Monetizing Loot Boxes in Gamblified Digital Business Models — The Role of Risk Avoidance and Loss Aversion

Konstantin Roethke  
*Technical University of Darmstadt*, roethke@ise.tu-darmstadt.de

Gregor Albrecht  
*Technical University of Darmstadt*, albrecht@ise.tu-darmstadt.de

Martin Adam  
*Technical University of Darmstadt*, adam@ise.tu-darmstadt.de

Alexander Benlian  
*Technical University of Darmstadt*, benlian@ise.tu-darmstadt.de

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MONETIZING LOOT BOXES IN GAMBLIFIED DIGITAL BUSINESS MODELS — THE ROLE OF RISK AVOIDANCE AND LOSS AVERSION

Research Paper

Roethke, Konstantin, Technical University of Darmstadt, Germany, roethke@ise.tu-darmstadt.de
Albrecht, Gregor, Technical University of Darmstadt, Germany, albrecht@ise.tu-darmstadt.de
Adam, Martin, Technical University of Darmstadt, Germany, adam@ise.tu-darmstadt.de
Benlian, Alexander, Technical University of Darmstadt, Germany, benlian@ise.tu-darmstadt.de

Abstract

Digital business models increasingly utilize gamblification (i.e., the use of gambling design elements in non-gambling contexts) to enhance traditional revenue generation. However, despite the increasing prevalence of gamblified digital business models, little is known about the influence of gamblification design on user behavior. We examine how gamblification in the form of differently designed loot boxes (i.e., gamblified virtual goods) and the connected effects of risk avoidance, previous endowment, and risk attitudes affects user purchase behavior. We conducted a contest-based online experiment with 180 participants, revealing that user purchase behavior is positively affected when loot boxes with a certain (vs. an uncertain) reward are offered. This risk avoidance effect increases when participants are either previously endowed with an unopened loot box or when they are risk-averse. Our findings yield theoretical and practical implications for gamblification in general and loot boxes complementing digital business models in particular.

Keywords: Gamblification, Gambling, Digital Business Models, Monetization, Loot Boxes, Prospect Theory.

1 Introduction

Digital business models increasingly employ digital design elements to experiment with new monetization strategies augmenting and enriching their conventional revenue streams (e.g., sales, ads, and subscriptions) (Hedman and Kalling, 2003). One approach to prevail against the stiff competition is gamblification, which we define analogously to the connected but distinct concept of gamification (Deterding et al., 2011b) as the use of gambling design elements (e.g., scratch cards, loot boxes) in non-gambling contexts to increase users’ meaningful engagement. Prior literature initially conceived gamblification as embedding full-fledged gambling (e.g., betting) into traditional sports (McMullan and Miller, 2008). Subsequently, the concept was adopted to social networks (Morgan Stanley, 2012), e-sports (Lopez-Gonzalez et al., 2019, McGee, 2020), and online games (Abarbanel and Johnson, 2020, Macey and Hamari, 2020). However—akin to how Liu et al. (2017) conceptualized gamification—we put forward that gamblification most adequately describes individual gambling design elements entailing gambling design objects (e.g., a lottery ticket) and gambling design mechanics (e.g., the lottery drawing or other chance-based mechanics) (Reinelt et al., 2021). These gambling design elements are typically linked to resource transfers (e.g., transaction, gifting). Hence, the impact of gamblification reaches beyond meaningful engagement alone (e.g., user onboarding, revisits) with the potential to shape digital business models (Shen et al., 2015, Fabbri et al., 2019, Mazar et al., 2017). In this regard, Google Pay (2020) employs digital scratch cards, and Starbucks (2020) offers augmented reality lotteries.
following product purchases. As such, gamblification promises an innovative approach to rethinking revenue models and enhancing digital business models (Veit et al., 2014, Wagner et al., 2014). Although gamblification has been debated controversially, is subject to ongoing restrictions (Zendle et al., 2020, Macey and Hamari, 2019), and is also linked to tremendous financial advantages for digital business models (Ma et al., 2014, Stehmann, 2019), little is known how gamblification design elements can be utilized to affect business outcomes such as purchase behaviors. In particular, loot boxes are widely employed gamblification design elements and have attracted much media and research interest in recent years (King and Delfabbro, 2019, Macey and Hamari, 2019, Griffiths, 2018). Loot boxes are consumable virtual goods (akin to lottery scratch cards) that contain chance-based selections of other virtual goods (e.g., weapons, armor) that are usable only within their virtual environment. The sale of these virtual goods in online games alone generated global revenues of almost $30 billion in 2018, equaling more than 20% of the global gaming market and is expected to grow by 70% until 2022 (Juniper Research, 2017). However, while digital business models, especially in the gaming market, rely on these virtual goods that feature uncertain rewards, other digital business models that provide online services offer virtual goods involving certain rewards (i.e., (micro)transactions) to augment and support traditional revenue generation (e.g., sales, ads, and subscriptions). For instance, Twitch, a digital streaming platform, offers virtual gift cards that can be purchased and transferred to support streamers (Twitch, 2020). Likewise, Apple’s iMessage service sells virtual stickers via in-app-purchases that can be used to customize private messages (Apple, 2020, Ghose and Han, 2014). The question arises under which conditions uncertain rewards may be supplemented by certain rewards to enhance revenue generation in digital business models.

To optimize their revenue models, digital businesses need to introduce complementary and innovative revenue streams (Voigt and Hinz, 2016, Guo et al., 2019). To accomplish this, they increasingly employ virtual goods that feature certain or uncertain rewards elements (e.g., loot boxes) (Adam et al., 2021). Consequently, users within these digital business models are faced with decisions in uncertain environments. Therefore, to investigate user behavior in these digital environments, it seems promising to draw on established literature on human decision-making under uncertainty. Indeed, extant research documents that gamblification elements can result context-specific in both optimal and sub-optimal user behavior outcomes: In general, a reward of probabilistic uncertainty (i.e., chance-based) can be more incentivizing and thrilling than a reward of a certain magnitude (Shen et al., 2015). However, extensive research has stressed out that users may also be risk-averse and prefer certain rewards, even willing to pay a premium for this certainty (Von Neumann and Morgenstern, 2007, Kahneman and Tversky, 1979). Furthermore, Kahneman et al. (1991) conceived the notion of loss aversion, which aims to explain a perceptual peculiarity where consumers consider the disutility of forgoing something to be greater than the utility corresponding with obtaining it (i.e., “losses loom larger than gains”). Many contemporary gamblified digital business models seem to utilize loss aversion by endowing users with virtual goods before offering any means to make those goods accessible for them. This may positively affect how much value users attach to virtual goods and, thus, their propensity to purchase these goods. In fact, previous IS research on digital business models has emphasized the vital role of loss aversion in affecting user purchase behavior (Koch and Benlian, 2017). Moreover, extant IS literature demonstrated that users’ attitudes towards risk might also influence the value perception of digital services and might also impact user purchase behavior (Baird and Raghu, 2015). As such, digital services that entail potential risk diminish in value for risk-averse users, while risk-seeking users’ perception is less likely to be affected. However, although the benefits of employing virtual goods to generate revenue in digital business models are widely acknowledged (e.g., Hamari and Keronen, 2017, Animesh et al., 2011), only little attention has been focused on investigating the differential effects of receiving a virtual good containing a certain vs. uncertain reward and their interaction with loss aversion and risk attitudes in the context of digital business models.

Against this backdrop, the main goal of our study is to examine (1) the effect of certain vs. uncertain rewards (as a comparison of traditional (micro)transactions and a prevalent form of gamblification design elements) on user purchase behaviors (i.e., risk avoidance effect); (2) how loss aversion
influences the risk avoidance effect; and (3) how users’ risk attitudes influence the risk avoidance effect. Therefore, we ask the following research questions:

\( RQ1: \) How does a certain vs. an uncertain reward affect user purchase behavior?

\( RQ2: \) How do loss aversion and risk attitudes interact with the effect of a certain vs. an uncertain reward on user purchase behavior?

To answer our research questions, we conducted a contest-based online experiment with 180 participants. Drawing on prospect theory (Kahneman and Tversky, 1979), we propose ideas on how gamification can be utilized to augment revenue generation within digital business models through uncertainty combined with previous endowment and users’ risk attitudes. Our study contributes to the emerging research on gamblified digital business models in several ways. First, we contribute to previous IS research on digital business models by providing insights into the role of gamblified design elements in the form of loot boxes—particularly their role in the interplay of certain and uncertain rewards in affecting revenue generation. Second, our study investigates two essential moderators of the risk avoidance effect—namely users’ loss aversion and risk aversion—both of which amplify the effect of a certain vs. an uncertain reward. In terms of revenue generation, our results imply an average increase in revenue of up to €0.90 per decision (+86.5%). Third and finally, we heed the call for future research into the cognitive dimension in digital decision contexts (Goes, 2013) by adding to the extant literature on cognitive biases in virtual environments. We do this by deriving actionable design recommendations for gamblified digital business models.

2 Theoretical Background

Despite the considerable attention researchers have paid to gamification, a closely related concept has so far been neglected in IS research—gamblification. We consider gamblification a specialized form of gamification since both phenomena share similar settings and contexts, yet they comprise distinguishable design elements and, thus, entail different effects on user behavior. Gamification commonly refers to the use of game design elements, including game design objects (e.g., points and badges) and mechanics (e.g., relative performance progression reflected on leaderboards) in non-gaming contexts (Deterding et al., 2011a, Liu et al., 2017). These design elements can be further supplemented by uncertainty-based (i.e., chance-based) gambling-related mechanics (e.g., lotteries, dice, cards) to drive users’ meaningful engagement and therefore improve desired business outcomes. We argue that gamblification enriches these gamified approaches by adding a gamblification-specific design element—resource-transfers. Thus, in order for a design to be considered gamblification, it not only requires specific game design elements and related chance-based mechanics but further requires a resource-transfer on top of gamification. To summarize, incorporating a transfer of resources (i.e., transactions, gifting) allows enhancing revenue generation in digital business models beyond what gamification offers.

**Loot boxes** present a particularly prominent and often employed approach of gamblified design elements in digital business models. They represent virtual goods that users can buy to gain a chance-based selection of other virtual goods (Hamari and Keronen, 2017, Macey and Hamari, 2019). Loot boxes are usually offered as different versions, each of which contains content with different probabilities (Riot Games, 2019). Loot boxes are particularly interesting for two main reasons. First, they are the most widespread and successfully applied variants of gamblification elements in gamblified digital business models. Besides being the predominant monetization strategy as lottery-like gamblification elements in most free-to-play gaming (e.g., Fortnite and League of Legends), these consumable virtual goods have also become widespread in fully-priced games and many other gamblified digital business models (e.g., *Forza 7* and *Overwatch*) (Macey and Hamari, 2019). Second, loot boxes demonstrate how gambling-related design elements can be incorporated in digital business models and, thus, provide us with a promising research opportunity. More concretely, by examining the impact of loot boxes, we can learn how to successfully design gamblified digital business models.
The impact of gamblification has been hitherto studied in diverse digital environments such as social networks or online streaming services (e.g., Abarbanel and Johnson, 2020). Although the influence of gamblification on business outcomes is acknowledged in these studies, their focus is different as they merely describe how specific gamblification design elements are employed in practice (e.g., betting mechanisms within the live streaming platform Twitch). In this regard, research on gamblification so far mainly provides only descriptive evidence on how different gamblification design elements might influence user behavior (Reinelt et al., 2021). Thus, despite the prevalence of gamblification in practice, there is still much particularly experimental research to be done on how digital business models can employ gamblification to foster sales, and, thus, how to optimally leverage uncertain outcomes (e.g., Hamari and Lehdonvirta, 2010, Roethke et al., 2020a).

According to prospect theory (Kahneman and Tversky, 1979), people tend to avoid risk and are more likely to opt for a certain outcome than for an uncertain outcome when faced with gain options. This risk avoidance tendency, which can be attributed to an underweighting of moderate and high probabilities relative to certain outcomes, may lead to a preference for a certain outcome, even if the uncertain outcome has a higher or an equal expected value (Holt and Laury, 2002, Kahneman and Tversky, 1984). Additionally, in the context of value perception and the related user purchase behavior, the concept of loss aversion is instructive. Loss aversion refers to the following perceptual peculiarity: Compared to a specific reference point, individuals consider the disutility of forgoing something to be greater than the utility corresponding with obtaining it (i.e., “losses loom larger than gains”) (Kahneman et al., 1990). Whereas in the domain of certain outcomes loss aversion unambiguously suggests a higher valuation of objects already in possession (i.e., previous endowment), empirical evidence indicates that loss aversion does not necessarily occur when uncertain outcomes are involved (Novemsky and Kahneman, 2005). Another concept that provides valuable insights into human decision-making under uncertainty is risk attitudes. Risk attitudes refer to a psychological trait that reflects peoples’ appetite for risk (i.e., engaging in activities that are generally rewarding yet involve some potential for loss) and is measured using a psychometric scale (Dohmen et al., 2018, Pennings and Smidts, 2000). This concept is typically utilized to investigate how individuals’ general attitudes towards risk-taking influence behavior (e.g., sourcing to a knowledge management system) (Mata et al., 2018, Gray and Durcikova, 2005).

Since gamblification features user behavior under uncertainty involving real-world rewards, both prospect theory and research on consumer behavior in uncertain environments seem to be suited to guide our study. More specifically, because deciding whether to purchase a loot box or not involves risk (i.e., potential real-world gains or losses), the risk avoidance tendency presumably affects user purchase behavior within gamblified digital business models. Moreover, investigating loss aversion in the context of gamblified digital business models is interesting both from a theoretical and a practical perspective. Indeed, extant IS research on digital business models demonstrates that loss aversion influences value perception and affects user purchase behavior (e.g., Koch and Benlian, 2017). Additionally, loot box design in practice where users are endowed with loot boxes prior to purchasing the means to gain access to the loot box suggests that practitioners aim at leveraging loss aversion to shape revenue generation (e.g., Overwatch Wiki, 2019). Likewise, because risk attitudes deliver useful explanations for user behavior when faced with decisions involving uncertainty, they are likely to provide valuable insights on how user behavior is shaped within gamblified environments as well.

However, despite the burgeoning research on human decision making in uncertain environments (e.g., Kahneman and Tversky, 1979, Shen et al., 2015) and the importance and prevalence of uncertain outcomes in gamblified digital business models in practice, there is only scant knowledge about how risk avoidance may shape purchase behavior and thus revenue generation in gamblified digital business models. Likewise, although risk attitudes and loss aversion has been already investigated in extant literature regarding their effect on value perception in the context of digital services and digital business models (e.g., Baird and Raghu, 2015, Ariely et al., 2005), little is known how their interactive effect with risk avoidance might influence purchase behavior and revenue generation within gamblified digital business models.
3 Research Model & Hypothesis Development

Drawing on prospect theory (e.g., Kahneman and Tversky, 1979) and research on consumer behavior (e.g., Conlisk, 1993), we develop a research model, depicted in Figure 1, that illuminates the effects of different probabilities (i.e., certain vs. uncertain) of receiving a reward on users’ decision to purchase a loot box (H1). We examine whether user purchase behavior changes when users are confronted with a loot box with uncertain reward compared to a loot box with a certain reward while keeping the expected values identical for both decisions. We then investigate the interaction effect between different probabilities of receiving the reward and previous loot box endowment (H2), followed by the interaction effect with risk attitudes (H3).

![Figure 1. Research model.](image)

3.1 Main Effect of Reward Winning Probability on Loot Box Purchase

The literature on human decision-making under uncertainty indicates that biased perceptions of probabilities may lead to individuals’ tendency to avoid risk and prefer certain outcomes over uncertain outcomes when faced with gain options (e.g., Kahneman and Tversky, 1979, Simonsohn, 2009). Since the valuation of uncertain gains and the connected perception of probabilities are likely to influence individuals’ loot box purchase behavior, we believe that research on the valuation of uncertain outcomes is most relevant in the context of loot box purchase decisions. When faced with a decision to purchase a loot box that involves a possible gain but also a possible loss (i.e., uncertain reward option), the risk avoidance tendency suggested by prospect theory and previous empirical research prompts individuals to opt for no purchase (i.e., a certain outcome) more often, compared to when they are faced with a certain reward option. In contrast, when individuals face a decision to purchase a loot box that involves a certain reward (i.e., receiving additional playtime), their behavior is presumably unaffected by the tendency to avoid risk. Thus, they are more likely to opt for the certain reward (i.e., purchase the loot box) compared to when faced with the uncertain reward option. Indeed, previous IS research on decision-making under uncertainty demonstrates that purchase behavior can be affected by risk avoidance, associated with a preference for certain outcomes (Roethke et al., 2020a).

**H1:** When faced with a choice whether or not to purchase one of two equally priced versions of a loot box with both versions having the same expected value, users are more likely to purchase the certain version (i.e., certain reward option) than the uncertain version (i.e., uncertain reward option) of a loot box (i.e., risk avoidance effect).

3.2 Interaction Effect of Reward Winning Probability and Previous Endowment

As empirical evidence indicates, individuals’ susceptibility to loss aversion depends on whether the outcome is certain or uncertain (Novemsky and Kahneman, 2005). H1 proposes that the risk avoidance effect urges users to be more likely to opt for a loot box (i.e., gain access to its content) when the reward it features is certain compared to when it is uncertain. Previous research and loot box design prevalent in practice suggest that firms can alter the loot box offering by previously endowing users with the loot
box and offer the means to open the loot box (i.e., a key) for sale (Kumar, 2014, Koch and Benlian, 2017). This altered loot box offering design raises the question of how the two loot box versions (certain reward vs. uncertain reward) affect purchase propensity when users are previously endowed with the loot box (but not with a key to open it) compared to when they are not. We propose that the previous endowment increases the risk avoidance effect leading to a higher purchase propensity. We theorize that users who face a certain reward version of the loot box and are previously endowed with the loot box are subject to loss aversion and, thus, more likely to opt for purchasing the loot box’s content compared to when there is no previous endowment. In contrast, when users are faced with the uncertain reward version of the loot box and previously endowed with the loot box, we argue that they are less susceptible to loss aversion, and thus the risk avoidance tendency prevails, leading to a similar purchase propensity compared to when there is no previous endowment.

**H2: Previous loot box endowment amplifies the risk avoidance effect such that loot box purchase propensity is higher when users are previously endowed with a loot box with a certain reward compared to when they are not.**

### 3.3 Interaction Effect of Reward Winning Probability and Risk Attitudes

Risk attitudes refer to a psychological trait that reflects a person’s appetite for risk (i.e., engaging in activities that are generally rewarding yet involve some potential for loss). They are frequently used in extant literature to assess individuals’ attitudes towards risk-taking, for instance, in the context of knowledge management systems or the design of optimal compensation strategies (Gray and Durcikova, 2005, Gomez-Mejia and Balkin, 1989). Since loot box purchase decisions typically involve risky decisions that might result in either losses or gains, risk attitudes are likely to influence loot box purchase behavior. We propose that, while risk-averse individuals are more likely to be affected by the risk avoidance effect hypothesized in H1, risk-seeking individuals are less likely to be affected. Specifically, previous research on digital business models indicates that users’ risk-taking behavior impacts conversion outcomes (e.g., Koch and Benlian, 2017).

**H3: Users’ risk attitudes interact with the risk avoidance effect such that risk-seeking users are less likely to purchase a loot box containing a certain reward than risk-averse users.**

### 4 Research Methodology

#### 4.1 Manipulation Design

To ensure internal validity and a high degree of realism, we framed our experiment as a warm-up phase for a subsequent online contest during which participants were able to win €20 Amazon vouchers. In doing so, we motivated participants to consider their behavior and decisions carefully during the experiment—they had “skin in the game.” The contest included a short self-developed game, and we told participants (but only after they decided whether to take part) that their chances of winning would mainly depend on their performance (i.e., a high score). For ethical reasons, however, all participants had equal chances of winning the voucher. By incorporating a game, we replicated a realistic context in which gamification elements seem plausible and valid. More concretely, as depicted in Figure 2, the game resembled a simplified version of Space Invaders, a well-known classic arcade game. The participants could earn points by navigating a spaceship to eliminate enemy spaceships while dodging the enemy’s lasers. Before the contest started, participants could prepare by testing the game’s controls and mechanics for two minutes. Besides skill, the most crucial factor for winning in our version of the game (and thus in the contest) was playtime: The more time a player had, the higher a score they could achieve. Before the actual contest started, the participants were presented with the option to purchase a loot box in return for a small payment that would be deducted from their eventual reward (i.e., the €20 Amazon voucher) in case they won. The loot boxes offered the chance to gain extra playtime and, thus, were attractive for players because it increased their chances of winning the contest. We chose to implement loot boxes featuring a reward with functional content (i.e., extra playtime) because this
category of virtual goods can be unambiguously operationalized and manipulated without laying out a complex story and environment (Hinz et al., 2015, Lehdonvirta, 2009).

Figure 2. Experimental version of “Space Invaders”.

Depending on the condition the respective participant was assigned to, they were presented with different loot box versions. As the middle part of Figure 3 exhibits, in the condition probability of winning the reward: uncertain, participants could choose whether they want to obtain an 80% chance of getting 25 seconds of extra playtime in exchange for €4 of their potential reward. Whereas in the condition probability of winning the reward: certain (lower part of Figure 3), they had the choice to obtain a 100% chance of getting 20 seconds extra playtime in exchange for €4 of their potential reward. The specific values of the probabilities were derived from extant literature (Allais, 1953, Kahneman, 2011). Likewise, our price design was in line with current loot box offerings (e.g., FIFA Analytics, 2020, FIFAUTEAM, 2020, Riot Games, 2019). We designed all manipulations so that the expected value of both loot box variants was identical (i.e., 5 seconds per € in all conditions) and equally attractive. Further, in a pretest, we validated the time range for the extra playtime (i.e., 20-25 seconds) to be relevant (i.e., not too small) and not too impactful relative to the initial playtime of 120 seconds.

<table>
<thead>
<tr>
<th>Manipulated Design Features</th>
<th>Explanation</th>
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</thead>
<tbody>
<tr>
<td><strong>Previous endowment</strong></td>
<td></td>
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<tr>
<td>Mandatory choice between one of three loot boxes</td>
<td></td>
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<tr>
<td>Chosen loot box is displayed during warm up</td>
<td></td>
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<tr>
<td><strong>Reward winning probability: Uncertain</strong></td>
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<tr>
<td>80% chance of getting 25 seconds extra playtime</td>
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<tr>
<td>Cost: €4</td>
<td></td>
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<tr>
<td></td>
<td>Buy</td>
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<tr>
<td></td>
<td>No interest</td>
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<tr>
<td><strong>Reward winning probability: Certain</strong></td>
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<tr>
<td>100% chance of getting 20 seconds extra playtime</td>
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<tr>
<td>Cost: €4</td>
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<tr>
<td></td>
<td>Buy</td>
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<tr>
<td></td>
<td>No interest</td>
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</tbody>
</table>

*Note: In the previous endowment condition, the chosen color of the loot box remained the same (e.g., red) for the subsequent loot box presentation where users actually decided whether to purchase the loot box or not.*

Figure 3. Manipulation design.
Before this loot box purchase event, participants in the condition *previous endowment: present* had to select one of three colored loot boxes presented to them, which created a sense of previous endowment. As depicted in the upper part of Figure 3, the chosen loot box was displayed on the screen during the tutorial. Afterward, during the loot box purchase event in the condition **previous endowment: present**, a key to open the previously chosen box is offered for sale to participants. During the purchase, participants were informed that the key offered is the only chance to open the loot box and that no further opportunities to purchase a key will occur.

### 4.2 Experimental Design & Procedure

To answer our research questions and test our hypotheses, we conducted an online experiment in line with procedures in extant literature (Lowry et al., 2013, e.g., Benlian, 2015). We employed a 2 (probability of winning the reward: uncertain vs. certain) × 2 (previous endowment: absent vs. present) between-subjects, full-factorial design. To implement our probability manipulations, we displayed different loot box versions during the purchase event.

As depicted in Figure 4, our experiment consisted of five steps. In the first step, we introduced the experiment’s outline and the contest conditions. In step two, participants in the condition **previous endowment: present** faced a mandatory choice between three different colored loot boxes. The game controls and mechanics were explained in the third step, and the tutorial (i.e., warm-up) with the training session started. The fourth step introduced the loot box purchase event featuring a loot box with the chance to win extra playtime for the contest. Whereas participants in the condition **previous endowment: absent** had to choose whether to buy a loot box, in the condition previous endowment present, they had to choose whether to buy a key to open the previously chosen loot box. Both purchase decisions allowed participants to open the loot box and get the chance of winning extra playtime. All loot boxes presented could be opened (through purchasing the box or the key) in exchange for a €4 reduction of the winnable reward. Participants were guided to a post-experiment questionnaire, which assessed demographics and other variables in the last step. Finally, we conducted the contest, where all participants were informed that they had equal chances to win. This rendered their actual performance in the game inconsequential for winning in the contest (i.e., the actual winner was drawn randomly from all participants). Thus, only the warm-up but not the actual contest was part of the experiment. Because all participants invested similar time and effort, we wanted to avoid any treatment favoring a specific group.

*Figure 4. Experimental procedure.*

After participants decided whether to purchase the loot box, we recorded their choice, and they were directed to the post-experimental questionnaire, where we recorded our moderating construct (i.e., risk attitudes). As depicted in Table A in the Appendix, we measured the construct risk attitudes with a 7-point Likert scale using two items based on Gomez-Mejia and Balkin (1989) and Gray and Durcikova (2005). Reliability for our construct was measured using Cronbach’s alpha, which had a value above .70 (Fornell and Larcker, 1981). Furthermore, we employed checks to ensure the participants
comprehended all instructions. Lastly, we included two manipulation checks (i.e., perceived certainty and perceived possession) to ensure that participants understood and recalled our manipulations correctly.

4.3 Sample Description and Manipulation Checks

Similar to previous experiments in contest-based studies (Lowry et al., 2013, e.g., Ho et al., 2011), we recruited participants from a heterogeneous subject pool within a large German university. Out of 236 participants, we excluded 29 due to suspicious click patterns (e.g., low response variability) and 27 due to failing at least one attention check resulting in a final sample of 180 participants used for data analysis. Of these 180 participants, 69 identified as females, 111 identified as males. 47 participants opted for purchasing the loot box, which yields an overall purchase rate of 26% across all four subgroups. The average age of our participants was 27 years, 41% have a university degree as the highest education level, 42% an A level, and 17% reported other educational qualifications. Our independent variable risk attitudes show the following values: M = 4.02, SD = 1.38.

5 Results

5.1 Main Effect of Changing the Probability of Winning

In line with extant IS research (e.g., Roethke et al., 2020b), we conducted a two-stage hierarchical logistic regression on our dependent variable purchase decision to test our hypotheses. In the first stage, we entered all control variables, as well as our independent variables probability of winning the reward (PWR), previous endowment (PE), and (negative) risk attitudes (RA). In the second stage, we added the interaction term of PWR and PE (2a) and the interaction term of PWR and RA (2b). Nagelkerke’s $R^2$ was computed to test the fit for both stages.

<table>
<thead>
<tr>
<th></th>
<th>Stage 1</th>
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<th>Stage 2a</th>
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<th>Stage 2b</th>
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<td>-2.31</td>
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<td>.58</td>
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<td>PWR x PE</td>
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<td>1.57*</td>
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<td>PWR x RA</td>
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Note: * p < .05; ** p < .01; *** p < .001; N = 180; Coef.: Coefficient, SE: Standard Error, PWR: Probability of winning the reward, PE: Previous Endowment, RA: Risk Attitudes

Table 1. Logistical regression analysis on purchase decision.

None of our controls had a significant effect on purchase decision. The results of our logistic regression’s first stage analysis demonstrated a significant positive main effect of changing the probability of winning
the reward \((b = .79; \text{Wald statistic } (1) = 4.99; p < .05)\) on purchase decision, supporting H1. Hence, participants who faced a choice potentially governed by the risk avoidance effect were more than twice \((\text{Exp}(b) = 2.2)\) as likely to buy the loot box (i.e., gain access to the loot box’s content) compared to when the probability of winning the reward was uncertain. The average revenue per decision in our group with the uncertain loot box version was €0.77, and in the scenario with the certain loot box version, it was €1.38. Thus, the change due to employing the risk avoidance effects results in an average increase in revenue of €0.61 per decision (+79.2%).

### 5.2 Interaction Effect Analysis of Changing the Probability of Winning and Previous Endowment

Our stage 2a analysis unveiled a significant two-way interaction of changing the probability of winning the reward and previous endowment \((b = 1.57; \text{Wald statistic } (1) = 4.2; p < .05)\) on purchase propensity, supporting H2. The change in preference due to the combination of the risk avoidance effect and loss aversion results in a nearly fivefold increase in purchase likelihood \((\text{Exp}(b) = 4.8)\) and an average increase in revenue of €0.90 per decision (+86.5%).

To further evaluate our H2 hypothesis, we conducted a contrast analysis. As depicted in Figure 5, the results highlight that when the probability of winning is certain, participants are more likely to purchase the loot box when previous endowment is present compared to when it is absent (48% vs. 26%; \(F = 4.37; p < .05\)). However, a significant difference in purchase decision between the presence (14%) and absence (22%; \(F = 1.02; p > .1\)) of previous endowment did not emerge when the probability of winning was uncertain, in support of H2.

![Figure 5](image)

**Figure 5.** Purchase decision when PE is absent vs. present.

### 5.3 Interaction Effect Analysis of Changing the Probability of Winning and Risk Attitudes

The results of our stage 2b additionally indicated a significant two-way interaction between changing probabilities of winning the reward and risk attitudes \((b = .89; \text{Wald statistic } (1) = 9.1; p < .01)\) on purchase propensity, supporting H3. As such, the change in preference due to the risk avoidance effect when users are risk-averse results in a more than twofold increase in purchase likelihood \((\text{Exp}(b) = 2.4)\) and an average increase in revenue of €0.82 per decision (+73.2%).

Likewise, to investigate our H3 hypothesis, we conducted a contrast analysis as exhibited in Figure 7. The results illuminate that when the probability of winning was certain, participants are more likely to purchase the loot box when risk attitudes were high (i.e., when RA exhibited a value higher than 4) as opposed to when it was low (i.e., when RA exhibited a value equal to or lower than 4) (49% vs. 24%; \(F = \ldots\)).
= 5.58; p < .05). However, in support of H3, when the probability of winning was uncertain, no significant difference in terms of decision to purchase occurred when risk attitudes were high as opposed to when it was low (17% vs. 21%; F = 0.29; p > .1).

![Probability of winning the reward](image)

### Figure 6. Purchase decision when RA were low vs. high.

#### 6 Discussion

Digital business models are increasingly faced with stiff competition for regular and new customers. In light of this, they are testing several new monetization strategies to increase revenues and thus evolve their business models. An auspicious and currently manifesting and strategy is gamblification, which augments and evolves traditional revenue streams through a gamblified design of service and product offerings. Against this background, our endeavor was navigated by two research questions. The first research question concentrated on how a certain vs. an uncertain reward in loot boxes affects user purchase behavior. Our results provide support for the assertion that the probability of winning a reward in loot boxes influences users’ loot box purchase decision.

Our second research question provides insights on the moderating role of previous endowment with an unopened loot box and risk attitudes, two factors that both had an intriguing effect on the risk avoidance effect. Our results reveal that previous loot box endowment augments the effect of different probabilities of winning (uncertain vs. certain) on users’ loot box purchase behavior. However, this effect leading to a higher valuation of objects already in possession seems to only occur in the domain of certain outcomes. Thus, loss aversion amplifies the risk avoidance effect such that users are even more likely to purchase the certain loot box version when previously endowed with an unopened loot box. Likewise, the risk avoidance effect is amplified when assessed together with risk attitudes, a psychological trait that reflects people’s appetite for risk (i.e., engaging in activities that are generally rewarding yet involve some potential for loss). Thus, users are more likely to purchase the certain loot box version compared to the uncertain version when they are more risk-averse.

#### 6.1 Theoretical Contributions

This study contributes to IS research on gamblified digital business models in three essential ways. First, we extend the body of knowledge in the nascent field of gamblified design elements and their promising role in digital business models. Following the research agenda proposed by Veit et al. (2014), we focus on digital business models that experiment with innovative monetization strategies to supplement their traditional revenue streams. One particularly promising strategy is to incorporate virtual goods in revenue models. We combine these virtual goods with gamblification design elements and examine their influence on users’ purchase behavior. By doing so, we draw on extant literature on the influences of cognitive biases on purchase intention of virtual goods (e.g., Animesh et al., 2011,
Concretely, we study the impact of different loot box designs combined with different probabilities of winning the loot box’s content (i.e., a reward) and users’ previous endowment of such. Our results support the premise that the probability of winning a reward (i.e., “uncertain” vs. “certain” rewards) has a significant impact on users’ purchase behaviors of virtual goods. Since loot box transactions today are among the most prevalent forms of gamification in digital business models and constitute a multi-billion dollar market (Juniper Research, 2017), these findings’ implications are considerable.

Second, we extend prior research in the context of purchase behaviors of virtual goods under uncertainty by considering two moderators that amplify the risk avoidance effect: Users’ previous endowment of these goods and users’ risk attitudes. Both loss aversion and users’ risk aversion amplify the risk avoidance effect. More fundamentally, we observe that loss aversion appears effective only for certain gain prospects (i.e., loot boxes with a certain reward) but not for uncertain reward options (i.e., loot boxes with uncertain outcomes). As such, we provide evidence that uncertainty in digital environments may diminish individuals’ susceptibility to loss aversion. This is surprising since uncertainty is an inherent feature of gamified digital business models, in which the concept of loss aversion is frequently leveraged to motivate user purchase behavior (Rietveld, 2018). Moreover, there exists an interaction effect between risk attitudes and the risk avoidance tendency. Specifically, when users are risk-averse (i.e., they exhibit a high risk aversion), the risk avoidance effect is amplified. In contrast, when users are risk-seeking (i.e., they exhibit little or no risk aversion), the risk avoidance effect is canceled out such that overall, these users do not prefer the certain over the uncertain gain prospect (i.e., a loot box with a certain vs. an uncertain reward). Consequently, we argue that researchers need to carefully consider users’ risk attitudes when investigating gamified digital business models in general and loot box designs (which utilize probabilistic uncertainty) in particular.

Third, heeding Goes (2013) call for more research into the cognitive dimension of judgment in digital decision contexts, our study adds fine-grained insights to the sprawling knowledge on cognitive biases in virtual environments. In particular, whereas extant research directed its attention predominantly on attributes of a cognitive bias (e.g., asymmetry and linearity of anchoring effects) affecting user behavior in e-tailing (e.g., Adomavicius et al., 2013, Bodoff and Vaknin, 2016), our insights from a randomized online experiment yield practical design recommendations on how the risk avoidance effect, distinctly and in combination with loss aversion and risk attitudes, can be employed to influence user purchase behavior and thus shape revenue generation and monetization within gamified digital business models. Taken together, we extend the body of knowledge in IS research on nascent gamified digital business models by emphasizing the promising impact of uncertainty-based monetization mechanisms. When employed carefully and deliberately, gamified design elements such as loot boxes can lastingly shape revenue models and thus ensure the success of gamified digital business models.

### 6.2 Practical Contributions

The findings of this study also equip digital business models facing the task of implementing loot box offerings with valuable practical knowledge and, more broadly, to aid better grasping mechanisms underlying the micro-level economic behavior of individuals in gamified digital business models. Our research furnishes accessible design recommendations on how the probability of winning a reward can be employed in isolation and jointly together with previous endowment to enhance user purchase behavior and, thus, revenues in digital business models. Regarding revenue generation, our findings imply an average increase in revenue of up to €0.90 per decision (+86.5%). Our design recommendations mainly apply to all digital business models within gamified information systems, which are especially widespread in the 150-billion-dollar market of digital games (Newzoo, 2020) and the 30-billion-dollar loot box market (Juniper Research, 2017). Furthermore, the implications of our findings can also be applied to uncertain offerings in online services, such as the offering of virtual surprise sticker sets for instant messaging services (i.e., randomized selection of virtual stickers to customize private messages). Furthermore, when implementing both certain and uncertain loot box versions, providers need to consider the effect of combining these different loot box versions with a prevalent practice of endowing
users with unopened loot boxes in order to urge users to purchase those loot boxes (i.e., gain access to the loot box’ content). On the one hand, when users are faced with the certain version of loot box offering and are also previously endowed with an unopened loot box, they are likely to purchase the loot box even more often compared to when there is no previous endowment. On the other hand, when faced with the uncertain version of loot box offering, a previous loot box endowment is unlikely to change users’ purchase behavior. As such, previous endowment is probably ineffective in increasing users’ purchase likelihood and, thus, the combination of two loot box designs may be employed to enhance user experience but not revenue generation.

6.3 Limitations and Directions for Future Research

This research represents an early experimental investigation of gamblified digital business models, and, therefore, we feel obliged to highlight some relevant limitations that provide new impetus for future research.

First, we examined gamblified digital business models solely from the perspective of loot box designs. Despite being the most prevalent gamblification elements, there exist many other forms (e.g., betting and card games) besides loot boxes that require research attention. Gamblification brings about many more opportunities for theoretical insights beyond the gamblification of loot box designs. Therefore, we urge future research to shed more light on what potentials and consequences gamblified digital business models entail.

Second, the probability of winning treatment was designed in a binary (i.e., uncertain vs. certain) fashion and specified values in both conditions (e.g., “80%” vs. “100%”) based solely on reference values in extant literature. In this regard, the question arises of how altering these reference values impacts conversion behavior and whether linear or non-linear relationships can be expected. Future research should thus conduct nuanced investigations of the potentially complex relationships between the degree of changing the probabilities of winning and conversion behavior in digital business models. Moreover, future research should confirm and refine the results in a field study and in other cultural contexts to increase the robustness of our findings.

Appendix

<table>
<thead>
<tr>
<th>Construct</th>
<th>Items</th>
</tr>
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| Risk Attitudes (Gray and Durcikova, 2005) (Cronbach’s alpha = .71) | – I am a cautious person who generally avoids risk
– I am very willing to take risks when choosing a job or project to work on |

Note: Items were measured on a 7-point Likert scale ranging from strongly disagree (1) to strongly agree (7); To avoid comprehension issues among our non-native English speaking subjects we dropped the third item.

Table A. Measurement items.
References


Juniper Research (2017). "In-game gambling –the next cash cow for publishers."


Morgan Stanley (2012). "Social Gambling: Click Here to Play."


