higher price and the other a lower probability of receiving a virtual good but in exchange for a lower price.

We then continue by elaborating on interaction effects between altering probabilities of receiving virtual goods and a previously experience of loss (H2). Participants experience a loss prior to loot box selection by receiving another loot box beforehand, which is believed to potentially incorporate a virtual good but contains nothing. We explain why we propose the relationships depicted in Figure 1 in the following sections.

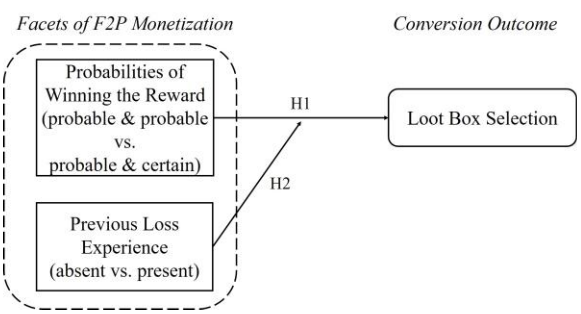

Figure 1: Research model

3.1. The effect of changing the probabilities of winning the reward on loot box selection

According to prospect theory, people overweight small probabilities and underweight high (near certain) probabilities [20]. Contrary to implications from expected utility theory, which predicts homogeneous preferences, this can lead to inconsistencies where the same individual acts risk averse and risk seeking, depending on whether the occurrence probability of a risk involving event is high or low [2, 30]. The underweighting of high (near certain) probabilities leads to a risk aversion phenomenon manifesting in a systematic preference of a sure gain over a near certain chance of winning a reward.

In contrast to expected utility theory which predicts a preference of the option with a higher expected value this risk averse preference even develops when the expected value is higher for the probable outcome than for the sure gain. When the outcome of both options is probable this systematic risk averse preference does not occur and a risk seeking behavior in line with predictions from expected utility theory (i.e. selection of the riskier option if it yields a higher expected value) can be observed. An explanation for these change in risk preferences is provided by the certainty effect. It refers to a psychological effect resulting from a reduction in the probability of winning a reward from certainty to probable (e.g., from 100% to 75%) which induces a perception of greater loss than a corresponding reduction (e.g., by ¼ from 80% to 60%) in the probability from probable to less probable [29].

By offering a set of options for purchasing virtual goods featuring loot boxes with varying probabilities for winning a specific virtual good (e.g., a customizable aesthetic in-game equipment [5]) for different prices publishers currently leverage expected utility theory. Since this theory predicts a preference for options with a higher expected value, to maximize revenue publishers offer pricier loot boxes with a higher expected value compared to cheaper loot boxes. However, when users can choose between two loot boxes which yield the same virtual goods, one with a probable and the other with a sure outcome, the certainty effect will govern user's behavior urging them to prefer the sure gain.

Leaning upon prospect theory we expect the certainty effect (instead of expected utility) to drive users' behavior when they are faced with a choice between winning a virtual good with certainty or with a specific probability.

H1: When faced with a choice to purchase one of two differently-priced loot boxes with the same expected value, users are more likely to choose the pricier loot box if it features a sure gain and the cheaper box only a chance of winning, in contrast to a situation where both options feature only a chance of winning the reward. (certainty effect)

3.2. Interaction effects between changing the probabilities of winning and previous loss experience

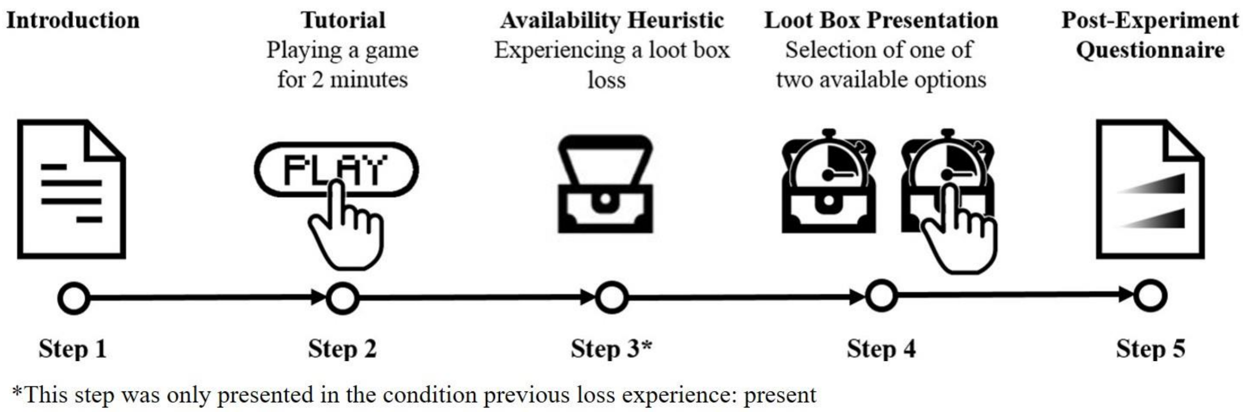

Figure 2: Experimental procedure

People evaluate the probability of uncertain events depending on previous experience and examples related to that event that immediately come to a given person's mind. If a related previous experience or example can be vividly recalled, the probability of the event in question will be evaluated higher compared to situations where a related examples or experiences cannot be recalled.
Consequentially, because recent information can be retrieved more easily people tend to weight their judgment toward more recent information. The availability heuristic refers to the effect leading to this biased evaluation of probabilities which is skewed towards information more readily available [28]. The availability heuristic can explain why recent loss experiences is negatively correlated with subsequent risk seeking [23].

This translates into F2P monetization by considering how previous loss experiences related to loot box
rewards potentially drives users in addition to the certainty effect to further overestimate the chance to lose. When users choose between the certain and the uncertain loot box, previous loss experience will boost the certainty effect such that users prefer the sure gain.

H2: Previous loss experience (vs. no such experience) will moderate the certainty effect.

4. Research methodology and results

4.1. Experimental design and treatments

We conducted a contest-based online experiment to test our hypotheses. The study was framed as a warm-up for a subsequent online contest to the study, where users had the chance of winning €20 depending on their performance in a self-developed game. Prior to participating in the contest, the tutorial explained the controls and mechanics of the game which was inspired by the classic game "snake". As depicted in figure 3 the game featured a representation of the eponymous reptile which was navigated by the player.

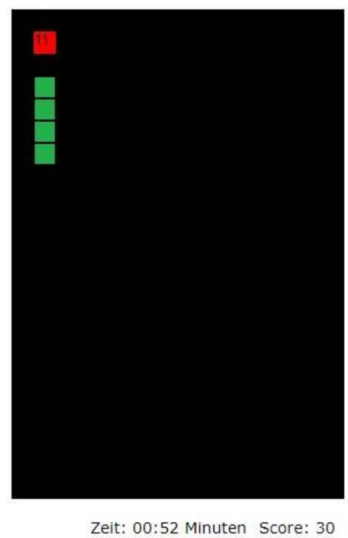

Figure 3: Experimental version of "snake"

The goal was to prevent the snake from colliding with the walls and itself as well as to guide it to pieces of food which are represented by red pixels randomly emerging on the screen. After the snake was successfully guided to a piece of food which was subsequently eaten, the length of the snake and the players' score increased. If the player's navigation leaded to a collision the game restarted. After the tutorial participants could test the game and train their skills for two minutes in preparation for the contest which took the same amount of time. In a subsequent step a loot box offering the chance to gain extra playtime in exchange for a part of the potential contest reward was presented.

We introduced the conditions of the contest to participants as follows: "After the survey is finished, you will be able to play the game again in a competition. The 50% best competitors have the chance to win one of four Amazon vouchers".

The score achieved during playing the game determined which participant would be among the 50% best participants. The score increased with every successful navigation of the snake to a piece of food. Starting with 10 points for the first piece of food, every time the snake successfully navigated to an additional piece of food the score obtained for eating another piece of food increased (11 points for the 2nd piece, 12 points for the 3rd piece, etc.). After a collision of the snake with the wall or its tail, the game continued but the points for eating a piece of food reset to 10 points and increased again in the manner descripted above. The score, however, was saved such that every further successful navigation adds to the score already obtained. Therefore, extra playtime indirectly led to a higher score and thus increased the chance for a participant to be among the best 50% participants.

We choose to present a virtual good with functional attributes, because this category of virtual goods can be unambiguously operationalized and manipulated without lying out a complex story and environment [17, 22]. Participants had to choose between two options in exchange for either €4 or €6 where the cheaper option provided a ten percentage points smaller chance of gaining extra playtime compared to the pricier option. However, the expected value of the price for both options was identical. In our online experiment two independent variables (probabilities of winning the reward (PWR) and previous loss experience (PLE)) were manipulated with a 2 (probabilities of winning the reward: probable and probable vs. probable and certain) x 2 (previous loss experience: absent vs. present) between subjects, full-factorial design.
Besides manipulating the probabilities of winning the reward for both options by adding 40 percentage points (probable and probable vs. probable and certain, i.e. a change from 50% & 60% to 90% & 100%), by presenting an event where players lost an amount of their potential reward through opening a chest optical similar to the loot box shown afterwards we also manipulated previous loss experience (absent vs. present).

We randomly assigned participants to one of the four conditions. In line with procedures in previous online experiments, we motivated subjects to participate in the study by informing each participant that they have a chance of winning a €20 reward.

To start the process subjects could click on a web link, posted on social media and online communities sites. As depicted in figure 2 we segmented the experiment into five parts. The first part introduced the experiments outline and the conditions of the contest, (Step 1). Second the game practices were explained and the tutorial with the training session started (Step 2). Third, participants in the condition *previous loss experience present* received a virtual chest in exchange for €5 of their potential reward with the information that the chest contains up to €10 of extra winnable reward but that it can also contain nothing what was actually the case. Afterwards participants in the previous loss experience condition were informed that their winnable amount decreased from €25 to €20. In this step participants in the condition previous loss experience absent were informed that their winnable was €20 (Step 3). The fourth step introduced the loot box selection event featuring two treasure chests with specific probabilities attached to contain extra play time for the contest providing the opportunity to earn extra points. Participants had to choose between two options. One option could be bought in exchange for a €4 reduction of the winnable reward and the other for a €6 reduction. Both options were labeled with a numeric combination of probability and extra playtime (e.g., 50% and 24 seconds) (Step 4). In the last step participants were guided to a post-experiment questionnaire which assessed demographics, previous gaming experiences and other variables (Step 5). Afterwards the actual contest was conducted. For ethical reasons all participant played for two minutes regardless which condition was assigned to them and could potentially win one of three €20 vouchers.

4.2. Manipulations and measured variables

To implement our change in probabilities manipulations, we displayed different versions during the loot box selection event.

Figure 4: Loot box selection, probable and probable

As depicted in Figure 4 in the condition probabilities of winning the reward: probable and probable participants could choose between a 50% chance of getting 24 seconds extra playtime for €4 or a 60% chance of getting 30 seconds extra playtime for €6.

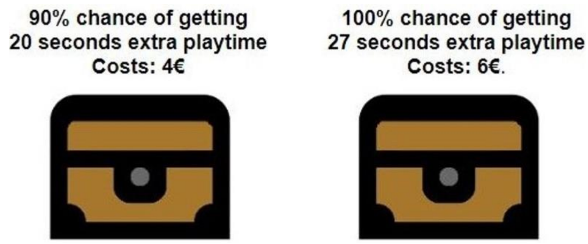

Figure 5: Loot box selection, probable and certain

Whereas in the condition *probabilities of winning the reward: probable and certain* (Figure 5) the choice was changed to a 90% chance of getting 20 seconds extra playtime for €4 vs. a 100% chance of getting 27 seconds extra playtime for € 6. To rule out expected utility-driven behavior we designed all manipulations in such a way that the expected value of the price for both eligible options was identical (e.g., 3 seconds per € in the condition probable and probable).

Prior to loot box selection, to create a previous immediate loss experience, participants in the condition *previous loss experience: present* received a treasure chest with a chance to increase their winnable amount and experienced a loss after the empty chest was presented. Participants were told prior to the loss event, that their total winnable amount is €25 (instead of €20 like the other group). In exchange for a €5 reduction of their winnable amount they receive a loot box which is believed to contain up to €10.

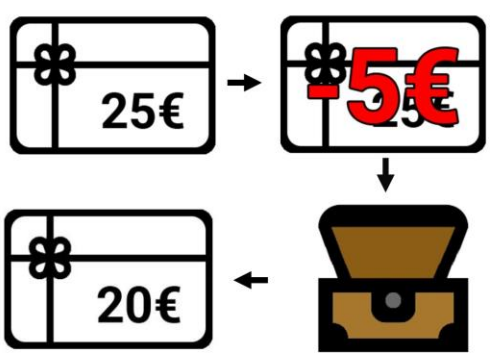

Figure 6: Previous loss experience

As Figure 6 exhibits the €5 reduction is illustrated through visualizations of the remaining winnable amount and by a depiction of the empty loot box representing the loss event. We measured participants purchase decision (selection of the pricier loot boxes), and whether they experienced a loss event previously. Both decisions were captured. Participants were then directed to the post-experimental questionnaire, where we recorded our control variables to rule out alternative explanations. We measured the following alternative drivers for loot box selection as controls in our experiment drawing on previous IS adoption literature [7, 10, 18], namely risk aversion, perceived monetary value and product involvement. For all items a 7-point Likert-type scale was employed with values ranging from strongly disagree (1) to strongly agree (7). Furthermore, we collected information on subjects' gaming experience, previous spending on loot boxes and demographic information. We further employed checks to assure the comprehension of all instructions and included two manipulation check questions to ascertain that our manipulations were perceived and remembered correctly.

4.3. Sample description, control and manipulation checks

Similar to previous experiment in contest-based study, we recruited participants for our study from representative student pool via social media and online survey exchange communities.

Table 1: Descriptive statistics of demographics, controls and dependent variables.

	Mean	StD
Demographics		
Age	25.5	8.43
Gender (male)	55%	
Controls		
Perceived Monetary Value	5.02	1.41
Risk Aversion	4.09	0.99
Gaming Experience	11.37	8.93
Product Involvement	2.60	2.05
Loot Box Spending	1.22	0.55
Selection (of the pricier loot box)		
PWR prob.& prob._PLE_absent	54%	
PWR prob.& cert._PLE_absent	62%	
PWR prob.& prob._PLE_present	49%	
PWR prob.& cert._PLE_present	86%	

Out of a total of 217 participants we excluded 24 due to suspicions click patterns (e.g., low response variability, high rate of missing values) and 34 due to failing at least on attention or manipulation check, resulting in a final sample of 159 participants used for data analysis. Of the 159 subjects, 71 were females and 88 were males. 97 participants purchased the pricier loot box, which results in an overall proportion of 61% across all four subgroups. Participants exhibited and average age of 25.5 and on average they had 11 years of experience in gaming. Table 1 summarizes the descriptive statistics of the data.

Table 2: Logistical regression analysis on loot box selection

	Stage 1		Stage 2	
	Coef.	**SE.**	**Coef.**	**SE.**
Intercept	-2.27	1.09	-1.72.	1.13
Manipulations				
PWR	.92**	.1.09	.27	.48
PLE	.45	.36	-.20	.49
PWR x PLE	-	-	1.51*	.76
Controls				
Perceived Monetary Value	.10	.13	.1	.13
Risk Aversion	.12	.18	.09	.18
Gaming Experience	.02	.02	.01	.02
Product Involvement	.16	.11	.14	.11
Loot Box Spending	.39	.47	.41	.11
Gender (male)	-.019	.38	.07	.38
Model Fit				
Log Likelihood		-95.88		-93.82
Nagelkerke R^2		.16		.19
Note: * p < .05; ** p < .01; *** p < .001; N = 159				

4.4. Main and interaction effect of changing the probabilities of winning and previous loss experience

As Table 2 exhibits to test our hypotheses, we conducted a two-stage hierarchical logistic regression on our dependent variable loot box selection. In the first stage, we entered all control variables, as well as our independent variables probabilities of winning the reward (PWR) and previous loss experience (PLE). In the second stage, we added the interaction term of PWR and PLE. Nagelkerke's R^2 were computed to test the fit for both stages.

None of our controls had a significant effect on selection decisions. The results of our logistic regression's first stage demonstrated a significant positive main effects of changing probabilities of winning the reward (b = .92; *Wald statistic* (1) = 6.54; p < .05) on loot box selection. Hence, participants that were faced with a choice potentially governed by the certainty effect was more likely to select the pricier loot box compared to when both probabilities of winning the reward were probable. Moreover, our second stage unveiled a significant two-way interaction of changing probabilities of winning the reward and previous loss experience (b = 1.51; *Wald statistic* (1) = 3.94; p < .05) on propensity to select the pricier loot box.

The positive interaction term suggests that the effect of changing probabilities of winning the reward on loot box selection is amplified when a previous loss event is experienced. To further evaluate our H2 hypothesis, we conducted a contrast analysis. As depicted in figure 7, the results highlight that when probabilities of winning were probable and certain, participants are more likely to select the pricier loot box when previous loss experience is present opposed to when it is absent (86% vs. 62%; F = 6.418; p < .05). However, a significant difference in loot box selection between the presence (49%) and absence (54%; F = 0.562; p > .1) of previous loss experience did not emerge when probabilities of winning were probable and probable.

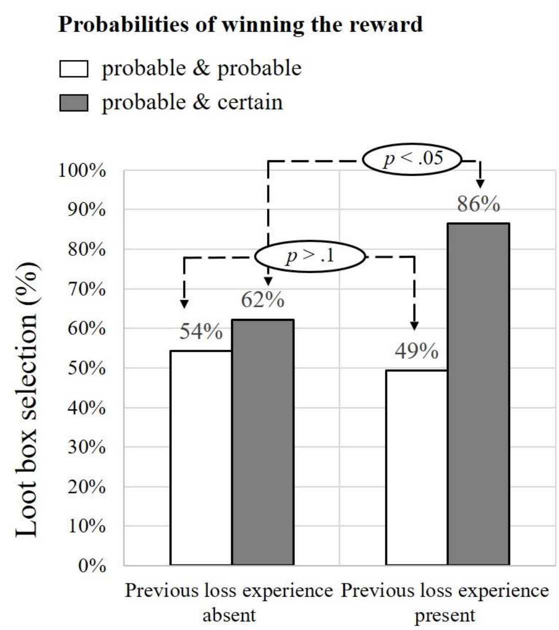

Figure 7: Loot box selection when PLE is absent vs. present in at PWR probable & probable and probable & certain

5. Discussion

This piece of research aimed to examine and reveal how changing the probabilities of winning the reward during loot box selection individually and in combination with previous loss experience affect purchasing behavior (i.e. loot box selection). Our findings support our premise that changing the probabilities of winning the reward during loot box selection increase users' selection of the pricier loot box. When employed together, previous loss experience augments the effect of changing the probabilities of winning on loot box selection. These patterns can be potentially explained through the certainty effect, which describes people preference of certain over near certain options, and the availability heuristic, which refers to an effect leading to a biased evaluation of probabilities weighted towards more recent information. Taken together, our research demonstrates that these two facets of F2P monetization are interdependent and highlight the importance of considering both in tandem when optimizing F2P conversion behavior.

5.1. Contribution to research

This study contributes to IS research in general and to game business model research specifically in three important ways. First, our research illuminates how changing the probabilities of winning the reward not only distinctly drives purchase behavior (i.e., loot box selection) in F2P business models, but also how in combination with previous loss experience conversion behavior is affected. Our results support the premise, that changing the probabilities of winning the reward from probable and probable to probable and certain has a positive causal impact on user's purchase outcome (i.e., they are more likely to choose the pricier option) which is further amplified when combined with previous loss experience.

We enrich game business model research by illustrating how concepts from behavioral economics translate to monetization strategies in F2P business models. Changing the probabilities of winning the reward presumably evokes the certainty effect urging users to prefer the certain yet pricier virtual good. When employed in combination with previous loss experience the availability heuristic potentially skews user's focus towards a vividly remembered loss when deciding which option to choose. As a result, the outcome of the probable option is evaluated as less likely to turn out positively. Consequently, the change of preferences presumably caused by the certainty effect is further augmented.

Second, by conducting a contest-based study involving monetary incentives which mirror real world economic incentives we undertook an economic experiment adding to the increasing strand of IS research employing this methodology (e.g., [26], [21]). By implementing an economic experiment in the context of F2P business models we aim at bridging the gap between rational economic models (i.e., expected utility theory) and actual human decision making [11]. We demonstrate that information processing relevant for F2P monetization (i.e., evaluation of probabilities) can distinctly deviate from rational decision making as postulated by expected utility theory. Thereby we assert that researchers and practitioners alike should take alternative theoretical explanations (e.g., prospect theory) into account when they investigate and design loot box menus which utilize probabilistic uncertainty.

Third, heeding Goes [8] call for further research into the cognitive dimension of judgement and decision contexts our study contributes nuanced insights to the burgeoning literature on cognitive biases in Internet-mediated environments. More specifically, while previous studies have largely focused their investigations on attributes of a cognitive bias (e.g., continuity and linearity of anchoring effects) influencing consumer preferences in e-commerce (e.g., [1], [4]), our findings from a randomized online experiment provide actionable design recommendations on how a cognitive bias, namely the certainty effect, distinctly and in combination with the availability heuristic can be employed to improve F2P conversion outcomes.

5.2. Practical contributions

This research has also important practical implications. First, our study provides actionable design recommendations on how changing the probabilities of winning the reward can be distinctly and in combination with previous loss experience employed to improve conversion behavior in F2P business models utilizing uncertain rewards. We demonstrate that practitioners can implement design elements leveraging insights from prospect theory (i.e. the certainty effect and the availability heuristic) to optimize revenue. By providing a choice between two loot boxes, one containing a certain and the other a probabilistic uncertain reward, they can leverage the motivating uncertainty effect (i.e., offering a game of chance) and simultaneously appeal to consumers whose preferences are primarily driven by risk aversion. Thus, they can improve optimize product differentiation in line with user's preference patterns.

Second, the proposed change of current F2P monetization would foster consumer protection. Unlike in current monetization strategies users would have the choice whether they want to participate in a game of chance or not when purchasing virtual goods. When virtual goods can be purchased either through a game of chance with an uncertain outcome or through a certain transaction users are prevented from potential exploitation through these game of chance elements.

6. Limitations and future research

As with all studies, there are limitations inherent in our study that pave avenues for future research. We implemented the change of probabilities of winning in a dichotomous (i.e., probable and probable vs. probable and certain) way and determined the specific values in both conditions (e.g., “50%” and “60%” vs. “90%” and “100%”) based on reference values in previous literature. However, it remains unclear how changing these reference values affect conversion behavior and whether linear or non-linear relationships can be expected. Future research is thus warranted to examine the linear or potentially non-linear relationships between the extent of changing the probabilities of winning and conversion behavior in F2P business models.

By utilizing a self-developed game which could be actually played and presenting animated loot box events during the experiment we mimicked a realistic setting, making it easy for participant to put their selves into the shoes of a player. But despite the high degree of realism of our experimental setting our dependent variable was design in such a way that it only captured a part of the conversion process. Participant had to choose between purchasing two different options. They were not able to decide whether they want to buy a virtual good or not. Therefore, it would be interesting how the findings of our study would translate to a setting where explicit purchase decisions are undertaken. Specifically, how presenting just one loot box option (e.g., the 90% option) without contrasting it with another affects purchase decision.

To conclude, we believe that examining uncertain probabilistic rewards in general and in F2P business models in particular is an important avenue for future empirical research. Understanding how uncertain rewards motivates users but also which caveats they involve is critical for the success of F2P business models as it becomes increasingly crucial to engage in monetization strategies which motivate converted user without impeding the experience of other players. We hope our study provides fresh impetus to fuel the stream of research on cognitive biases relevant for F2P monetization and also helps F2P service providers to refine their knowledge about how they can design more effective F2P business models.

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