The Impact of Social Influence and Risk Assessment Cues on User Conversion in Gam(bl)ified Digital Business Models

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Abstract

Information systems (IS) research that examines individual user-system interaction naturally relies on human cognition, judgment, and decision-making. Accordingly, this branch of IS research has employed psychological theories since its inception. However, only in recent years have IS researchers started to investigate how insights from cognitive psychology, social psychology, and behavioral economics can be leveraged within IS design. Especially the utilization of cognitive biases in combination with gamification currently attracts a lot of research attention. Both concepts aim at designing IS in a way that motivates users towards a target behavior. Despite calls for IS research on gamification to leverage insights from behavioral economics and social psychology in the context of gam(bl)ified IS (i.e., IS that use game/gambling design elements for non-entertainment purposes), there is only sparse research investigating how information cues can address cognitive biases to affect outcomes within gam(bl)ified IS. To advance the emergent research in these connected fields, this thesis investigates how information cues embedded in user-interface design elements can account for two important categories of cognitive biases regarding their influence on user behavior. More specifically, this thesis examines how information cues that address social influence biases and risk assessment biases impact user conversion (i.e., the process of turning visitors into active and/or paying users) within gam(bl)ified IS[1].

Against this backdrop, five studies were conducted and published across four articles. The first study lays the foundation for the research context and setting. More specifically, a taxonomy of gamification elements is developed and extended to account for the novel gamification-related concept of gamblification. While gamification is often defined as the use of game design elements in a non-gaming context, gamblification can be viewed as the use of gambling design elements in non-gambling contexts. Gamblification is a unique concept that can be distinguished from gamification because it additionally relies on chance-based uncertainty and user-system resource transfer. Both gamification and gamblification provide a suitable setting for examining how cognitive biases can be accounted for in regard of their impact on user behavior. This is because gamification is often concerned with social interactions (e.g., competition or cooperation) and therefore frequently relies on social psychology as a theoretical foundation. Gamification is thus predestined to investigate the role of social influence biases

[1] While the impact (and the eventual exploitation) of cognitive biases is of great importance for practitioners, this thesis takes a neutral observer perspective by demonstrating that user conversion is affected by information cues that account for cognitive biases and explaining how and why this is the case.

(i.e., cognitive biases based on social influence theory) in motivating users towards a target behavior. Likewise, the emergent gamblification research setting is intriguing for investigating cognitive biases. Due to the inherent characteristics of gamblification (i.e., chance-based uncertainty and resource transfer) particularly risk assessment biases (i.e., cognitive biases that are induced by biased risk assessment) are highly relevant in this environment.

The second article is situated in a gamified IS environment and investigates the role of social influence biases in fostering user conversion behavior (i.e., user registration) on an e-commerce platform. Drawing on social influence theory, two social influence cues (i.e., information cues that account for social influence biases), namely reciprocity cues and social proof cues, are embedded in the gamification design element 'user onboarding' and investigated in an e-commerce setting. The article's findings indicate that both, reciprocity and social proof, have positive direct effects on user registration. However, depending on how reciprocity is implemented, the interactive effect of reciprocity and social proof attenuates or amplifies the positive direct effect.

The third article examines risk assessment cues (i.e., information cues that aim to account for risk assessment biases) positioned within the gamblification element of a 'loot box menu'. By illuminating how these risk assessment cues can address a group of risk assessment biases, namely probability evaluation biases (i.e., cognitive biases that result from a skewed evaluation of probabilities during risk assessment) their role in affecting product selection in a digital gaming context is investigated. More specifically, drawing on prospect theory, information cues are designed to account for two different probability evaluation biases, the certainty effect and the availability bias. The study's results demonstrate that offering users loot box menus with two different probabilities of winning a reward (i.e., the choice between two different uncertain rewards vs. the choice between a certain and an uncertain reward) may trigger the certainty effect which influences user conversion behavior (i.e., product selection). Moreover, combining these different loot box menu designs with a previous loss experience causes users to be subject to the availability bias and amplifies the certainty effect. In contrast, when users are subject to the optimism bias, the certainty effect is attenuated.

The fourth and last article investigates how risk assessment cues embedded in differently designed product offerings (i.e., gamblified vs. transaction-based) in the context of a digital gaming service can address a different group of risk assessment biases (i.e., stability biases)

and thereby influence user conversion behavior (i.e., user purchase behavior). More specifically, drawing on literature on decision-making under risk, information cues are designed to address two stability biases, namely the risk avoidance effect and the endowment effect. Moreover, the effect of a general personal trait that is relevant for risk assessment (i.e., risk aversion) is examined. The results reveal that a gamblified product offering (i.e., a loot box with an uncertain reward) vs. a transaction-based product offering (i.e., a loot box with a certain reward) triggers the risk avoidance effect that influences user conversion. This effect is amplified when users are either subject to the endowment effect (i.e., when they experience a previous endowment with a loot box) or when they are risk-averse.

Taken together, this thesis highlights the importance of considering the role of social influence and risk assessment biases and how information cues can be designed within gam(bl)ified IS to address these cognitive biases to motivate users towards a target behavior. Moreover, the results contribute to IS research by exploring the impact of manifold information cues that account for social influence and risk assessment biases as well as context-dependent interacting variables in various gam(bl)ified IS environments. Alongside these contributions to research, this thesis provides several interesting and actionable recommendations on how to implement information cues that take cognitive biases into account. This is primarily aimed at practitioners tasked with designing gam(bl)ified IS with the goal of optimizing user conversion behavior.

Zusammenfassung

Die Forschung im Bereich der Informationssysteme (IS), die sich mit der Interaktion zwischen Benutzer und System befasst, betrachtet naturgemäß auch die menschliche Kognition, Urteilsfähigkeit und Entscheidungsfindung. Dementsprechend stützt sich dieser Zweig der IS-Forschung seit seinen Anfängen auf psychologische Theorien. Allerdings haben IS-Forscher erst in den letzten Jahren begonnen zu untersuchen, wie Erkenntnisse aus der kognitiven Psychologie und der sozialpsychologischen Forschung für die Gestaltung von IS genutzt werden können. In diesem Zusammenhang genießen derzeit vor allem die Berücksichtigung kognitiver Verzerrungen und Gamification große Aufmerksamkeit in der Forschung. Beide Konzepte zielen darauf ab, IS so zu gestalten, dass sie die Nutzer zu einem bestimmten Verhalten motivieren. Trotz der Aufforderung an die IS-Forschung zu Gamification, Erkenntnisse aus der Verhaltensökonomie und der Sozialpsychologie im Kontext gamifizierter IS zu nutzen, gibt es bisher nur wenige Untersuchungen dazu, wie in Informationshinweisen (d.h. Informationen über einen Stimulus, die Individuen bei der Ausführung einer Aufgabe verarbeiten müssen) kognitive Verzerrungen in Hinblick auf ihre Auswirkungen innerhalb von gamifizierten IS berücksichtigt werden können. Um die Forschung in diesen Bereichen voranzutreiben, untersucht diese Arbeit, wie Informationshinweise, die in Design-Elementen der Benutzeroberfläche eingebettet sind, zwei wichtige Kategorien kognitiver Verzerrungen hinsichtlich ihres Einflusses auf das Nutzerverhalten berücksichtigt werden können. Genauer gesagt wird in dieser Arbeit untersucht, wie sich Informationshinweise, die Verzerrungen durch sozialen Einfluss und Verzerrungen durch Risikobewertung berücksichtigen, auf die Konversion von Nutzern (d.h. der Prozess, Besucher in aktive und/oder zahlende Nutzer zu verwandeln) in gam(bl)ifizierten IS auswirken[2].

Vor diesem Hintergrund wurden fünf Studien durchgeführt und in vier Artikeln veröffentlicht. Die erste Studie legt dabei den Grundstein für den Forschungskontext und -rahmen. Dazu wird eine Taxonomie von Gamification-Elementen entwickelt und erweitert, um dadurch das neue mit Gamification in Zusammenhang stehende Konzept Gamblification angemessen einführen zu können. Während Gamification häufig als die Verwendung von Spiel-Design-Elementen in einem Nicht-Spiele-Kontext definiert wird, kann Gamblification als die Verwendung von Glücksspiel-Design-Elementen in einem Nicht-Glückspiel-Kontext verstanden werden.

[2] Während die Auswirkung (und die etwaige Ausnutzung) kognitiver Verzerrungen für Praktiker von großer Bedeutung ist, wird in dieser Arbeit eine neutrale Beobachterperspektive eingenommen, indem die Beeinflussung der Konversion von nutzern durch Informationshinweise, die kognitive Verzerrungen berücksichtigen, festgestellt wird und erklärt wird, wie und warum dies der Fall ist.

Gamblification ist ein einzigartiges Konzept, das sich von Gamification unterscheidet, weil es zusätzlich auf zufallsbasierter Unsicherheit und dem Ressourcentransfer zwischen Benutzer und IS beruht. Sowohl Gamification als auch Gamblification bieten einen geeigneten Rahmen, um zu untersuchen, wie kognitive Verzerrungen im Hinblick auf ihre Auswirkungen auf das Nutzerverhalten berücksichtigt werden können. Dies liegt daran, dass sich Gamification häufig mit sozialen Interaktionen (z.B. Wettbewerb oder Kooperation) befasst und daher häufig auf die Sozialpsychologie als theoretische Grundlage zurückgreift. Gamification ist daher prädestiniert um die Rolle von Verzerrungen durch sozialen Einfluss (d.h. kognitiver Verzerrungen, die auf der Theorie des sozialen Einflusses basieren) hinsichtlich der Motivation von Nutzern zu einem bestimmten Verhalten zu untersuchen. Ebenso ist das aufkommende Forschungsfeld der Gamblification interessant für die Untersuchung kognitiver Verzerrungen. Aufgrund der inhärenten Charakteristika von Gamblification (d.h. zufallsbedingte Unsicherheit und Ressourcentransfer) sind insbesondere Verzerrungen durch Risikobewertung (d.h. kognitive Verzerrungen, die durch eine verzerrte Risikobewertung hervorgerufen werden) in diesem Umfeld von großer Bedeutung.

Der zweite Artikel ist in einer gamifizierten IS-Umgebung angesiedelt und untersucht die Rolle von Verzerrungen durch sozialen Einfluss (d.h. kognitive Verzerrungen, die auf der Theorie des sozialen Einflusses basieren) bei der Förderung des Konversionsverhaltens von Nutzern (d.h. die Benutzerregistrierung) auf einer E-Commerce-Plattform. Auf der Grundlage der Theorie des sozialen Einflusses werden zwei soziale Einfluss-Hinweise (d.h. Informationshinweise, die Verzerrungen durch sozialen Einfluss ansprechen), nämlich Reziprozität Hinweise und sozialer Nachweis Hinweise, in das Gamification-Design-Element ‘Benutzer-Onboarding’ eingebettet und in einem E-Commerce-Umfeld untersucht. Die Ergebnisse des Artikels zeigen, dass sowohl Reziprozität als auch sozialer Nachweis positive direkte Effekte auf die Benutzerregistrierung haben. Je nachdem, wie Reziprozität umgesetzt wird, schwächt oder verstärkt der interaktive Effekt von Reziprozität und sozialer Nachweis jedoch den positiven direkten Effekt.

Der dritte Artikel untersucht Riskobewertungshinweise (d.h., Informationshinweise, die darauf abzielen, Risikobewertungsverzerrungen zu berücksichtigen), die innerhalb des Gamblification-Elements ‘Lootbox-Menü’ positioniert sind. Es wird beleuchtet, wie diese Risikobewertungshinweise eine Gruppe von Risikobewertungsverzerrungen, nämlich Verzerrungen durch Wahrscheinlichkeitsbewertungen (d.h. kognitive Verzerrungen, die aus einer verzerrten Bewertung von Wahrscheinlichkeiten während der Bewertung von Risiken

resultieren), ansprechen können und welche Rolle sie bei der Produktauswahl in einer digitalen Spielumgebung spielen. Unter Rückgriff auf die Prospect-Theorie werden Informationshinweise so gestaltet, dass sie zwei verschiedene Verzerrungen durch Wahrscheinlichkeitsbewertungen ansprechen, nämlich den Sicherheitseffekt und die Verfügbarkeitsheuristik und -verzerrung. Die Ergebnisse zeigen, dass das Angebot von Lootbox-Menüs mit zwei unterschiedlichen Gewinnwahrscheinlichkeiten (d.h. die Wahl zwischen zwei verschiedenen unsicheren Belohnungen im Vergleich zur Wahl zwischen einer bestimmten und einer unsicheren Belohnung) tatsächlich den Sicherheitseffekt auslöst, der wiederum das Konversionsverhalten der Nutzer (d.h. die Produktauswahl) beeinflusst. Darüber hinaus führt die Kombination dieser verschiedenen Lootbox-Menü-Designs in Kombination mit einer früheren Verlusterfahrung dazu, dass die Nutzer der Verfügbarkeitsverzerrung unterliegen, die den Sicherheitseffekt verstärkt. Im Gegensatz dazu wird der Sicherheitseffekt abgeschwächt, wenn die Nutzer der Optimismusverzerrung unterliegen.

Im vierten und letzten Artikel wird untersucht wie Risikobewertungshinweise, die in unterschiedlich gestaltete Produktangebote (d.h. gamblifiziert im Vergleich zu transaktionsbasiert) im Kontext digitaler Spiele eingebettet sind, eine andere Gruppe von Verzerrungen durch Risikobewertung (d.h., Stabilitätsverzerrungen) auslösen können und dadurch das Konversionsverhalten (d.h. das Kaufverhalten) der Nutzer beeinflussen. In Anlehnung an die Literatur zur Entscheidungsfindung unter Risiko werden Informationshinweise so gestaltet, dass sie zwei Stabilitätsverzerrungen auslösen, nämlich den Risikovermeidungs- und den Besitztumseffekt. Darüber hinaus wird die Auswirkung eines allgemeinen persönlichen Merkmals, das für die Risikobewertung relevant ist (d.h. die Risikoaversion), untersucht. Die Ergebnisse zeigen, dass ein gamblifiziertes Produktangebot (d.h. eine Lootbox mit einer unsicheren Belohnung) im Vergleich zu einem transaktionsbasierten Produktangebot (d.h. eine Lootbox mit einer sicheren Belohnung) den Risikovermeidungseffekt auslöst, der die Konversion der Nutzer beeinflusst. Dieser Effekt wird verstärkt, wenn die Nutzer entweder dem Besitztumseffekt unterliegen (d. h., wenn sie eine frühere Belohnung mit einer Lootbox erfahren haben) oder wenn sie risikoavers sind.

Insgesamt unterstreicht diese Arbeit wie wichtig es ist die Rolle von kognitiven Verzerrungen zu berücksichtigen, die durch sozialen Einfluss und Risikobewertung ausgelöst werden. Zudem wird beleuchtet wie Informationshinweise in gam(bl)ifizierten IS so gestaltet werden können, um diese kognitiven Verzerrungen anzusprechen und die Nutzer zu einem bestimmten Verhalten zu motivieren. Darüber hinaus leisten die Ergebnisse einen Beitrag zur IS Forschung,

indem die Arbeit die Auswirkungen vielfältiger Informationshinweise, die Verzerrungen durch sozialen Einfluss und Verzerrungen durch Risikobewertung sowie kontextabhängige interagierende Variablen berücksichtigen, in verschiedenen gam(bl)ifizierten IS Umgebungen erforscht. Neben diesen Beiträgen zur Forschung gibt diese Arbeit mehrere interessante und umsetzbare praktische Empfehlungen zur Implementierung von Informationshinweisen, die kognitive Verzerrungen berücksichtigen. Dies richtet sich vor allem an Praktiker, die mit dem Design von gam(bl)ifizierten IS beauftragt sind, mit dem Ziel das Konversionsverhalten der Nutzer zu optimieren.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

AVE	Average Variance Extracted
CMB	Common Method Bias
Coef.	Coefficient
CR	Composite Reliability
DSS	Decision Support Systems
eWOM	Electronic Word-of-Mouth
HCI	Human-Computer Interaction
IS	Information Systems
LLCI	Lower Limit of Confidence Interval
M	Mean
MTurk	Amazon Mechanical Turk
PBC	Perceived Behavioral Control
PE	Previous Endowment
PLE	Previous Loss Experience
PWR	Probabilities of Winning the Reward
RA	Risk Attitudes
RWR	Riskiness of Winning the Reward
SD	Standard Deviation
SE	Standard Error
S-O-R	Stimuli-Organism-Response
ULCI	Upper Limit of Confidence Interval

Chapter 1: Introduction

1.1 Motivation and Research Question

Cognitive research in the field of information systems (IS) covering decision support systems (DSS) and human-computer interaction (HCI) has received significant scholarly attention in recent years (e.g., Browne and Parsons 2012; Lee and Joshi 2017). In particular, human information processing and decision-making are prominently investigated in this field (Goes 2013). In this regard, a phenomenon vital for human decision-making has been adapted to IS research from behavioral economics and psychological research: cognitive biases (Arnott and Gao 2019; Fleischmann et al. 2014). Cognitive biases are consistent errors in subconscious thinking that occur when individuals process and interpret information from their environment and that affect their decisions and judgments (Baron 2007). The consequences of cognitive biases are objectively non-rational decisions that often lead to suboptimal outcomes (Wilkinson and Klaes 2017).

Two particularly interesting categories of cognitive biases which are highly relevant for human decision-making, namely social influence biases and risk assessment biases, stem from social psychology and behavioral economics, respectively. Social influence biases (i.e., cognitive biases based on social influence theory) occur when individuals are faced with uncertain and complex decisions and they draw on social signals and social norms to infer appropriate behavior (Hogg 2010). This bias category is of particular importance in decision environments that feature social interactions. A prominent example for the impact of social influence biases is (irrational) herding behavior in financial markets (e.g., Clement and Tse 2005; Trueman 1994). However, in situations where individuals are faced with decisions under uncertainty, they may be subject to another crucial category of cognitive biases. Unlike the uncertainty stemming from inferring appropriate behavior in social interactions, a different category of uncertainty and cognitive biases arise from individuals' evaluation of the prospects involved in risky decisions (Kahneman and Tversky 1979). Due to individuals' biased assessment of risk, they are prone to make biased decisions that deviate from rational behavior. These risk assessment biases (i.e., cognitive biases that are induced by biased risk assessment) are particularly relevant when individuals may receive rewards and thus need to evaluate the prospective gains or losses (Thaler and Ganser 2015). A prime example for the results of risk assessment biases is the possibility effect: When an outcome is possible but not probable (e.g., winning a lottery), individuals tend to overestimate its chance of occurring (Kahneman 2011).

Despite the high relevance of cognitive biases for the IS research in the context of user decision-making in electronic marketplaces or digital business models, only sporadic IS research on the

effect of cognitive biases in these contexts has been conducted (e.g., Cheng and Wu 2010; Tan et al. 2012). Against this backdrop, current IS research on digital business models[3] provides initial evidence on the role of information cues (i.e., pieces of information about the stimulus that individuals must process in performing a task) that are designed to account for cognitive biases in affecting user behavior with beneficial outcomes for providers of digital business models (e.g., Klumpe et al. 2020; Koch and Benlian 2017; Terres et al. 2019). These publications examine how information cues can be designed and implemented as digital nudges to deliberately trigger cognitive biases that nudge users towards a target behavior (Mirsch et al. 2018; Weinmann et al. 2016). Interestingly, the related IS research stream on gamification addresses a similar goal and also aims at using digital design elements to motivate users towards a target behavior. Gamification refers to the use of design elements for games in non-game contexts with the goal to enhance user experience and to motivate users towards target behaviors, ultimately improving societal or organizational outcomes (Bui et al. 2015; Deterding et al. 2011a). Despite the conceptual similarity and calls for gamification research to utilize theories whose subject matter are cognitive biases (i.e., social influence theory and prospect theory) (Liu et al. 2017) or to even integrate the concepts of gamification and digital nudging (Schöbel et al. 2020a), there is only little research at the intersection between these two research streams.

Because social interactions play a pivotal role in many types of gamification design elements (e.g., elements featuring competition or cooperation) and also in the context in which gamification is typically applied (e.g., exercising or social networking), this field seems to provide a fertile ground for investigating social influence biases (Hamari and Koivisto 2013; Hamari and Koivisto 2015). In a similar vein, the emerging, gamification-connected field of gamblification yields a suited environment to probe the effectiveness of a different category of cognitive biases. Gamblification refers to the use of gambling design elements in non-gambling contexts and – similar to gamification – aims at motivating users towards preferred behavior. However, unlike gamification, gamblification relies on gambling-inspired, chance-based design elements that typically involve resource transfers (Reinelt et al. 2021). As such, in gamblification environments, individuals are inherently faced with risky decisions that involve real-world rewards and thus are likely to be subject to risk assessment biases (i.e., cognitive biases that are induced by biased risk assessment) which makes these environments an intriguing research context to investigate this category of biases.

[3] Business models whose "…business logic uses entirely IT-mediated processes and digital products or services for value creation and transfer" (Steininger 2019).

Heeding the calls for research in gamification research and IS research on cognitive biases (Arnott and Gao 2019; Goes 2013; Liu et al. 2017), this thesis proposes to advance research at the intersection of both research streams by examining the effectiveness of information cues that are positioned within gam(bl)ification design elements (i.e., gamification and gamblification design elements) and take cognitive biases regarding how they can motivate users towards a target behavior into account. Drawing on task complexity research and social influence theory, this thesis considers social influence cues to be information cues designed to take social influence biases into account (Burnkrant and Cousineau 1975; Nadkarni and Gupta 2007). Similarly, drawing on task complexity research and prospect theory, this thesis considers risk assessment cues to be information cues designed to account for risk assessment biases (Kahneman and Tversky 1979; Nadkarni and Gupta 2007). In general, information cues are likely to be most influential when user tend to be confident in their ability to draw behavioral guidance from the information cues (Wells et al. 2011). This is the case when information cues trigger a cognitive bias and urge individuals to subconsciously approve the information contained in these information cues. However, information cues that are designed to account for cognitive biases do not work in a vacuum, but require a specific target activity and an aligned context (Mirsch et al. 2018; Weinmann et al. 2016). Therefore, building on extant research on the role of cognitive biases in fostering user conversion (i.e., the process of turning visitors into active and/or paying users) in digital business models (e.g., Klumpe et al. 2020; Koch and Benlian 2017), this thesis examines user conversion behavior in gam(bl)ified digital business models (i.e., digital business models that employ gam(bl)ification design elements) as target user behavior and specific context, respectively. Since uncertainty stemming from social interaction is the primary reason why individuals are subject to cognitive biases in gamification contexts while this source for cognitive biases is negligible in gamblification contexts, this thesis focuses on investigating the effects of social influence cues only in gamified digital business models. Similarly, as uncertainty resulting from decision-making under risk is the dominant factor triggering cognitive biases in gamblification contexts while being negligible in gamification contexts, this thesis focuses on investigating the effects of risk assessment cues only in gamblified digital business models. As such, this thesis focuses on the following two overarching research questions:

RQ1: How can social influence cues affect user conversion in gamified digital business models?

RQ2: How can risk assessment cues affect user conversion in gamblified digital business models?

To answer these questions, five empirical studies were published in four articles. The first article introduces the context of gamification as well as gamblification and identifies which gam(bl)ification elements are suited for examining information cues that aim to address cognitive biases and thereby affect user behavior. The remaining three articles investigate the effects of embedding various social influence and risk assessment cues within different gamification and gamblification design elements on user conversion behavior.

1.2 Theoretical Foundations

In this section, the foundation is laid out to introduce the theoretical concepts which are used in this thesis. The first subsection explains the occurrence of cognitive biases and how social influence theory as well as prospect theory contribute to our understanding of cognitive biases. Subsequently, the second subsection discusses how insights from behavioral economics and psychological research on cognitive biases were adapted to (design-oriented) IS research on digital nudging. Furthermore, the conceptual alignment of digital nudging with the related design-oriented approaches of gamification, and emergent gamblification, is examined. Moreover, the highly relevant application context of digital business models and the target behavior 'user conversion' is motivated. Finally, in the third subsection, the distinct roles of social influence cues and risk assessment cues in impacting user conversion are presented to outline the positioning and the relevance of the thesis.

1.2.1 Cognitive Biases, Social Influence, and Decision-Making under Risk

A cognitive bias is a systematic (and thus predictable) deviation from norm or rationality that creates a subjective reality leading to biased judgment and decision-making (Baron 2007). According to Tversky and Kahneman (1974), cognitive biases may arise as a malfunction of heuristics (i.e., a fundamental part of the brain's function for quick and effortless decision-making), which are normally a source of effectiveness in human decision making. Heuristics are generally beneficial for human decision-making because they provide mental shortcuts to evaluate uncertain outcomes while bypassing possible information processing limits of the human brain (Simon 1955; Simon 1990). Although, according to this notion, cognitive biases should only occur occasionally (i.e., when the application of heuristics fails), there is a tremendous amount of research demonstrating that cognitive biases and the resulting irrational behavior occur in a replicable and predictable way (Ariely and Jones 2008; Kahneman 2011; Thaler and Ganser 2015). Against this background, over the past decades, a continually evolving list of cognitive biases has been identified and described in extant research (Gilovich et al. 2002; Kahneman et al. 1982; Kahneman and Tversky 2013).

Although being a central tenet for cognitive biases, the source of the uncertainty under which decisions are made is left rather unspecified in the explanations outlined so far. In this regard, two distinct sources of uncertainty give rise to a set of prominent cognitive biases. On the one hand, uncertainty stemming from attempts to infer appropriate behavior in social interactions may be a source of cognitive biases. The effects of this 'social uncertainty' are investigated in research on social influence. On the other hand, uncertainty arising from situations where individuals are faced with potential losses or gains may as well lead to the occurrence of cognitive biases. This 'risky uncertainty' is the subject matter of prospect theory as well as the connected literature on decision making under risk. To introduce the central concepts of both research streams, the following paragraphs provide a brief overview of the literature on social influence theory as well as the literature on prospect theory and decision making under risk.

Social influence theory examines the effect of words, actions, or the mere presence of other social actors on an individuals' beliefs, attitudes, and behaviors (Hogg 2010). These effects can be categorized into informational and normative social influence (Burnkrant and Cousineau 1975; Deutsch and Gerard 1955). Whereas informational social influence urges individuals to rely on the behavior of other social actors as a trustworthy source of information, normative social influence urges individuals to conform with what other people deem acceptable (Cialdini and Goldstein 2004; Cialdini et al. 1991). Both types of social influence are sometimes also considered as social norms (i.e., implicit rules for acceptable behaviors, values, and beliefs) (Cialdini and Trost 1998; Sanfey et al. 2014) and provide guidance in decision environments that involve uncertainty with respect to adequate social behavior. Through evolutionary and socialization processes, these rules for social interaction are typically deeply embedded in individuals and thus act as social heuristics (Hertwig and Hoffrage 2013) that lead individuals to unconsciously rely on the appropriateness of the rules (Blau 2017). As such, social influence may give rise to social influence biases (i.e., cognitive biases triggered by social influence) (Krueger and Funder 2004).

As a seminal evidence-based theory within behavioral economics, prospect theory deals with human decision-making in risky situations (Thaler and Ganser 2015). In contrast to uncertainty stemming from ambiguity regarding appropriate behavior in social interactions, in prospect theory, risky situations give rise to uncertainty due to prospective (monetary) gains or losses that only potentially materialize (Kahneman and Tversky 1979). The fundamental notion of prospect theory is that while individuals tend to avoid risks when they face potential gains they take risks when facing potential losses (Tversky and Kahneman 1992). This may result in irrational behavior triggered by so called stability biases because this notion does not only hold

when different individuals assess potential gains or losses, but also when the same individual is faced with a potential loss or gain (Barberis 2013). A second related, but distinct concept postulated by prospect theory is concerned with individuals' biased evaluation of probabilities (i.e., probability evaluation biases) which is relevant for making decisions under risk. According to the concept of probability evaluation biases, individuals tend to overweight small probabilities and underweight high (near-certain) probabilities (Kahneman 2011). This may as well lead to internal inconsistencies (i.e., irrational behavior), 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 (Allais 1953; Von Neumann and Morgenstern 2007). Another phenomenon related to decision-making under risk may as well lead to biased evaluation of probabilities. In this regard, the availability heuristic refers to the biased evaluation of probabilities which is skewed towards information more readily available (Tversky and Kahneman 1973). According to this heuristic, individuals evaluate the probability of uncertain events depending on their previous experiences and examples related to that event that immediately comes to a person's mind. Because all of the risk assessment concepts described in this section operate on the basis of quick and effortless reasoning, they regularly induce cognitive biases (Kahneman 2011; Kahneman and Tversky 1996). Taken together, prospect theory and literature on decision-making under risk propose two types of cognitive biases that are induced by biased risk assessment (i.e., risk assessment biases): Stability biases and probability evaluation biases. On the one hand, stability biases as a type of risk assessment biases may result from the biased assessment of potential losses or gains (Kahneman et al. 1991; Novemsky and Kahneman 2005), while on the other hand, probability evaluation biases as another type of risk assessment biases stem from the biased evaluation regarding the probability of risk involving events to occur (Kahneman 2011; Kahneman and Tversky 1984).

1.2.2 Digital Nudging, Gamification and Gamblification

Recent IS research acknowledges that these insights from behavioral economics and social psychology need to be actively accounted for because users are subject to cognitive biases that influence their decision-making (Dennis et al. 2020). In this regard, a promising approach is digital nudging defined as using user-interface design elements to influence user behavior by accounting for established biases in human decision-making (Schneider et al. 2018). It transfers the concept of nudging which is referred to as "[...] any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives." by Thaler and Sunstein (2008) into digital (choice) environments (Weinmann et al. 2016). Thus, both, nudging and digital nudging operate by

designing a decision-making environment that takes heuristics and cognitive biases into account in order to urge individuals towards preferred behaviors while retaining individuals' freedom of choice (Sunstein and Thaler 2003). Within digital environments, nudges can take the form of various user-interface design elements, such as providing a personalized anchor (i.e., a fixed percentage of an individual's disposable income) in technology-mediated financial investment decisions (Adam et al. 2019), or preselecting an option by setting a default option in reward-based crowdfunding (Wessel et al. 2019).

Over the last decade, another interesting concept has emerged in IS and HCI research: gamification. Similar to digital nudging, gamification aims at utilizing user-interface design elements to encourage a target user behavior. Gamification refers to the use of game-like design elements in non-entertainment-based contexts to motivate IS users towards preferred behavior (Bui et al. 2015; Deterding et al. 2011b; Schöbel et al. 2020b). In practice, design elements such as badges, bonuses, or leaderboards have been shown to have great potential to foster good learning habits, skill acquisition, and behavior change in fields such as education, health care, or e-commerce (Hamari et al. 2014; Santhanam et al. 2016; Wang et al. 2020). Gamification design elements (i.e., game-like design elements) are the central tenet of gamification and comprise all components and aspects that are necessary for designing and understanding a gamified (IS) environment (Schöbel et al. 2020b). These design elements can be further divided into two broad categories: gamification objects and mechanics (Liu et al. 2017). Gamification objects as design elements are the basic building blocks used to create a gamified (IS) environment that entails a gameful experience (Blohm and Leimeister 2013; Schöbel et al. 2020b). Gamification mechanics refer to the rules that govern the interaction between users and gamification objects (e.g., which specific user action results in a badge reward) determining the dynamics (i.e., how users experience the interaction with a gamification object) and ultimately the way user behavior is impacted (Deterding et al. 2011b; Liu et al. 2017; Teh et al. 2013). For instance, the gamification design element user onboarding (i.e., the active guidance of visitors to become registered users on a digital platform) comprises several gamification objects (e.g., registration layers to join the platform, visual representations of the platforms' main features and benefits offered) as well as gamification mechanics (e.g., user information disclosure within the registration layer as a prerequisite to becoming a registered user) (Liu et al. 2017; Roethke et al. 2020b). Importantly, the effects of these gamification design elements on user behavior can only be understood, when considering how these elements operate together (Schöbel et al. 2020b).

In addition to this, a gamification-related, yet distinct concept is currently emerging in IS research. Alongside game design elements, gambling design elements (e.g., lottery tickets, scratch cards, or betting) are prominently implemented in the contexts of (e-)sports and video gaming (e.g., Abarbanel and Johnson 2020; Macey and Hamari 2019). The use of these elements is referred to as gamblification and, just like gamification, aims at urging users towards a target behavior. Gamification and gamblification typically share the same setting and goals but attain these goals with different means (i.e., use of gamification vs. gamblification design elements). As such, gamblification comprises individual gambling design elements that entail 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). However, unlike gamification, these gambling design elements predominantly draw on chance-based uncertainty and usually involve resource transfers with real-world value resulting in differences in how gamblification impacts user behavior. To illustrate how these concepts act in conjunction to create a gamblified IS environment, the prominent gamblification element loot box (i.e., a single-use virtual good that randomly assign rewards they contain) can be considered (Macey and Hamari 2019). It comprises gamblification objects (e.g., visual representation of the loot box, or the content that the loot box contains) as well as gamblification mechanics (e.g., events that result in receiving a loot box, the probability for receiving a specific content) which only together shape user behavior.

Despite the conceptual alignment of the three concepts, digital nudging, gamification, and gamblification, and calls for research to investigate boundary conditions and the potential for conceptual integration (Hamari and Koivisto 2015; Schöbel et al. 2020a), there is only little research at the intersection of these research fields. All three concepts promote the use of digital (user-interface) design elements in order to urge users towards a target behavior (Benner et al. 2021). Therefore, this thesis proposes to investigate how cognitive biases can be addressed within gam(bl)ified IS environments. More specifically, it investigates how digital nudges can be embedded within gam(bl)ification design elements and how they impact user behavior. To do so, the first article advances an extant gamification taxonomy (Schöbel et al. 2020b) to account for novel design elements stemming from gamblification. Through advancing this taxonomy, different categories of gam(bl)ification design elements, that are particularly suited to embed digital nudges, emerged. Considering the results for gamification elements, one particular prevalent category are elements that draw on social interaction (i.e., cooperation and competition) (Schöbel et al. 2020b). This is in line with extant literature reviews on gamification research, indicating that social elements and design elements that draw on social influence, are

among the most frequently used categories of gamification design elements (Hamari and Koivisto 2015; Koivisto and Hamari 2019). Accordingly, social influence biases arising from uncertainty and ambiguity in social interactions are the main category of cognitive biases individuals are subject to in gamification contexts. However, because uncertainty stemming from social interaction is less important in gamblification environments, social influence biases are largely negligible in gamblification contexts. Regarding gamblification elements, the advancement of the taxonomy proposed in the first article indicates, that especially chance-based uncertainty and resource transfers characterize gamblification elements. Therefore, gamblification comprises user interaction that involves uncertain real-world rewards (i.e., decision-making under risk). Due to this risk-based uncertainty that prevails in gamblification, individuals are dominantly subject to risk assessment biases in gamblification environments. Since, risk-based uncertainty is usually absent in gamification environments, risk assessment biases are for the most part irrelevant in these gamification environments. Against this background and heeding calls for research within gamification and behavioral IS to draw on social influence theory and literature on human decision-making under risk (Goes 2013; Liu et al. 2017), this thesis contents that gamified IS provide a promising environment to investigate how social influence biases can be accounted for regarding their impact on user behavior. Likewise, gamblified IS provide an intriguing context to examine how risk assessment biases can be addressed in regard of how they affect user behavior.

1.2.3 Social Influence Cues, Risk Assessment Cues, and User Conversion

Regardless of how suitable the environment may be for addressing cognitive biases, cognitive biases can only have an effect on individuals when they are perceived by them. In this regard, IS literature on information cues and cue utilization provides valuable guidance on how environmental cues might affect user cognition and behavior. Information cues are pieces of information about the stimulus that individuals must process in performing a task and that are pivotal because users need to interact with the information cues (i.e., draw inferences from them) in online environments to achieve their online task (e.g., the decision whether to register or not on a digital platform) (Nadkarni and Gupta 2007; Wood 1986). Moreover, according to the literature on cue utilization, information cues are most influential when they are easy to observe and when users are confident in their ability to use and judge a cue accurately (Richardson et al. 1994; Wells et al. 2011). As such, this thesis considers social influence cues and risk assessment cues as information cues that aim to address social influence biases and risk assessment biases, respectively. When applied successfully (i.e., when they actually trigger the respective category of cognitive biases), information cues are likely to be most influential

because due to the triggered cognitive bias, users tend to be confident in their ability to draw behavioral guidance from the information cues. The reason is that when information cues trigger a cognitive bias, users are prone to subconsciously approve the information contained in these information cues.

Drawing on literature analyses of top-rated journal articles in IS research regarding the investigation of cognitive biases in various IS contexts (Arnott and Gao 2019; Fleischmann et al. 2014) and a review of IS literature on the role of social influence and risk assessment biases that was conducted for this thesis, Table 1-1: IS Journal Publications on Social Influence and Risk Assessment BiasesTable 1-1 identifies and categorizes the most frequently examined social influence and risk assessment biases. When it comes to referring to the different bias categories, it is important to consider that extant literature does not employ a consistent terminology for the presented concepts but applies context-dependent terminologies. For instance, as described earlier in subsection 1.2.1, while the notion of informational social influence (i.e., individuals' tendency to rely on the behavior of other social actors as a trustworthy source of information), is often referred to as herding (e.g., Brandt and Neumann 2015), it is also conceptualized as popularity information (e.g., Thies et al. 2016), electronic word-of-mouth (eWOM) (e.g., Goes et al. 2014), informational cascading (e.g., Liu et al. 2015), or social proof (e.g., Posey et al. 2010).

The overarching bias category 'risk assessment biases' comprises two subcategories of risk assessment biases: 'probability evaluation biases' and 'stability biases'. In this regard, the bias category 'probability evaluation biases' draws from the two bias groups perception biases as well as pattern recognition biases proposed by Fleischmann et al. (2014) and refers only to cognitive biases that affect individuals' evaluation of probabilities that are relevant for decision-making under risk. More specifically, this thesis considers the following set of biases as 'probability evaluation biases': the representativeness bias, the recency effect, the certainty effect, and the availability bias. Likewise, in the context of risk assessment, the subcategory 'stability biases' comprises the endowment effect, loss aversion, and the risk avoidance effect.

As depicted in Table 1-2, several information cues may act as triggers for the aforementioned social influence and risk assessment biases. Social influence cues can rely on either informational or normative social influence. An information cue that relies on informational social influence can be, for instance, facilitated via the view counter functionality on the video platform YouTube because it indicates the popularity of the content (i.e., a video) (e.g., Song et al. 2019).

Social Influence Biases	Articles
Herding / Informational Social Influence	Duan et al. (2009); Li and Hitt (2008); Posey et al. (2010); Ma et al. (2013); Hu and Lai (2013); Wang et al. (2013); Cheung et al. (2014); Liu et al. (2015); Dinev et al. (2015); Brandt and Neumann (2015); Burtch et al. (2016); Gao et al. (2017); Burtch et al. (2018); Huang et al. (2019a); Huang et al. (2019b); Mejia et al. (2020); Wu et al. (2021b); Qiu et al. (2021)
Social Norms / Normative Social Influence	Kankanhalli et al. (2005); Skågeby (2010); Posey et al. (2010); Chou and He (2011); Xia et al. (2012); Johnson et al. (2014); Ray et al. (2014); Burtch et al. (2016); Zhao et al. (2016); Ye et al. (2018); Kim et al. (2018); Barlow et al. (2018); Wang et al. (2018); Qiu et al. (2018); Tan et al. (2019a); Kokkodis et al. (2020); Ke et al. (2020); Wu et al. (2021a)
Risk Assessment Biases	**Articles**
Probability Evaluation Biases: Perception Biases, Pattern Recognition Biases	Lim and Benbasat (1996); Chen and Lee (2003); Bhandari et al. (2008); Pathak et al. (2010); Hong et al. (2011); Piramuthu et al. (2012); Purnawirawan et al. (2012); Ghose et al. (2013); Ma et al. (2014); Greenwood and Gopal (2015); Khan et al. (2017); Gerlach et al. (2019); Li et al. (2021)
Stability Biases: Endowment Effect, Loss Aversion	Rafaeli and Raban (2003); Benlian (2013); Jain and Thietart (2013); Chiu et al. (2014); Dinev et al. (2015); Zhao et al. (2015); Park et al. (2016); Hardin et al. (2017); Goel et al. (2017); Zheng et al. (2017)

Table 1-1: IS Journal Publications on Social Influence and Risk Assessment Biases

Following the notion of informational social influence, this information cue provides users with guidance regarding appropriate behavior because it reveals how other social actors behaved (i.e., whether or not to consume the content) in a similar situation. Normative social influence may be evoked, for example, by information cues indicating that the majority of a relevant user group complies with a cyber-security policy (e.g., Barlow et al. 2018). Normative social influence biases can be triggered by these information cues, as they provide information about what behavior other users are most likely to find acceptable (i.e., comply with the given policy). Whereas risk assessment cues in the form of probability evaluation cues can be designed by drawing on probability evaluation biases, risk assessment cues in the form of prospective loss cues account for stability biases. In the context of technology-mediated investment decisions,

information cues that exhibit a price chart of a stock, with a timeframe that suggests a sustained upward price trend, can act as probability evaluation cues and trigger a probability evaluation bias (i.e., the representativeness bias). This is because users overweight the probability of a continued upward trend when deciding whether to invest or not (e.g, Bhandari et al. 2008). Additionally, in the context of user-generated product reviews, the design of information cues can trigger a further probability evaluation bias. Information cues exhibiting user-generated reviews that are arranged in such a way that users perceive either predominantly positive or negative reviews right before their purchase decision are likely to make users being subject to the recency bias (e.g., Piramuthu et al. 2012). Due to this bias, users are heavily influenced by the most recently seen reviews and thus, are urged to either overweight or underweight the probability of the product having favorable characteristics, potentially leading to biased purchase decisions. A different category of risk assessment cues aims at triggering stability biases (i.e., tendency to stick with established or familiar decisions). Information cues that aim at triggering loss aversion (i.e., prospective loss cues) may convey that something the user already possesses or has access to might be taken away, depending on the user's behavior. In the context of spear-phishing, information cues that notify students about their potential loss of access to a course registration platform urged them to be more likely to be susceptible to phishing (Goel et al. 2017).

Social Influence Cues		Risk Assessment Cues	
Informational Social Influence Cues	Normative Social Influence Cues	Probability Evaluation Cues	Prospective Loss Cues
e.g., providing social information regarding product demand or popularity	e.g., providing a voucher code prior to solicit user action, thereby triggering norms from daily social interactions	e.g., providing information regarding the probability of receiving a reward before a digital scratch card is used	e.g., providing information regarding the risk, that users might not receive a virtual good they purchase

Table 1-2: Examples for Social influence and Risk Assessment Cues

Although extant IS research draws on cognitive biases to investigate phenomena in various contexts, research on gamification and digital nudging suggests that addressing different cognitive biases by employing information cues is highly context-dependent (Schneider et al. 2018; Schöbel et al. 2020b). As a result, insights on how gam(bl)ification design elements and digital nudges can be implemented in one specific context are not easily transferable to other contexts (Schöbel et al. 2020a). Therefore, building on previous research on digital nudging

(e.g., Dennis et al. 2020; Schneider et al. 2020), and on the utilization of information cues (e.g., Tan et al. 2019b) as well as on gamification research (e.g., Wang et al. 2020), this thesis focuses on user conversion in gam(bl)ified digital business models as the focal user behavior and context, respectively.

The notion of user conversion originates in the cross-disciplinary topic of customer conversion which posits that the customer purchase process comprises multiple stages, resembling a customer conversion funnel (e.g., Luo et al. 2012; Moe and Fader 2004). In the context of digital business models (e.g., e-commerce, Internet services) users progress through different stages (e.g., consideration stage, evaluation stage) and reach the end of the conversion funnel when they have purchased a product and/or became a regular user of a service (Hoban and Bucklin 2015; Lambrecht et al. 2011). Extant research shows that especially at the onset of the conversion process, users actively engage in information-seeking behavior, looking for signals in the online environment that help them to progress within the funnel (e.g., Bleier and Eisenbeiss 2015; Huang et al. 2019a). In this regard, several information cues (e.g., seller feedback score, product past sales volume) have been identified as valuable guidance that facilitate users' progression through the conversion process (e.g., Cheung et al. 2014; Huang et al. 2019b; Tan et al. 2019b).

Gamification research frequently investigates how gamification elements affect user motivation but often tends to neglect the impact on behavioral outcomes beyond user-system interaction (Koivisto and Hamari 2019). Therefore, user conversion in gamblified digital businesses (i.e., digital business models that employ gam(bl)ification design elements) seems to be a promising research context, as user conversion represents an accessible outcome variable with tangible consequences.

1.3 Thesis Positioning

To investigate how information cues that aim at accounting for cognitive biases might affect user cognition and subsequent behavior, this thesis draws on the stimuli-organism-response (S-O-R) model from environmental psychology (Mehrabian and Russell 1974; Woodworth 1958) in order to derive a research framework for this thesis. Several IS studies utilize the S-O-R framework to examine how websites' features may impact users' internal cognitive processes and the resulting behaviors (e.g., Ding et al. 2015; Liu et al. 2013). The S-O-R model posits that external stimuli from an individuals' environment attract the individuals' attention and influence internal cognitive and affective processes (organism), which in turn affect their intentions as well as behaviors (response) (Woodworth 1958). In the context of consumer research, a stimulus is an external contextual cue that shapes consumers' responses (Belk 1975).

Transferring this notion to IS research on e-commerce, these contextual cues can occur in manifold ways, such as an online store's visual design (e.g., Jacoby 2002), and are often conceptualized as information cues (e.g., Cheung et al. 2014; Tan et al. 2019b). Accordingly, considering social influence cues and risk assessment cues (i.e., two variants of information cues) as environmental signals that affect cognitive processes (i.e., cognitive biases) as well as subsequent responses (i.e., user conversion) within the context of gam(bl)ified digital business models provides a suited foundation for this research endeavor. Figure 1-1 provides an overview of the articles' main content embedded in the S-O-R model.

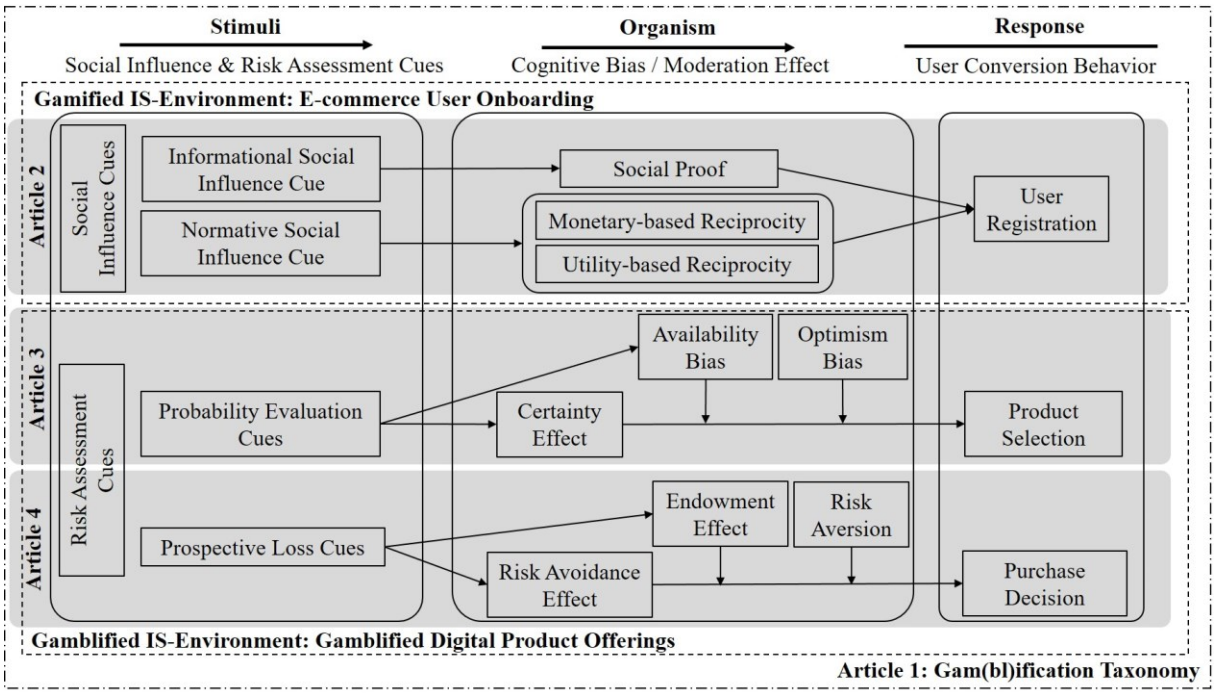

Figure 1-1: Research Framework

The first article (Chapter 2) lays the foundation for the research context (i.e., gamified and gamblified IS) by providing an overview and a categorization of the design elements that serve as vehicles for the embedded information cues in the subsequent articles. The second article (Chapter 3) examines how two social influence cues (i.e., informational and normative social influence cues) embedded in the gamification element 'user onboarding' can distinctly and jointly influence user conversion (i.e., completed platform registration) on an e-commerce platform. The following third article (Chapter 4) investigates the effects of two probability evaluation cues (i.e., a group of risk assessment cues) embedded in the gamblification element 'loot box menu' on user conversion (i.e., product selection) in the context of a digital gaming service. Alongside the direct effects, the interaction between the cues' effects and an important personal trait relevant for decision-making under risk (i.e., ambition to win/overconfidence) is examined. The subsequent fourth article (Chapter 5) illuminates how two prospective loss cues (i.e., another group of risk assessment cues) embedded in the gamblification element 'loot box

offering' can impact user conversion (i.e., loot box purchase) in the context of a digital gaming service. Besides the interactive effects of the two prospective loss cues, the interactive effect of one of prospective loss cues and the personal trait risk aversion is examined.

1.4 Structure of the Thesis

This thesis is organized into six chapters. To answer the overarching research question, five studies were conducted and published in peer-reviewed IS outlets across four research articles. Following the introductory chapter that motivates the two overarching research questions and outlines the theoretical foundations, the four subsequent chapters present the four published articles. The final chapter summarizes the main theoretical and practical contributions and provides directions for future research. The included articles have been slightly adapted to achieve a consistent appearance throughout the thesis. Table 1-3 provides an overview of the chapters and articles.

Study 1	**Chapter 2** Article 1	**Gambling Design Elements within Gamification Research** Reinelt, A.; Adam, M.; Roethke, K.; (2021). "Accounting for gambling design elements: A proposal to advance gamification taxonomies." In: *European Conference on Information Systems (ECIS)*. A Virtual AIS Conference. **VHB: B**
Study 2 & 3	**Chapter 3** Article 2	**Social Influence Tactics in E-commerce User Onboarding** Roethke, K.; Klumpe, J; Adam, M.; Benlian, A. (2020). "Social influence tactics in e-commerce onboarding: The role of social proof and reciprocity in affecting user registrations." *Decision Support Systems* (DSS), Volume 131, 2020, 113268. **VHB: B**
Study 4	**Chapter 4** Article 3	**Probability Evaluation Cues in Gamblified Menu Designs** Adam, M.; Roethke, K.; Benlian, A. (2021). "Gamblified digital product offerings: an experimental study of loot box menu designs." *Electronic Markets*. **VHB: B**
Study 5	**Chapter 5** Article 4	**Prospective Loss Cues in Gamblified Product Offerings** Roethke, K.; Albrecht, G.; Adam, M.; Benlian, A. (2021). "Monetizing Loot Boxes in Gamblified Digital Business Models — The Role of Risk Avoidance and Loss Aversion." In: *European Conference on Information Systems (ECIS)*. A Virtual AIS Conference. **VHB: B**

Table 1-3: Overview of Articles

In the following, each of the five articles is summarized and the main findings and contributions to the research questions are presented. These articles use the first-person plural point of view (i.e., 'we'), as multiple authors were involved in their creation.

Article 1 – Chapter 2: Gambling Design Elements within Gamification Research

The effectiveness of gamification in fostering user engagement, motivation, and behavior has been widely acknowledged and the game design elements to bring these goals about have been identified and categorized in extant research (e.g., Schöbel et al. 2020b). However, recently emerging design elements drawing on gambling mechanics (e.g., chance-based outcomes) have receive little IS research attention so far. The first article (Chapter 2) describes the development of an advanced taxonomy of gamification design elements accounting for these novel gambling design elements. By rigorously employing methods and procedures from taxonomy development literature (Nickerson et al. 2013) we propose a common classification method for gaming and gambling design elements applied in gamification and gamblification contexts. More specifically, new dimensions and characteristics to extend extant gamification taxonomies are derived from gamification literature and validated with the help of practical case examples. This advanced classification system allows for a more comprehensive examination of how design elements in general, and design elements incorporating information cues that account for social influence and risk assessment biases in particular, determine gamification's and gamblification's effectiveness in impacting user behavior.

Article 2 – Chapter 3: Social Influence Tactics in E-commerce User Onboarding

The second article (Chapter 3) aims to answer the first overarching research question (*RQ1*) on how social influence tactics (i.e., the employment of social influence cues with the intention to affect user behavior) can impact user conversion behavior in digital business models. Using a multi-method approach (i.e., a combination of different quantitative approaches), we conducted two studies in the context of user onboarding in an e-commerce platform context. We first conducted a randomized online experiment and a follow-up survey with 249 participants, where two different social influence tactics (i.e., social proof and reciprocity) were positioned within the gamification element of user onboarding (i.e., registration layers guiding the website visitor to become a registered user) and that were examined in a full factorial 2x2 design. Subsequently, we partnered up with a large e-commerce platform to conduct a randomized field experiment with 475,495 participants in a similar experimental design where the two social influence tactics 'social proof' and 'reciprocity' were investigated regarding their effectiveness in fostering user onboarding. The results of the two studies consistently demonstrate that embedding social proof and reciprocity cues within the gamification element user onboarding is effective in impacting user conversion. While the effects of social proof and reciprocity are unambiguously positive when employed in isolation, there is a positive or a negative interaction effect between the two

social influence tactics depending on how reciprocity is implemented which highlights the importance of carefully designing and implementing different social influence tactics together

Article 3 – Chapter 4: Probability Evaluation Cues in Gamblified Menu Designs

Accounting for the novel phenomenon gamblification, the third article (Chapter 4) addresses the second overarching research question (*RQ2*) on how risk assessment cues can impact user conversion in digital business models. It investigates how different probability evaluation cues can be employed within the gamblification element loot box menu to impact user conversion by affecting product selection behavior. The results of a randomized online experiment with 159 participants revealed that probability evaluation cues, designed to trigger the certainty effect, have a positive effect on product selection (i.e., increased selection of a loot box with a certain reward) and thus user conversion. This effect amplifies when additionally, probability evaluation cues that address the availability bias are employed. This effect is however attenuated when users are subject to the optimism bias.

Article 4 – Chapter 5: Prospective Loss Cues in Gamblified Product Offerings

The fourth article (Chapter 5) continues to investigate the effects of risk assessment cues embedded in gamblification elements to foster user conversion in digital business models. However, whereas the third article examines two differently designed gamblification elements the fourth article probes different risk assessment cues by contrasting the effects of prospective loss cues embedded within a gamblified product offering (i.e., a risky reward) and a transaction-based product offering (i.e., a riskless reward) on conversion behavior (i.e., user purchase behavior). Empirical evidence provided by a randomized online experiment with 180 participants demonstrates that triggering the risk avoidance effect in a gamblified versus a transaction-based product offering has a negative impact on user purchase behavior. This effect intensifies when these two offerings are combined with a prospective loss cue that address the endowment effect. However, it is mitigated when users are risk-averse.

Additional Articles (not included in the thesis):

In addition to the publications listed above, the following articles were also published or submitted for publication during my time as a Ph.D. candidate. These articles are, however, not part of the thesis.

Submitted for publication:

- Adam, M.; Roethke, K.; Benlian, A. – Automated and Human Sales Agents: Distinct and Joint Effects on Customer Micro-Conversions in B2B Email Communication (third round of review at the Journal *Information Systems Research*). **VHB: A+**

- Adam, M.; Reinelt, A.; Roethke, K. – Gam(bl)ified Monetary Reward Designs and Their Differential Effects on User Registrations in E-Commerce (second round of review at the Journal *Information Systems Journal*). **VHB: A**

Published:

- Werner, D.; Croitor, E.; Roethke, K.; Manakov, V.; Adam, M.; Benlian, A. (2021) "Ad Quantity Customization and Its Effects on User Engagement – A Randomized Field Experiment" In: *International Conference on Information Systems (ICIS)*. A Virtual AIS Conference. **VHB: A**

- Albrecht, G.; Toutaoui, J.; Roethke, K. (2021) "The Intricate Effects of Complexity and Personalization on Investment Intention in Robo-Advisory." *55th Hawaii International Conference on System Sciences (HICSS), Maui, Hawaii, USA, 4-7 January.* **VHB: C**

- Wallbach, S.; Lehner, R.; Roethke, K.; Elbert, R.; Benlian, A. (2020) "Trust-Building Effects of Blockchain Features – An Empirical Analysis of Immutability, Traceability and Anonymity." In: *European Conference on Information Systems (ECIS)*. A Virtual AIS Conference. **VHB: B**

- Roethke, K.; Adam, M.; Benlian, A. (2020). "Loot Box Purchase Decisions in Digital Business Models: The Role of Certainty and Loss Experience." *53th Hawaii International Conference on System Sciences (HICSS), Maui, Hawaii, USA, 7-10 January*.[4] **VHB: C**

[4] This research article was nominated for a best paper award.

- Winkler, N.; Roethke, K.; Siegfried, N. (2020). “Lose Yourself in VR: Exploring the Effects of Virtual Reality on Individuals’ Immersion.” In: *53th Hawaii International Conference on System Sciences (HICSS)*, Maui, Hawaii, USA, 7-10 January. **VHB: C**

Chapter 2: Gambling Design Elements within Gamification Research

Title: Accounting for gambling design elements: A proposal to advance gamification taxonomies

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Martin Adam, Technische Universität Darmstadt, Germany

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Abstract

Gamification has been touted as a powerful means to incite user engagement and behavioral changes. Recently, the rise of design elements characteristic of gambling design (e.g., chance-based outcomes) has received increased attention in gamification and started to spark a debate of what is gaming in contrast to gambling, and consequently what is gamification in contrast to gamblification. Therefore, to clearly delineate gamblification and associated design elements within the overarching gamification domain, we argue a comprehensive, common classification method is needed for game and gambling design elements applied to non-game and non-gambling contexts. Accordingly, we propose new dimensions and characteristics to extend gamification taxonomies and validate these along practical case examples. This advancement of classification systems can serve as basis for closer examination of design elements determining gamification's and gamblification's effectiveness in spurring user experience and engagement and for novel designs of gamified and gamblified systems.

Keywords: Gamification, gamblification, classification, taxonomy

2.1 Introduction

User engagement has long been one of the most crucial goals and prerequisites of successful information systems (IS) design (McKeen et al. 1994). In this context, gamification has emerged as an increasingly relevant concept for researchers and practitioners alike over the past decade, utilized to boost user engagement across a diverse set of application fields (Koivisto and Hamari 2019). Application contexts have covered a vast range including education (Bonde et al. 2014; Dicheva et al. 2015; Frost et al. 2015), health and exercise (Hassan et al. 2019; Hassan et al. 2020; Schmidt-Kraepelin et al. 2020b), marketing (Hsu and Chen 2018; Yang et al. 2017), e-commerce (Adaji and Vassileva 2017; Meder et al. 2018), sustainability (Beck et al. 2019; Lounis et al. 2014), and human resource management (Cardador et al. 2017; Sarangi and Shah 2015) – to name only a few. Gamified IS are employed to enhance user experience and enjoyment, make tasks more engaging, motivate users towards target behaviors, and ultimately improve societal or organizational outcomes (Bui et al. 2015; Koivisto and Hamari 2019; Liu et al. 2017).

One of the most common definitions regards gamification as the "use of design [rather than game-based technology or other game-related practices] elements [rather than full-fledged games] characteristic for games in non-game contexts" (Deterding et al. 2011a). In addition to game design elements, we observe a recent rise of *gamble design elements* being implemented most prominently in the (e-) sports and video gaming domains (Abarbanel and Johnson 2020; Lopez-Gonzalez and Griffiths 2018; Macey and Hamari 2019; Macey and Hamari 2020). These elements include betting and loot boxes among others, and – much like traditional gamification elements – aim for increased user engagement and organizational outcomes such as revenue growth. The use of loot boxes and skins gambling was responsible for $30 billion revenues in 2018 and is expected to reach $50 billion by 2022 (Zendle et al. 2020) – and it has already sparked debate whether respective elements should be considered gaming or gambling (Griffiths 2018).

However, despite posing a theoretically unique concept and recently gaining in practical and economic relevance, gamble design elements have often been overlooked in gamification concepts and have been subject to little scrutiny in theoretical work. This has resulted in a blurred differentiation between gamification and *gamblification* – which is considered the use of gamble design elements in non-gamble contexts. IS researchers have proposed a multitude of frameworks for gamification in the past (Khan et al. 2020; Mora et al. 2017; Treiblmaier et al. 2018), but have not yet included gamble design elements in gamification terminology or categorizations.

In order to address the emergence of gamble design elements in practice, we argue a shared, consolidated understanding of game and gamble design elements and their characteristics is needed as a joint basis and starting point to resolve questions of effectiveness and effect mechanisms. As such, in order to extend our current understanding of gamification and gamblification, we intend to answer the following two research questions:

- RQ1: How can gamble design elements and their characteristics be described and classified in a gamification taxonomy?
- RQ2: How can gamblification design be distinguished from gamification design?

To this end, our paper contributes by advancing an existing gamification taxonomy to classify design elements of gamblified systems. We reinforce gamblification (i.e., the use of gamble design elements in non-gamble contexts) as a unique subdomain of gamification and provide a more comprehensive taxonomy, ensuring a shared language and understanding and allowing researchers and practitioners to derive novel gamification and gamblification designs.

We will begin by providing an overview of related gamification and gamblification work as well as established frameworks as a foundation for our taxonomy development. We will then describe our approach to advance the taxonomy and accordingly propose new taxonomic dimensions to account for gamble design elements in non-gamble contexts. Finally, we will apply the adapted taxonomy to practical case examples.

2.2 Related work and theoretical background

2.2.1 Gamification, gambling, and gamblification

Gamification is most frequently cited as the use of game design elements in non-game contexts (Deterding et al. 2011a). Another popular definition refers to gamification as “a process of enhancing a service with affordances for gameful experiences in order to support users’ overall value creation” (Huotari and Hamari 2012; Huotari and Hamari 2017). The leading application area for gamified information systems is by far the educational field, with close to half of all gamification-related publications in this domain, followed by information systems and applications related to the health industry (Bozkurt and Durak 2018; Koivisto and Hamari 2019; Schlagenhaufer and Amberg 2015).

Gamification design elements can comprise a wide range of affordances (i.e., perceivable possibilities for action (James et al. 2019)), including affordances focused on achievement and progression (e.g., points, challenges, status bars), social features (e.g., cooperation, networking, competition), immersion (e.g., avatars, narrative) or real-world orientation (e.g., motion

tracking, check-ins) (Koivisto and Hamari 2019). Most frequently observed across publications are points, scoring, badges, and leaderboards (Koivisto and Hamari 2019; Schlagenhaufer and Amberg 2015).

Gambling refers to behaviors in which individuals risk money on the outcome of an unknown event to achieve a potential monetary gain (Laffey 2007; Ma et al. 2014). Definitions of gambling include characteristics such as uncertainty of outcomes at the time of staking money, chance determination of the outcome, and reallocation of monetary value (Griffiths 2018). Some of the most commonly observed practices of gambling are "wagering in casinos and on lotteries, horse and dog racing, card games, and sporting events" (Potenza et al. 2002).

Gamification and gambling denote two clearly different concepts. Whereas gamification describes the practice of incorporating game design elements in various contexts, gambling refers to a specific type of behavior holistically (rather than the use of selected elements). One could claim that both gamification and gambling are characterized by the engagement of individuals, or the pursuit thereof, but an important distinction is the direction of initiation. Whereas gamification is initiated by a designer or provider (e.g., of a gamified information system) to engage users, gambling is initiated by a user or player who chooses to engage in gambling behavior. The increased accessibility of gambling, facilitated among others by the rise of online gambling (Hou et al. 2019), has also helped to spread the incorporation of gambling design elements in non-gambling contexts (i.e., gamblification). For example, designers have widely discovered the use of gambling elements in contexts such as e-sports and gaming (Macey and Hamari 2019). One prominent example of this are loot boxes (i.e., chance selections of virtual items in video games purchased with real money), which have already been controversially debated with regard to whether they should be considered as gambling (Griffiths 2018; Koeder et al. 2018; Zendle et al. 2020). Design elements characteristic of gambling introduced in other contexts further include chance-based elements and unpredictable rewards to increase engagement on the live streaming website Twitch (Abarbanel and Johnson 2020), skins lotteries, loot boxes, and betting in video gaming (Lichtenberg and Brendel 2020; Macey and Hamari 2019; Macey and Hamari 2020), betting and fantasy games in sports, notably soccer (Lopez-Gonzalez and Griffiths 2018), lottery-based rewards for recycling empty bottles (Pantelotteriet 2018), and lottery-based rewards for purchasing tickets on public transport (Fabbri et al. 2019).

Gamification and gamblification denote two unique but closely related concepts. They both describe the practice of applying game or gambling design elements, respectively, to other

contexts in order to engage users and achieve target outcomes. They differ in types of design elements used, in mechanisms determining user outcomes and interactions, and in non-financial vs. financial outcomes. Additional differences between gamification and gamblification can stem from theoretical foundations of their respective effectiveness. For example, due to intrinsically motivating aspects of gamification designs and potential extrinsically motivating incentives included in gamblification designs (Deci and Ryan 2002; Ryan and Deci 2017), the specific effect mechanisms and mediators at play could diverge, as observed in studies of intrinsic and extrinsic motivation in other contexts (Kuvaas et al. 2017).

We view gamblification as a unique branch of gamification, defined as the use of gamble design elements in non-gamble contexts and target IS to enhance user experience, engagement, and target system monetization. The differentiation between gamblification and gamification without gamble design elements can therefore be made based on the type of design elements utilized. As proposed by the authors, the following three key attributes of gamble design elements set gamblification specifically apart within the overarching concept of gamification:

(1) Specific **game design objects** and corresponding affordances (e.g., lotteries and dice),

(2) Related **chance-based** game mechanics determining outcomes, and

(3) User-system **resource transfers**, meaning outcomes (e.g., stakes, rewards) with objective value are transferred.

The design of an information system is considered an example of applied gamblification only if it fulfills all three aspects of this definition. Only then can we clearly differentiate it from other variations of gamification and start to focus on understanding its design elements and their effectiveness in detail.

Considering recent applications (and at times controversy) of gambling design elements and the prominence of gamified information systems, we firmly believe that gambling design elements will become increasingly relevant for IS design in the future. It is therefore indispensable that IS researchers and practitioners develop a shared and structured theoretical understanding of the new phenomenon of gamblification for further examination of gamblification-specific effects and targeted application of gamblification designs. For instance, there are already indications that chance-based mechanics could affect users' preferences, motivation, and enjoyment differently than certain outcomes (Abuhamdeh et al. 2015; Gaertig et al. 2018; Shen et al. 2019). Effectiveness of gambling design elements may also be determined by specific contexts or personal dispositions.

As gamification researchers have called for more work to determine the value of specific design elements in driving user motivation (Seaborn and Fels 2015), the field requires a shared classification system of gamified and gamblified IS, encompassing game and gambling design elements respectively, as a basis for expanding our knowledge of gamification and gamblification effects and investigating potential differences in theoretical foundations of either's effectiveness. We aim to assess how to make gamification taxonomies inclusive of gamblification characteristics and thereby to develop a common structure and terminology for design elements of gamblification as a basis for future research avenues.

2.2.2 Taxonomies

A common approach to structure knowledge within a certain field is the development of taxonomies (i.e., classification systems). Glass and Vessey (1995) maintain that taxonomies "facilitate systematic research into the differences among, and the needs of, particular domains". By grounding research and practice in shared terminology and structure, taxonomies allow systematic descriptions, research of predicted relationships among concepts, and exchange between research communities (Feine et al. 2019; McKnight and Chervany 2001). According to Nickerson et al. (2013) useful taxonomies have five qualitative attributes: They are concise, robust, comprehensive, extendible, and explanatory.

Several frameworks and taxonomies have previously been established for gamification and elements of gamified IS (e.g, Schmidt-Kraepelin et al. 2020a; Seaborn and Fels 2015). One widely cited framework for design and research of gamified systems was put forward by Liu et al. (2017). The authors postulate that gamification objects and gamification mechanics (united under the overarching term of gamification design elements) are applied to a target system (defined by its user, task, and technology) to form a gamified system. Gamification design principles govern how user-system interactions are shaped to achieve meaningful user engagement in the form of experiential and instrumental outcomes. Liu et al.'s framework can easily be transferred to describe how gamblification attributes are employed in an IS to achieve meaningful user engagement, hereby reinforcing that gamblification can be considered a subdomain of gamification: Gamblification objects (i.e., design objects characteristic of gamble design) are implemented as part of the gamblified system. As an additional design element, gamblification mechanics (i.e., chance-based mechanisms) rule interactions between user and system. And finally, gamblified user-system interactions include the transfer of resources between users and system, ultimately leading to experiential, engagement, and monetization outcomes.

Based on this understanding of gamblification as a specific variation on gamification, displaying specific objects, mechanics, and additionally transfer of resources, we will therefore draw upon existing gamification taxonomies to extend them for gamble design elements.

One of the most recent taxonomies in the field of gamification was developed by (Schöbel et al. 2020b) and recommends ten dimensions of game logic and game design: (1) Reward (Rewarding, Documenting), (2) Punishment (Punishing, Neutral), (3) Bonus (Bonus, No Bonus), (4) Interdependency (Independent, Dependent,), (5) Development (Developing, Static), (6) User Design (Partial Involvement, Prescribed by Developer), (7) Competition (Competitive, Individual), (8) Cooperation (Cooperation Possible, Cooperation Impossible), (9) Surprise (Surprising, Regular), and (10) Initial Motivation (Intrinsic, Extrinsic).

We will focus on this latter taxonomy (Schöbel et al. 2020b) as we continue. We build on their structure and examine how it can account for gamblification to provide a more thorough understanding of gamification and gamblification design elements. A comprehensive gamification taxonomy should not only enable a conversation about good gamification designs vs. poor designs, but also about differences between gamification and gamblification and their respective effects.

2.3 Methodology

Nickerson et al. (2013) established a method for taxonomy development in IS research, suggesting two possible approaches, which can also be combined. In their empirical-to-conceptual approach, researchers identify objects and common characteristics of these objects, and then formulate taxonomic dimensions on this basis. In their conceptual-to-empirical approach, new characteristics are conceptualized, objects examined for these characteristics, and a taxonomy created or revised on this basis. We followed three steps along these approaches to advance an existing classification system of gamification to account for gamble design elements, summarized in Figure 2-1 below.

First, we aimed to find examples of gamble design elements in previously published work to discover which types of elements a taxonomy would need to encompass. In this empirical-to-conceptual step, we hoped to identify instances in which empirical work had been conducted within the overarching context of gamification but had leveraged design elements characteristic of gambling, as gamblification has not yet been widely established as a commonly accepted concept and set term.

Second, we took a conceptual-to-empirical approach and considered a recent taxonomy of gamification (Schöbel et al. 2020b). We examined the suitable fit of this taxonomy in classifying gamble design elements in light of our literature review results and of each attribute of the definition of gamblification. The goal of this step was to conclude if and which taxonomy extensions would be required to make the taxonomy inclusive of gamblification characteristics.

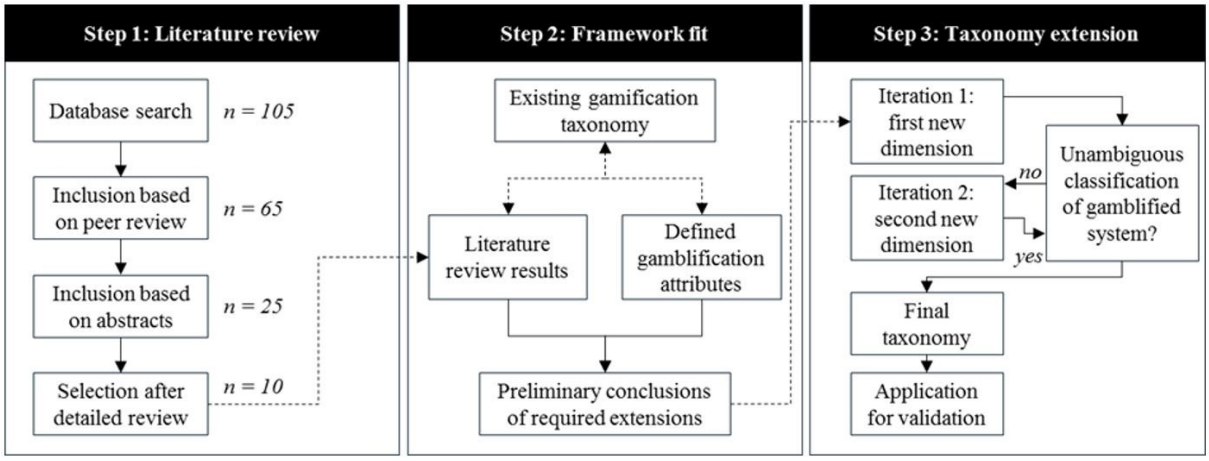

Figure 2-1: Methodology for advancement of an existing gamification taxonomy

And third, we deduced two new dimensions to build a comprehensive taxonomy of gamification and gamblification, guided by our insights from Step 1 and 2. The meta-characteristic of our taxonomy extension (Nickerson et al. 2013) were characteristics of gamblified information systems, for which we developed explanatory classifications in two iterations. We defined the ending condition for the taxonomy extension process as the unambiguous discrimination between gamblification and gamification without gamble design elements. After the first extension, individual design elements of information systems could be classified as gamblified, but potential overlaps with gamified systems still remained. Only after the second extension of the taxonomy, we determined that an identification of a system as clearly gamblified was feasible based on taxonomic characteristics of the design elements, and therefore concluded the development process. In order to validate the final taxonomy, we applied it along two recent practical case examples and distinguished these between one example of gamblification and one specific form of gamification in practice.

Figure 2-1 provides an overview of the three steps taken based on the approach observed in previous taxonomy development in IS research (Feine et al. 2019).

2.4 Taxonomy development

In the following, we present the results of our approach to extend existing gamification frameworks, including results of a respective literature review, fit with an existing taxonomy, new taxonomic dimensions, and a practical application of the extended classification system.

2.4.1 Literature review results

We conducted the literature search across the Association for Information Systems Electronic Library (AISeL) and EBSCOhost, extending the search beyond the IS area due to the interdisciplinary nature of the gamification concept, and selecting only a limited number of comprehensive databases for the search as recommended for reproducible and rigorous reviews (Cram et al., 2020; Koivisto & Hamari, 2019; Paré et al., 2015). We searched for all publications containing gamif* in their title, subject, or abstract "AND" (i.e., in combination with) at least one gamblification search term in title, subject, or abstract. We derived the following list of gamblification search terms from the definition of gamblification as the use of gamble design elements in non-gamble contexts displaying chance mechanisms and resource transfers: uncertain, chance, lottery, stake, risk, gambl*, luck, raffle, bet. Inclusion criteria for publications were, in a first instance, if publications were peer reviewed, English language, and not duplicate. Upon further review, publications were included if we observed any analysis or review of gamble design element use, as opposed to use of exclusively design elements in the "traditional" sense of gamification (i.e., points, badges, levels, and other elements not characteristic of gamble design).

Figure 2-2 provides an overview of the literature review search process based on the approach observed in previous taxonomy development in IS research (Feine et al. 2019). Figure 2-1 illustrates the number of publications considered in each step of the literature review, as elaborated in the following.

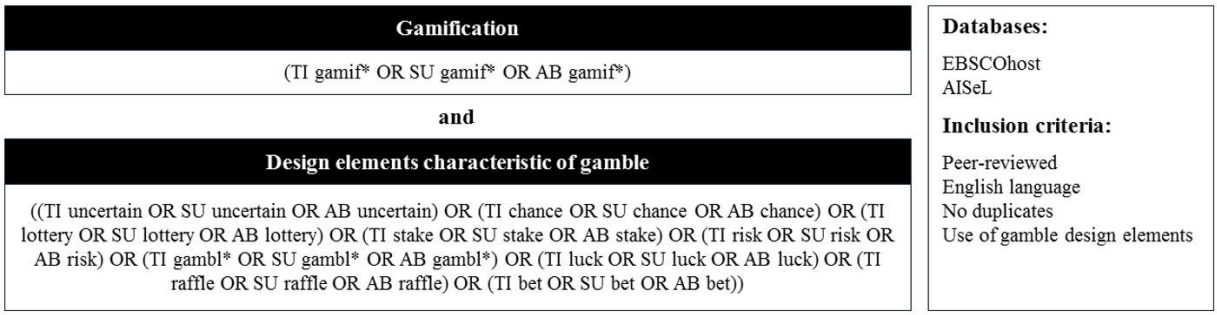

Figure 2-2: Search strategy for literature review

Our literature search across the two databases resulted in 105 results. Focusing the search to peer-reviewed scholarly publications narrowed the results down to 65. Further excluding

duplicate publications resulted in 62 publications for review. We reviewed titles and abstracts of these 62 publications in order to discern whether they did in fact contain gamification operationalized with gamble design elements (e.g., involving chance or betting) or whether they had implemented gamification in the most commonly observed, "traditional" sense (e.g., involving in-game point rewards or challenges). This closer review yielded 25 publications, which we deemed potentially relevant and therefore calling for further assessment. Upon analysis of full text and respective operational interpretations of gamification therein, we identified 10 empirical works that employed gamification with design elements resembling gamble design elements and were therefore different from game design elements covered in the majority of existing gamification frameworks and taxonomies. We observed that these 10 gamification examples demonstrated design elements borrowed from games of chance or gambling, which included (1) chance selection of user outcomes, (2) user ability to gamble outcomes, (3) chance selection of content presented to users, and (4) real-money consequences for users. An overview is provided in Table 2-1.

2.4.1.1 Chance selection of user outcomes

Game design elements in non-game contexts often serve the purpose of offering a desirable outcome to incentivize user engagement (Bozkurt and Durak 2018). Users engage to receive acknowledgement of their skills shown, performance tracking, or effort invested, therefore striving for a positively rewarding or even neutrally documenting outcome for their behavior (Schöbel et al. 2020b).

However, it seems random, chance-based user outcomes are also implemented as design elements to engage users: Woźniak (2020) examined an incentive scheme for sales representatives, which not only consisted of points to be collected and exchanged for rewards, but also bonus draws among groups of employees. Rey et al. (2016) tested random lottery-based reward schemes for public transit usage during off-peak hours to determine if gamification could sustainably shift travel behavior. Woźniak (2017) also varied types of rewards in gamified motivation schemes for employees of small and medium enterprises, implementing badges, levels, achievements, and points collection for rewards but also rewards based on lotteries. Finally, Macey and Hamari (2019) assessed the role of "gambling-like" design elements introduced in video games. For example, they considered the use of loot boxes, which contain virtual items determined by chance and are largely acquired with real-world currency.

Based on design elements observed in gamification-related empirical publications, we conclude a comprehensive gamification taxonomy should therefore enable classification of design

elements that operationalize the determination of user outcomes by chance, such as lucky draws, lotteries, and loot boxes.

2.4.1.2 User ability to gamble outcomes

In many gamification contexts, users receive reward outcomes – be they determined by performance, effort, or as described above by chance – as the final step of an activity (e.g., marking the completion of a task, achievement of a level, or conclusion of a transaction) (Richter et al. 2015).

In a study by Howard-Jones et al. (2016), the authors implemented a learning game, in which participants could win points for giving a correct answer, but could also choose to subsequently "game" their points on a wheel of fortune. For each round they gave a correct answer and committed to a gamble, they could therefore double or lose the points depending on the outcome of the wheel.

Based on this design element reminiscent of wagering money in a gamble, we conclude that a comprehensive gamification taxonomy should therefore enable classification of design elements that operationalize users putting potential rewards at stake.

2.4.1.3 Chance selection of content presented to users

In addition to chance selection of user outcomes, as previously described, we also observed design elements that incorporated chance selection of information or content available to users.

Goldklank Fulmer and Reich (2019) set out to introduce playfulness into consumers' online shopping experience through selecting by chance which products would be promoted. This chance rather than intentional selection process was communicated to consumers and seemed to increase preferences for respective products. Boyle et al. (2018) examined web-based intervention methods for individuals' drinking behavior and introduced the design element of a game-like spinner to select question and feedback topics for participants seemingly at random. This appearance of chance-based uncertainty aimed to lower cognitive reactance. Earle et al. (2018) and Boyle et al. (2017) both employed similar chance design elements in the same intervention context. Boyle et al. (2017) implemented a gamified intervention method in the frame of a Facebook-connected social game, which featured an animated slot machine to select topics for each participant session by chance. In a smartphone-based version of the game examined by Earle et al. (2018), representation of chance selection of intervention question and feedback topics was again achieved through use of the slot machine design element.

Based on these elements of chance observed in e-commerce and web-/app-based interventions, we conclude that a comprehensive gamification taxonomy should enable classification of chance-based mechanisms to display products or content to users, and related design elements such as spinners and slot machines.

2.4.1.4 Real-money consequences for users

Bayuk and Altobello (2019) examined consumer preferences for features of financial game mobile applications. They assessed the effect on preferences of both social design elements, including achievements and leaderboards, and economic design elements, including potential to earn real money or better interest rates, of the personal finance apps.

Based on such game design elements offering real-currency rewards for user behavior, we conclude that a comprehensive gamification taxonomy should enable researchers and practitioners to distinguish between types of user incentives that could range from in-game points to real-world money.

We have summarized these observed design elements in Table 2-1. We do not conclude that the listed examples should all qualify as examples of gamblification in practice. They rather serve as a source of information as we consider how to extend existing classification systems of gamification and to expand our understanding of the range of gamification design elements. We will proceed to examine how these objects and mechanisms relate to or differ from an established gamification framework.

Gamble design elements	Empirical examples	References
Chance selection of user outcomes	Bonus draw	Woźniak (2020)
	Lottery	Rey et al. (2016); Woźniak (2017)
	Loot box	Macey and Hamari (2019)
User ability to gamble outcomes	Wheel of fortune for chance to multiply or lose points won	Howard-Jones et al. (2016)
Chance selection of user presented content	Chance selection of products	Goldklank Fulmer and Reich (2019)
	Chance spinner	Boyle et al. (2018)
	Animated slot machine	Boyle et al. (2017); Earle et al. (2018)
Real-money consequences	Chance to earn real money	Bayuk and Altobello (2019)

Table 2-1: Gamble design elements observed in literature review

2.4.2 Review against existing frameworks

The definition of gamification as the "use of design elements characteristic for games in non-game contexts" (Deterding et al. 2011a) in order to "improve user experience (UX) and user engagement" (Deterding et al. 2011b) is one of the most widely accepted understandings of the concept (e.g., Blohm and Leimeister 2013; Morschheuser et al. 2018; Seaborn and Fels 2015). In line with this definition, gamblification is considered the use of gamble design elements in non-gamble contexts and a specific subdomain of gamification, with both concepts pursuing similar design approaches and goals. Gamification and gamblification both describe approaches of finding inspiration for concrete design features of information systems in game design and gamble design, respectively. Also, both gamification and gamblification describe the practice of applying these specific features to contexts that are different than the contexts from which they were taken. And finally, both gamification and gamblification share mutual goals of engaging users and shaping user behaviors. As the concepts are closely related, we proceed to examine aspects of gamblification in light of an established taxonomy of gamification.

For this purpose, we draw upon the recent gamification taxonomy of Schöbel et al. (2020b), spanning across four dimensions of *underlying game logic* and six *game design* dimensions, and providing examples of construction elements (i.e., gamification objects and mechanics), which are allocated to one or both characteristics within each dimension. We considered this taxonomy as the starting basis for our taxonomy extension. We set out to refine the structure to account for gamble design elements by comparing it to our literature review observations as well as to defined attributes of gamblification.

As described above, our literature review had resulted in four key design elements published in a gamification context but using gamble design elements. Next, we assess these four elements against dimensions and characteristics offered by the gamification taxonomy:

(1) *Chance selection of user outcomes*: Chance mechanisms are not covered by the dimensions and characteristics in the existing taxonomy. There are several dimensions describing possible mechanics such as the interdependency of design elements and the possibility of cooperation or competition. The taxonomy also differentiates purposes of rewards as either positively rewarding or neutrally documenting. But neither mechanics nor reward dimensions allow a distinct classification of the use of chance or luck to determine rewards or other user outcomes.

(2) *User ability to gamble outcomes*: The option for a user to consciously vary (e.g., gamble) their outcomes or rewards is not explicitly covered by the dimensions and

characteristics offered by the taxonomy. However, one of the "game logic" dimensions describes degrees of user involvement as "partial involvement" or "prescribed by developer". Whilst this does not distinctly describe the action of a user to alter their potential outcomes (e.g., putting their rewards at stake), this ability could be a possible construction element to operationalize user involvement.

(3) *Chance selection of user presented content*: Following the argument for design element (1) above, chance mechanisms determining products or content to be shown to users at random are a mechanism not yet described by the taxonomy at hand.

(4) *Real-money consequences*: Real-money consequences for users are not covered by the types of rewards and mechanisms defined by the taxonomy. It includes dimensions of rewards and bonus, but a transfer of actual resources between user and system does not fit within the classification characteristics offered.

Based on the reconciliation of literature review results with Schöbel et al.'s taxonomy, we conclude that the taxonomy should be extended for possible classifications of random rewards and objective-value implications.

We next reconsidered the three central attributes of gamble design elements per the gamblification definition to compare these also with the taxonomy:

(1) *Game design objects and corresponding affordances characteristic of gamble design*: The examples of construction elements provided along the existing taxonomy in Schöbel et al. (2020b)'s work do not include gamble-specific design objects or affordances, indicating that the taxonomy may not be comprehensive of gamblified systems. However, such gamble design objects (e.g., lotteries, dice) are specific embodiments of underlying dimensions and characteristics of the respective gamified or gamblified system rather than individual categories – objects should be classified using dimensions and characteristics of the taxonomy, but not every object must be explicitly named within the taxonomy (according to Nickerson et al. (2013), a taxonomy is comprehensive once all objects within the domain of interest can be classified). It would therefore be sufficient to ensure dimensions and characteristics of the existing taxonomy are extended to classify further construction elements including gamble design objects in the future.

(2) *Chance-based game mechanics determining outcomes:* As concluded in the reconciliation of literature review results (1) and (3) above, the taxonomy does not yet permit classification of chance-based mechanisms central to gamblification design.

(3) *Resource transfers between user and system*: Also as concluded in the reconciliation of literature review results (4) above, the taxonomy classifies rewards and bonuses but does not yet support classification of a transfer of resources.

We conclude that gamblification as a unique variation of gamification warrants coverage in frameworks and taxonomies alike in order to clearly identify respective design elements. The reconciliation of literature review results and the gamblification definition with Schöbel et al.'s taxonomy confirmed that it lacks dimensions to classify chance mechanisms and resource transfers, whilst specific gamble design objects and affordances should be possible to classify using a taxonomy extended accordingly and do not require addition of individual dimensions. We therefore proceeded to develop additional dimensions and characteristics to advance the existing taxonomy.

2.4.3 Development of an advanced taxonomy

In order to define characteristics of a comprehensive taxonomy of gamification and gamblification, we identified *characteristics of gamblified information systems* as the meta-characteristic to guide our development process (Nickerson et al. 2013). We probed our conclusions from the empirical-to-conceptual (literature review) and conceptual-to-empirical (taxonomy fit) approaches previously described against this meta-characteristic.

In a first iteration, we introduced the taxonomic characteristics of *chance-based uncertainty* as opposed to *performance-based uncertainty* under a new game design dimension *uncertainty*. This distinction is in line with previously established segmentations. For example, skill and luck have been contrasted as determinants of different motivation forms in the context of gambling games (Chantal and Vallerand 1996). Also, difficulty level, goals, information level, and randomness have been discussed as potential origins of outcome uncertainty in the context of motivation theory (Malone 1981). We therefore argue that the suggested game design dimension of uncertainty and related characteristics are important additions to a gamification taxonomy. They allow us to differentiate whether the uncertainty of occurrences and outcomes within an information system stem from a dependence on respective user skills, performance or usage behavior, or if they in contrast stem from actual randomness. We note that *(chance-based) uncertainty* and the dimension of *surprise* already included in the existing taxonomy are mutually exclusive: Whilst surprising elements are not expected by a user and could therefore be perceived as "random" in the general sense, chance-based uncertain outcomes can be expected by the user but still rely on luck or probability in their occurrence, form, and value.

After this advancement, the ending condition of our taxonomy development was not yet met. Even systems including an element of chance could still qualify as a non-gamblified form of gamification rather than clearly gamblification. Design objects based on chance, such as dice, have already been established as tools of gamification (Morschheuser et al. 2018), whilst luck and random outcomes have even been listed as common game mechanics (Dale 2014). The taxonomy therefore requires further characteristics to allow an unambiguous classification of gamblified systems.

Consequently, we proceeded to add the dimension of *resource transfer* in a second iteration. Similar to how the act of risking money on an outcome transforms a game of chance into a gamble (Laffey 2007), the combination of chance-related mechanics with user-system resource transfers makes the difference between a gamified and a gamblified system. Accordingly, the characteristics of the *resource transfer* dimension vary between *no objective value* being transferred as opposed to resources with *objective value* being transferred.

As these two new taxonomy dimensions were sufficiently exhaustive to classify a gamblified system without remaining ambiguities, we terminated the taxonomy extension development at this point. A final view of the advanced gamification and gamblification taxonomy is illustrated in Figure 2-3, with newly added dimensions and characteristics highlighted in color. We propose the integration of *uncertainty* as a new dimension of game design, whilst *resource transfer* extends beyond game design and underlying game logic, therefore constituting a separate new category for implications.

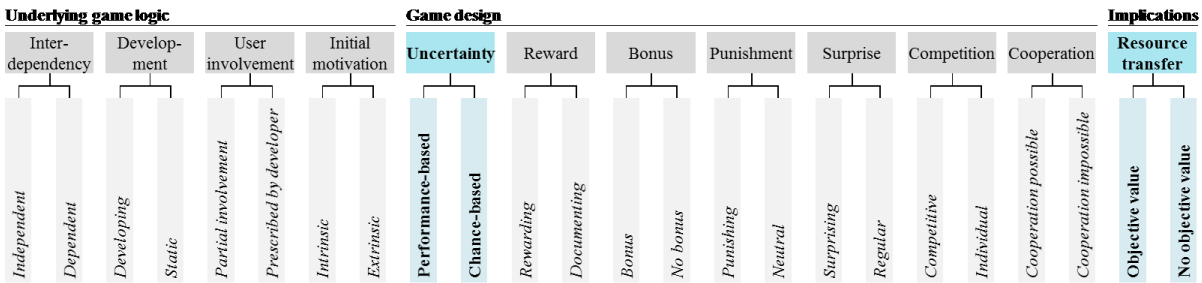

Figure 2-3: Advanced gamification taxonomy for classification of gamblification design elements

Finally, we will examine two practical examples. As we aim to apply the advanced taxonomy to validate its use in determining characteristics of gamified or gamblified systems, we chose illustrative case examples that promised to display different characteristics of the new taxonomic dimensions (i.e., forms of uncertainty and resource transfer). We particularly searched for examples involving transactions with real money because objective-value resource transfers are the characteristic that can finally set apart a gamblified system from a chance-

based gamified system. Further search criteria for suitable examples included recency and low entry barriers for use to ensure the chosen examples were tangible and potentially widely used. We therefore selected two cases oriented towards consumer users (as opposed to business users), which we observed advertised in the U.S. in October of 2020 and offered in the Apple App and Google Play stores on an ongoing basis, respectively (Charity Miles 2020; Starbucks 2020).

2.4.3.1 Case example 1

The global coffee chain Starbucks generally offers a reward program, in which its customers can earn rewards ("stars") for purchases they make and later redeem these for drinks, food, or merchandise offerings. For a limited time, they additionally offered "Starland", an augmented reality (AR) game (Starbucks 2020). The AR game could be accessed online or in the respective app, allowing a user to scroll across starry skies and choose stars for a chance to win instant prizes or receive raffle tickets. In order to participate in the AR game, users were required to become a Starbucks Reward member and earn up to two plays each day by making a purchase at Starbucks.

We apply our taxonomy advancement to determine if this case leverages gamification or clear gamblification design elements:

- Customers playing Starland were confronted with **uncertain outcomes**. As they played the game, they did not yet know if they would win any of the instant prizes nor if their raffle ticket would offer any value. This uncertainty was not due to customers' individual behavior, skills, or performance in the game. They simply chose one of the stars in the AR environment, upon which an outcome would be revealed to them. The uncertainty of outcomes was therefore purely **chance-based**.
- Participants of the AR game also engaged in **resource transfers** carrying objective value. By making purchases as qualification to play the game, they hoped to achieve a potential gain by winning a prize. These potential rewards for participants had **real-currency value**.

Based on these design characteristics, Starland qualifies as an example of gamblification in practice. By incentivizing customers to make more purchases, enabling more frequent plays and thereby higher chances to win prizes, Starbucks used gamblification to increase monetization of its rewards system.

2.4.3.2 Case example 2

Charity Miles is a free mobile application that rewards its users for physical activity with donations to a charity of their choice (Charity Miles 2020). The app tracks all activities selected by the user (e.g., running or biking). Money is donated to the user-chosen charity based on the amount of activity (e.g., a certain value per mile biked or per mile ran by the user).

Again we apply our taxonomy to determine potential gamification or gamblification design elements:

- User of Charity Miles face **performance-based uncertainty**. The outcome (i.e., money donated to their chosen charity) is dependent on the users' performance in terms of frequency and distance of their exercise. No chance mechanism is involved – users know how much money will be donated per unit of exercise and they choose the receiving charity in advance.
- Users of the app do not engage in transfers of objective-value resources. No purchase is made by the user as the app is free to download. The donation determined by user behaviors is made in real currency, but the user does not place or receive any money-equivalent input or stake into or from the system. The investment on the part of app users is the time and effort of exercising, which carry **no monetary value** per se.

Based on these design characteristics, Charity Miles is an example of gamification rather than gamblification. As demonstrated by these two examples, the extended taxonomy of gamification and gamblification allows us to differentiate game and gamble design features in target systems.

2.5 Discussion

This paper extends an established gamification taxonomy to account for gamble design elements used in non-gamble contexts and their respective characteristics. We conducted a review of gamification literature for potential applications of gamble design elements, assessed gaps within a recent gamification taxonomy based on the gamblification understanding, and proposed the addition of two new dimensions accordingly: *uncertainty* (performance-based or chance-based) and *resource transfer* (objective value or no objective value). Finally, we validated the advanced taxonomy along one customer reward program and one mobile application as practical case examples.

2.5.1 Theoretical and practical contributions

Our paper contributes to taxonomic theories of gamification by advancing an existing taxonomy to classify design elements of gamblified systems. These advancements offer theoretical and practical benefits to both researchers and IS designers. By accounting for gamble design elements through added dimensions and characteristics, we increase the comprehensive quality of the taxonomy and thereby improve it according to attributes of a useful taxonomy in IS contexts (Nickerson et al. 2013). Following established criteria for contributing to taxonomic theories and revising previous classification systems (Gregor 2006), we ensure that the categories are meaningful and natural, and do not omit important elements needed for a complete and exhaustive taxonomy.

We reinforce gamblification as a unique subdomain of gamification, offering a foundation for shared language among IS researchers and across disciplines. Clearly identify a target system as gamblified provides an additional avenue in finding potential explanations for observed effects on user engagement and motivation. The taxonomy is therefore also a basis for making systematic predictions about different outcomes and distinct effect mechanisms of gamification and gamblification design elements, which can then be tested in targeted empirical research. The defined characteristics could also inform future exchanges in debates whether certain behaviors and user applications should be classified as gaming or gambling, facilitating conversations between different research communities.

In practice, the gamification taxonomy now reflecting gamblification can guide IS designers in deriving novel gamification and gamblification designs. Deliberately employing gamble design elements, they can create new ways of engaging users and nudging users towards desired behaviors based on implementation and testing of specific elements. They can further explore a broad potential range of application areas for gamblification, taking inspiration from the wide

spread of gamification designs in the past. The extended taxonomy moves gamblification closer towards the spotlight within the field of gamification, providing a basis for researchers and designers to gain a more nuanced understanding of design element characteristics and to pursue insights into potential variations in their effectiveness.

2.5.2 Limitations and future research

We aimed to be thorough and systematic in our approach to this paper, but certain limitations remain. For example, our literature review for uses of gamble design elements in gamification contexts may have overlooked relevant publications and thereby potential other design objects or mechanics. As our literature review was limited to gamification publications, papers also applying gamble design elements but not explicitly naming or examining gamification would not be included in the search results. In addition, we only considered one gamification taxonomy and its possible extensions for gamblification in detail, despite a large number of frameworks present in the gamification field. However, the chosen classification system is among the most recent methodological works, providing a robust foundation for our advancements. Finally, further steps could be taken to validate our extended taxonomy. Beyond application to practical case examples, the classification characteristics could be tested with expert researchers and practitioners (e.g., through card sorting (Moore and Benbasat 1991) in a next step for additional validation that it is a useful taxonomy (Nickerson et al. 2013).

In light of these considerations, we suggest four essential focus areas for future research. First, resultant from the final consideration above, we call upon IS design researchers to further refine, extend, and validate the latest taxonomy for gamification and gamblification. Second, IS researchers should gain a better understanding of the mediating mechanisms and concepts underlying gamification. So far only limited work has been done and proven conclusive on untangling the individual effect mechanisms of the plethora of gamified design elements on user behavior (e.g., Hamari 2013; Nicholson 2012; Zuckerman and Gal-Oz 2014). We should aim for a clearer view of relationships between specific design elements, the type of user motivation they induce, which psychological needs they satisfy, and specific mediating or moderating constructs. Third, we propose a closer examination of gamification's context dependency. Literature reviews have indicated that gamification effects can depend on their implementation context and the respective user (Hamari et al. 2014). In order to guide IS designers in practice, it would be important to understand better under which circumstances, including application areas and users' personal dispositions, gamblification and gamification respectively are particularly effectiveness in enhancing engagement. Finally, there is a lack of clear guidelines for designing gamblified systems. In order to enable researchers and

practitioners to leverage existing conceptual and empirical knowledge on gamblification, future research could examine the design of specific gamble design elements following the design science research approach (Hevner et al. 2004).

2.5.3 Conclusion

For more than a decade now, gamification has been a popular and promising concept to instigate user motivation, engagement, and desired behaviors. More recently, the use of gamble design elements has increased to pursue similar motives. We argue that the domain is in dire need of a common terminology and shared understanding of design element characteristics to guide future conversations and designs of gamified and gamblified systems. We propose a first taxonomy consolidating and differentiating both gamification and gamblification design elements to reduce ambiguities and direct a more systematic assessment of gamification and gamblification design effectiveness.

Chapter 3: Social Influence Tactics in E-commerce User Onboarding

Title: Social influence tactics in e-commerce onboarding: The role of social proof and reciprocity in affecting user registrations (2020)

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Abstract

Given the increasing competition to attract new customers, e-commerce providers (i.e., e-tailers) are being urged to optimize their website onboarding journeys. Design mechanisms employing social influence tactics seem to be promising avenues to effectively improve user onboarding experiences. Specifically, two social influence tactics—namely, reciprocity and social proof—are widely used in practice to reliably enhance user registrations. Yet, researchers have only tentatively examined how these combined tactics affect user onboarding behavior. While combining both tactics may hold synergistic potential, it may also be counterproductive, as too much social influence may backfire. We address this research gap by investigating the distinct and joint effects of reciprocity and social proof on user registration behavior. Drawing on two forms of reciprocity (i.e., utility- and monetary-based reciprocity), we conduct an online experiment (N = 249) and a related randomized field experiment (N = 475,495) to compare both reciprocity variants in combination with social proof and investigate their efficacy for actual user onboarding decisions (i.e., user registrations). Our results show that both social influence tactics and both reciprocity variants have positive effects on users' registration behavior if applied individually. However, when both tactics are employed together, the effect of reciprocity is moderated by social proof such that social proof nullifies the effect of monetary-based reciprocity whereas it amplifies the effect of utility-based reciprocity. Our study thereby contributes to a more advanced understanding of the interactive relationship between reciprocity and social proof and their joint effect on user onboarding decisions.

Keywords: User onboarding; E-commerce; Social influence; Reciprocity; Social proof; User registration

3.1 Introduction

User onboarding has become a critical challenge for almost all e-commerce platform providers (i.e., e-tailers). For example, fierce competition has led to a landscape in which less than 25% of visitors return after their first use (e.g., Grennan 2016). Since the probability of selling to an existing user is 60–70% compared to only 5–20% for selling to a new prospect (Farris et al. 2017), practitioners have started to draw on user onboarding, which is defined as a set of methods and tools to actively guide visitors to become registered users on a digital platform and make them appreciate the service that the platform offers (Liu et al. 2017; Renz et al. 2014). Therefore, the behavior of these registered users can be identified and tracked more easily, which in turn facilitates crucial activities for retaining users and optimizing services (e.g., behavioral insights and targeted advertising). To date, considerable research effort has been put into investigating the antecedents of successful user onboarding on e-commerce platforms and has unveiled critical drivers (Jiang et al. 2013; Lee et al. 2011). As the diffusion of unfamiliar services is a social phenomenon, much of the work has focused on the effects of social influence (i.e., processes that affect an individual's beliefs, attitudes, and behaviors) to increase e-commerce success such as increasing consumers' purchase behaviors (Aral 2011; Benlian et al. 2012; Hogg 2010). While many researchers have investigated how social influence tactics (i.e., tactics that are built upon social influence theory[5]) affect user onboarding, there has been minimal to no research on the interplay between social influence tactics. Moreover, investigations into how social influence tactics can be translated into actionable design elements in user onboarding have been neglected in the extant research.

We intend to address this gap by examining the distinct and joint effects of two social influence tactics—namely, reciprocity and social proof—and how they affect user onboarding in the context of user registration decisions. We focus on reciprocity and social proof because they are the most important social influence tactics in the information systems (IS) and consumer behavior literature, and they are abundantly used by e-tailers in practice. The norm of reciprocity refers to an obligation to respond to an action with another similar action (Cialdini 2007). Research has demonstrated that reciprocity can trigger a feeling of indebtedness that arises after receiving an uninvited favor (Berry and Kanouse 1987; Hogg 2010). This tactic manifests, for example, in the ubiquitous e-tailer practice of providing free product trials to visitors, causing these visitors to reciprocate by providing better product ratings (Lin et al. 2019). Social proof, on the other hand, refers to a social influence tactic where people assume

[5] This theory explains the effect of different types of social influence on individuals' cognitions and behaviors.

what the actions of others are in an attempt to identify the correct behavior (Cialdini et al. 1999). By recommending products and displaying sales rankings, e-tailers leverage social proof by indicating the behavior of prior users, thus allowing prospective users to infer the popularity of a given product. Although both tactics are abundantly employed in practice and have been investigated separately as drivers of e-commerce sales, little is known about their efficacy for user onboarding. Furthermore, research is still needed on the interplay between reciprocity and social proof and how they jointly affect users. As combining social influence tactics often yields unintended consequences, the interplay between both social influence tactics could potentially unveil substituting, complementary, or even cannibalizing effects (Brehm and Brehm 2013). In this regard, it remains to be examined whether social proof will augment or attenuate the influence of reciprocity favors on user registrations and whether this interaction differs when two different variants of reciprocity are used. Therefore, we analyze the potential of these two widely used social influence tactics in increasing user registrations. Taken together, the objective of this article is to address the following research questions:

RQ1. What distinct effects do reciprocity and social proof have on user registration decisions during user onboarding?

RQ2. How do monetary-based and utility-based reciprocity interact with social proof in affecting user registrations during user onboarding?

To answer our research questions, we used a multi-method approach comprising an online experiment (N = 249) and a related randomized field experiment (N = 475,495). Thus, we examined the separate and joint effects of reciprocity and social proof on user registrations. By combining these two related experiments, we aim to corroborate our findings regarding the most important social influence tactic (i.e., social proof) and to capture a richer, more complete picture regarding the two types of reciprocity (Venkatesh et al. 2013).

Our article contributes to the IS research in three important ways: First, our research sheds light on how social proof and reciprocity distinctly affect user registrations and demonstrates the efficacy of combining both tactics. Although both social influence tactics have been studied separately in previous e-commerce research, little is known about how they operate together to improve user registrations in e-commerce user onboarding. Our findings support the existence of an interactive effect between these two social influence tactics and highlight the importance of accounting for this interdependence when optimizing user onboarding. Second, we advance previous research by distinguishing between two widely used, yet under-researched types of reciprocity—namely, monetary- and utility-based reciprocity—to investigate their interactive

effects with social proof on user registrations. Surprisingly, we find the opposite in terms of the interaction effect patterns: While social proof nullifies the effect of monetary-based reciprocity on user registrations, it amplifies the effect of utility-based reciprocity. Our findings show that monetary-based reciprocity is faced with increased scrutiny that might discourage users from signing up to the e-commerce platform. Taken together, our insights emphasize the importance of carefully considering the effects of specific kinds of reciprocity to gain an advanced understanding of the effectiveness of social influence tactics in user onboarding. Third, addressing Goes (2013)'s call for future research into the social dimension of judgment and decision contexts, we add to the nascent and emerging literature on social influence in virtual environments by contributing actionable design recommendations for two distinct social influence tactics regarding how they can be employed together for user onboarding.

3.2 Theoretical background

3.2.1 User onboarding and social influence

User onboarding refers to a set of design principles (e.g., make users engage right from the start but do not overwhelm them with tasks that are too demanding) that help new visitors to become familiar with the service that a digital platform offers and guide them to become registered (i.e., activated) users (Liu et al. 2017; Renz et al. 2014). For instance, a visitor can easily become a user of the basic functionalities of a digital platform, thereby "adopting" the platform. However, the visitor oftentimes does not need to register on the platform to use it, thereby not fulfilling the ultimate goal of user onboarding to turn visitors into registered and identifiable users (i.e., thus becoming "activated" users). Therefore, user onboarding as a gamification design element facilitates the user registration process, thus allowing platform providers to analyze and react to user behavior, helping to build a better relationship between the user and the platform provider.

While previous research on user onboarding has mainly focused on digital gamification, research on using a combination of different social influence tactics has largely been neglected (Liu et al. 2017). However, social influence tactics to improve user onboarding seem to be promising for e-tailers (Gourville 2006): The previous IS literature has often addressed user onboarding by drawing on social influence theory to explain user behaviors (e.g., Datta 2011; Wang et al. 2013; Wessel et al. 2019). Furthermore, due to the uncertainty during user onboarding, individuals are particularly susceptible to social signals and influence (i.e., social processes that affect the individual's beliefs, attitudes, and behaviors) (Hogg 2010). In this regard, it is promising to consider how tactics relying on social influence theory (i.e., social

influence tactics) can be leveraged to enhance user onboarding (Koch and Benlian 2017; Schneider et al. 2020; Wessel et al. 2019). In e-commerce contexts, practitioners abundantly employ social influence tactics during activation phases (e.g., Cheung et al. 2014; Schumann et al. 2014; Ye et al. 2018). Previous research on social influence tactics in e-commerce has primarily focused on examining different social influence tactics in isolation from one another (e.g., Cheung et al. 2014; Lin et al. 2019; Thies et al. 2016; Ye et al. 2018). While the separate effects of distinct social influence tactics are well understood, research has yet to investigate how social influence tactics work in tandem (Thies et al. 2016; Zhou and Guo 2017). Against this backdrop, our article aims to examine the interplay between different social influence tactics and their joint influence on user onboarding. We focus on social proof and reciprocity as social influence tactics because these two tactics are widely used in practice (e.g., Gu et al. 2017; Klumpe et al. 2020; Schumann et al. 2014; Ye et al. 2018). Yet, these social influence tactics have not been investigated together, even though their joint consideration promises the intriguing possibility that they may serve as complements to or substitutes for one another. More broadly, regardless of the scholarly attention that has been paid to single social influence tactics, there have only been a few contributions on how these insights can be used actively in user onboarding. Heeding the call of Goes (2013) for research on design and action-oriented research, we aim to address these gaps by examining the separate and joint effects of reciprocity and social proof tactics on user registration. We now turn our attention to the norm of reciprocity and the different types of reciprocity being implemented on e-commerce platforms.

3.2.2 Reciprocity

The norm of reciprocity requires us to respond to positive or negative actions with similar actions, thus repaying the original actions (Cialdini 2007). Reciprocity is internalized from an early age to teach social cohesion and mutual benefit and thereby manifests as an intrinsic moral belief causing feelings of guilt when violated (Whatley et al. 1999). Therefore, reciprocity plays a central role in social exchanges as it creates trust and helps to stabilize relationships (Molm et al. 2007). As a social influence tactic drawing on social exchange theory, it has also been found to enhance decision-making outcomes in the context of survey participation (Cialdini 2007). For example, Berry and Kanouse (1987) observed that participants were more likely to complete a questionnaire when they were given a financial gift beforehand, triggering their need to reciprocate, as opposed to when they were promised a gift after completion (i.e., contingent financial incentives). In digital environments, voucher codes with explicit monetary value attached to them are widely employed on e-commerce platforms (e.g., nakedwines.com offers a free £30 wine voucher for new customers) (Dubé et al. 2017). Thus, in line with previous

findings and current practices, monetary-based reciprocity cues provide users with monetary benefits (e.g., in the form of a digital voucher code) prior to any subsequent request. Besides monetary-based reciprocity, e-tailers commonly provide intangible benefits on their platforms by offering valuable information and guidance (e.g., www.springlane.de offers ideas for recipes for free that can be prepared by using products sold on the website). In this regard, utility-based reciprocity cues encompass functional content that is provided to users to improve their decision-making capacity.

Taken together, despite valuable contributions to the research on reciprocity in online and offline contexts, we still know little about how monetary-based vs. utility-based reciprocity cues can be employed during user onboarding. Although reciprocity holds the potential to nudge new users to register on a website, reciprocity may also backfire and eventually put potential users off (Cialdini and Trost 1998). Therefore, we aim to uncover how monetary-based and utility-based reciprocity cues compare in terms of how they affect users' likelihood to reciprocate (i.e., to register on a website) and how they interact with other social influence tactics such as social proof, to which we turn next.

3.2.3 Social proof

Social proof is a social influence tactic that indicates product demand and popularity (Cialdini 2007). In situations of uncertainty, people draw on social proof as a source of information to derive guidance for their own actions (Cialdini and Trost 1998). Firms often use social proof to leverage the fact that people habitually follow each other's behavior in situations of uncertainty (Klumpe et al. 2020; Thies et al. 2016). E-commerce websites utilize social proof to diminish users' concerns and therefore implement social proof cues to build up trustworthiness (Burtch et al. 2018; Schneider et al. 2020). While social proof has been employed in e-commerce contexts to study its impact on the provision of public information goods such as reviews (e.g., Burtch et al. 2018; Chen et al. 2010), to the best of our knowledge it has not yet been investigated in the context of user onboarding. Social proof cues are implemented during user onboarding to indicate a service's popularity by displaying how many people have already registered on a platform or rated a product. More importantly, previous research has neglected to study social proof in conjunction with other social influence tactics, which is widely practiced, yet largely overlooked in the extant research.

3.3 Hypothesis development and research framework

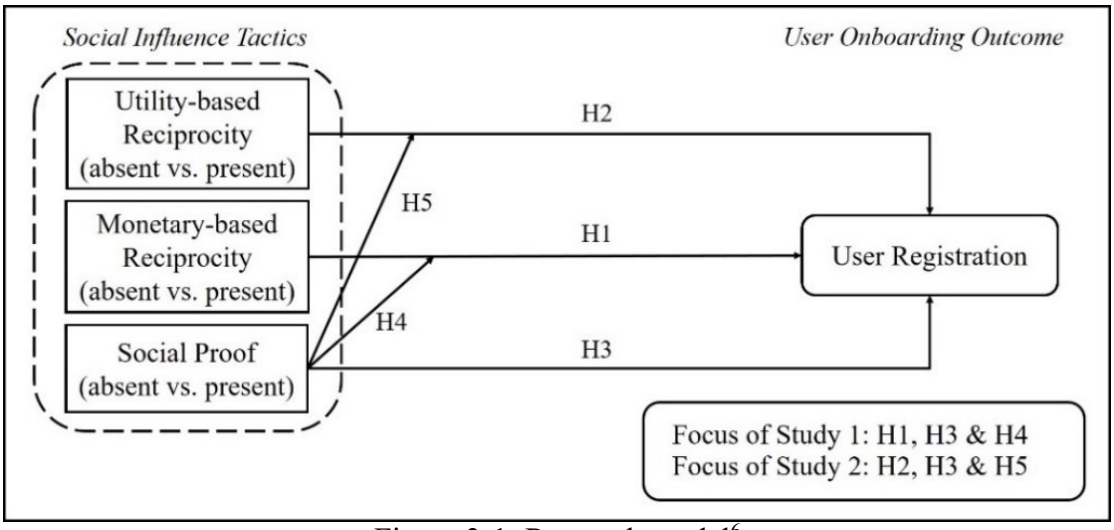

Figure 3-1: Research model[6]

Drawing on social influence theory (Cialdini 2007) as a theoretical foundation, we develop a research model that first sheds light on the distinct effects of monetary-based reciprocity, utility-based reciprocity, and social proof on user registrations (H1/H2/H3). We then continue by theorizing on the interactive effects of monetary- and utility-based reciprocity with social proof on user registrations (H4/H5). We expound upon each of the posited relationships depicted in our proposed research model in Figure 3-1 in the following sections. Whereas we focus on H1, H3, H4 in Study 1, H2, H4, and H5 are at the center of our research attention in Study 2.

3.3.1 The effect of reciprocity on user registrations

Based on social influence theory (Cialdini 2001), reciprocity has been found to make individuals more likely to comply with a specific request when they have received a gift or a concession prior to the request. The underlying mechanism of reciprocity follows the felt obligation to repay good actions in kind, which is internalized from an early age to foster social cohesion. An effective and widely employed way for e-tailers to draw on the norm of reciprocity is to use monetary-based reciprocity (e.g., a digital voucher code) (Dubé et al. 2017; Lin et al. 2019). By offering new users a financial benefit prior to complying with a request, they should be more inclined to follow their internal obligation to reciprocate this request. Given this reasoning and previous empirical findings, we argue that when monetary-based reciprocity cues are present (vs. absent) in user onboarding, we expect the likelihood of new users registering to be higher (Berry and Kanouse 1987). As such, we hypothesize:

[6] Note: A registered user account is mandatory to fulfill any transaction. This registration requirement cannot be bypassed (e.g., by a “check out as a guest” option).

H1) New users will be more likely to register during user onboarding when a monetary-based reciprocity cue is present compared to when it is absent.

Similar to financial benefits, intangible benefits (e.g., exclusive information or functional content) can also foster reciprocal behavior in the form of information disclosure (Jiang et al. 2013). For example, when an e-tailer provides information on how to effectively select and use its offered products to new users, it leverages utility-based reciprocity, enabling its users to receive additional benefits. In this respect, we suggest that a utility-based reciprocity cue from an e-tailer, which discloses functional content, emulates an investment into a social relationship with users (Molm et al. 2007). To gather and provide useful content to a new user, an e-tailer needs to anticipate the user's concerns when evaluating the e-tailer's offering. Therefore, by disclosing actual useful content, the e-tailer demonstrates an initial upfront investment into the relationship with its new users. Specifically, it creates an intangible benefit to new users and thus should increase their likelihood of reciprocating the favor by disclosing personal information; that is, registering during user onboarding. Based on this reasoning, we hypothesize that:

H2) New users will be more likely to register during user onboarding when a utility-based reciprocity cue is present compared to when it is absent.

3.3.2 The effect of social proof on user registrations

According to social influence theory, social proof signals validated behavior (Cialdini and Trost 1998). In practice, online platforms facilitate this behavior by indicating which product or service is particularly popular among users. Platforms commonly draw on social proof to help users overcome their uncertainties and potential concerns (Cialdini 2007; Goldstein et al. 2008). They often implement visual cues with quantitative information indicating a product's popularity (e.g., number of downloads of a particular app, number of product ratings). While social proof acts as a collective signal, it creates a positive reputation for and trust toward a platform (Gu et al. 2017; Thies et al. 2016). Furthermore, according to previous research, the underlying knock-on effect (also called the bandwagon effect) explains that users have an urge to follow other users. The logical explanation for this herding behavior is that users fear missing out on a superior option that is unveiled by the action of others (Klumpe et al. 2020). Applied to the user onboarding context, we suggest that social proof also drives new users to be more likely to disclose personal information in user onboarding. More specifically, we expect user registrations to be more likely when social proof is present than when social proof is absent.

H3) New users will be more likely to register during user onboarding when social proof is present compared to when it is absent.

3.3.3 The Interaction effects between reciprocity and social proof

In our hypotheses H1, H2, and H3, we argued that both monetary- and utility-based reciprocity variants as well as social proof positively affect user registrations. On the one hand, monetary- and utility-based reciprocity cues draw on an internalized obligation to repay others' actions. On the other hand, social proof drives users to follow others' behavior. With regard to their joint effects, however, we suggest that monetary-based reciprocity cues interact differently with social proof cues than utility-based reciprocity cues do.

First, we argue that when monetary-based reciprocity and social proof cues are employed together, the effect of monetary-based reciprocity is canceled out by the effect of social proof. Previous literature suggests that when social influence tactics are combined, users are more likely to realize an attempted manipulation and are therefore more prone to psychological reactance (i.e., the reluctance to consider behavioral advice, which the targeted person perceives as a constraint on his or her personal freedom of choice) (Friestad and Wright 1994). Research has shown that psychological reactance leads to suppressed receptivity to social influence tactics, indicating that too much social influence may backfire (Weiger et al. 2018). For instance, research on discount vouchers suggests that users are more likely to perceive gifted discounts as compensation for information disclosure, which then increases the users' scrutiny of subsequent requests (Brehm and Brehm 2013). Therefore, as monetary-based reciprocity cues are often implemented in the form of providing discount vouchers, users should perceive them with increased scrutiny (Hoffman et al. 1999). When monetary-based reciprocity and social proof are combined, this scrutiny is further amplified. Thus, increased psychological reactance behaviors, including reduced compliance to a request, are more likely to occur, decreasing the likelihood of user registrations.

H4) Social proof will moderate the relationship between monetary-based reciprocity and user registrations such that social proof will attenuate or even cancel out monetary-based reciprocity's effect on user registrations.

Second, we posit that when utility-based reciprocity and social proof cues are used jointly, the effect of utility-based reciprocity on user registration is amplified by the effect of social proof. Previous research has found functional content (e.g., product guides and samples) to be useful information for users and it is created by e-tailers to guide users toward better decision-making (Schumann et al. 2014; Ye et al. 2018). When users are supplied with functional content, the e-

tailer attempts to initiate and foster social exchanges, which is in accordance with the users' experiences from daily social interactions (Jiang et al. 2013). As such, in contrast to monetary-based reciprocity cues, which offer a favor in a blunt and obtrusive way, utility-based reciprocity cues are more subtle and thus create minimal to no suspicion without arousing any suspicions regarding ambiguous intentions (Molm et al. 2007).

In addition, utility-based reciprocity has been found to be a genuine way to initiate a give-and-take scenario between users and e-tailers, representing an investment into an ongoing relationship (Skågeby 2010). In this regard, we argue that in contrast to the negative moderating effect of social proof in H4 when users appreciate the social exchange initiated by a utility-based favor (without evoking suspicion and scrutiny), social proof cues should augment this appreciation given that they underscore that many other users have already benefited from this offer. As such, social proof should act like a multiplier, boosting the effect of utility-based reciprocity on user registration. Taken together, we propose that new users are more likely to follow their obligation to "repay" (i.e., to sign up for a service in our context) when utility-based reciprocity is provided together with social proof.

H5) Social proof will moderate the relationship between utility-based reciprocity and user registrations such that social proof will augment utility-based reciprocity's effect on user registrations.

3.4 Research studies and results

We employed a multi-method approach featuring two independent quantitative studies to investigate the hypotheses of our proposed research model. The first was an online experiment with a convenience sample of e-commerce users; we used this study to demonstrate the effects of reciprocity (i.e., implemented as monetary-based reciprocity in the form of discount vouchers) and social proof on user registrations and to examine the interaction between these two social influence tactics. We then conducted a follow-up randomized field experiment (Study 2) with actual users of a real-world e-commerce platform to test the robustness and generalizability of our core findings. Moreover, instead of monetary-based reciprocity, we employed utility-based reciprocity in the form of functional content by granting users access to a useful product guide that helped them orient themselves on the platform.

Taken together, following methodological guidelines by Mingers (2001), Venkatesh et al. (2013), and Venkatesh et al. (2016), our research design aimed to meet three goals of multi-method research: corroboration, expansion, and compensation. First, we used the two studies to triangulate how our findings regarding core theoretical relationships (i.e., the distinct and

interactive effects of social proof and reciprocity on user registrations) converge (or diverge) across methods and samples. Corroboration regarding the effect of social proof on the registration decision across studies using two independent samples with different experimental methods and sampling procedures also reduces the likelihood that the observed relationships are spurious and increases the reliability of our conclusions. Second, the field experiment expanded the online experimental study by introducing and elaborating on a different variant of reciprocity—namely, utility-based reciprocity—to look at potential differences in the interaction with social proof compared to Study 1. Finally, our design leveraged the strengths and compensated for the limitations of each approach. In this regard, the online experiment demonstrated high internal validity (i.e., high control), while the randomized field experiment ensured high external and ecological validity (i.e., high realism). By investigating our theoretical model in the field and in a controlled online environment, we were able to pursue both the generalizability and causality of the hypothesized relationships (Karahanna et al. 2018).

3.5 Study 1: Online experiment research methodology

3.5.1 Experimental design and treatments

Monetary-based Reciprocity		Social Proof	
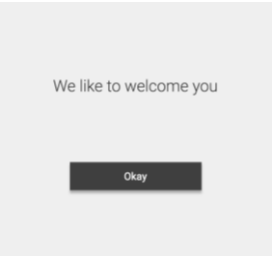	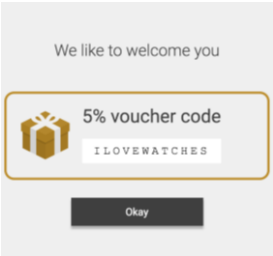	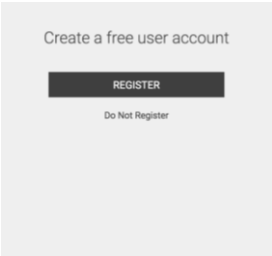	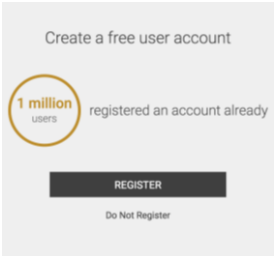
Figure 3-2: Welcome layer (monetary-based reciprocity: absent)	Figure 3-3: Welcome layer (monetary-based reciprocity: present)	Figure 3-4: Registration layer (social proof: absent)	Figure 3-5: Registration layer (social proof: present)

In our first study, we conducted an online experiment based on a self-developed, fictitious e-commerce platform called Watch24. Two independent variables (i.e., reciprocity and social proof) were manipulated in this experiment with a 2 (monetary-based reciprocity: absent vs. present) × 2 (social proof: absent vs. present) between-subjects, full-factorial experimental design. We randomly assigned the subjects to one of the four conditions.

The self-developed e-commerce platform featured a product catalog that listed various watches with their product name, image, and price, all of which were crawled from an established e-commerce platform for watches. In so doing, we followed recommendations in the

methodological literature that suggest improving realism in the stimulus presentation by increasing the level of immersion and similarity between the experimental and natural settings (Aguinis and Bradley 2014). After clicking on a product, another website layer popped up that welcomed the participants and, if the participants were in the monetary-based reciprocity treatment, a free voucher code was displayed and presented like a welcome gift (see Figure 3-3), while those participants who were not in the monetary-based reciprocity treatment only saw the welcome message (see Figure 3-2). In line with previous research, the voucher code advertised a 5% discount and was given to participants without any requirements attached (Berry and Kanouse 1987). Thereafter, the participants proceeded to a subsequent registration layer by clicking on a button labeled "Okay." The registration layer featured a headline (i.e., "Create a free user account") and two buttons that displayed the options to register or not to register, recording our dependent variable "user registration". Specifically, those subjects in conditions including social proof saw a visual cue that informed them that 1 million user accounts had already been registered on Watch24 (see Figure 3-5), while participants who were not in the social proof treatment did not see this cue (see Figure 3-4).

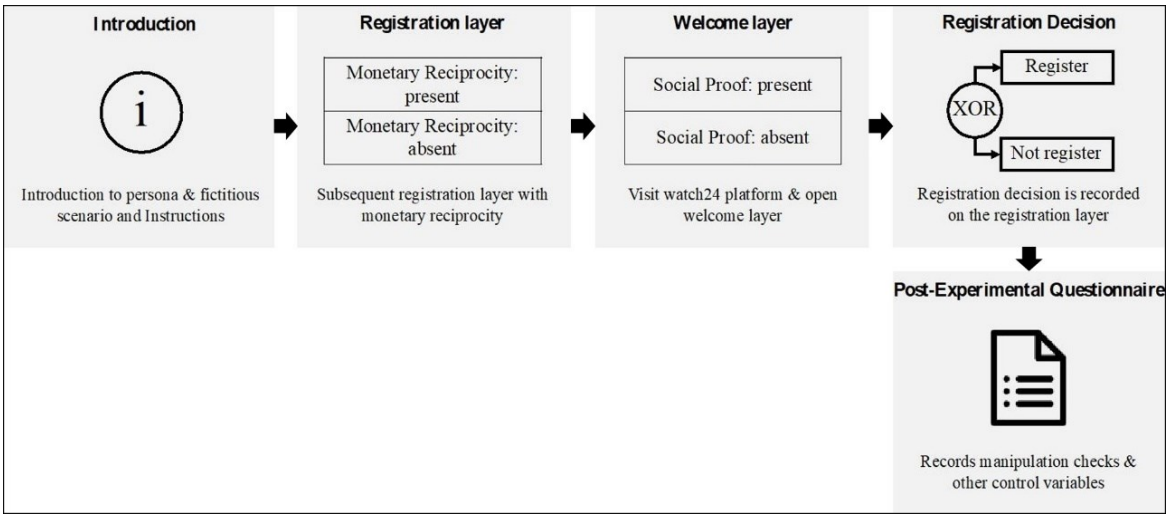

Figure 3-6: Experimental procedure and conditions

As depicted in Figure 3-6, the experiment proceeded in five major steps: First, as a cover story, we informed the subjects that they were helping an e-commerce company to improve its services. Second, in line with previous vignette-based experimental research (e.g., Benlian et al. 2020), we asked participants to put themselves into the shoes of a persona (a fictional protagonist named "Alex") as a proxy to eliminate potential response biases (Nederhof 1985). The vignette methodology was chosen for our experiment to control the participants' experiences and avoid social desirability bias (Aguinis and Bradley 2014), thus allowing us to accurately examine the effects on our dependent variable. Third, thereafter, the participants were randomly assigned to an experimental condition and redirected to our fictitious e-

commerce platform where they started to explore the offers. After clicking on a product, the welcome layer was presented, either with or without monetary-based reciprocity. After clicking on a button to continue, they were confronted with the registration layer where they were either exposed to social proof or not and had to decide whether they would choose to register or not to register. Finally, the registration decision was captured and participants were redirected to the post-experimental questionnaire that recorded our manipulation check variables as well as several covariates. At the end of the survey, the participants were debriefed and thanked for their participation.

3.5.2 Manipulation checks and measurement validation

We developed our stimuli and evaluated the realism of our scenarios and persona by conducting a pretest involving 50 participants (M_{age} = 24; 60% male). To evaluate our monetary-based reciprocity manipulation, we could confirm that perceived reciprocity was higher when our monetary-based reciprocity manipulation was present (M = 5.60; SD = .87) than when it was absent (M = 4.84; SD = 1.28; $F(1,48) = 6.04$; $p < .05$). Similarly, our manipulation check for social proof demonstrated that the perceived popularity of the e-commerce platform was higher when social proof was present (M = 5.84; SD = 1.01) compared to when it was absent (M = 4.71; SD = 1.32; $F(1,48) = 10.23$; $p < .01$). To keep the questionnaire focused, we only used single items, as the predictive validity of single items is considered comparable to multi-item measures (e.g., Bergkvist and Rossiter 2007). To prevent common method bias (CMB), we took several precautions (Podsakoff et al. 2003): We measured the participants' registration decision via log-file data collected in a database storing all clickstream information. Subjects could either register by clicking on a button labeled "Register" or refuse to register by clicking on a button that was labeled "Do not Register." After deciding whether to register or not, the choice was captured and the participants were redirected to a post-experimental questionnaire where we recorded the control variables to rule out alternative explanations, and socio-demographic information. Besides taking precautions to prevent CMB, we also tested for possible CMB by applying the Harman one-factor extraction test (e.g., Pavlou et al. 2007). Using a principal component analysis for all items of the latent variables included in our leaner model, we found three factors with eigenvalues greater than 1, accounting for 94% of the total variance. As the first factor accounted for only 39% of the total variance (i.e., less than 50% of the total variance), this test suggests that CMB is not a major concern in this study.

We further measured the following alternative driver of user onboarding as a control in our experiment (Agarwal and Prasad 1998): Personal innovativeness on 7-point Likert-type scales, ranging from 1 (strongly disagree) to 7 (strongly agree). Furthermore, we collected information

on subjects' Internet experience on an ordinal scale ranging from 1 (daily) to 6 (never), as well as demographic information about the participants' age, gender, and nationality. We evaluated the internal consistency of the measured variables (see Table A1 in the Appendix). As all variables showed adequate internal consistency, we averaged the items of each construct to form composite scores for further statistical analysis. Convergent validity was confirmed via confirmatory factor analysis and each scale's average variance extracted (AVE) surpassed multiple squared correlations, indicating that all discriminant validity requirements were met (Klumpe et al. 2020). To confirm the random assignment of subjects to the different experimental conditions, we performed a series of one-way analyses of variance. There were no significant differences in gender ($F = 1.23$; $p > .05$), age ($F = 1.20$; $p > .05$), education ($F = 1.34$; $p > .05$), Internet experience ($F = 1.22$; $p > .05$), nationality ($F = 2.40$; $p > .05$), or personal innovativeness ($F = .67$; $p > .05$) among the four experimental conditions, thus confirming that the random assignment of subjects to the conditions was successful.

3.5.3 Sample descriptives

In line with previous research, we recruited 280 participants via Amazon Mechanical Turk (MTurk) by following best practices (e.g., selecting "high-quality" participants who had completed at least 50 tasks and who had higher than 80% approval ratings) for collecting MTurk data (Lowry et al. 2016). Out of a total of 280 participants, we excluded 31 due to suspicious mouse click patterns (e.g., low response variability, high rate of missing values), resulting in a final sample of 249 participants used for the data analysis. Of the 249 subjects, 92 were females and 157 males. Sixty-seven participants converted to register on Watch24, resulting in an overall proportion of 27% across all four subgroups. Participants exhibited an average age of 29.4, typically stated that they had only moderate experience in Internet usage, and 65% of them were US residents. Table A3 in the Appendix reports the descriptive statistics and correlations of the variables in our model.

3.5.4 Main and interaction effects of monetary-based reciprocity and social proof

	Stage 1			Stage 2		
Construct	Coefficient	*SE*	Exp(B)	Coefficient	*SE*	Exp(B)
Intercept	−1.72	1.01	.18	−2.89	1.21	.01
Manipulations						
Monetary-based Reciprocity	1.07**	.32	2.90	2.50**	.77	12.18
Social Proof	1.16***	.31	3.19	2.69**	.78	14.73
Monetary-based Reciprocity × Social Proof	-	-	-	−2.06*	.87	.13
Control Variables						
Personal Innovativeness	−.01	.15	.99	.01	.16	1.01
Internet Experience	−.10	.16	.91	−.13	.16	.88
Gender (male)	−.40	.32	.67	−.36	.32	.70
Model Fit						
Log Likelihood	−130.19			−126.61		
Nagelkerke R^2	.16			.20		
Omnibus Model $\chi 2$	29.63***			36.79***		
Note: * $p < .05$; ** $p < .01$; *** $p < .001$; $N = 249$						

Table 3-1: Binary logistic regression analysis on registration decision

To test our hypotheses, we conducted a two-stage hierarchical binary logistic regression on our dependent variable of user registration (see Table 3-1). In Stage 1, we entered all the control variables as well as our independent variables of reciprocity and social proof. In Stage 2, we added the interaction term of monetary-based reciprocity and social proof. Nagelkerke's R^2 and $\chi 2$ statistics were computed to test the fit for both stages. None of our controls had a significant effect on registration decisions. The results of Stage 1 demonstrate significant positive main effects of monetary-based reciprocity (b = 1.07; Wald statistic(1) = 10.79; p < .01) and social proof (b = 1.16; Wald statistic(1) = 13.95; p < .001) on user registration. Hence, participants who are primed with monetary-based reciprocity are more likely to register than when monetary-based reciprocity is absent (36% vs. 16%; F = 12.68; p < 0.001). Additionally, in the presence of social proof, participants are also more likely to register than when it is absent (39% vs. 17%; F = 16.51; p < 0.001). Moreover, Stage 2 unveils a significant two-way interaction between monetary-based reciprocity and social proof (b = −2.06; Wald statistic(1) = 5.64; p < .05) on user registration. The negative interaction term suggests that the effect of monetary-

based reciprocity on user registration is attenuated in the presence of social proof. To further evaluate H4, we conducted a moderation analysis based on Hayes (2018, Model 1) with 10,000 samples and 95% bias-corrected confidence intervals.

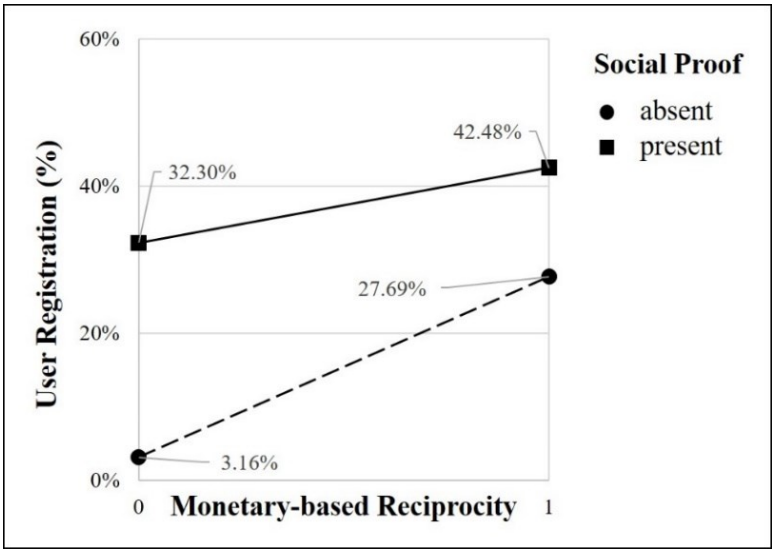

Figure 3-7: Moderating effect of social proof on the effect of monetary-based reciprocity on user registration

As depicted in Figure 3-7, the results highlight that when social proof is absent, participants are more likely to register when monetary-based reciprocity is present (28%) than when it is absent (3%; $F = 17.27$; $p < .001$). However, a significant difference in user registration between the presence and absence of monetary-based reciprocity does not emerge when social proof is present (42% vs. 32%; $F = 1.34$; $p > .05$), in support of H4.

Social Proof	Coefficient for the Effect of Monetary-based Reciprocity on User Registration	Boot *SE*	Boot LLCI	Boot ULCI
absent	2.36	.79	.95	3.91
present	.54	.43	−.33	1.27
Note: Coefficients were computed based on a moderation analysis including all controls and using bootstrapping with 10,000 samples and a 95% bias-corrected confidence interval (Hayes 2018).				

Table 3-2: Conditional effect of monetary-based reciprocity on user registration in the presence and absence of social proof

Additionally, Table 3-2 shows that the effect of monetary-based reciprocity on user registration is contingent on the presence of social proof. When social proof was absent, reciprocity had a positive, significant effect on user registration, while when social proof was present, the positive, significant effect of monetary-based reciprocity on user registration disappeared (i.e.,

the confidence interval contains 0). Thus, these results suggest that social proof nullifies or cancels out the effect of monetary-based reciprocity on user registration, in support of H5.

3.6 Study 2: Field experiment research methodology

3.6.1 Experimental design and treatments

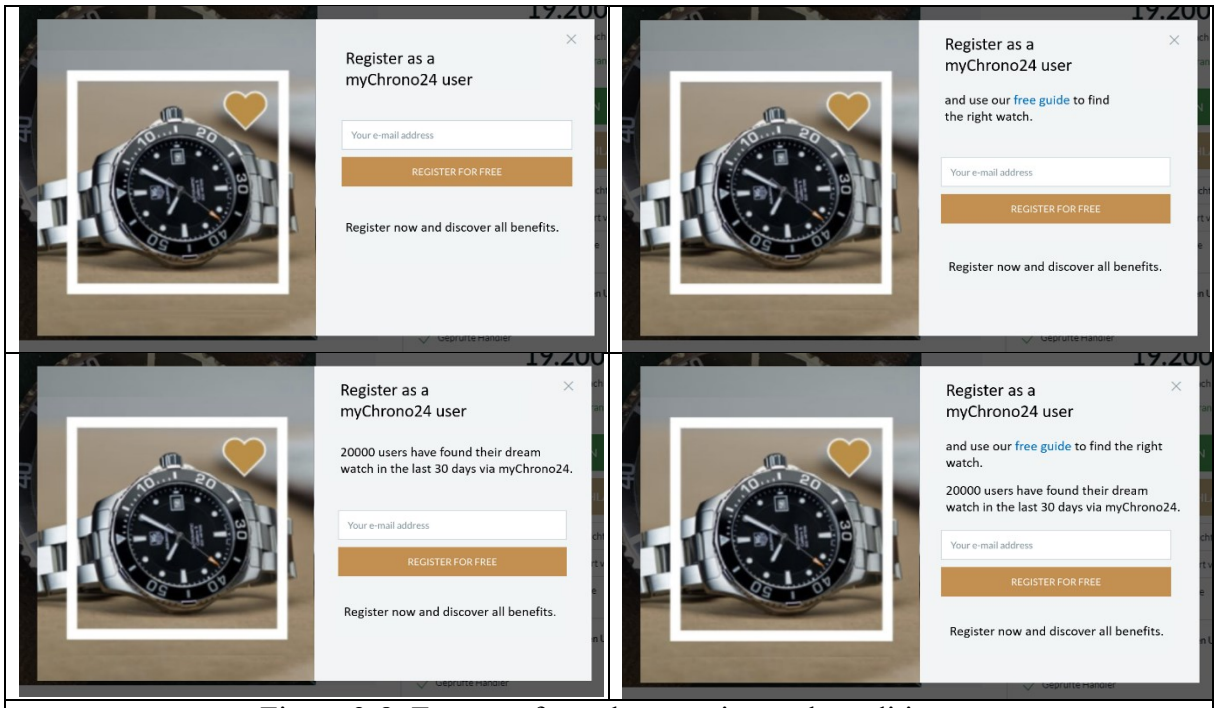

Figure 3-8: Excerpts from the experimental conditions

Note: The screenshots in the upper half show the layer in the absence and presence of our utility-based reciprocity manipulation. The screenshots on the left side show the layer in the absence and presence of our social proof manipulation.

We had the opportunity to partner up with the provider of a leading global online marketplace for luxury watches (Chrono24) that enables third-party dealers to feature and sell their watches to buyers. Around 12,500 dealers (including professional dealers and private sellers) offer more than 350,000 watches on Chrono24 with more than 7 million unique visitors per month and a transaction volume of more than €1.2 billion per year. Together with our partner, we designed and conducted a randomized field experiment to test the hypotheses H2, H3, and H5. We employed a 2 (utility-based reciprocity: absent vs. present) × 2 (social proof: absent vs. present) between-subjects, full-factorial experimental design.

Table A2 in the Appendix reports the descriptive statistics and the correlations of the variables in our model[7]. The manipulations were placed within a layer that was displayed when users

[7] Note that the variables collected in the randomized field study were limited given that we were not able to collect more specific user information beyond the clickstream analysis.

were browsing the e-commerce platform for the first time. After a specific number of interaction events were invoked by the user (equal across all experimental conditions), the layer was triggered and displayed as an overlay in the visual center of the website. The layer displayed an image of a luxury watch to capture the user's interest on the left-hand side next to a form that prompted the user to provide his or her email address on the right side (see Figure 3-8). The form comprised a headline that prompted the user to register for a myChrono24 user account, two text elements (that either induced our manipulations or were completely absent, depending on the experimental condition), and a text input field with a submit button (labeled "register for free") to submit his or her personal email address. In conditions where our utility-based reciprocity manipulation was present, we displayed a text element that described our offer to find the right watch by downloading functional content about a free watch guide (i.e., a PDF document with guidance to find the right watch[8]). In conditions where our social proof manipulation was present, we displayed a text element that informed participants that 20,000 users had registered within the last 30 days for a myChrono24 account to find their watch (see Figure 3-8). The experiment proceeded as follows: First, after a new user of the platform reached a certain threshold of interaction events, the layer that contained our experiment popped up. Second, the layer presented the registration form that contained our manipulations and that prompted the user to disclose his or her personal email address. Next, the user had the option to either submit his or her personal email address or dismiss the registration prompt with a click on a close icon. If the user decided to submit the email address, he or she was asked to provide a username and a password, which then led to a confirmation message. Lastly, the user received an email from Chrono24 to confirm the email address, recording our dependent variable of "confirmed user registration" (Jiang et al. 2013).

3.6.2 Confirmed registration as a dependent variable

In line with Moe and Fader (2004), we defined our dependent variable of "confirmed user registration" as the number of actual users who decided to submit their personal information to register a new user account and who confirmed their registration via an email. We measured the confirmed registration as a binary dummy variable with 1 = "confirmed user registration" and 0 = "no (confirmed) user registration".

3.6.3 Data collection

We recorded user registrations via clickstream analysis over a 2-month period from August to October 2018. In this period, we collected a random sample of 806,271 unique visitors. We

[8] The watch guide PDF can be obtained from the authors upon request.

discarded 330,776 users who were exposed to our treatments for less than 1 second to eliminate unintentional quitters and users who were exposed to more than 60 seconds to eliminate potential effects that stem from idling. Both cut-off conditions (i.e., 1s & 60s) are roughly equal to the lower and upper quintiles of distribution for the exposure time. Our final sample consisted of 475,495 users who entered our data analysis. We found that a total of 5,129 new users submitted their personal information (of which 4,502 confirmed their email address), while 472,430 new users did not register. Through the user language preferences, we found the following distribution of new user nationalities, which is consistent with the distribution in Chono24's entire customer base: German 221,629 (38%), English 147,924 (26%), Italian 140,450 (24%), and French 71,022 (12%). There were no significant differences in new user nationalities across the four experimental conditions. The exogenous random assignment of new users to our experimental conditions alleviated several endogeneity problems (e.g., omitted variables, self-selection, or unobserved heterogeneity) and ruled out alternative explanations that could confound any analysis of such a causal question based on observational data (Wooldridge 2015). Users were also unaware that they were participating in an experiment, so observer bias was not applicable. As such, the subjects in our sample were observed without their knowledge while making real-life decisions with real consequences. Our results are thus not constrained by reporting biases inherent in survey or vignette-based experimental research, nor are they skewed due to self-selection, since the subjects were observed even when they chose not to register.

3.6.4 Main and interaction effects of utility-based reciprocity and social proof

	Stage 1			Stage 2		
Construct	Coefficient	*SE*	Exp(B)	Coefficient	*SE*	Exp(B)
Intercept	−4.92***	.03	.01	−4.87***	.03	.01
Manipulations						
Utility-based Reciprocity	.09**	.03	1.10	.03	.05	1.03
Social Proof	.08*	.03	1.09	.02	.05	1.02
Utility-based Reciprocity × Social Proof	-	-	-	.13*	.07	1.14
Model Fit						
Log Likelihood	−21,994			−21,992		
Omnibus Model $\chi 2$	14.28**			18.18***		
Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; $N = 475{,}495$						

Table 3-3: Logistical regression analysis on confirmed registration

To test H2 and H3 of our research model, we conducted a two-stage hierarchical binary logistic regression on our dependent variable of confirmed user registration (see Table 3-3). In Stage 1, we examined the main effects of utility-based reciprocity and social proof on confirmed user registrations. In Stage 2, we added the interaction term of utility-based reciprocity and social proof. The results of Stage 1 demonstrate significant positive effects of utility-based reciprocity (b = .09; Wald statistic(1) = 8.03; p < .01) and social proof (b = .08; Wald statistic(1) = 6.42; p < .05) on confirmed registration. Hence, participants who are primed with utility-based reciprocity are more likely to register and confirm their registration than when utility-based reciprocity is absent (.76% vs. .83%; p < .01). Moreover, in the presence of social proof, participants are also more likely to register and confirm their registration than when social proof is absent (.76% vs. .83%; p < .05). Furthermore, Stage 2 unveils a significant positive interaction effect between utility-based reciprocity and social proof (b = .13; Wald statistic(1) = 3.90; p < .05) on confirmed registration, indicating that the effect of utility-based reciprocity is amplified by social proof.

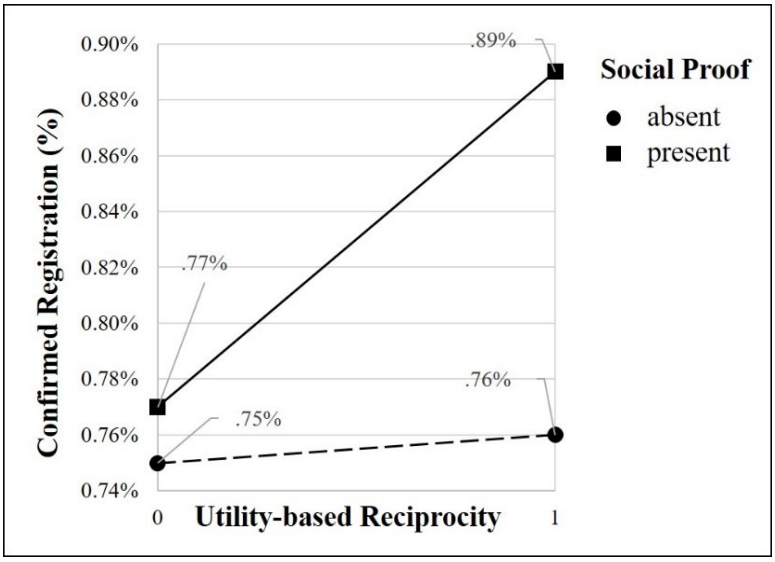

Figure 3-9: Moderating effect of social proof on the effect of utility-based reciprocity on user registration

To further assess H5, similar to Study 1, we conducted a moderation analysis based on Hayes (2018, Model 1) with10,000 samples and 95% bias-corrected confidence intervals. The results in Figure 3-9 highlight that when social proof is present, participants are more likely to register when utility-based reciprocity is present than when utility-based reciprocity is absent (.89% vs. .77%; $p < .05$). However, a significant difference in registration likelihood between the presence and absence of utility-based reciprocity does not emerge (.75% vs. .76%; $p > .05$) when social proof is absent, in support of H5.

Social Proof	Coefficient for the Effect of Utility-based Reciprocity on Confirmed Registration	Boot *SE*	BootLLCI	BootULCI
absent	.03	.05	−.07	.12
present	.16	.05	.07	.24
Note: Coefficients were computed based on a moderated analysis including all controls and using bootstrapping with 10,000 samples and a 95% bias-corrected confidence interval (Hayes 2018).				

Table 3-4: Conditional direct effect of utility-based reciprocity on confirmed user registrations in the presence and absence of social proof

Table 3-4 sheds further light on the effect of utility-based reciprocity on confirmed registration in the presence and absence of social proof. The results show that the effect of utility-based reciprocity on confirmed registration is significant only in the presence but not in the absence of social proof, in support of H5.

3.7 Discussion

This piece of research aimed to examine and reveal how reciprocity and social proof—two widely employed social influence tactics in e-commerce—individually and jointly affect user registrations in user onboarding. We also sought to advance our understanding of how the two distinct variants of reciprocity—namely, monetary- and utility-based reciprocity—differ in their interplay with social proof. Our findings support our premise that reciprocity and social proof tactics both increase user registrations when employed individually. However, when employed together, intriguing effect patterns emerge: While social proof negates the effect of monetary-based reciprocity on user registrations, it amplifies the effect of utility-based reciprocity.

3.7.1 Contributions to research

We believe that this study contributes to IS research in general and to user onboarding research specifically in three important ways. First, our research illuminates how reciprocity and social proof not only distinctly affect user registrations in e-commerce onboarding, but also how they work together in shaping user registrations. While both types of social influence have been widely researched in offline and online contexts as individual drivers of e-commerce outcomes, researchers to date have neglected to study how both tactics interact to affect user registrations. We extend previous research by showing that the two social influence tactics are interdependent, thus highlighting the importance of considering both in tandem when optimizing user onboarding.

Second, we contribute to previous research by distinguishing between two commonly employed yet under-investigated types of reciprocity—namely, monetary- and utility-based reciprocity—to explore their interactive effects with social proof on user registrations. Previous studies have largely focused on one type of reciprocity (favors) to the exclusion of the other type and have neglected to study their impact in combination with social proof. We advance previous research by revealing the intriguing finding that a combination of reciprocity and social proof can have diverging effects depending on the type of reciprocity employed. On the one hand, utility-based reciprocity and social proof exhibit synergistic properties when influencing user sign-ups, indicating that their combination is mutually beneficial and thus more than the sum of the individual social influence tactics alone. On the other hand, mixing monetary-based reciprocity favors with social proof cues is ineffective in increasing user registrations beyond social proof cues alone. Taken together, our findings underscore the value of disentangling the impact of specific types of reciprocity favors to flesh out a more nuanced understanding of the effectiveness of social influence tactics in e-commerce user onboarding.

Third, heeding Goes (2013)'s call for further research into the social dimension of judgment and decision contexts by leveraging the promising features of randomized field experiments that combine the strengths of high internal validity and high realism (see also Karahanna et al. (2018)), we contribute nuanced insights to the burgeoning literature on social influence in virtual environments. More specifically, while previous studies have largely focused their investigations on different attributes of social influence (e.g., tie strength, embeddedness) (e.g., Aral and Walker 2014; Bapna and Umyarov 2015), our study leverages the strengths of different types of experiments to advance our understanding of the intricate nature of different social influence tactics and how they can be employed together to improve user onboarding.

3.7.2 Practical contributions

This research also has important practical implications. First, we provide actionable design recommendations on how two reciprocity variants—namely, monetary-based reciprocity and utility-based reciprocity—and social proof can be employed to improve user onboarding. As our findings show, social proof and reciprocity tactics can be employed separately to increase user registrations. While social proof cues are consistently effective in increasing user sign-ups across our two studies, we demonstrate that practitioners can implement different variants of reciprocity (i.e., monetary- and utility-based reciprocity) for users who are onboarding to improve user registrations. However, a caveat of monetary-based reciprocity tactics (e.g., in the form of discounts) is that they come at the cost of increased suspicion. Hence, e-tailers should be aware of these potential downsides when designing user onboarding for their platform.

Second, if e-tailers plan to employ multiple social influence tactics simultaneously in user onboarding, they are well advised to attempt to understand the intricate interplay between specific types of social influence tactics prior to their implementation. In particular, we find in our Study 2 that utility-based reciprocity (i.e., functional content) and social proof work hand in hand by displaying a complementary, synergistic effect on user registration because they mutually amplify each other in persuading users to sign up. In contrast, combining monetary-based reciprocity (i.e., discounts) with social proof is likely to be a less effective strategy and should raise a red flag for e-tailers given that both social influence tactics had a negative interactive effect on user registrations. Given these results, the business goals and scope of a given e-commerce platform must be weighed up and prioritized when deciding the types and combinations of social influence tactics to be implemented in the user onboarding stages. More broadly, our findings highlight the interdependent nature of social influence tactics and suggest that e-tailers can benefit from our findings by carefully A/B testing and monitoring the

effectiveness of different social influence tactics—applied in isolation as well as in combination—on their platforms.

3.8 Limitations and future research

As with all articles, there are limitations inherent in our article that provide opportunities for future research. First, in both of our experiments, we implemented the reciprocity and social proof treatments in a dichotomous (i.e., absence vs. presence) way and determined the specific values in the presence conditions (e.g., "5% discount," "20,000 users have found their dream watch") based on reference values. However, it remains unclear how changing these reference values would affect user registrations 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 social influence and user decisions in e-commerce onboarding. It would be particularly interesting to understand at what precise threshold values social proof cues would amplify or attenuate the effects of reciprocity cues, and vice versa.
Second, in our large-scale randomized field experiment, we were not able to combine the experimental data with additional survey data to rule out alternative explanations for the identified relationships. Although we think that our multi-method approach compensates for this shortcoming to some extent, we invite future research to validate the psychological mechanism underlying our results and to illuminate alternative pathways (e.g., felt obligation or uncertainty attenuation) through which both social influence tactics affect user registrations. By extension, other moderators may be of interest to future researchers. For example, it would be interesting to investigate how individual differences (e.g., independent vs. interdependent self-construal; (Stapel and Koomen 2001)) affect the relationships of reciprocity and social proof with user registrations.

Third, we focused our research on two prominent examples of social influence in the IS and consumer behavior literature, although there is still much room to expand our understanding of the intricate interplay between social influence tactics in e-commerce onboarding. Specifically, it would be interesting to examine how other social influence cues such as scarcity or consistency (Cialdini 2001; Wessel et al. 2019) interact to shape important user decisions in the onboarding stage. In brief, social influence tactics are different but often intricately linked, which requires researchers to examine them simultaneously and in greater depth.

Fourth, the samples for our two studies were based in different locations (the sample for Study 1 was mostly US based, whereas the sample for Study 2 was European). However, although our manipulations leverage universal rules from human social interaction, cultural differences

may yet exist (Cialdini et al. 1999). Finally, our research explicitly focused on user onboarding on e-commerce platforms and thus looked at user registrations as the key criterion variable. Future research could examine the effects of social influence tactics on other important outcome criteria (e.g., net promoter score, sales conversion rate, shopping cart abandonment). Similarly, future studies are encouraged to include mediating mechanisms for monetary-based and utility-based reciprocity (e.g., perceived uncertainty, trust) to shed further light on the underlying psychological processes that explain the effects of social influence tactics.

Chapter 4: Probability Evaluation Cues in Gamblified Menu Designs

Title: Gamblified digital product offerings: an experimental study of loot box menu designs (2021)

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Abstract

To augment traditional monetization strategies, digital platform providers increasingly draw on gamblification (i.e., the use of gambling design elements). By means of gambling design elements (e.g., lottery tickets, scratch cards, loot boxes), platform providers do not only entertain users but also incentivize them to purchase digital products. Yet, despite the increasing prevalence of gamblified digital platforms, little is known about how gamblification influences user conversion behaviors. Drawing on prospect theory, we investigate gamblification in the form of loot box menu designs and the associated effects of uncertainty, loss experience and behavioral control on user conversion behavior. Specifically, we conducted a contest-based online experiment with 159 participants, finding that platform providers can profit from offering loot boxes with certain (vs. uncertain) rewards in loot box menus. Furthermore, this effect intensifies when participants previously experienced a loss and decreases when they perceive to have more control over the result. Thus, our findings provide theoretical and practical insights for a better understanding of gamblification in general and of loot box menu designs for enhancing digital business models in particular.

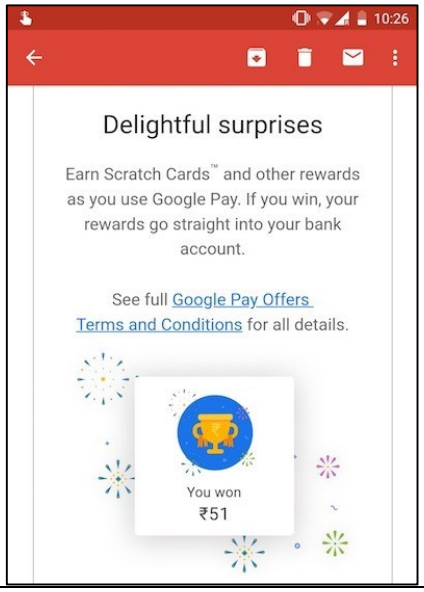
Keywords: Gamblification, Gambling, Digital Business Models, Monetization, Loot Boxes, Prospect Theory

4.1 Introduction

Because competition among digital platforms for regular and new customers has intensified, digital platform providers find it increasingly difficult not only to channel users to their platforms but also to encourage them to complete and repeat transactions (e.g., Roethke et al. 2020b; Schneider et al. 2020; Weinmann et al. 2016). Consequently, digital platform providers attempt to enhance their digital business models and thus increasingly experiment with new monetization strategies based on digital design elements to complement and/or support their traditional revenue streams (e.g., sales, ads and subscriptions). One strategy to stand out in the fierce competition is *gamification*, which can be defined as the use of game design elements (e.g., points, badges and leaderboards) to increase user engagement in the form of experiential (e.g., motivation, enjoyment) and instrumental outcomes (e.g., revenues, profit) (Liu et al. 2017). As such, gamification promises to enhance digital business models through fundamental changes in the way business is carried out and revenues are generated (Veit et al. 2014; Wagner et al. 2014).

A gamification-related but hitherto neglected phenomenon is *gamblification*, which we analogously define as the use of gambling design elements (e.g., lottery tickets, scratch cards, loot boxes) to increase user engagement. As such, gamblification and gamification usually share the same settings (e.g., a user interacts with a digital platform) and goals (e.g., user engagement) but work with different means to attain the goals: Whereas gamification adapts the digital platform through the levers of game design elements (e.g., Uber introducing badges, which have no to little value outside the Uber ecosystem) (Rosenblat and Stark 2016; Uber 2020), gamblification uses the levers of gambling design elements (e.g., Starbucks utilizing an augmented reality lottery, providing users the prospect to win cash-equivalent rewards) (Starbucks 2020). This difference introduces new opportunities to design digital platforms and thus digital business models. Gamblification broadly implies individual gambling design elements (e.g., dice, cards, chance-based mechanisms) that can be used in isolation or in combination. As such, gamblification impacts digital platforms' revenue streams (e.g., sales, ads and subscriptions) through improving user engagement with a digital platform (e.g., user onboarding, revisits, activity) (e.g., Fabbri et al. 2019; Mazar et al. 2017; Shen et al. 2015). For instance, Google Pay (Google 2020) uses digital scratch cards and Starbucks (2020 employs augmented reality lotteries after the purchase of products to entertain users and incentivize repurchases, thus gamblifying their digital product offerings (see Figure 4-1).

Online Gaming: E.g., Loot Boxes (Riot Games 2019)



E-Commerce: E.g., Scratch Cards (Google 2020)

Figure 4-1: Examples of Gamblified Digital Product Offerings

While gamification has been widely investigated enjoying immense popularity both among researchers and practitioners (e.g., Hamari et al. 2014; Hamari and Lehdonvirta 2010; Koivisto and Hamari 2019), there is only scarce knowledge on how gamblification is implemented and how it may influence conversion behaviors. More specifically, because users who face gamblified digital product offerings act in inherent uncertain environments, they are subject to psychological effects that may largely differ from non-gamblified interactions. As such, these effects may urge some users to be attracted by gamblified digital products offerings while others may refrain from any interaction with gamblified digital products offerings. In particular, *loot boxes* (i.e., virtual goods that contain chance-based selections of other virtual goods) are abundantly used gamblification design elements and have recently received increasing media and research attention (e.g., Griffiths 2018; King and Delfabbro 2019; Macey and Hamari 2019).

Although some research indicates how to optimize the monetization of digital business models (e.g., Guo et al. 2019; Voigt and Hinz 2016), only recently the importance of focusing on user engagement and user decision-making in uncertain environments has been recognized (Harviainen et al. 2018). Moreover, it remains to be examined, particularly in the context of product offerings within digital business models that rely on loot boxes and related loot box menus, how platform providers can gamblify their menus to generate additional revenues and how users react to different loot box menu designs. Indeed, literature on consumer behavior documents that – depending on the context – gamblification design elements can trigger optimal

or sub-optimal user behavior: One the one hand, an option with a reward of probabilistic uncertainty (i.e., random/chance-based/algorithm-based) can be more motivating and exciting than an option with a reward of a certain magnitude (Shen et al. 2015). On the other hand, substantial research has demonstrated that users are risk-averse and prefer certain rewards, even willing to pay a premium for this certainty (Allais 1953; Kahneman and Tversky 1979; Von Neumann and Morgenstern 2007). As such, in the context of product offerings within digital business models that built on loot box menus to generate revenues, the question arises whether a certain (vs. uncertain) reward in a loot box menu can lead to improved user decision-making and thus higher revenues for the digital platform. Likewise, user behavior and decision making in gamblified environments are presumably governed to a larger extend by psychological effects that are less salient in non-gamblified environments. In particular, motivations such as ambition-to-win or fear-of-losing generally seem to be important behavioral drivers within gamblified environments. In this regard, it remains to be examined how these effects influence user behavior when faced with gamblified digital product offerings.

Against this backdrop, the objective of our study is to investigate (1) the effect of a certain (vs. uncertain) reward in loot box menus – as a comparison of two different loot box menu designs – on user conversion behaviors (i.e., *certainty effect*); (2) how perceived loss experience – as a common experience in interactions with gambling design elements that may amplify the fear-of-losing– influence the certainty effect; and (3) how user perceptions in form of behavioral control – a perception that has been frequently analyzed in gambling literature and presumably reflects ambitions-to-win – influence the certainty effect. Consequently, we ask the following research questions:

RQ1: How do certain vs. uncertain rewards affect user conversion behavior?

RQ2: How do previous loss experience and perceived behavioral control interact with the effect of certain vs. uncertain rewards on user conversion behavior?

To investigate our research questions, we performed a contest-based online experiment with 159 participants. Drawing on prospect theory (Kahneman and Tversky 1979), we provide ideas on how gamblification can be employed and modified to increase revenue generation in digital business models through an enhanced loot box menu design. Our study contributes in three major ways to the still nascent research on gamblification in general and on loot box menu designs for enhancing digital product offerings within digital business models in particular: First, we contribute to previous IS research by shedding light on gamblification and providing insights into its role in the form of loot boxes, particularly the role of certain vs. uncertain rewards in loot box menu designs. Second, our study sheds light on two crucial moderators of

the effect, namely previous loss experience and perceived behavioral control, which exhibit intriguing opposite moderating effect patterns on the effect of certain vs. uncertain rewards. Third and last, addressing the call for future research into the cognitive dimension of digital decision contexts (Goes 2013), we add to the emerging literature on cognitive biases in virtual environments by deriving actionable and easily implementable design recommendations for loot box menus designs.

4.2 Theoretical Background

Gamification has become an established phenomenon in IS research (e.g., Hamari et al. 2014; Huotari and Hamari 2017; Liu et al. 2017; Schöbel et al. 2020b). For instance, through the earning and collection of digital points, users can demonstrate their performance in leaderboards and thus drive competition and excitement among users of the digital platform (Liu et al. 2019). Excitement surrounding gamification results from its many potential organizational and commercial benefits, such as making monotonous tasks enjoyable (Thiebes et al. 2014) and allowing for cost savings and performance improvements (Penenberg 2015). Consequently, organizations and digital platforms apply gamification in various ways to engage, steer and nudge all kinds of individuals toward desired goals (e.g., Adam et al. 2020; Roethke et al. 2020b; Schneider et al. 2020; Weinmann et al. 2016).

Although IS researchers have paid considerable attention to gamification, little research has been conducted on *gamblification*. We consider gamblification a gamification-related but under-investigated phenomenon and analogously define the term as the use of gambling design elements. The term covers both the employment of isolated or combined gambling design elements without necessarily incorporating full-fledged gambling in the context. In addition to a general elaboration of this business practice (i.e., gamblification in various business settings), the particularities in an online setting – especially through the augmented possibilities of interactivity and multi-media content – are especially interesting and worthwhile for gamblification as an information systems phenomenon.

Loot boxes are gamblification design elements in the form of virtual goods that have substantially increased in importance and can be usually bought by users to gain a selection of goods (Hamari and Keronen 2017; Macey and Hamari 2019). Loot boxes typically contain one or more contents from a set of different virtual goods, which are not necessarily obtained with certainty, but with a specific probability (e.g., a loot box can contain several goods, one with a 50% chance, another with a 25% chance, etc.) (Overwatch Wiki 2019). To generate additional revenue and to provide a rich user experience, an loot box menu of different prized loot boxes is usually offered, where the more expensive loot box contains the “better deal” (e.g., the same

good can be obtained with a 40% increased chance of winning, but only a 15% price increase) (Riot Games 2019). Loot boxes and related loot box menu designs are particularly interesting for two main reasons: First, from a theoretical perspective, these gamblification design elements inspire intriguing new research questions and may ultimately provide novel theoretical insights. Second, from a practical perspective, loot boxes are the most common and successful forms of gamblified digital product offerings within digital business models. Indeed, loot boxes do not only represent predominant means of monetization in most free-to-play gaming (e.g., *Fortnite*, *Battle Royale* and *League of Legends*) (e.g., Koch and Benlian 2017; Wagner et al. 2014), but have also increasingly become prevalent in fully priced games and many other gamblified digital business models (e.g., *Forza 7* and *Overwatch*) (Macey and Hamari 2019). Thus, the analysis of loot boxes and related loot box menu designs is of utmost importance for platform providers who rely on the success of these gamblified design elements to increase revenues and even ascertain the prosperity and sustainability of their business.

Despite the prevalence of gamblification in practice, the question still remains how to gamblify digital product offerings to optimally leverage uncertain outcomes in the design of loot box menus to increase user engagement (e.g., Hamari and Lehdonvirta 2010; Liu et al. 2017). Indeed, researchers recommend that users need to appreciate the possible lottery-results without the feeling that the gambling experience is deliberately designed to extract revenues (Hamari and Keronen 2016), thus promoting purchases without impeding user experiences (Hamari and Keronen 2017). For instance, Starbuck's Starland (2020) multi-million dollar event transformed the rather profane purchase of coffee into an exciting gambling adventure through an in-app augmented reality lottery for 16 million Starbucks Rewards members, only to entertain and incentivize further Starbuck's visits and purchases. However, despite acknowledging the importance of how goods should function and how to visually design them within the specific digital surrounding, there has been only scant research on the effects of designing reward option menus (e.g., loot box menus), such as the conditions under which goods can be purchased (Hamari and Keronen 2016; Harviainen et al. 2018).

Previous research has revealed that uncertainty can enhance motivation in form of investments in effort, time and money (Shen et al. 2015). Likewise, uncertain incentives in the form of uncertain price promotion has been demonstrated to evoke the same level of positive responses compared to certain incentives (Goldsmith and Amir 2010). Moreover, in the context of retailing Mazar et al. (2017) highlights that consumers prefer a probabilistic free price promotion to the deterministic price promotion. However, when promotions displayed very high probabilities (greater than 90%) no evidence for the aforementioned preference of

probabilistic to deterministic price promotions was found. Besides research on consumer behavior, the effect that the result of people's evaluation when comparing two lotteries changes if one of the lotteries is riskless has been as well investigated in the context of gambling (Bleichrodt and Schmidt 2002; Wärneryd 1996).

Moreover, previous research has indicated that crucial contextual variables, such as previous loss experience (Tversky and Kahneman 1973) and perceived behavioral control (Weinstein and Lachendro 1982), can define and severely influence the experience of uncertain offerings and thus the decision outcome. Because uncertainty is a defining aspect of gamblified interactions, these interactions are arguably affected by psychological mechanisms relevant for decision making under uncertainty (e.g., ambition-to-win or fear-of-losing) to a larger extent compared to interactions that involve little or no uncertainty. Since interactions within such uncertain environments are central to and characteristic for gambling, insights from research on gambling behavior are instructive to investigate interactions with product offerings in gamblified digital business models. In the context of gambling behavior, a substantial amount of research has demonstrated that previous loss experience may evoke fears-of-losing. As such, these previous loss experience frequently alters gamblers' risk-perception and thus influences subsequent gambling behavior (Croson and Sundali 2005; Guryan and Kearney 2008). For instance, Croson and Sundali (2005 showed that 80% of subjects quit roulette gambling after losing on a spin, but only 20% did so after a winning spin. Likewise, perceived behavioral control and the related optimism bias (Klein and Helweg-Larsen 2002) may boost ambitions-to-win and have been investigated as important drivers of engaging in gambling behavior in particular (Gibson and Sanbonmatsu 2004; Rogers 1998). Consequently, the certainty effect, previous loss experience and perceived behavioral control are crucial aspects that have demonstrated to individually influence gambling behavior and are important to consider when investigating gamblification design elements involving uncertainty (i.e., the purchase of loot boxes) to provide a better and more holistic understanding of the role and effectiveness of uncertain vs. certain reward in loot box menus. Taken together, insights from consumer behavior and gambling literature demonstrate that uncertainty regarding the conditions under which loot boxes are sold can enhance motivation and increase purchases. Since probabilistic outcomes are defining features of gamblification design elements (in contrast to gamification design elements) and thus of loot box menus, it stands to reason to investigate the under-researched question of how probabilistic uncertainty regarding the result of the purchase of loot boxes affects user purchase decisions and how previous loss experience and perceived behavioral control moderate this effect.

4.3 Research Model and Hypothesis Development

Drawing on prospect theory (Kahneman and Tversky 1979), we develop a research model that illuminates the effects of altering the eligible probabilities of receiving a reward on users' choices between two loot boxes (H1). We hereby compare whether user conversion behavior changes when users are confronted with two loot boxes with uncertain outcomes (i.e., uncertain & uncertain) vs. one loot box with an uncertain outcome and one loot box with a certain outcome (i.e., uncertain & certain), while keeping the expected values similar for each decision. We then continue by elaborating on the interaction effect between altering probabilities of receiving rewards and a previously experience of loss (H2) as well as on the interaction effect between altering probabilities of receiving rewards and perceived behavioral control (H3). In the following sections, we expound upon each of the posited relationships depicted in Figure 4-2.

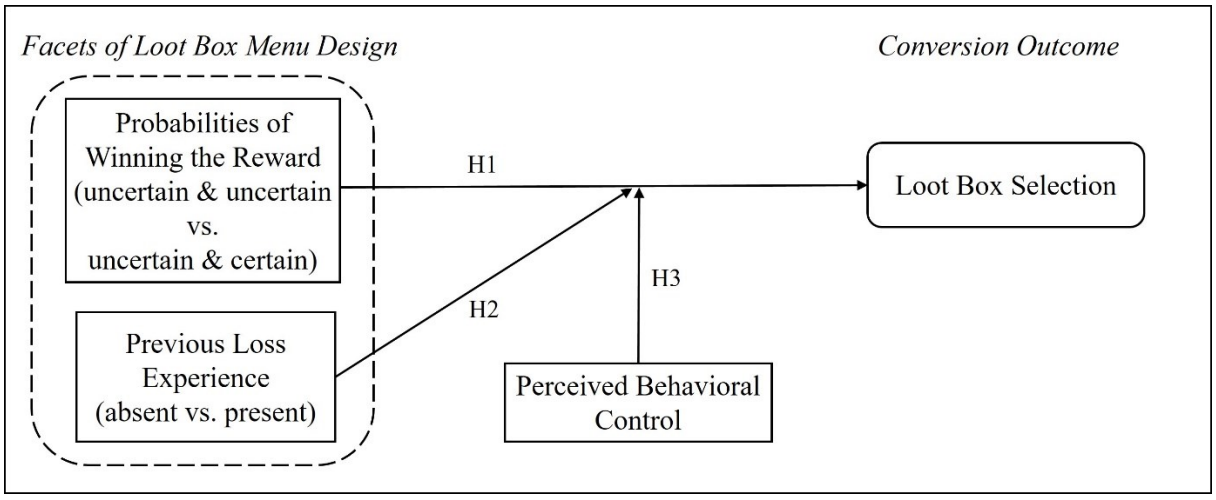


Figure 4-2: Research model

4.3.1 The Main Effect of Reward Winning Probability on Loot Box Selection

According to prospect theory (Kahneman and Tversky 1979), people overweight small probabilities and underweight high (near certain) probabilities, being contrary to implications from expected utility theory. This propensity 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 (Allais 1953; Von Neumann and Morgenstern 2007). The underweighting of high (near certain) probabilities leads to a risk aversion phenomenon manifesting in a systematic preference of a certain gain over a near certain chance of winning a reward.

In contrast to expected utility theory, which predicts a preference of the loot box with a higher expected value, this risk averse preference even develops when the expected value is higher for the uncertain outcome than for the certain gain. When the outcome of both loot boxes is uncertain, 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 loot box if it yields a higher expected value) can be observed. An explanation for this 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 uncertain (e.g., from 100% to 75%) which induces a perception of greater loss than a corresponding reduction (e.g., from 80% to 60%) in the probability from uncertain to more uncertain (Tversky and Kahneman 1986).

Thus, we argue that when users face a decision to choose between two differently priced loot boxes with the same expected value, they are more likely to choose the more expensive loot box if it is certain vs. if it is uncertain. This is in accordance with previous research on the certainty effect (e.g., Daniels and Zlatev 2019; Mazar et al. 2017; Tversky and Kahneman 1986) in that users prefer certain gains over uncertain gains.

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 more expensive loot box if it features a certain gain vs. when it features only an uncertain gain (i.e., certainty effect).

4.3.2 The Interaction Effect of Reward Winning Probability and Previous Loss Experience

Next, we look at the interaction effect of certainty effect and perceived loss experience – a common experience in interactions with gambling elements. To hypothesize on the interaction effect we draw on the availability heuristic, which refers to the biased evaluation of probabilities which is skewed towards information more readily available (Tversky and Kahneman 1973). According to this heuristic, 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.

Accordingly, we propose that when users experience a loss (i.e., a gambling element does not contain the desired good), users' motivation to engage in further gambling (i.e., subsequent

purchase of loot boxes with uncertain content) will be impeded. This is also in line with substantial research on gambling, demonstrating that the availability heuristic can explain why recent loss experiences is negatively correlated with subsequent risk seeking in that previous loss experiences drives users to overestimate their chances to lose (e.g., Fortune and Goodie 2012; Goodie and Fortune 2013; Ma et al. 2014). Consequently, we hypothesize that when users choose between the certain and the uncertain loot box, previous loss experience will boost the certainty effect such that users prefer the certain gain.

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

4.3.3 The Interaction Effect of Reward Winning Probability and Perceived Behavioral Control

An important precondition for users to participate in and enjoying gambling is their believed skill to master the challenges and objectives they encounter while gambling. If they perceive that they have the necessary knowledge and capabilities (i.e., perceived behavioral control) to master gambling, they enjoy gambling and focus their attention on the affective experience of gambling rather than on the outcome of gambling (Shen et al. 2015; Takatalo et al. 2010). In this regard, optimism bias, defined as the irrational assessment of one's own behavioral control in a given situation and the belief to be less likely to experience negative events (Dunning et al. 2004; Klein and Helweg-Larsen 2002), seems to be a strong predictor for increased risk-taking (i.e., choosing an uncertain loot box).

In light of this, we investigate user perceptions in form of behavioral control – a perception that has been frequently analyzed in gambling literature. We suggest that when users choose between the certain and the uncertain loot box, perceived behavioral control attenuates the certainty effect such that users prefer the uncertain reward. Indeed, extant research has investigated that biases from personal assessment about one's own capabilities can lead to an overly optimistic evaluation of situations and to increased risk-taking increasing ambitions-to-win (Dunning et al. 2004; Weinstein and Lachendro 1982). Specifically previous research on digital business models demonstrates that conversion behavior is influenced by biased risk assessments, such that situations are overly optimistically evaluated which leads to increased risk-taking (Helweg-Larsen and Shepperd 2001; Koch and Benlian 2017). Given the above arguments and empirical evidence, we hypothesize that

H3: Perceived behavioral control attenuates the certainty effect.

4.4 Research methodology

In the following, we describe how our experiment was designed and implemented as well as how we operationalized the probabilities of winning the rewards and previous loss experience. Further, we discuss the choice, the reliability and validity of the variables we chose to measure.

4.4.1 Experimental Design and Treatments

In line with procedures in previous online experiments (e.g., Koch and Benlian 2017; Lowry et al. 2013), to test our hypotheses, the study was framed as a warm-up for a subsequent online contest in a self-developed game, where users had the chance of winning €20 depending on their performance. Consequently, our entire experiment was aligned to ascertain that (1) it replicates a real surrounding in which gamblification elements could potentially exist and (2) users were well motivated and involved in the upcoming decisions of the experiment. To comprehend the overall setting and which steps participants completed in the course of the study please refer to Figure 4-3. However, to fully understand the procedure, first we explain how the overall setting built upon the game and the connected procedure.

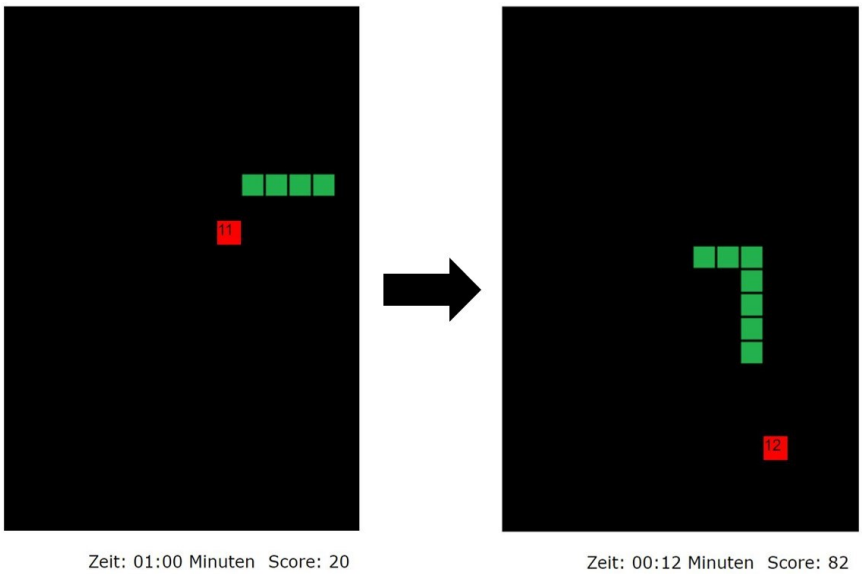


Figure 4-3: Experimental version of ‘Snake’

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 4-3, the game featured a representation of the eponymous reptile which was navigated by the player. The goal was to prevent the snake from colliding with the walls and its tail as well as to guide it to pieces of food which are represented by red pixels randomly generated on the screen. After the snake was successfully navigated to a piece of food, which was subsequently eaten, the length of the snake and the players’ score increased. If the player’s navigation led 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 three 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 that were eligible for winning a voucher.

We chose to present a loot box including a reward with functional attributes because this category of goods can be unambiguously operationalized and manipulated without lying out a complex story and environment (Hinz et al. 2015; Lehdonvirta 2009). Participants had to choose between two loot boxes in exchange for either €4 or €6 where the cheaper loot box provided a ten percentage points smaller chance of gaining extra playtime compared to the more expensive loot box (see Figure 4-4). However, the expected value of the price for both loot boxes 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: uncertain and uncertain vs. uncertain and certain) x 2 (previous loss experience: absent vs. present) between subjects, full-factorial design (e.g., Benlian 2015).

4.4.2 Manipulations and Measured Variables

To implement our probabilities manipulations, we displayed different versions during the loot box selection event. As depicted in the upper part of Figure 4-4, in the condition *probabilities of winning the reward: uncertain and uncertain* 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 (resulting in the same expected value of 3 seconds per €). Whereas in the condition *probabilities of winning the reward: uncertain and certain* (middle part of Figure 4) 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 loot boxes was identical (e.g., 3 seconds per € in the condition uncertain and uncertain) and thus equally attractive in regard of their expected value. We choose 50% & 60% and 90% &100% as probabilities because these are among the proposed combinations that were used when researchers first investigated and introduced the certainty effect (Allais 1953; Kahneman 2011). The proposed prices (i.e., €4 & €6) were used because they are within the range of prices for contemporary loot boxes (e.g., FIFA Analytics 2020; Fifauteam 2020; Riot Games 2019).

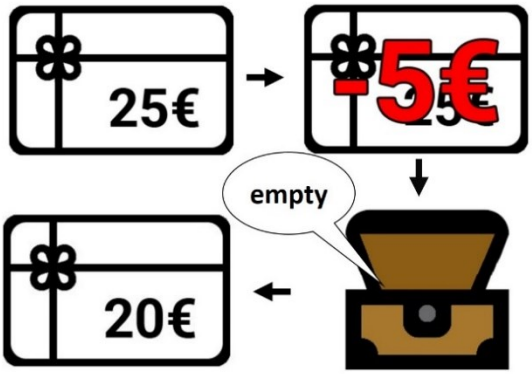
Manipulated Design Features	Explanation
50% chance of getting 24 seconds extra playtime Costs: 4€  60% chance of getting 30 seconds extra playtime Costs: 6€. 	Reward winning probability: uncertain & uncertain
90% chance of getting 20 seconds extra playtime Costs: 4€  100% chance of getting 27 seconds extra playtime Costs: 6€. 	Reward winning probability: uncertain & certain
	Previous loss experience

Figure 4-4: Manipulation Treatments

Prior to loot box selection, to create a previous immediate loss experience, participants in the condition *previous loss experience: present* had to purchase a separate loot box that could contain up to €10 in exchange for a €5 reduction of their winnable amount. Participants were told prior to the loss event that their total winnable amount is €25 (instead of €20 like the other group). As the lower part of Figure 4-4 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.

To start the process subjects clicked on a web link. As depicted in Figure 4-5, we segmented the experiment into five parts. The first part introduced the experiment's outline and the conditions of the contest (Step 1). Second, the game practices were explained and the tutorial (i.e., warm-up) 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 in form of a voucher decreased from €25 to €20. In this step participants in the condition previous loss experience absent were informed that their winnable amount in form of a voucher 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 loot boxes. One loot box could be bought in exchange for a €4 reduction of the winnable reward and the other for a €6 reduction. Both loot boxes were labelled with a numeric combination of probability and extra playtime (e.g., 50% and 24 seconds, see the upper two panels of Figure 4-4) (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 contest was conducted. However, because all participant could choose to participate in the contest or not, 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 make sure that no treatment favored a specific group. Therefore, for ethical reasons, all participant had the choice to play for two minutes, regardless which condition was assigned to them. Afterwards, all participants who chose to provide their email address could potentially win one of three €20 Amazon vouchers.

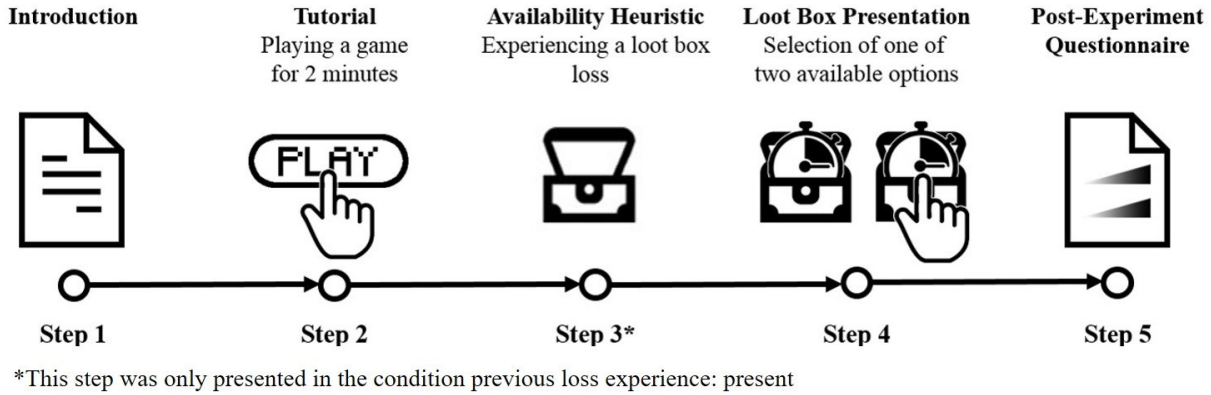


Figure 4-5: Experimental procedure

The connection of the experiment and the contest was necessary so that participants had something at stake (i.e., "skin in the game"), motivating them to carefully consider their

decision. Further, this combination was chosen to make the user understand during the warm-up why the content of the loot box is useful in the context of the game and thus for the contest. We measured participants' purchase decision (selection of the more expensive 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 moderating construct (i.e., perceived behavioral control) and our control variables to rule out alternative explanations. Perceived behavioral control was measured on a 7-point Likert scale ranging from (1) strongly disagree to (7) strongly agree using two items based on (Hong and Tam 2006) (see Table A4 in Appendix A).

We measured the following alternative drivers for loot box selection in our experiment drawing on previous IS adoption literature (Fuller et al. 2009; Gray and Durcikova 2005; Hong and Tam 2006), 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). We chose the construct risk aversion because the decision involved risk (i.e., potential loss of money) and could be thus governed by general attitudes toward risk. Perceived monetary value was included because we wanted to rule out that the certain loot box had only be chosen due to its higher perceived value, not because it was certain. Likewise, we measured product involvement and loot box spending to rule out that the decision to choose the more expensive loot box was driven by a general interest in loot boxes/previous spending on loot boxes.

For our constructs, the reliability was measured by using Cronbach alpha, composite reliability (CR) and average variance extracted (AVE) (see Table A4 in Appendix A). The alphas of the constructs had a value above .75, which is a proper value. The CR of all constructs was above .5, which is also a satisfying value. The AVE met the requirements for a suitable level of reliability as well (Fornell and Larcker 1981). Furthermore, we collected information on subjects' gaming experience, previous spending on loot boxes (see Table A5 in Appendix A), 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.

4.4.3 Sample description and manipulation checks

Similar to previous experiments in contest-based studies (e.g., Ho et al. 2011; Koch and Benlian 2017; Lowry et al. 2013), we recruited participants via social media from a subject pool of students operated by a large German university. The pool of participants were recruited from various media channels (e.g., flyers, and online advertisement) to assure a heterogeneous

sample and limit any potential selection biases (MacKenzie et al. 2011). We choose to draw our sample from a student subject pool because they are highly knowledgeable regarding digital games and are typically also among the most frequent buyers of loot boxes (Juniper Research 2017).

We conducted a power analysis using G*power 3.1 (Faul et al. 2009; Schneider et al. 2020) specifying the parameters as follows: four groups (2 × 2 full-factorial design), a moderate effect size, and a desired power level of .90. The results yielded that a sample size of 143 is sufficiently powerful to detect significant effects (Baroudi and Orlikowski 1989; Cohen 1992). Out of a total of 217 participants, we excluded 24 due to suspicious click patterns (e.g., low response variability, high rate of missing values) and 34 due to failing at least on attention or manipulation check (Benlian et al. 2020), 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 more expensive loot box, which results in an overall proportion of 61% across all four subgroups. Table 4-1 summarizes the descriptive statistics of the data.

	Mean	**SD**
Demographics		
Age	25.5	8.43
Gender (male)	55%	
Moderator		
Perceived Behavioral Control	6.12	1.01
Controls		
Perceived Monetary Value	5.02	1.41
Risk Aversion	4.09	.99
Gaming Experience	11.37	8.93
Product Involvement	2.60	2.05
Loot Box Spending	1.22	.55
Note: All variables with exception of Gender (binary) and Gaming Experience (years) were measured on 7-point-Likert Scales		

Table 4-1: Descriptive statistics of demographics, controls and dependent variables

4.5 Results

4.5.1 Main Effect Analysis of Changing the Probabilities of Winning

As Table 4-2 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), previous loss experience (PLE), and perceived behavioral control (PBC). In the second stage, we added the interaction term of PWR and PLE as well as the interaction term of PWR and PBC. Nagelkerke's R^2 was 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 effect of changing probabilities of winning the reward (b = .92; *Wald statistic* (1) = 6.50; p < .05) on loot box selection, supporting H1. Hence, participants that were faced with a choice potentially governed by the certainty effect were more likely to select the more expensive loot box compared to when both probabilities of winning the reward were uncertain. The average revenue per decision in the group with only uncertain loot boxes was €4.98 and in our scenario with one certain loot box €5.46. Thus, the change in preference due to employing the certainty effects results in an average increase in revenue of €0.48 per purchase (+9.6%).

	Stage 1		**Stage 2**	
	Coef.	**SE.**	**Coef.**	**SE.**
Intercept	-4.71*	1.02	-6.46	2.27
Manipulations				
PWR	**.92***	.37	4.60*	2.62
PLE	.45	.38	-.25	.52
PBC	.06	.18	.70	.27
Interaction				
PWR x PLE	-	-	**1.77***	.80
PWR x PBC	-	-	**-.73***	.41
Controls				
Perceived Monetary Value	.09	.14	.11	.14
Risk Aversion	.13	.23	.13	.23
Gaming Experience	.02	.02	.01	.02
Product Involvement	.17	.11	.22	.12
Loot Box Spending	.39	.48	.29	.50
Gender (male)	-.04	.27	-.05	.39
Age	.00	.02	.00	.03
Model Fit				
Log Likelihood		-87.56		-91.80
Nagelkerke R^2		.22		.28

Note: * p < .05; ** p < .01; *** p < .001; N = 159; Coef.: Coefficient, SE: Standard error, PWR: Probabilities of winning the reward, PLE: Previous loss experience, PBC: Perceived behavioral control

Table 4-2: Logistical regression analysis on loot box selection

4.5.2 Interaction Effect Analysis of Changing the Probabilities of Winning and Previous Loss Experience

Moreover, our second stage unveiled a significant two-way interaction of changing probabilities of winning the reward and previous loss experience (b = 1.67; *Wald statistic* (1) = 4.52; p < .05) on the propensity to select the more expensive loot box, supporting H2. 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. With regards to monetary consequences, this positive interaction is associated with an average increase in

revenue of €0.82 per purchase (+16.2%). To further evaluate our H2 hypothesis, we conducted a contrast analysis. As depicted in Figure 4-6, the results highlight that when probabilities of winning were uncertain and certain, participants are more likely to select the more expensive loot box when previous loss experience is present compared to when it is absent (86% vs. 62%; F = 6.418; p < .05). However, a significant difference in loot box selection between the presence (45%) and absence (54%; F = .614; p > .1) of previous loss experience did not emerge when probabilities of winning were uncertain and uncertain, in support of H2.

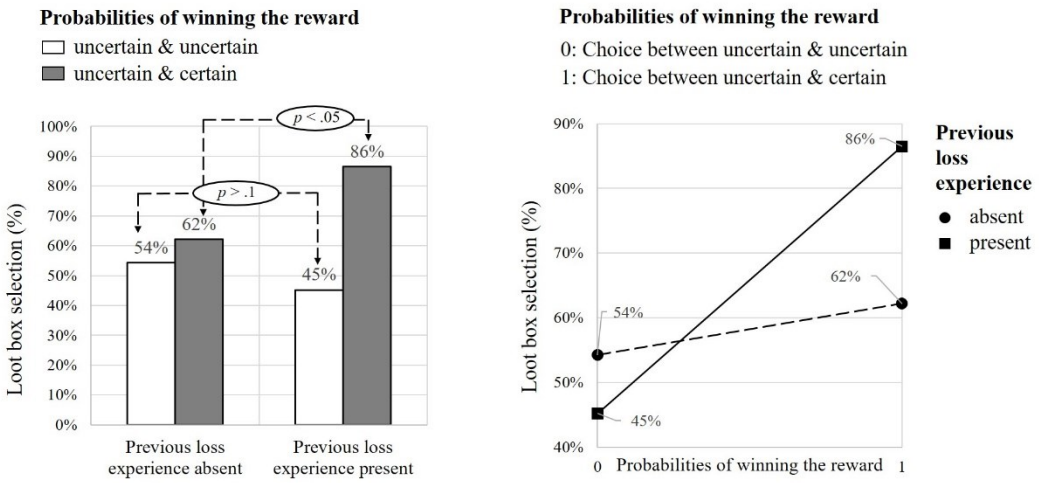


Figure 4-6: Loot box selection when PLE is absent vs. present

4.5.3 Interaction Effect Analysis of Changing the Probabilities of Winning and Perceived Behavioral Control

The results of the second stage additionally indicated a significant two-way interaction between changing probabilities of winning the reward and perceived behavioral control (b = -.77; Wald statistic (1) = 3.86; p <.05) on the propensity to select the more expensive loot box, supporting H3. The negative interaction term documents that the effect of changing probabilities of winning the reward on loot box selection is attenuated by perceived behavioral control. As such, the change in preference due to the certainty effect when perceived behavioral control is high results in an average increase in revenue of only €0.30 per purchase (+6.0%).

Likewise, to investigate our H3 hypothesis, we conducted a contrast analysis as exhibited in Figure 4-7. The results illuminate that when perceived behavioral control was low (i.e., when PBC exhibited a value of smaller than 6), participants are more likely to select the more expensive loot box when probabilities of winning were uncertain and uncertain opposed to when they were uncertain and certain (39% vs. 86%; F = 12.43; p < .01). However, in support of H3, when perceived behavioral control was high (i.e., when PBC exhibited a value equal to or higher than 6), no significant difference in terms of selection of the more expensive loot box

occurred when probabilities of winning were uncertain and uncertain as opposed to when they were uncertain and certain (53% vs. 69%; F = 2.80; p >.05).

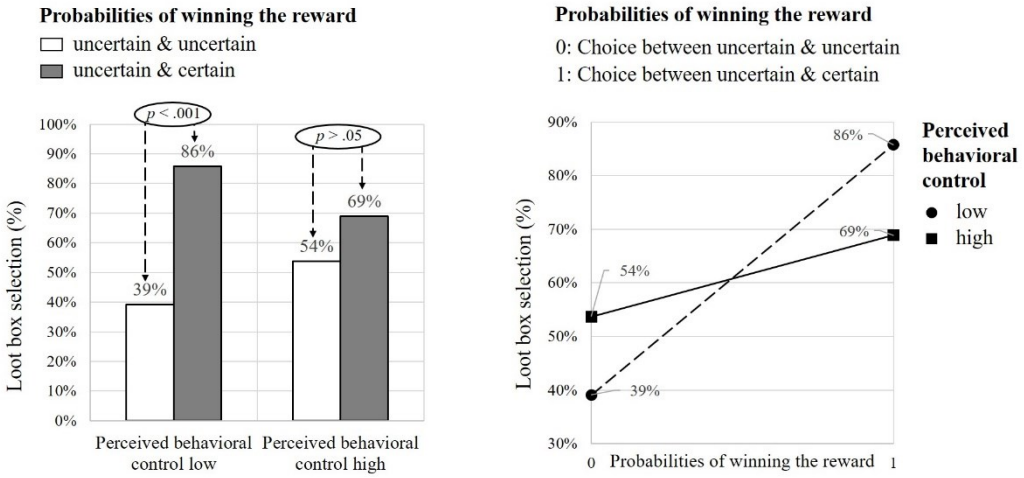


Figure 4-7: Loot box selection when PBC is low vs. high

4.6 Discussion

Digital platform providers find it increasingly difficult to compete for regular and new customers and therefore experiment with various new monetization strategies to increase revenues and thus enhance digital product offerings within their digital business models. One emerging and promising strategy is gamblification, which complements and supports traditional revenue streams through a gamblified design of digital product offerings. Against this background, our research was guided by two research questions. The first research question focused on the effect of certain vs. uncertain rewards in loot box menus on user conversion behavior. The findings support our premise that the probabilities of winning rewards in loot box menus influence users' loot box selection.

Our second research question sheds light on the moderating role of previous loss experience and perceived behavioral control, two factors that had a potentially intriguing effect on the certainty effect. Our results reveal that previous loss experience augments the effect of different probabilities of winning on users' loot box selection. Although the effects of this changed evaluation of the uncertain loot box should be unambiguous when users have a choice between a certain and an uncertain loot box (i.e., they should be more likely to opt for the certain loot box), it is less straight forward for the situation involving the choice between two uncertain loot boxes. On the one hand, participants could be urged to opt for the less risky loot box with less monetary resources at stake (i.e., the cheaper loot box). On the other hand, to counterbalance the previously experienced loss (i.e., "break-even effect") (Thaler and Johnson 1990), participants could be as well urged to opt for the loot box with the potentially higher reward, despite the higher stakes involved. Thus, it is not entirely clear which of these two effects

prevail when participants have to choose between two uncertain loot boxes. In contrast, when paired together with perceived behavioral control, the certainty effect is attenuated, such that users are more likely to prefer an uncertain loot box when they perceive to be more in control.

4.6.1 Theoretical Contributions

This study contributes in three important ways to the emerging research on gamblification in general and on loot box menu designs for enhancing digital product offerings within digital business models in particular.

First, we contribute to IS research by providing insights on the nascent research on gamblification. From a broader perspective, we tease the unique features of gamblification and how gamblification elements differ from gamification elements. Whereas substantial research has investigated gamification and explicitly acknowledged the possibility of "uncertain" outcomes in game elements (e.g., Bartle 1996; Liu et al. 2017), the more distinct and specific characteristics and effects of gamblification elements have received little attention so far. Our study not only answer calls for research that stress the importance of peculiarities of design elements (e.g., Hamari et al. 2014; Huotari and Hamari 2017; Schöbel et al. 2020b) but also advances theory and research by providing insights for a more nuanced understanding of the impact of design elements by highlighting their contextualized usage through gamblification. As such, following the framework by Corley and Gioia (2011), we believe that gamblification provides (1) a new perspective on digital design elements for research and (2) important insights for practice by covering the prevalent phenomenon of gamblified digital product offerings in general and the multi-billion dollar market of loot box transactions in particular. In this study, we focused on the loot box menu design as one of the most prevalent forms of gamblification that currently shape many digital business models. Precisely, we investigate the effect of uncertain vs. certain rewards in loot box menu designs and how different combinations of probabilities of winning rewards drive conversion behavior (i.e., loot box selection) and thus revenue generation. Our results support the premise that probabilities of winning a reward in the form of "uncertain and uncertain" vs. "uncertain and certain" has an impact on users' conversion behavior. Specifically, we demonstrate that information processing relevant for digital gaming monetization (i.e., evaluation of probabilities) can deviate from rational decision making as postulated by expected utility theory. Thereby, we assert that researchers should take alternative theoretical explanations (e.g., prospect theory) into account when they investigate and design loot box menus that utilize probabilistic uncertainty. Taken together, we enrich the nascent gamblification research by emphasizing the design of uncertainty-based mechanisms and how they may shape the success of digital business models through enhanced revenues.

Second, we shed light on the peculiar role of uncertainty in gamblified digital product offerings and highlight that due to the inherent uncertainty in gamblified settings the psychological effects governing user behavior are presumably different compared to non-gamblified settings. In particular, we investigate behavioral drivers specific to and salient in interactions in uncertain environments. In this regard, fear-of-losing which may be triggered by contextual factors such as loss previously experience is an important behavioral driver to consider. Additionally, individual factors such as ambitions-to-win which are represented by users' perceived behavior control is as well a crucial behavioral driver in gamblified settings. More specifically, our study provides knowledge on how to amplify and attenuate the certainty effect by considering two intriguing moderators that exhibit opposite effect patterns: Whereas previous loss experience amplifies the certainty effect, perceived behavior control attenuates the certainty effect. Consequently, we shed light on what factors in the environment need to be considered when designing and evaluating loot box menus, as the loot box menu does not exist in a vacuum but in tandem with variables in the digital surrounding.

Third and last, heeding Goes (2013) call for further research into the cognitive dimension of judgment in digital decision contexts, our study contributes nuanced insights into the burgeoning literature on cognitive biases in digital 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., Adomavicius et al. 2013; Bodoff and Vaknin 2016), our findings from a randomized online experiment provide actionable design recommendations on how the certainty effect, distinctly and in combination with the availability heuristic and optimism bias, can be employed to shape conversion outcomes.

4.6.2 Practical Contributions

This research has also important practical implications for digital platforms tasked with designing loot box menus and, more broadly, to help better understand the mechanism behind the microscopic economic behavior of individuals. Our study provides actionable design recommendations on how probabilities of winning a reward can be employed distinctly and in combination with previous loss experience to improve conversion behavior and thus revenues in digital business models. This particularly applies to all digital business models incorporating uncertain elements, which are particularly prevalent in the 150-billion-dollar market of digital games (Newzoo 2020) and in particular in the 30-billion-dollar loot box market (Juniper Research 2017). Moreover, our insights can also be transferred to uncertain offerings in e-commerce, such as the offering of surprise boxes (i.e., boxes containing uncertain selections of

items fitting the customer preferences) (Xu 2020). By providing a choice between two design elements, one containing a certain and the other an uncertain reward, providers can leverage the motivating uncertainty effect and simultaneously appeal to consumers who prefer to avoid uncertainty. Thus, they can optimize product differentiation in line with users' preference patterns. Nonetheless, when implementing those changes to better match users' preference patterns practitioners need to consider users' subjective perceptions and individual differences regarding their capabilities of mastering the gambling game. On the one hand, when users perceive a high level of behavioral control and thus believe their capabilities to be sufficient enough to master the gambling game increasing their ambitions-to-win, they are more likely to exhibit risk-seeking behavior (i.e., selecting a loot box with uncertain content) reducing the necessity for platform providers to offer different loot boxes with a certain or uncertain reward. On the other hand, when users perceive a low level of behavioral control their preferences are likely to be motivated by risk avoidance such that the product differentiation proposed above would lead to a better match of users' preference patterns. Likewise, practitioners need to consider contextual factor such as previous loss experience that may reduce the appeal of loot boxes with uncertain rewards. Taken together, practitioners should design their loot box menus with at least one certain reward should be offered to users with less ambitions to win and to users who previously experiences a loss. Conversely, users with a high ambition-to-win or users who didn't experience a loss beforehand are presumably attracted by loot boxes with uncertain rewards making it reasonable to offer these type of loot box menus to these user groups.

4.6.3 Limitations and Directions for Future Research

The conducted study is an initial empirical investigation into the realm of gamblification and, thus, needs to be understood with respect to some noteworthy limitations that pave avenues for future research.

First, we investigated gamblification only in the form of gamblified digital business models through loot box menu designs. Although loot boxes represent one of the most common contemporary gamblification elements, several other forms (e.g., betting and card games) exist and require research. Indeed, gamblification comprises much more and promises many more venues for theory development above and beyond the gamblification of loot box menu design. Consequently, we encourage future research to shed more light on the potentials and consequences of gamblification. For instance, future studies can examine gamblification in a number of different non-gambling contexts besides digital business models, such as enterprise systems and organizational contexts.

Second, utilizing a self-developed game and animated loot boxes during the experiment, we mimicked a realistic setting, making it easy for participants to be involved. Despite this high degree of realism of our experimental setting, our dependent variable was designed in such a way that it only captured a part of the conversion process. Participants had to choose between purchasing two different loot boxes. They were not able to decide whether they want to buy a loot box 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 (e.g., the 90% loot box) without contrasting it with another or how presenting more than two loot boxes affects user purchase decisions.

Third, we implemented the probabilities of winning in a dichotomous (i.e., uncertain and uncertain vs. uncertain 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 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.

4.6.4 Conclusion

Because competition among digital platforms for regular and new customers has intensified, platform providers increasingly rethink how to design their digital business models to improve user onboarding and conversion outcomes. Gamblification promises not only to evoke excitement in users but also to increase revenues. In this research, we explain how loot box menus can be designed to increase revenue generation by shaping user decision-making. Specifically, we investigate through a contest-based online experiment how certain vs. uncertain rewards in loot box menus influence user conversion behavior. Our results demonstrate that platform providers can profit from offering certain (vs. uncertain) rewards in loot box menus. Moreover, this effect increases when participants previously experienced a loss and decreases when they perceive to have more control over the result. Thus, our findings provide insights on loot box menu designs to increase revenue generation. We hope that our findings not only provide an impetus for scholars to advance understanding of gamblification, but also offer actionable guidelines for providers to refine their knowledge about how they can effectively gamblify their digital business models.

Chapter 5: Prospective Loss Cues in Gamblified Product Offerings

Title: Monetizing Loot Boxes in Gamblified Digital Business Models — The Role of Risk Avoidance and Loss Aversion (2021)

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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

5.1 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 (Fabbri et al. 2019; Mazar et al. 2017; Shen et al. 2015). 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 (Macey and Hamari 2019; Zendle et al. 2020), 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 (Griffiths 2018; King and Delfabbro 2019; Macey and Hamari 2019). 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 2019). 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 (Guo et al. 2019; Voigt and Hinz 2016). 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 (Kahneman and Tversky 1979; Von Neumann and Morgenstern 2007). 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., Animesh et al. 2011; Hamari and

Keronen 2017), 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 gamblification 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.

5.2 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) (Gray and Durcikova 2005; Mata et al. 2018).

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., Ariely et al. 2005; Baird and Raghu 2015), little is known how their interactive effect with risk avoidance might influence purchase behavior and revenue generation within gamblified digital business models.

5.3 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 5-1, 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).

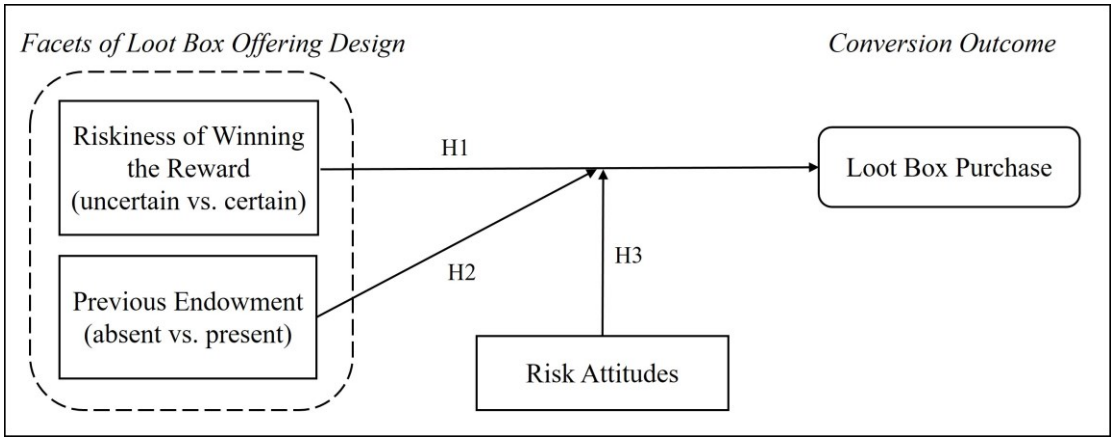


Figure 5-1: Research model

5.3.1 Main Effect of Reward Winning Riskiness 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).

5.3.2 Interaction Effect of Reward Winning Riskiness 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 (Koch and Benlian 2017; Kumar 2014). 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.

5.3.3 Interaction Effect of Reward Winning Riskiness 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 (Gomez-Mejia and Balkin 1989; Gray and Durcikova 2005). 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.

5.4 Research Methodology

5.4.1 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 gamblification elements seem plausible and valid.

Figure 5-2: Experimental version of 'Space Invaders'

More concretely, as depicted in Figure 5-2, 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).

Depending on the condition the respective participant was assigned to, they were presented with different loot box versions. As the middle part of Figure 5-3 exhibits, in the condition *reward winning risk: 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 *reward winning risk: certain* (lower part of Figure 5-3), 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.

Before this loot box purchase event, participants in the condition *previous endowment:*

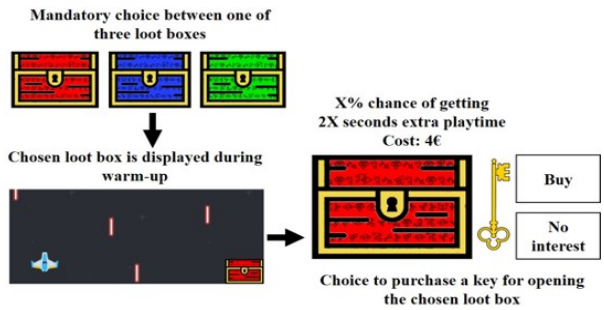
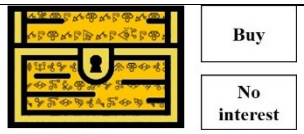
Manipulated Design Features	**Explanation**
	Previous endowment
	Reward winning risk: Uncertain
	Reward winning risk: Certain
Note: In the previous endowment condition, the chosen color of the loot box remained the same (e.g., red) for the subsequent loot box presentation where users actually decided whether to purchase the loot box or not.	

Figure 5-3: Manipulation design

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 5-3, 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.

5.4.2 Experimental Design & Procedure

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

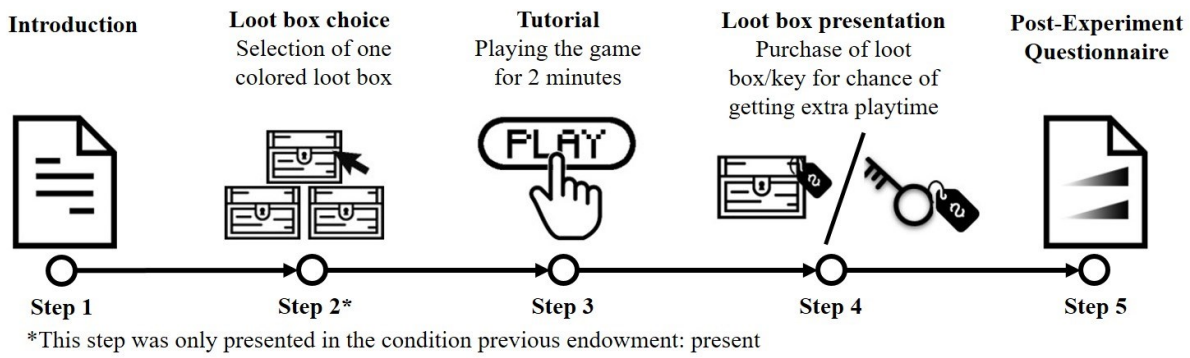


Figure 5-4: Experimental procedure

As depicted in Figure 5-4, 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.

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 A6 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.

5.4.3 Sample Description and Manipulation Checks

Similar to previous experiments in contest-based studies (e.g., Ho et al. 2011; Lowry et al. 2013), 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.

5.5 Results

5.5.1 Main Effect of Changing the Riskiness 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 riskiness of winning the reward (RWR), previous endowment (PE), and (negative) risk attitudes (RA). In the second stage, we added the interaction term of RWR 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.

	Stage 1		Stage 2a		Stage 2b	
	Coef.	**SE.**	**Coef.**	**SE.**	**Coef.**	**SE.**
Intercept	–2.75**	.86	–2.31	.89	–.93	1.00
Manipulations						
RWR	**.79***	.35	0.19	.45	–2.89*	1.26
PE	.28	.36	–.59	.58	.21	.37
RA	.24	.13	–.23	.14	–.22	.20
Interaction						
RWR x PE	–	–	**1.57***	.76	–	–
RWR x RA	–	–	–	–	**.89****	.29
Controls						
Income	.02	.09	.01	.09	.04	.09
Age	.01	.02	.01	.02	.01	.02
Education	.24	.37	.33	.37	.23	.38
Gender (male)	–.10	.37	–.16	.67	.01	.39
Model Fit						
Log-Likelihood	–98.35		–96.12		–93.29	
Nagelkerke R^2	.08		.11		.16	

*Note: * p < .05; ** p < .01; *** p < .001; N = 180; Coef.: Coefficient, SE: Standard Error, RWR: Riskiness of winning the reward, PE: Previous Endowment, RA: Risk Attitudes*

Table 5-1: Logistical regression analysis on purchase decision

None of our controls had a significant effect on purchase decision. As Table 5-1 exhibits the results of our logistic regression's first stage analysis demonstrated a significant positive main effect of changing the riskiness of winning the reward (b = .79; 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 (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 riskiness 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%).

5.5.2 Interaction Effect Analysis of Changing the Riskiness of Winning and Previous Endowment

Our stage 2a analysis unveiled a significant two-way interaction of changing the riskiness of winning the reward and previous endowment (b = 1.57; 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 (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 5-5, the results highlight that when the riskiness 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 riskiness of winning was uncertain, in support of H2.

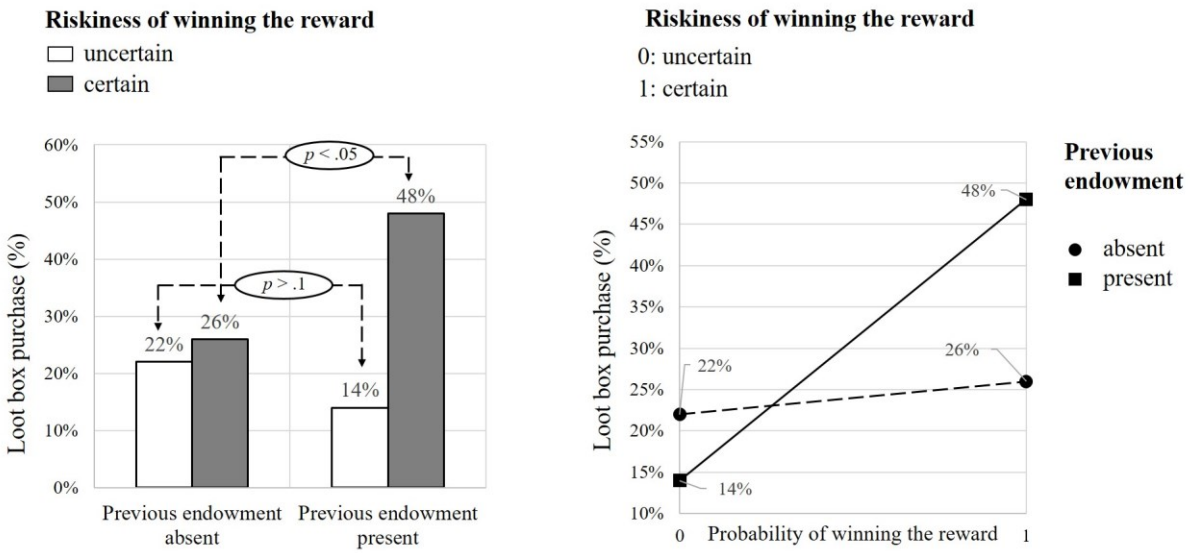


Figure 5-5: Purchase decision when PE is absent vs. present

5.5.3 Interaction Effect Analysis of Changing the Riskiness of Winning and Risk Attitudes

The results of our stage 2b additionally indicated a significant two-way interaction between changing riskiness of winning the reward and risk attitudes (b =.89; 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 (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 5-6. The results illuminate that when the riskiness 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 = 5.58; p < .05). However, in support of H3, when the riskiness 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).

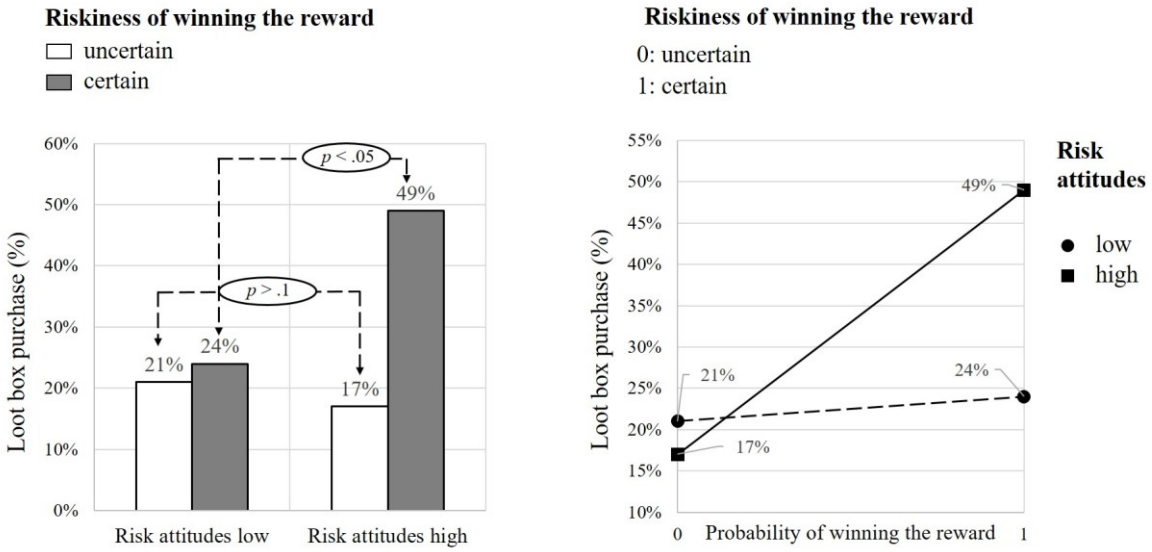


Figure 5-6: Purchase decision when RA were low vs. high

5.6 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.

5.6.1 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; Hamari and Keronen 2017). Concretely, we study the impact of different loot box designs combined with different risk of winning the loot box's content (i.e., a reward) and users' previous endowment of such. Our results support the premise that the riskiness 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 gamblification 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 gamblified 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 gamblified 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 gamblified digital business models.

Taken together, we extend the body of knowledge in IS research on nascent gamblified digital business models by emphasizing the promising impact of uncertainty-based monetization mechanisms. When employed carefully and deliberately, gamblified design elements such as loot boxes can lastingly shape revenue models and thus ensure the success of gamblified digital business models.

5.6.2 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 gamblified 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 gamblified 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

5.6.3 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 risk 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 riskiness 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.

Chapter 6: Thesis Conclusion and Contributions

Decision-making in environments governed by uncertainty and the connected phenomena of cognitive biases have become an increasingly relevant topic in IS research and practice. This thesis is motivated by the growing importance of digital nudging that accounts for users' cognitive biases and motivates them towards a desired behavior. The goal of this thesis is to illuminate two categories of cognitive biases, social influence biases, and risk assessment biases, and to provide a deeper and more comprehensive understanding of how information cues can address these bias categories to affect outcomes (i.e., user conversion) in a specific IS environment (i.e., gam(bl)ified digital business models). Against this backdrop, five studies in four research articles have been published. The thesis primary contributes by providing a novel perspective on how information cues that account for social influence biases and risk assessment biases can affect user behavior in general. Moreover, the thesis' findings also demonstrate how these information cues might be implemented specifically within gam(bl)ification design elements to address cognitive biases within gam(bl)ified IS environments. As such, by combining the two design-oriented approaches, that is, gam(bl)ification and digital nudging, this thesis also provides fresh impetus and actionable design recommendations for practitioners. The following two sections summarize and discuss the main theoretical and practical contributions of the published studies. Subsequently, the final section summarizes the thesis's limitations, considers steps towards future research, and concludes this thesis.

6.1 Theoretical Contributions

The first article provides a foundation for the research context of this thesis and advances the understanding of how the emerging concept of gamblification complements the existing research on gamification. More specifically, the article proposes how gamblification design elements can be integrated into an existing taxonomy of gamification design elements. Thereby, two important themes, that are characteristic for gamification and gamblification design elements are identified. While gamification elements predominantly feature social interaction (i.e., competition or cooperation), gamblification is characterized by chance-based uncertainty as well as resource-transfers. The development of an advanced and more comprehensive taxonomy additionally revealed that besides education and healthcare, gamification and gamblification are prominently examined in the e-commerce and digital gaming contexts, respectively. Taken together, the first article contributes to IS research by establishing gamblification design elements alongside gamification design elements and providing a novel perspective on how these elements might affect user motivation and behavior. Moreover, by

highlighting the importance of social interaction within gamification design elements and chance-based uncertainty as well as resource-transfers within gamblification design elements, the necessity to investigate gamification vis-à-vis gamblification from different theoretical perspectives becomes apparent. As such, while theories from social psychology (i.e., self-determination theory or social influence theory) provide valuable insights regarding the effects of gamification design elements, literature on decision-making under risk (i.e., prospect theory or research on gambling behavior) seems to be more appropriate to investigate the effects of gamblification design elements. Building on the insights of the first article the remaining three studies draw on social influence theory and research on decision-making under risk to investigate how information cues that account for cognitive biases might be embedded in gam(bl)ification design elements to affect and optimize user conversion in digital business models.

Despite the theoretical relevance and prevalence of social influence theory for explaining user behavior in e-commerce (e.g., Datta 2011; Wang et al. 2018; Ye et al. 2018) and gamification research (e.g., Hamari and Koivisto 2015; Koivisto and Hamari 2019), there has been only sporadic attempts to examine how social influence theory may be accounted for in regard of their impact on user behavior (Klumpe et al. 2020; Schneider et al. 2020). Against this background, addressing the overarching research question *RQ1: How can social influence cues affect user conversion in gamified digital business models?,* the second article investigates how two social influence cues can be implemented as social influence tactics (i.e., utilization of cognitive biases stemming from social influence) within the gamification design element 'user onboarding' to affect user conversion (i.e., user registration). The results from two studies indicate that the two social influence tactics reciprocity and social proof distinctly and jointly affect user registration. While the direct effect of social proof and reciprocity on user registration is unambiguously positive, the interactive effect depends on how reciprocity is implemented. The direct positive effect of monetary-based reciprocity is mitigated when employed together with social proof, whereas social proof amplifies the positive effect of utility-based reciprocity.

The findings of the second article thereby reveal that social influence cues embedded in gamification design elements can positively affect user conversion in digital business models. However, the results also highlight that social influence cues need to be carefully designed and tailored as they may enhance but also attenuate one another. Thus, these findings advance

previous research by demonstrating that social influence cues may be interdependent and their effect on user behavior does not necessarily add up in a linear fashion.

As in the case of social influence theory, literature and theories on decision-making under risk have been frequently employed in IS research to explain user behavior in diverse contexts such as information privacy, recommender systems, or investment decision support (e.g., Gerlach et al. 2019; Hardin et al. 2017; Piramuthu et al. 2012). However, IS research has hitherto largely neglected how insights from this literature can be taken into account regarding their impact on user behavior. This is surprising when considering that the very notion of cognitive biases and the related concept of nudging originates in research on decision-making under risk (i.e., prospect theory, heuristics, and bias approach) (Kahneman et al. 1982; Kahneman and Tversky 1979; Thaler and Sunstein 2008). As such, besides sporadic attempts in IS research to harness risk assessment biases (Goel et al. 2017) there is little to no research on how this major bias category can be accounted for regarding their impact on user behavior (Arnott and Gao 2019). Therefore, addressing the overarching research question *RQ2: How can risk assessment cues affect user conversion in gamblified digital business models?* the third and fourth article examine the impact of employing two types of risk assessment cues (i.e., probability evaluation and prospective loss cues) embedded in a gamblification design element on user conversion behavior (i.e., product selection, and purchase decision).

In this regard, the third article investigated how two probability evaluation cues embedded within the gamblification design element 'loot box menu' can trigger the certainty effect as well as the availability bias – two prominent probability evaluation biases – influencing user conversion behavior (i.e., product selection). More specifically, the article investigates the effect of uncertain vs. certain rewards in loot box menu designs and how probability evaluation cues (i.e., different combinations of probabilities of winning rewards offered within these menus) can foster user conversion (i.e., loot box selection). The findings of the study reveal that combining probabilities of winning a reward in the form of 'certain and uncertain' has a positive impact on user conversion compared to the combination of probabilities of winning a reward in the form of 'uncertain and uncertain'. Moreover, the results further demonstrate that this effect is amplified when an additional probability evaluation cue designed to trigger the availability heuristic (i.e., user experience that a potential loot box reward may lead to a loss) is embedded within the loot box selection event. In contrast, this effect is attenuated when users are ambitious to win and potentially overly optimistic in regard of the chances of winning the reward. The study thus highlights the effectiveness of probability evaluation cues embedded within

gamblification design elements to impact user conversion behavior. It thereby advances previous IS research by supporting the premise that literature on decision-making under risk is not only suited to explain user behavior but does also play an important role in influencing it. Moreover, these insights contribute to research by fleshing out the need to consider important behavioral and individual drivers relevant in uncertain environments (i.e., fear-of-losing, or ambition-to-win) when implementing probability evaluation cues as they may affect their effectiveness in influencing user behavior.

Building on the findings of article three, the fourth article aims at answering the overarching *RQ2* as well but focuses on the effect of prospective loss cues – a different type of risk assessment cues – in affecting a separate aspect of user conversion (i.e., purchase behavior) in gamblified digital business models. In more detail, the article examines how implementing a prospective loss cue within the gamblification element 'loot box offering' (i.e., informing users that purchasing the loot box involves the risk of not receiving a reward) affects user purchase decisions. Additionally, by investigating how endowing users with an unopened loot box prior to their purchase affects their decision, the role of a different prospective loss cue is illuminated. Moreover, the study examines how risk aversion – an important individual driver for decision-making under risk – impact the effect of the prospective loss cues on user conversion. The findings indicate, that embedding a prospective loss cue within a loot box offering triggers the risk avoidance effect that negatively affects user conversion. However, while this effect is amplified when users are previously endowed with a loot box it is attenuated when users are risk-seeking. The study contributes to previous research by examining the role of prospective loss cues that are embedded within gamblification design elements in impacting user conversion in digital business models. Moreover, the findings highlight that the risk avoidance effect does not operate in a vacuum but is affected by important contextual and individual drivers that are important to consider when implementing risk assessment cues within gamblification design elements.

Taken together, this thesis advances the nascent gamblification research by demonstrating how implementing gamblification design elements together with information cues acting as digital nudges that are aligned with the uncertainty inherent in gamblification can impact user conversion behavior in digital business models. Moreover, it contributes to the intersection of research on gamification and digital nudging. The thesis showcases how combining gam(bl)ification design elements and information cues acting as digital nudges that are aligned with the social dimension of gamification as well as the risk-based uncertainty of gamblification

can influence user behavior fostering outcomes in digital business models. Thereby, this thesis heeds the call of Goes (2013) for more IS research into the cognitive dimension of judgment in digital decision context and adds fine-grained insights to the sprawling knowledge on cognitive biases in virtual environments. As such, the thesis also addresses to call of Liu et al. (2017) for providing a more holistic and diverse theoretical foundation in gamification research by employing extant literature on human-decision making namely social psychology (e.g., social influence theory) and behavioral economics (e.g., prospect theory, nudging).

6.2 Practical Contributions

Beyond the theoretical contributions, this thesis also highlights several crucial insights and recommendations for IS practitioners tasked with developing and implementing digital business models. In fact, the choice of social influence and risk assessment cues as the focal point of this thesis is greatly motivated by their abundant application and high relevance for optimizing digital business in IS practice. As such, IS practitioners may use the findings described in this thesis to understand how information cues that address cognitive biases can be applied in gam(bl)ified digital business models in a targeted way to achieve favorable conversion outcomes.

In this regard, the results of the first article acknowledge the prevalence and relevance of gamification design element but as well pinpoint the importance for practitioners to consider the genuine aspects of gamblification design elements. As such, it encourages practitioners to employ gamblification design elements such as the incorporation of chance-based uncertainty that differentiates them from their gamification counterparts and to deliberately account for the new ways gamblification design elements motivate users towards desired behaviors. The second article provides valuable practical insights in the form of actionable design recommendations, as it demonstrates how two social influence cues (i.e., reciprocity and social proof cues) can be implemented within 'user onboarding' – a set of specific gamification design elements prevalent in IS practice – to impact user conversion on e-commerce platforms. While social proof and reciprocity employed separately are consistently effective across two studies in increasing user registrations, practitioners need to carefully implement both tactics in combination, as they might amplify or even cancel out one another depending on how reciprocity is applied.

The findings of the third article highlight how probability evaluation cues can be implemented distinctly and in combination in the emerging gamblification design elements 'loot box menu' to improve conversion behavior and thus revenues in digital business models. The results

demonstrate, that when practitioners carefully design probability evaluation cues embedded within gamblification design elements while also considering important contextual and individual behavioral drivers in uncertain environments, they can indeed optimize revenue generation in gamblified digital business models. In this regard, they might differentiate their loot box menu design by offering loot box menus that either contain at least one uncertain reward or only certain rewards, depending on users' preferences (i.e., ambitions to win vs. fear-of-losing). The fourth article demonstrates how prospective loss cues – a different risk assessment cue – can be embedded within the gamblification design element 'loot box offering' to impact user conversion in digital business models. Additionally, by highlighting the importance for practitioners to consider individual preference patterns, the results indicate that revenue generation gamblified digital business models employing loot boxes might be optimized when depending on users' risk preferences, different loot box versions are offered (i.e., loot boxes with risky rewards for risk-seeking users and loot boxes with certain rewards for risk-averse users).

6.3 Limitations, Future Research, and Conclusion

Despite the theoretical and practical contributions outlined in the preceding sections, this thesis is also subject to some noteworthy limitations that nevertheless provide valuable guidance and several pathways for future research. This thesis is one of the first research endeavors at the intersection between gam(bl)ification and digital nudging research investigating the effects of information cues embedded in gam(bl)ification design elements on user conversion. Therefore, as information cues that account for other cognitive bias categories embedded within different gam(bl)ification design elements might affect user behavior differently, the results should be treated with caution when generalized and transferred to other contexts and usage scenarios. Consequently, future research may explore the generalizability of the thesis's findings for other IS contexts.

Furthermore, although this thesis employed various empirical approaches including randomized online and field experiments, the findings are still subject to methodological limitations, as the cross-sectional methods applied are only capable of capturing user behavior at a single point in time. This is important to consider, since besides impacting user behavior in the short term, both, gam(bl)ification and digital nudging, also aim at the behavioral change in the longer-term (Bui et al. 2015; Sunstein 2017). Therefore, future research may support and complement this thesis' findings by conducting longitudinal laboratory and field studies (e.g., Benlian 2020; Benlian 2021).

Lastly, while this thesis findings demonstrate that embedding information cues that account for cognitive biases within gamblification design elements can affect user conversion behavior, and also identify intriguing interactive effect patterns, it was beyond the scope of the conducted studies to account for possible psychological pathways that explain the observed user behavior. As the lack of trust and uncertainty are considered among the biggest challenges in computer-mediated environments and for user conversion in digital business models in particular (e.g., Kim et al. 2008; Pavlou and Gefen 2004; Tan et al. 2019b), future research may extend this thesis' research framework by incorporating potential mediating factor such as trust in platform provider or uncertainty attenuation in order to gain a deeper understanding of the effects of information cues utilizing cognitive biases on user' behavioral outcomes.

To conclude, this thesis is one of the first attempts to investigate the role of information cues that account for cognitive biases in impacting user behavior at the intersection of IS research on gamification, gamblification, and digital nudging. As such, it provides initial steps towards a more in-depth understanding of how the design of IS artifacts within the gam(bl)ification domain interacts with users' biased information processing and decision-making in affecting user behavior. Therefore, this thesis advances prior IS research by highlighting the crucial role of human factors in the IS discipline. Moreover, it provides a greater understanding of how cognitive biases can be taken into account regarding their influence on user conversion within digital business models. While important product and service-related factors such as the overall value proposition drive user conversion, it is equally pivotal to consider psychological factors such as cognitive biases when designing user-system interaction in digital business models. I hope this research endeavor provides fresh impetus for future studies encouraging further IS research on the role of cognitive biases in gam(bl)ified environments and for IS practitioners to account for users' biased decision-making when they design gam(bl)ified IS.

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Appendix

Construct	Items
Perceived Reciprocity (Pervan et al. 2009)	• Overall, Alex and WATCH24 provided each other with equal benefits.
Perceived Popularity (Van Herpen et al. 2009)	• Alex thinks that many people register on WATCH24.
Personal Innovativeness (Agarwal and Prasad 1998) (α = .862)	• I like to experiment with new information technologies. • Among my peers, I am usually the first to try out new information technologies. • If I heard about a new information technology, I would look for ways to experiment with it.
Note: Items were measured using a 7-point Likert scale ranging from strongly disagree (1) to strongly agree (7); α = Cronbach's alpha.	

Table A1 Measurement items

	Variable	Mean	*SD*	1	2	3	4
1	Country (GER in %)	.30	.23	.041**	--		
2	Social Proof	.018	.133	−.022**	−.001	--	
3	Reciprocity	.017	.130	−.024**	−.003*	−.003*	--
4	Confirmed Registrations	.0079	.088	.057**	−.005**	.003*	.003*
Note: N = 475,495; *p < .05; **p < .01							

Table A2 Descriptive Statistics and correlations (Study 2)

	Variable/Construct	Mean	*SD*	1	2	3	4	5	6	7	8	9
1	Gender (male)	.63	.48	--								
2	Country (US in %)	.65	.48	−.12	--							
3	Education (BA in %)	.61	.49	.02	−.06	--						
4	Age	29.4	5.35	−.01	.26**	−.02	--					
5	Personal Innovativeness	5.07	1.53	.22**	−.21**	.26**	−.19**	**.78**				
6	Internet Experience	2.49	1.01	−.13*	−.02	−.04	.02	−.21**	--			
7	Reciprocity	.55	.50	−.07	−.03	−.04	.09	.02	.04	--		
8	Social Proof	.47	.50	−.05	−.19**	.05	−.08	.03	.00	.05	--	
9	User Registration	.27	.44	−.10	−.07	.07	−.15*	.00	−.03	.22**	.25**	--
N = 249; *p < .05; **p < .01; Square root of AVE (bolded cell).												

Table A3 Descriptive statistics and construct correlations (Study 1)

Construct	Items
Perceived Monetary Value (Hong and Tam 2006) (α = .87, AVE = .75, CR = .88)	• I expect the option I have chosen to have a reasonable price. • My chosen option offers a good value for its price. • I believe that my chosen option offers a good value for its current price.
Risk Aversion (Gray and Durcikova 2005) (α = .75, AVE = .54, CR = .57)	• 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 • I usually play it safe, even if it means occasionally losing out on a good opportunity
Product Involvement (Fuller et al. 2009)	• I am interested in loot boxes.
Perceived Behavioral Control (Venkatesh et al. 2003) (α = .82, AVE = .69, CR = .82)	• I have the resources necessary to play the game. • I have the knowledge necessary to play the game.
Note: Items were measured using a 7-point Likert-type scale ranging from strongly disagree (1) to strongly agree (7); α = Cronbach's alpha; AVE = Average variance extracted CR = Composite reliability.	

Table A4 Measurement items

	Loot Box Spending	N	
1	0 to 10€	133	83.6%
2	11 to 50€	18	11.3%
3	51 to 150€	7	4.4%
4	over 150€	1	0.7%

Table A5 Frequency distribution of loot box spending scale

Construct	Items
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 A6 Measurement items