Gamification and User Engagement on Digital Platforms

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List of Abbreviations

Abbreviations	Full Description
AIS	Association of Information Systems
AISeL	Association of Information Systems eLibrary
ANOVA	Analysis of Variance
BIC	Bayesian Information Criteria
CAD	Canadian Dollar
CAIS	Communications of the Association for Information Systems
DUE	Daily User Engagement
HCI	Human-Computer Interaction
ICIS	International Conference on Information Systems
IDV	Individual Index Value
IEEE	Institute of Electrical and Electronics Engineers
IS	Information Systems
IT	Information Technology
LL	Local Leaderboard
MIS	Management Information Systems
MISQE	Management Information Systems Quarterly Executive
RQ	Research Question
SD	Standard Deviation
SJR	SCImago Journal & Country Rank
SQL	Structured Query Language
THCI	Transaction on Human-Computer Interaction
UGC	User-Generated Content
VIF	Variance Inflation Factors
WOM	Word-of-Mouth
XP	Experience Point

ABSTRACT

User engagement has been widely discussed as a critical factor for the success of digital platforms. Among the various mechanisms for increasing user engagement in digital environment, gamification as a design strategy has gained popularity over the last ten years engendering a multitude of empirical analyses. Gamification, which is the use of gamified design in non-gaming contexts, has been criticized for lacking theory driven research despite its popularity and interest from both practice and academia. This thesis addresses this research gap by providing theory-based explanations of gamification as a construct and its relationship with user engagement and free riding behaviors on digital platforms. Three interconnected essays are presented. The first essay contributes to enhancing the knowledge of gamification by creating a typology through the lens of task-technology fit that may maximize user engagement. Following this conceptual piece, the second and third essays empirically examine gamification design that structure competition and cooperation on digital platforms, respectively. These essays build upon theoretical frameworks from various disciplines including management, psychology, behavioral economics and social psychology. Through building and testing theories, this thesis improves a theoretical understanding of gamification that emphasizes human factors, which enables organizations with digital platforms to devise tailored gamification strategies that work best for them to enhance user engagement in their business.

RESUME

L'engagement des utilisateurs a été largement discuté comme un facteur critique pour le succès des plateformes numériques. Parmi les différents mécanismes permettant d'accroître l'engagement des utilisateurs dans l'environnement numérique, la gamification en tant que stratégie de conception a gagné en popularité au cours des dix dernières années, engendrant une multitude d'analyses empiriques. La gamification, qui est l'utilisation de la conception gamifiée dans des contextes non liés au jeu, a été critiquée pour son manque de recherche axée sur la théorie malgré sa popularité et l'intérêt de la pratique et du milieu universitaire. Cette thèse comble cette lacune de la recherche en fournissant des explications théoriques de la gamification en tant que construction et de sa relation avec l'engagement des utilisateurs et les comportements de paresse sociale sur les plateformes numériques. Trois essais interconnectés sont présentés. Le premier essai contribue à améliorer la connaissance de la gamification en créant une typologie à travers le prisme de l'adéquation tâche-technologie qui peut maximiser l'engagement de l'utilisateur. Suite à cette pièce conceptuelle, les deuxième et troisième essais examinent empiriquement la conception de la gamification qui structurent respectivement la concurrence et la coopération sur les plateformes numériques. Ces essais s'appuient sur des cadres théoriques de diverses disciplines, notamment la gestion, la psychologie, l'économie comportementale et la psychologie sociale. En construisant et en testant des théories, cette thèse améliore une compréhension théorique de la gamification qui met l'accent sur les facteurs humains, ce qui permet aux organisations dotées de plateformes numériques de concevoir des stratégies de gamification sur mesure qui leur conviennent le mieux pour améliorer l'engagement des utilisateurs dans leur entreprise.

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Finally, but not least, I thank all my friends. Through this journey I have realized how incredibly lucky I am for having friends from so many different places and times. Life tends to erase the valuable memories with friends for being too busy with imminent life events – in this case finishing my PhD. Meeting and communicating with friends either in person or online has made me a much more stable being that could carry on with these difficult cognitive tasks. Even a memory of friends whom I have not contacted for years has become the force of my life that has enabled me to move forward. I wish my time spent with them could do the same in their lives.

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CONTRIBUTION TO ORIGINAL KNOWLEDGE

This doctoral thesis contributes to original scholarship and knowledge. First, this thesis improves theoretical knowledge of gamification as a construct. The first essay of this thesis theorizes gamification as a multidimensional construct through the lens of task-technology fit and combines its subdimensions - task seriousness and technology playfulness - to identify six ideal types of gamification design that may maximize user engagement. This distinguishes from earlier work on gamification that focused on classifying gamification elements using taxonomies or providing design principles using case studies. Second, this thesis provides an empirical study of gamification that focuses on finding an effective competitive structure that increases user engagement on digital platforms. The second essay of this thesis uses availability and anchoring heuristics from behavioral economics to explain the changes of behaviors on digital platform provoked by leaderboards. The originality of this research is in a novel design of leaderboards that creates competitive structures unique to each user by showing the competitors around them. We call this design *local leaderboards* and compare this against the traditional design of *global leaderboards*, which typically show only the top ranked users. Finally, this thesis provides an empirical study of gamification that focuses on finding an effective collaborative gamification design that reduces free riding behaviors in virtual collaborative environments. The third essay of this thesis combines the lenses of management and social psychology to explain the changes of collaborative behaviors of free riders on digital platforms provoked by team leaderboards. The originality of this research is a novel design of team leaderboards that combines team leaderboards with individual performance feedback that considers either social comparison or social norms.

CONTRIBUTION OF AUTHORS

The first author of all manuscripts included in this thesis is Sumin Song. The co-authors of the first essay are Dr. Animesh, Dr. Kunsoo Han, and Dr. Ryad Titah (in alphabetical order). The co-authors of the second and third essays are Dr. Animesh, and Dr. Kunsoo Han (in alphabetical order). The main contributions of the first author are to initiate, research and write the manuscripts in their entirety. The main contributions of the co-authors are to help brainstorming ideas, provide feedback and review manuscripts to improve the narrative and writing of the essays.

I. INTRODUCTION

Over the last 20 years, studies of digital platforms have garnered an enormous amount of interest from both academics and practitioners. These innovative virtual spaces that facilitate effective and efficient interactions among users have been examined in a range of new business contexts including e-commerce, mobile app markets, sharing economies, social media, and online communities. The new contexts have ushered in new ways of creating and managing information systems and have led to substantial societal changes. A vast number of successful technology-led businesses such as Facebook, YouTube, and Uber were born of this disruption. These types of business have prospects for continued existence and growth. The future promises even more advanced technologies and information systems, which may challenge our understanding of these entities and their relationships with users. Thus, it is imperative to study how digital platform adept businesses will develop as cyberspace grows to include digital natives and the next billion users[1] who will no doubt add diversity and dynamism to the online space, as well as find better ways of explaining the mechanism of how digital platforms facilitate new ways of working and living.

User engagement is a critical factor for the success of digital platforms (Sebastian et al., 2020). Accordingly, organizations that use digital platforms as their main instrument for their operation and management devise a wide variety of tactics. They proactively design and develop tools and features to maximize user engagement, which may lead to increased retention, greater loyalty, and improved revenue (Gu et al., 2022; Sebastian et al., 2020). For instance, popular social

[1] https://nextbillionusers.google/our-research/

networking sites such as Instagram and YouTube use augmented “like” buttons to constantly encourage users to react to the content posted on their platforms.

Among various mechanisms to increase user engagement, of particular interest is gamification design. This thesis defines gamification as *the use of gamified design in information systems that assimilates the playful experience of games into non-gaming contexts to achieve instrumental outcomes* (Deterding et al., 2011; Huotari & Hamari, 2017; Koivisto & Hamari, 2019; Liu et al., 2017; Schöbel et al., 2020; Treiblmaier et al., 2018). Gamification has been touted as an effective means to motivate users in digital environments (Blohm & Leimeister, 2013; Koivisto & Hamari, 2019; Liu et al., 2017). For example, gamification design such as leaderboards (Landers et al., 2017) and badges (Goes et al., 2016; Von Rechenberg et al., 2016; Wang et al., 2020) are found to increase user engagement. Further, examinations of digital platforms with various gamification designs show their positive impact over non-gamified platforms (Bernecker & Ninaus, 2021; Santhanam et al., 2016; Silic & Lowry, 2020; Suh et al., 2017; Wiethof et al., 2021; Yang & Li, 2021).

Despite the advancement of gamification research, designing and implementing gamification on digital platforms is neither straightforward nor simple, for a number of reasons. First, gamification design heavily relies on context (Koivisto & Hamari, 2019), which may have contributed to finding mixed results (Bai et al., 2021; Leung et al., 2022; Mekler et al., 2017; Santhanam et al., 2016; Sheffler et al., 2020; Wang et al., 2020) or even negative effects (Hanus & Fox, 2015). Second, as reviews of gamification have consistently argued (Koivisto & Hamari, 2019; Liu et al., 2017; Schöbel et al., 2020; Treiblmaier et al., 2018), our understanding of gamification is limited due to the lack of theoretical explanations of the relationships between gamification and its outcomes as well as the theorization of the construct itself (i.e., gamification). Even the studies that applied theoretical lenses to build and test hypotheses tend to focus on the perspectives of psychology such as self-determination theory (Chen et al., 2018; Donnermann et al., 2021; Kuo & Chuang, 2016; Mattke & Maier, 2021; Mekler et al., 2017) and goal-setting theory (Bojd et al., 2022; Goes et al., 2016; Hamari, 2017; Landers et al., 2017; Santhanam et al., 2016; Yang & Li, 2021). Thus, our theoretical explanation is limited to the intention of users and relies heavily on intrinsic motivation, which is valuable but difficult to apply in practice due to its variability. Third, continuing our concerns raised in relation to theoretical explanations, several reviews of gamification have heralded a skeptical view of gamification research. They underlined issues in gamification research such as the lack of (1) theoretical explanations, (2) explanatory power attributed to context dependency, and (3) robust research methods (Johnson et al., 2016; Koivisto & Hamari, 2019; Liu et al., 2017; Treiblmaier et al., 2018; Trinidad et al., 2021).

Thus, gamification research needs better strategies. It requires further academic discourse that theorizes gamification as a multidimensional construct to better understand what gamification is and expanded applications of theoretical perspectives that go beyond psychology to describe the relationship between gamification and its outcomes. Further, more in-depth theoretical explanations for individual gamification design that appreciate different contexts would increase the applicability of gamification. Lastly, gamification studies should implement robust research methods (both for data collection and analysis) that detail the procedures, so as they might be replicated and examined in varied situations.

To enhance our knowledge on gamification, this thesis proposes three essays that investigate the fundamental mechanisms of gamification design on digital platforms. We draw on the gamification literature and the theoretical frameworks developed and examined in management, behavioral economics, and social psychology. The first essay proposes a typology of gamification design that conceptualizes six ideal types by integrating task and technology in a unique way to maximize user engagement. This essay theorizes gamification as a multidimensional construct through the lens of task-technology fit and conceptualizes subdimensions of task seriousness and technology playfulness. The second and third essays provide empirical studies that focus on finding gamification design that structures competition or cooperation to increase user engagement on digital platforms. The second essay applies availability and anchoring heuristics from behavioral economics to explain the changes in behaviors on digital platform provoked by *local leaderboards*, which create competitive structures unique to each user by showing the competitors around them. We compare this design against the traditional design of *global leaderboards*, which typically show only the top ranked users. The third essay combines the lenses of management and social psychology to explain the changes of collaborative behaviors of free riders on digital platforms provoked by gamification, in the form of team leaderboards. In particular, this study integrates individual performance feedback on team leaderboards to account for the design that promotes social comparison or social norms.

The main contribution of this thesis is providing theoretical frameworks and integrating social constructs such as competition and cooperation into gamification research. This thesis advances the theory-based knowledge of gamification by establishing a typology of gamification design and empirically examining the impact of competitive and cooperative design on user engagement. From a practical standpoint, this thesis contributes to the knowledge-in-practice by providing organizations with a scientific explanation of gamification that can be applied to the digital platforms that they manage or use.

II. COMPREHENSIVE REVIEW

Introduction

The purpose of this section is to describe in detail the current state of gamification studies. To achieve this aim, we conducted a scoping review of gamification research by answering the following research questions.

1) *What is gamification?* Despite the popularity of gamification this concept has been interpreted and used in various ways across studies. Some explained gamification as a tool that influences outcomes; others explained gamification as a proxy that partially demonstrates the characteristics of gamification.
2) *How is the relationship between gamification and user engagement?* Gamification research finds the relationship between gamification and user engagement as positive with some mixed effects. The way in which this relationship is explained is unclear and fragmented. Further, like gamification, user engagement is defined and operationalized in various ways across studies.

A scoping review is a systematic and transparent process of reviewing an emergent topic (De Guinea & Paré, 2017; Paré et al., 2015) such as gamification. Its main purpose is to provide a comprehensive overview of the topic, so it tends to answer broad research questions with a wide-ranging search strategy that goes beyond a specific study area (De Guinea & Paré, 2017; Paré et al., 2015). This kind of review typically surveys both conceptual and empirical research with clear inclusion and exclusion criteria (Paré et al., 2015). Once the final list of studies is selected for in-depth review, a qualitative analysis is conducted based on the identified themes and content (De Guinea & Paré, 2017; Paré et al., 2015).

Research Method

Preparation

This review followed four basic steps of conducting a literature review - design, conduct, analyze, and write the review (Snyder, 2019). To design our review, we first clarified the purpose. This review aims to summarize prior knowledge on gamification by addressing what gamification is (RQ1) and how the relationship between gamification and user engagement is (RQ2). Once we defined the overall boundary of this review through research questions, we examined earlier reviews on gamification to further specify the review scope and to avoid any redundant work. From the gamification literature, we found two insightful reviews that presented a broad understanding of gamification (Koivisto & Hamari, 2019; Trinidad et al., 2021).

Koivisto and Hamari (2019) conducted a scoping review that analyzed 273 empirical studies on gamification from 2011 to 2015. This review revealed that gamification has mostly positive impact on user engagement (both psychological and behavioral) but with some mixed results (Koivisto & Hamari, 2019). They also found that education, health and crowdsourcing are the most applied context; and points, badges and leaderboards are the most studied elements (Koivisto & Hamari, 2019). As conclusion, this review suggested that the future gamification research needs to broaden themes and theoretical contributions as well as increase the rigor of research methods. (Koivisto & Hamari, 2019).

Extending this review, Trinidad et al. (2021) conducted a bibliometric analysis of gamification covering the studies from 2011 to 2019. This quantitative review presented descriptive analysis of gamification studies and confirmed the findings from the earlier review. This review, however, provided a unique perspective by dividing gamification studies into three periods; the first period between 2011-2013, the second period between 2014-2016 and the third period between 2017-2019 (Trinidad et al., 2021). According to the review, the first period engendered gamification research that separated the concept of gamification from games in the educational contexts; the second period broadened the study contexts (e.g., crowdsourcing, sustainability, health, management, and software engineering) and underlined the user-centered design of gamification; and the third period expanded the publishing of theory-driven research even though most studies inclined to applying self-determination theory (Trinidad et al., 2021). Through this analysis Trinidad et al. (2021) recommended better explanations of the relationships between various gamification elements and their outcomes including motivation, engagement, and performance. Further, they underscored the importance of examining various gamification elements and accounting for specific contexts and users (Trinidad et al., 2021).

Journal Selection

Considering the comprehensive nature of the two systematic reviews (Koivisto & Hamari, 2019; Trinidad et al., 2021), and the maturity of the gamification research that examines each individual gamification elements based on theory-driven hypotheses (Nacke & Deterding, 2017; Trinidad et al., 2021), we narrow down the scope of our review to focus on the gamification studies in the Information Systems (IS) field. Thus, we reviewed gamification studies published in the field of management of information systems (MIS) and human-computer interaction (HCI). In order to select the list of journals to be included in our scoping review, we visited the platforms of Association for Information Systems (AIS) and SCImago Journal & Country Rank (SJR). We selected these two sources because AIS is the central hub for many IS scholars and SJR provides a peer reviewed index that ranks academic journals from varied databases. Table 1 provides the detailed descriptions of the two research sources.

Sources	Descriptions
Association for Information Systems (AIS)[2]	AIS is one of the largest IS association that has a mission of advancing the knowledge and practice of information systems. It has a large body of members from around 100 countries, and it coordinates the International Conference on Information Systems (ICIS) every year, which is one of the most prestigious conferences in the IS field. AIS has published a Senior Scholars' Basket of Journals in 2007 and updated it in 2011.
SCImago Journal & Country Rank (SJR)[3]	SJR is a publicly available online platform that provides an indicator that assesses academic journals and countries for their scientific research. This peer reviewed indicator ranks academic journals found in the databases of Scopus, SciELo, and the Web of Science core collection (WoS) by their significance. This indicator describes "the average number of weighted citations received in the selected year (2021) by the documents published in the selected journal in the three previous years" (SCImago, n.d.). The SJR index is constantly updated, and its detail can be found in the study by Guerrero-Bote and Moya-Anegón (2012).

Table 1 Descriptions of the Selected Sources

From AIS, we selected eight journals chosen by the college of MIS senior scholars (a.k.a., the basket of eight). In addition, we included two more journals reviewed in the Senior Scholars Journal Review Quality Survey conducted in 2020 by AIS. These journals are Communications of the Association for Information Systems (CAIS) and MIS Quarterly Executive (MISQE). Finally, to account for the topics of HCI, we added AIS Transaction on Human-Computer Interaction (THCI), a peer-reviewed journal of AIS.

From SJR, we identified top 10 journals of MIS, among which five were already included in the list of the AIS basket of eight journals. To account for the topics of HCI, we added top 10 journals of HCI ranked by SJR index as well. Table 2 provides the final list of selected journals.

[2] For further information on AIS refer to https://aisnet.org/page/AboutAIS
[3] For further information on SJR refer to https://www.scimagojr.com/help.php

Fields	**Journals**	**Sources**
MIS	Communications of the Association for Information Systems	AIS
MIS	European Journal of Information Systems	AIS, SJR
MIS	Information and Management	SJR
MIS	Information and Organization	SJR
MIS	Information Systems Journal	AIS
MIS	Information Systems Research	AIS, SJR
MIS	International Journal of Information Management	SJR
MIS	Journal of Association for Information Systems	AIS
MIS	Journal of Information Technology	AIS
MIS	Journal of Management Information Systems	AIS, SJR
MIS	Journal of Strategic Information Systems	AIS, SJR
MIS	Journal of Supply Chain Management	SJR
MIS	Knowledge-Based Systems	SJR
MIS	Management Information Systems Quarterly	AIS, SJR
MIS	Management Information Systems Quarterly Executives	AIS
HCI	AIS Transaction on Human-Computer Interaction	AIS
HCI	Computers in Human Behavior	SJR
HCI	Foundations and Trends in Machine Learning	SJR
HCI	IEEE Robotics and Automation Letters	SJR
HCI	IEEE Transactions on Affective Computing	SJR
HCI	IEEE Transactions on Cybernetics	SJR
HCI	IEEE Transactions on Systems, Man, and Cybernetics: Systems	SJR
HCI	International Journal of Computer-Supported Collaborative Learning	SJR
HCI	International Journal of Intelligent Systems	SJR
HCI	Nature Machine Intelligence	SJR
HCI	Transactions of the Association for Computational Linguistics	SJR

Table 2 Selected Journals for Review by Topic and in Alphabetical Order

Search Strategy

We selected the databases of WoS and AIS eLibrary (AISeL) to conduct a comprehensive search of gamification studies in the IS field. WoS is the oldest scientific citation index that has "a selective, structured, and balanced database with complete citation linkages and enhanced metadata that supports a wide range of information purposes" (Birkle et al., 2020, p. 364); and AISeL is the database that indexes the most comprehensive and extensive academic research in the field of IS. Following the suggestions of Snyder (2019) we first performed a pilot test of review process and protocols by querying various search terms with various conditions to generate the most appropriate list of studies. This allowed us to construct our search terms as "gamif* to account for the variation of the usage of the term such as gamification, gamify, and gamified. We queried this search term within the title, subject (or keyword) and abstract of the peer-reviewed journals from the databases of WoS and AISeL.

Databases	**Search Terms**	**Conditions**	**Results**
WoS	Title=(gamif*) OR Abstract=(gamif*) OR Keywords Plus=(gamif*)	Include articles only from the selected peer-reviewed journals. Exclude articles written in other than English.	127
AISeL	title: gamif* OR subject: gamif* OR abstract: gamif*	Include articles only from the selected peer-reviewed journals. Exclude articles written in other than English.	15

Table 3 Search Strategy

For our selection criteria, we included only the selected peer-reviewed journals from the field or subject of MIS and HCI. We excluded conference publications as they are usually research in progress or research presented for feedback before sending them to journals. Instead, we included early access articles (i.e., articles available online to be published in the next edition of the journals). This choice enabled us to avoid any incomplete work (e.g., research in progress) as well as any redundant or incomprehensive work (e.g., research to be published with modification or substantial discussion). We also excluded any articles not written in English. Table 3 above summarizes our search terms and conditions (i.e., inclusion/exclusion criteria) for each database.

Study Selection

We conducted our database search in June 2022 and retrieved a total of 142 query results. We then checked and removed six duplicated entries. This yielded 136 studies of which 24 studies (i.e., 22 research and 2 editorials) were published in the IS basket of eight journals, which may point to the increased interest to gamification in the IS field. We further removed editorials and reviews as they are opinion articles introducing the topic in academic journals. This left us with 124 studies. We examined the title and abstract of each study to discard the research that did not fit into the scope of our research questions (i.e., what is gamification (RQ1), and how is the relationship between gamification and user engagement (RQ2)). To be as systematic as possible, we created inclusion and exclusion criteria for this process as summarized on Table 4.

Main Objectives	Criteria	Description
• To identify the meaning of gamification • To identify the relationship between gamification and user engagement	Inclusion	**Gamification** is used as the **main construct** **Context** in which gamification has been used is **non-gaming contexts and clearly defined** **Theories** are used to investigate gamification or to explain the relationship between gamification and user engagement **Methods** of studies are clear for both conceptual and empirical research **Outcomes** of gamification is user engagement
	Exclusion	**Gamification** is represented as **games** **Context** in which gamification has been used is **games** **Outcomes** of gamification are **post-behaviors or reuse** **Antecedents** of gamification are **the focus** of the research

Table 4 Main Objectives and Protocols for the Review of Title and Abstracts

We included studies that use gamification as the main construct in non-gaming contexts. Further, we included studies that have theories and methods that either investigate gamification as a construct or study the relationship between gamification and user engagement. However, we did not specify the way in which user engagement is measured to enable the flexibility of its use on various contexts. In terms of exclusion criteria, we removed studies about full-fledged games or that focused on game contexts. We made this choice as the game elements used in games have different implications to the game elements used in non-gaming contexts. For example, the means and the ends in an education game (e.g., winning the game) and those in a learning platform that applies gamification (e.g., learning mathematics) are different. For a similar reason, we removed location-based mobile games such as Pokemon Go from our list. We also excluded studies that interpreted virtual reality or augmented reality as gamification unless their game elements were used in non-gaming contexts. With regards to the outcomes, we removed studies focusing on post-adoption or reuse behaviors since those constructs were closely related to user retention rather than user engagement. The studies focusing on the antecedents of gamification were excluded as well. While understanding the antecedents such as the intention of using or adopting gamification is an interesting research avenue, these types of research consider gamification as part of IT use rather than a design strategy.

Based on these criteria, we reviewed titles and abstracts and retrieved total of 66 studies (1st Screening). We applied the same inclusion and exclusion criteria to the full texts to discard research not identified during the 1st screening process. This left us with total of 51 studies (2nd Screening). Figure 1 visually summarizes the entire selection process of the gamification studies.

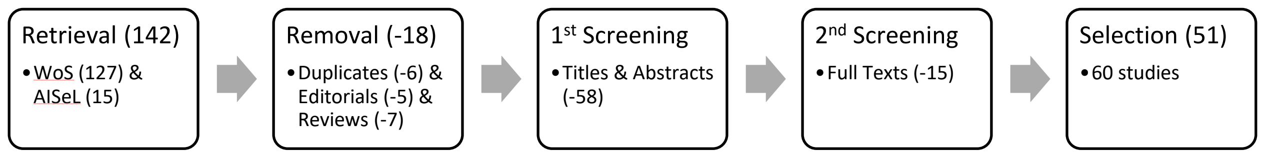

Figure 1 Study Selection Process

Strategy for Analysis

We followed a concept-centric review approach to organize our studies according to the important concepts rather than the central authors (Webster & Watson, 2002). The concepts were extracted from our research questions. As our research questions focused on clarifying the conceptual definition of gamification and its relationship with user engagement, we classified the final set of our studies by the types of gamifications (i.e., tool, proxy or ensemble), the dimensions of user engagement (i.e., cognitive, emotional, or behavioral), and the effects of gamification on outcomes (i.e., positive, mixed, or negative). Table 5 displays a concept matrix complied from our review. We used this table as the basis for our discussion.

Authors (Year)	Gamification			User Engagement			Effects		
	Tool	Proxy	Ens.	Cog.	Emo.	Beh.	Pos.	Null	Neg.
Alcivar and Abad (2016)	x			x		x	x		
Barber et al. (2021)		x		x	x	x	x		
Behl and Dutta (2020)	x			x			x		
Bernecker and Ninaus (2021)	x			x	x	x	x		
Bojd et al. (2022)	x					x	x		x
Çakıroğlu et al. (2017)	x			x	x	x	x		
Chang et al. (2022)	x			x	x	x	x		
Dincelli and Chengalur-Smith (2020)		x		x	x	x	x	x	
Ding (2019)	x			x	x	x	x	x	
Donnermann et al. (2021)	x			x	x			x	x
Feng et al. (2018)	x			x	x		x	x	
Fitz-Walter et al. (2017)	x			x	x	x	x	x	
Georgiou and Nikolaou (2020)	x			x	x		x		
Goes et al. (2016)			x			x	x		
Ha et al. (2021)	x			x			x		
Hamari (2017)	x					x	x		
Hamari and Koivisto (2015)	x						x		
Hamari and Koivisto (2014)		x			x		x		
Hassan et al. (2019)	x			x	x		x		

Holzer et al. (2020)		x		x	x	x	x		
Hsu and Chen (2018)	x			x	x		x		
Kuo and Chuang (2016)		x				x	x		
Landers and Armstrong (2017)	x				x		x	x	
Landers et al. (2017)	x			x		x	x		
Leung et al. (2022)	x					x	x	x	
Liu et al. (2017)		x			x	x	x		
Lopez and Tucker (2017)		x				x	x		
Maican et al. (2016)	x					x	x		
Mattke and Maier (2021)	x			x	x		x	x	
Mekler et al. (2017)	x			x	x	x	x	x	
Moro et al. (2019)	x					x	x		
Rodrigues et al. (2017)	x			x			x		
Rodrigues et al. (2016)	x			x	x		x		
Sailer et al. (2017)	x			x			x	x	
Santhanam et al. (2016)	x			x	x	x	x	x	
Schöbel, Janson and Söllner (2020)		x		x	x	x	x		
Da Rocha Seixas et al. (2016)	x			x		x	x		
Sheffler et al. (2020)			x			x	x	x	
Silic and Lowry (2020)		x		x	x	x	x		
Simonofski et al. (2022)		x		x			x		
Suh et al. (2017)		x		x	x		x		
Tenorio et al. (2016)	x					x	x		
Trang and Weiger (2021)	x			x	x		x		
Treiblmaier et al. (2018)		x		x	x	x	x		
Triantoro et al. (2019)	x			x	x		x		
Wang et al. (2020)	x			x	x		x	x	
Weretecki et al. (2021)	x			x	x		x		
Wiethof et al. (2021)		x		x	x		x		
Yang and Li (2021)			x			x	x		
Yin et al. (2022)		x		x			x	x	
Zhang et al. (2021)	x			x	x		x		

Table 5 A Concept Matrix of Gamification and User Engagement

Discussion

We structured and wrote our review as follows. First, we answered our first research question, *what is gamification?* We reported our analysis on the gamification research by first discussing how this construct has been defined across studies, then we classified them into three perspectives - tool, proxy, or ensemble views. These perspectives were discussed as a way of theorizing IT artifacts (Orlikowski & Iacono, 2001). Second, we answered our second research question, *how is the relationship between gamification and user engagement?* To answer this question, we discussed how user engagement as an outcome variable has been defined and measured in gamification studies. Then, we reported our analysis of the main findings from the empirical studies to highlight the relationship between gamification and user engagement.

RQ1. What is Gamification?

Many studies in gamification describes gamification as the use of game like design in non-gaming contexts (Deterding et al., 2011). Over the last ten years, gamification was studied as a design strategy to increase motivation and consequently user engagement on digital platforms (Blohm & Leimeister, 2013; Koivisto & Hamari, 2019; Liu et al., 2017). The popularity of gamification engendered active academic discourses on how to theorize (Deterding et al., 2011; Koivisto & Hamari, 2019; Schöbel, Janson, Jahn, et al., 2020; Treiblmaier et al., 2018), measure (Bojd et al., 2022; Goes et al., 2016; Leung et al., 2022; Santhanam et al., 2016; Zhang et al., 2019), and evaluate gamification (Liu et al., 2017; Schöbel, Janson, Jahn, et al., 2020; Treiblmaier et al., 2018). In particular, the gamification community focused on producing empirical studies that found the positive causal relationships between gamification and its outcomes including user motivations and behaviors (Koivisto & Hamari, 2019; Liu et al., 2017). However, not all findings were positive. Some studies found mixed results and even negative effects (Bojd et al., 2022; Donnermann et al., 2021). This encouraged studies to investigate theoretical explanations deriving from individual gamification designs (Goes et al., 2016; Von Rechenberg et al., 2016; Wang et al., 2020) and individual user contexts (Bojd et al., 2022; Leung et al., 2022; Santhanam et al., 2016).

The explosive interests toward gamification and the constant call for better explanations of its impact (Koivisto & Hamari, 2019; Liu et al., 2017) created academic discourse demanding for better explanation of the concept with concerted theoretical arguments (Liu et al., 2017; Schöbel, Janson, Jahn, et al., 2020; Treiblmaier et al., 2018). Few studies and seminal work analyzed the usage of gamification in practice and academia (Deterding et al., 2011; Huotari & Hamari, 2017; Koivisto & Hamari, 2019; Liu et al., 2017; Schöbel, Janson, Jahn, et al., 2020; Treiblmaier et al., 2018). They showed that depending on the focus of gamification research, different conceptual definition of gamification was created. Some considered gamification as a tool to achieve its outcomes (i.e., tool view); others studied this construct to explain its property and traits (i.e., proxy view); and other few considered it as a structure (i.e., ensemble view) (Orlikowski & Iacono, 2001).

The tool view of Information Technology (IT) artifact assumes that human can define and control IT as it is created with a designer's intention to achieve certain outcomes (Orlikowski & Iacono, 2001). Most gamification studies in our review took this view, which placed gamification as technology that can be easily substituted with something else. For instance, Mekler et al. (2017) used points, leaderboards and levels to examine their impacts on cognitive tasks, but their gamification design elements were expendable. Leung et al. (2022) provided more nuanced application of leaderboards and badges by explaining them as IT artifacts that provide performance feedback. However, their approach still suffered from substitutability by not only other gamification elements but also non-game elements. Despite the drawback of the tool view, we think that this perspective can be applied in a nuanced and useful manner. For instance, Landers et al. (2017) examined leaderboards for brainstorming tasks and established theoretical arguments that users who received leaderboards placed their implicit goals to the top or near the top. Leaderboards in their experiment was the essential part of their argument, which could not be substituted to other gamification design elements.

The issue of the tool view of gamification is that it makes it difficult to differentiate between game like design and non-game like design. Earlier IS studies found that general IT artifacts used on digital platforms are strongly correlated with emotional excitement (Agarwal & Karahanna, 2000; Beaudry & Pinsonneault, 2010; De Guinea & Markus, 2009; Van der Heijden, 2004). Thus, applying the tool view of gamification undermines our understanding and limits the application of gamification as a mere subset of IT artifact. In order for us to advance the academic discourse on gamification, we need to theorize it to unfold its real meaning and implication, which cannot be described nor explained using the tool view (Grover & Lyytinen, 2015; Orlikowski & Iacono, 2001).

The proxy view of IT artifact focuses on the elements that represent the property or characteristic of IT (Orlikowski & Iacono, 2001). Studies included in our review revealed that one of the most applied definitions of gamification is *"the use of design elements characteristics for games in non-game contexts"* (Deterding et al. 2011, p. 13). This definition differentiates gamification from games (or serious games), and highlights parts over whole. More importantly, it positions gamification as structured forms of play that is bounded by rules and goals (i.e., gaming) and compares it against free forms of play that is open, expressive, and exploratory (i.e., playing) (Deterding et al., 2011). This conceptual defintion uses a proxy view by accentuating the property of gamification and enables a reasonable conceptual boundary when examining gamification as a technology in various contexts.

Conceptual studies included in our review mostly took the proxy view of gamification. For example, Liu et al. (2017) examined gamified information systems by assessing real-world examples, then built a taxonomy of gamification elements that became the basis of their suggested gamification design principles. The proxy view is also observed commonly in the studies that take design science approach. Our review identified studies that created and tested gamified digital platforms (Dincelli & Chengalur-Smith, 2020; Holzer et al., 2020; Silic & Lowry, 2020; Wiethof et al., 2021). Their approach necessitated studies to describe gamification in depth. This evidence suggests that the proxy view has the advantage of theorizing gamification in more detail by focusing on itself in comparison to the theorization of the tool view of gamification.

Despite the efforts put in place by the studies that took the proxy view, the current conceptual definition has been reduced and simplified to an abstract form that has created a surplus of interpretations among scholars in gamification. From the outset, the use of game like design in non-gaming contexts (Deterding et al., 2011) appears to hold the gist of gamification, but when it is applied to various context, the definitino is too abstract. This limits the the way in which it can be explained and interpereted in relation to users and systems.

Studies that took the tool view of gamifcation attempted to integrate the proxy view in building its conceptual defintion. For example, Koivisto & Hamari (2019) in their literature review argued that gamification represents the rise of motivatoinal information system by increasing the utility of information systems through the design that motivates emotions. Similarly, Liu et al. (2017) argued that gamification aims to achieve both experiential (e.g., sense of enjoyment, satisfaction) and instrumental (e.g., completing tasks, achieving objectives) outcomes. These studies demonstrate how gamification has evolved over time reflecting both hedonic and utilitarian motivations in its conceptual definition. (Baptista & Oliveira, 2019; Koivisto & Hamari, 2019).

Over ten years of gamification studies appear to expand the academic discourse of gamification to combine both tool and proxy views. For instance, Liu et al. (2017) defined gamification as *"the* *incorporation of game design elements into a target system while retaining the target system's instrumental functions"* (Liu et al., 2017, p. 1013). This definition reflects the property of gamification as game design elements and the outcomes as instrumental functions. Similarly, Koivisto and Hamari (2019) defined gamification as *"designing information systems to afford similar experiences and motivations as games do, and consequently, attempting to affect user behavior"* (p. 191). This definition accentuates the property of gamification as affording similar experience and motivation of games to achieve the outcomes of influencing user behavior.

Nevertheless, the way in which researchers have conceptualized gamification is still too simple. Whether gamification is regarded as a tool or perceived to be measured as a proxy, both views consider gamification as a fixed entity that is *"single, seamless, stable and the same every time and everywhere"* (Orlikowski & Iacono, 2001, p. 131). This perspective limits its applicability. The inconsistent findings from empirical studies and the lack of theoretical explanations of those findings may have been attributed to our limited understanding of gamification as a construct (Schöbel, Janson, Jahn, et al., 2020).

Thus, this review suggests using an ensemble view to overcome the simplistic conceptual definition of gamification that either takes a tool or proxy view. The ensemble view considers IT artifact as an assembly of components that extends the meaning of technology by adapting factors relevant to socio-economic activity (Orlikowski & Iacono, 2001). Orlikowski & Iacono (2001) explained that technology can be embedded system or structure, and we think that gamification is a good candidate for a structure that determines the intention of information systems. Gamification as a structure "*is enmeshed in the conditions of its use"* (Orlikowski & Iacono, 2001, p. 127). Goes et al. (2016) used badge rewarding system as a way to enmeshed incentive hierarchy system that changes user behaviors over time on digital platforms. Sheffler et al. (2020) demonstrated that badges can be used as rewards that become signifiers and completion logic in a bike community program.

To apply an ensemble view of gamification we suggest creating a multidimensional construct of gamification. This would increase our understanding on how gamification comes to be and is used. More specifically, it will enable us to understand *"the meanings, capabilities and uses of IT artifacts, their multiple, emergent, and dynamic properties, as well as the recursive transformations occurring in the various social worlds in which they are embedded"* (Orlikowski & Iacono, 2001, p. 133). We applied an ensemble view in our first essay of this thesis by theorizing gamification as a multidimensional construct. We will present our first essay in chapter 3. For now, as our first step, we define gamification by synthesizing conceptual definitions from both tool and proxy views. Gamification is *the use of gamified design in information systems that assimilates the playful experience of games into non-gaming contexts to achieve instrumental outcomes*. This definition will enable us to further explore the construct reflecting the ensemble view that situations gamification in its use.

RQ2. Relationship between Gamification and User Engagement?

To explicate the relationship between gamification and user engagement, we first defined user engagement. User engagement is a term widely used in both academia and practice to describe user experience relevant to information systems in digital era (O'Brien & Cairns, 2016). This construct has been conceptualized and operationalized in various ways depending on the theoretical stance of the research (O'Brien & Cairns, 2016). Research in the IS field has considered user engagement as a context specific measurement that shows frequency and intensity of system use such as the number of posted comments, likes, shares, click-throughs as well as user efforts and contribution (Chen et al., 2018; Goes et al., 2016; Gu et al., 2022; Lee et al., 2018; Zhang et al., 2019). Research in HCI conceptualized user engagement as a process of engagement that changes over time through the experience that touches upon emotion, cognition and behaviors of users (O'Brien & Toms, 2008). This understanding is echoed in the marketing research where user engagement is perceived as an analogue of customer engagement. Customer engagement is a multidimensional construct that has both psychological and behavioral concerns accompanied by specific outcomes that may have economic implications (Brodie et al., 2011; Gu et al., 2022). Table 6 shows the summary of definitions of user engagement used in different fields of study.

Fields	**Definitions**	**Focus**	**Authors**
IS	A context specific measurement that shows frequency and intensity of system use. This construct is often operationalized as the number of posted comments, likes, shares, click-throughs as well as user efforts and contribution	Cognitive and Behavioral	(Chen et al., 2018; Goes et al., 2016; Gu et al., 2022; Lee et al., 2018; Zhang et al., 2019)
HCI	A process of engagement that changes over time through the experience that touches upon emotion, cognition and behaviors of users "a quality of user experience with technology characterized by the perceived usability and aesthetic appeal of the system, focused attention, novelty, felt involvement, and endurability" (O'Brien, 2016, p. 3)	Cognitive, Emotional, and Behavioral	(O'Brien & Toms, 2008; O'Brien et al., 2018)
Marketing	A customer engagement or consumer engagement, which is a multidimensional construct that describes psychological state enabled by the customer experience	Cognitive, Emotional, and Behavioral	(Brodie et al., 2011; Vivek et al., 2014)

Table 6 Definitions of User Engagement

In gamification research, studies operationalized user engagement as outcome variables in various ways depending on the focus of the studies and their contextual boundaries. Some gamification studies explained user engagement as the path from psychological to behavioral outcomes (Koivisto & Hamari, 2019). Others describe it as meaningful engagement to accentuate simultaneous achievement of both experiential (e.g., sense of enjoyment and satisfaction) and instrumental outcomes (Liu et al., 2017). We synthesized earlier discourses from both gamification and other fields, and defined user engagement as *user cognitive, emotional, and behavioral interaction with information systems bound with its frequency and intensity*.

User engagement has been studied often in relation to gamification to describe and explain the effectiveness of gamification in empirical analyses (Koivisto & Hamari, 2019). For instance, prior studies examined the impact of gamification on user engagement as cognitive absorption (Santhanam et al., 2016), user responses (Burtch et al., 2018; Huang et al., 2019), improved learning (Bai et al., 2021; Landers et al., 2017; Leung et al., 2022), user contributions (Chen et al., 2018; Goes et al., 2016; Liu et al., 2022; Wang et al., 2020), and weight loss (Bojd et al., 2022). Table 7 displays some empirical studies on gamification published in the AIS basket of eight journals up to June 2022. This table shows applied gamification design, dimensions of user engagement, and the main findings of the studies.

Authors	**Gamification**	**User Engagement**	**Main Findings**
Bojd et al. (2022)	Leaderboards	Behavioral	Gamified challenges has a positive effect on weight loss but not including a numeric goal, focusing on an exercise-only behavioral goal, and including a large active group size are effective.

Dincelli and Chengalur-Smith (2020)	Visual storytelling	Cognitive, Emotional, Behavioral	Using visual storytelling for security training is better at improving experiential outcomes while text-based design is better at improving instrumental outcomes.
Goes et al. (2016)	Badges	Behavioral	Users exert their efforts just before achieving the next level status (badges), then significantly drop their contribution.
Holzer et al. (2020)	Gamified profile; visual environment	Cognitive, Emotional, Behavioral	Gamification design improved user engagement and knowledge sharing in knowledge management system for humanitarian organizations.
Leung et al. (2022)	Leaderboards; badges	Behavioral	Users with a strong performance-avoidance goal orientation improve their engagement when gamification with no social comparison is presented, while users with a strong mastery goal orientation decrease their engagement with the same feedback.
Santhanam et al. (2016)	Trivia-based mini games (one-on-one matching)	Cognitive, Emotional, Behavioral	Individuals learn better when competing against a lower-skilled competitor due to peer appraisal, while they engage better when competing against an equally skilled competitor due to being in the state of flow.
Sheffler et al. (2020)	Badges	Behavioral	Badges as rewards increase ridership, as signifiers (self-interest vs. pro-env) are indifferent and as completion logic from fix to relative goal increase ridership.
Silic and Lowry (2020)	Various gamification	Cognitive, Emotional, Behavioral	Gamified security training has positive impact on behavioral changes such as phishing prevention.
Wang et al. (2020)	Badges	Cognitive, Emotional	Gamified Word-of-Mouth (badges) leads WOM consumers to perceive the competence of WOM contributors as positive.

Table 7 Selected Empirical Studies

The relationship between gamification and user engagement were explored in various ways. However, the way in which they were explained tend to focus on a few psychological lenses. As analyzed by Trinidad et al. (2021), only few reference theories (e.g., self-determination theory, and goal-setting theory) were emphasized to explain the relationship between gamification and user engagement on digital platforms (Goes et al., 2016; Landers et al., 2017; Mekler et al., 2017; Santhanam et al., 2016; Von Rechenberg et al., 2016). However, the comforting prospect is that the recent gamification research has extended these theories with added conditions such as personality traits (Leung et al., 2022), social comparison (Bojd et al., 2022), peer-recognition (Goes et al., 2016; Wang et al., 2020) and reciprocity (Liu et al., 2022). Our review shows that other theories were also applied in gamification studies such as flow or hedonic values (Hamari & Koivisto, 2014; Hassan et al., 2019; Hsu & Chen, 2018; Silic & Lowry, 2020; Suh et al., 2017) and social cognitive theory (Santhanam et al., 2016; Wang et al., 2020).

The analysis of our review suggests the continuation of exploring new theories through various lenses. Liu et al. (2017) and Treiblmaier et al. (2018) provided excellent summaries of theories that can be applied in the gamification research. Using reference theories to explain the relationship between gamification and user engagement will provide stronger arguments. Further, our review suggests that the relationships between gamification and user engagement need to be interpreted in more nuanced ways. Considering different conditions and contexts that gamification is applied on will advance our knowledge and provide much richer understanding of gamification.

Conclusion

We have answered our research questions postulated for this comprehensive review of gamification literature. We conducted a scoping review that focused on the studies produced in the IS field to avoid any superfluous work and deepen our understanding of conceptualizing gamification as an IT artifact and its relationship with user engagement.

Our review suggested a new definition of gamification - *the use of gamified design in information systems that assimilates the playful experience of games into non-gaming contexts to achieve instrumental outcomes*. This definition not only integrates the tool and proxy views, but also reflects the ensemble view that sheds light on the possibility of conceptualizing gamification as a multidimensional construct. Defining gamification as a multidimensional construct takes into consideration of how this construct is situated in its use. This is going to be the main topic for our first essay. The first essay explicated the conceptual definition of gamification through the framework of task-technology fit and proposed six ideal types of gamification design by uniquely combining task seriousness and technology playfulness.

Another insight from our review is the identification of research gaps with regards to the relationship between gamification and user engagement. From our review, we found that this relationship needs further theoretical explanations that have many research paths that calls for further examinations. For instance, how can we leverage gamification design to create effective competitive structures that improve user engagement on digital platforms? What is the role of gamification in virtual collaborative environments? Does gamification help to increase cognitive and emotional user engagement for those who feel less enthusiastic about the virtual collaboration? Our second and third essays answered some of these questions.

The second essay examined the design of gamification that accentuated competitive structures to improve user engagement on digital platforms. This study used leaderboards as gamification and applied a lens of behavioral economics to argue that users are affected by the information presented to them when they make decisions under uncertainty. The third essay examined the use of gamification in a collaborative digital setting to nudge individuals with lower user engagement (i.e., free riders). This study underlined the importance of making tasks unique through individual feedback to reduce free riding behaviors.

In the following chapters this thesis presented three independent manuscripts. The first manuscript proposed a typology of gamification through redefining the conceptual definition of gamification as a multidimensional construct that integrated technology playfulness and task seriousness. The second and the third manuscripts presented empirical studies that examined the relationship between gamification and user engagement through theoretical lenses of behavioral economics, management and social psychology.

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POSITIONING OF ESSAY 1

Essay 1 presents a conceptual piece that overarches the entire thesis. It describes and explains the process of building a typology theory of gamification that hypothesized to maximize user engagement. This essay renders an abstract analysis that examines various mechanisms of gamification applied on digital platforms borrowing the framework of task-technology fit. Formally, this essay answers the following research question: *How can we conceptualize gamification ideal types on digital platforms that maximize user engagement?*

The rationale behind this theoretical work is as follows. First, most studies describe gamification as a single-dimension construct that assumes to have a clear boundary that is applicable in any contexts. However, numerous empirical findings and reviews on gamification suggest that gamification is affected by contexts such as the types of platforms the design is applied to (e.g., education, health, and crowdsourcing), the types of tasks the design needs to encourage (e.g., individual work or collaborative work), or the types of users the design interacts with (e.g., low motivated vs. high motivated users). Second, the conceptual definition of gamification is applied in various ways across studies creating discrepancy among researchers in where to focus and how to theorize gamification in a way that accentuates the contexts that they are interested in.

Thus, the first essay clarifies a conceptual definition of gamification as a multidimensional construct and identifies six ideal types of gamification design that maximizes user engagement. This essay provides the foundation of this thesis that supports rest of the narrative. Further, the second and third essays apply the conceptual definition created from the first essay.

III. WHY SO SERIOUS? A TYPOLOGY OF GAMIFICATION ALIGNING TECHNOLOGY PLAYFULNESS AND TASK SERIOUSNESS

Abstract

Gamification refers to the use of gamified design for non-gaming context in digital platforms. This concept has been widely applied in the digital economy where user engagement is critical for the success of businesses and organizations. Despite the popularity of gamification, we know little why and how this works as the focus has been on the outcomes. This has hindered a better understanding of gamification as a design strategy that increases user engagement. Thus, this study explores the concept of gamification as an IT artifact of a multidimensional construct. Using the framework of task-technology fit, this study conceptualizes technology playfulness and task seriousness as the subdimensions of gamification. These subdimensions are combined to theorize six ideal types that may maximize user engagement. This study expands the discourse on the gamification research by proposing a typology that integrates utilitarian and hedonic views of information systems. Consequently, it improves our understanding on how gamification comes to be and to be used. The created abstract ideal types provoke new research avenues for future empirical analysis that deal with specific instances. Further, they provide practical guidance on how to apply gamification for the tasks of different nature that involve various characteristics of users.

Keywords: Gamification, Typology, Technology Playfulness, Task Seriousness, Task-Technology Fit, User Engagement

Introduction

User engagement describes user cognitive, emotional, and behavioral interaction with information systems (O'Brien & Toms, 2008) bound with its frequency and intensity (Gu et al., 2022). User engagement has been an important issue for the growth of digital platforms in digital economy (Goes et al., 2016; Gu et al., 2022). The recent proliferation of digital platforms has underscored the significance of this cyberspace to facilitate efficient and effective interactions among users within and across organizations (Sebastian et al., 2020). This has directed organizations to devise various tactics to increase user engagement. They create and update features and functionalities in their digital platforms. For instance, Snapchat, a popular photo and video messaging platform, has leveraged "snap" as its core engagement feature enabling users to share photos transiently[4]. Meta, previously Facebook, which is the largest social media company, continues adding new functionalities in their platform such as augmenting its "Like" button with a multidimensional "Reactions" feature[5].

Various mechanisms of digital platforms guide users to collectively agree on the acceptable behaviors in their platforms. For example, social media platforms typically leverage "Like" buttons to enable users to express their feelings on posts. Although each user may have different criteria on when to use "Like" buttons, the implied consensus is that users press those buttons when they agree or like the content that they see. The emergence of implied rules can be interpreted as the realization of practice through the entanglement between human agent (i.e., social) and technologies (i.e., material) (Orlikowski, 2010). This type of practice is quite common in the culture of video games (Koivisto & Hamari, 2019). However, for non-gamers this practice may

[4] For further information on features of Snapchat refer to https://creators.snap.com/learn-get-started-explore-snapchat
[5] For further information on reaction feature refer to https://www.facebook.com/brand/resources/facebookapp/reactions

not be intuitive as it does not come with instructions. Further, users are required to learn new features and functionalities constantly added on digital platforms. Thus, new platform users or non-digital natives may struggle to navigate through these platforms. This gives rise to the need for a well-thought-out design on digital platforms. The design needs to facilitate users to be engaged in the activities conducted on or through digital platforms.

Over the last ten years, gamification, the use of game-like design in non-gaming context (Deterding et al., 2011), has gained enormous amount of attention as a design strategy that motivates users to engage in the activities on digital platforms (Blohm & Leimeister, 2013; Koivisto & Hamari, 2019; Liu et al., 2017). Numerous empirical analyses have been generated. They mostly suggest that gamification has positive influence on changing user motivation and behaviors (Koivisto & Hamari, 2019). Despite the promising empirical findings, reviews on gamification studies found that gamification research has little discourse on the questions of why and how (Koivisto & Hamari, 2019; Liu et al., 2017; Treiblmaier et al., 2018). Some argue that the context specific nature of gamification compels researchers to focus on each empirical analysis without delving into theoretical explanations (Koivisto & Hamari, 2019). However, not accounting for theoretical explanations diminishes the value of gamification research by putting it behind practice. Given the current availability of data and analytical tools, companies that manage digital platforms can easily use A/B testing to measure the performance of the two different versions of design (Gallo, 2017). However, their focus is on the prediction of their performance in the short-term. Thus, their findings are not explained nor generalized to other contexts. Academic research is interested in explicating the intricate nature of gamification that influences the behaviors of users both in the short-term and the long-term. Explaining these causal relationships require theories especially because they are dealing with human (Landers et al., 2018) that is complex and less predictable. Thus, to advance the discourse on this topic our study elucidates why and how gamification works on digital platforms.

To address the shortcomings of gamification studies, this essay points out two main issues. The first issue is unclear and simplistic conceptual definition of gamification. In order to advance the discourse in the information systems (IS) field, gamification as an IT artifact needs to be theorized (Schöbel et al., 2020). Thus, this study suggests gamification as a multidimensional construct that integrates playfulness and seriousness. The term gamification is convoluted with an implied idea of "fun" or "playful" when information systems deal with "serious" issues of collecting, processing, storing, and distributing data. This study proposes disentangling the term gamification by interpreting the role of gamification as adding playful technologies to serious tasks on digital platforms to motivate users to engage more on the platforms. This is in line with the perspective that integrates both utilitarian and hedonic views of gamification (Baptista & Oliveira, 2019; Koivisto & Hamari, 2019).

The second issue is treating gamification as homogenous. This study argues that gamification may have heterogenous effects depending on the nature of technologies and tasks. Consequently, it suggests interpreting the use of gamification in more detail. For instance, in terms of technologies, rewarding badges on digital platforms has different implications to showing users leaderboards. Current gamification studies rarely discern these differences because both are likely to lead to the same conclusion, improved user engagement. However, if we were to explain why these gamification elements work (or not work) to induce user engagement, each story may differ in relation to the psychological effect. Further, tasks that are mapped with these gamification elements may also have an impact on the results. Thus, this study proposes gamification ideal types built on the framework of task-technology fit (Goodhue & Thompson, 1995; Zigurs & Buckland, 1998). More specifically, this study elaborates each gamification ideal type from theoretically derived concepts of technology playfulness and task seriousness.

To guide the logical flow of this study, we formalize our research question as follows: *How can we conceptualize gamification ideal types on digital platforms that maximize user engagement?* To answer this question, this study delves into the accumulated knowledge in gamification research and identifies the gaps in the literature. Then, this study conceptualizes subdimensions of gamification using the framework of task-technology fit. The subdimensions are the tasks defined by the degree of seriousness and the technologies defined by the degree of playfulness. These are combined to create and assess ideal profiles of gamification design, which are derived from or illustrated with real examples.

This study contributes to the gamification research that expands our understanding on how to design and manage effective digital platforms. Our conceptual framework underlines the multidimensionality of gamification by demonstrating the degree of technology playfulness and the degree of task seriousness. In particular, this study highlights the significance of playfulness to enable less stressful access to information systems through enjoyment that lowers the barrier of completing serious tasks. This study expands the discourse on the gamification design principles (Liu et al., 2017) by creating a typology of gamification through the lens of task-technology fit (Goodhue & Thompson, 1995). Through the process of conceptualizing ideal types of gamifications, this study sheds light on the mechanism of gamification that may maximize user engagement. The increased understanding of gamification design helps respond to the rapid advancement of technologies and ever-expanding user base, which may drastically change information systems applied on digital platforms and add complexity to their use. Thus, creating a typology of gamification offers accessible strategies to motivate users, which increase the usability of digital platforms and help reduce digital divide that may appear from the evolution of digital platforms. Finally, but not least, this research responds to the current change of hybrid working environment, which emphasizes organizational efforts to increase user engagement in virtual spaces. In this regard, the conceptual framework of gamification provides the basis for creating practical guidance to organizations that leverage digital platforms. For instance, the typology may help describe clear use case scenarios of each gamification design and thus aid business to justify their strategies to implement gamification techniques that motivate and change the behaviors of their platform users.

Theoretical Background and Literature Review

This section provides the overview of gamification research to spot the neglected aspect of this literature. Then, we build an argument to conceptually clarify gamification as a construct to advance this stream of research. We conduct an in-depth analysis of gamification as a construct followed by a review of user engagement as its outcome.

Gamification Research

Gamification is the use of game like design in non-gaming contexts (Deterding et al., 2011). This construct has gained vast interest over the last ten years (Deterding et al., 2011; Liu et al., 2017) as a design strategy that motivates users to engage in the activities on digital platforms (Blohm & Leimeister, 2013; Koivisto & Hamari, 2019; Liu et al., 2017). The popularity of gamification led to active academic discourse on how to theorize it (Deterding et al., 2011; Koivisto & Hamari, 2019; Schöbel et al., 2020; Treiblmaier et al., 2018), how to measure it (Bojd et al., 2022; Goes et al., 2016; Leung et al., 2022; Santhanam et al., 2016; Zhang et al., 2019), and how to evaluate its impact using theoretical explanations (Liu et al., 2017; Schöbel et al., 2020; Treiblmaier et al., 2018). In particular, gamification studies lend themselves to abundant empirical research that explores the causal relationship between gamification and its outcomes. Most gamification research finds gamification as having a positive impact on changing user engagement (Koivisto & Hamari, 2019). For instance, gamification design such as leaderboards (Landers et al., 2017), and badges (Goes et al., 2016; Wang et al., 2020) are found to increase user engagement. However, a few studies found gamification such as leaderboards as having mixed effects depending on the ranks of the users (Bai et al., 2021) or even negative effects in the educational context (Hanus & Fox, 2015). Although a few, some empirical studies provide theory-driven explanations that typically apply self-determination or goal-setting theories to explain the reason behind the improved user engagement on digital platforms (Goes et al., 2016; Landers et al., 2017; Mekler et al., 2017; Santhanam et al., 2016; Von Rechenberg et al., 2016). More recently, we witness other studies that extend these assumptions with additional conditions such as personality traits (Leung et al., 2022), social comparison (Bojd et al., 2022), prosocial behaviors (Burtch et al., 2018; Huang et al., 2019), peer-recognition (Chen et al., 2018; Hamari, 2017; Wang et al., 2020) and reciprocity (Chen et al., 2018; Liu et al., 2022).

The maturity of gamification research has been celebrated for examining hypotheses built upon theories and isolating individual gamification elements for evaluation (Nacke & Deterding, 2017). However, several reviews on gamification studies have demonstrated a skeptical view that overall gamification research leans toward breadth over depth. According to these reviews, gamification research lacks theoretical explanations, uses weak research methods, and relies on specific contexts (Johnson et al., 2016; Koivisto & Hamari, 2019; Liu et al., 2017; Treiblmaier et al., 2018).

Given the nascent nature of gamification studies, expanding empirical research in breadth over depth has the merit of accelerating the gamification discourse with empirical evidence. However, this comes with an expensive price tag. The explanations tend to scratch only the surface level of what has been observed from data. Consequently, this tendency impedes researchers from creating a higher level of gamification theory. Further, it leaves the conceptualization of gamification as an IT artifact that works as a tool or proxy, which bounds the purpose of gamification as mainly assessing the impact of its outcomes (Orlikowski & Iacono, 2001).

Thus, our study moves back to the conceptual research that focuses on disentangling the meaning of gamification rather than observing and analyzing empirical evidence. Our study is in line with the panel discussion on gamification research carried out in 2019 (Schöbel et al., 2020). This discussion has revealed that even the theory-driven research applies a simple conceptual definition of gamification that depends on a research focus. From this view, the panels all agreed that to advance the gamification filed, it is imperative to conduct in-depth studies on "what gamification is, why we need it, and how it works" (Schöbel et al., 2020, p. 30). In particular, understanding what gamification is and how it works implies to theorize it as an IT artifact, which would advance the IS field (Grover & Lyytinen, 2015; Orlikowski & Iacono, 2001). In the following this study explores the current understanding of gamification as a construct to unveil its underlying tension.

Gamification as a Construct

A few earlier studies analyzed how gamification as a construct is used in academia and practice (Deterding et al., 2011; Huotari & Hamari, 2017; Koivisto & Hamari, 2019; Liu et al., 2017; Schöbel et al., 2020; Treiblmaier et al., 2018). Reviews on gamification studies identify that different focus of gamification research leads to different conceptual definition of gamification

(Huotari & Hamari, 2017; Schöbel et al., 2020). Some considered gamification from the perspective of outcomes while others considered it from the perspective of systems (Schöbel et al., 2020). These differences enable us to categorize gamification as an IT artifact that is viewed either as a tool or as a proxy. IT artifact as a tool assumes that IT is definable and controllable by human because it is created with a designer's intention in mind to achieve certain outcomes (Orlikowski & Iacono, 2001). On the other hand, IT artifact as a proxy focuses on "one or a few key elements in common that are understood to represent or stand for the essential aspect, property or value of" gamification (Orlikowski & Iacono, 2001, p. 124).

From the tool view, Treiblmaier et al. (2018) went through a systematic process of validating gamification as a construct. They leveraged common wisdom by going through the process of sorting concepts (Moore & Benbasat, 1991). They first identified 23 gamification definitions from the published academic papers, then asked ten varied educational and societal discussants who are put in teams to cluster these concepts (Treiblmaier et al., 2018). The definition derived from this process describes gamification as *"using game-design elements in any non-game system context to increase users' intrinsic and extrinsic motivation, help them to process information, help them to better achieve goals, and/or help them to change their behavior"* (Treiblmaier et al., 2018, p. 134). This definition is reflected in gamification studies that explicate the relationship between gamification and motivation through the lenses of self-determination or goal-setting theories (Ašeriškis & Damaševičius, 2014; Blohm & Leimeister, 2013; Koivisto & Hamari, 2019). Despite the insightful definition of gamification derived from a systematic process, this definition overlooks the significance of being playful or having fun when implementing gamification. Theoretically it makes sense to hide a "fun" or "playful" aspect of gamification under intrinsic motivation. However, this act blurs the line that differentiates the meaning of game like design from the meaning of non-game like design. Numerous studies reported that even non-game like design in information systems are strongly correlated with emotional excitement (Agarwal & Karahanna, 2000; Beaudry & Pinsonneault, 2010; De Guinea & Markus, 2009; Van der Heijden, 2004). Thus, treating gamification as a tool that focuses on the outcomes limits its nuanced understanding. Further, this view enables substituting gamification with any other technology like a black box. This restricts reflecting any changes of the meaning and the usage of gamification. Even the intention and the outcome of gamification becomes part of any IT artifact that is not distinguishable.

From the proxy view, Deterding et al. (2011) defines gamification as *"the use of design elements characteristics for games in non-game contexts"* (p. 13). This conceptual definition distinguishes gamification against games (or serious games) by accentuating parts over whole; and gamification against playful design by accentuating gaming (i.e., structured forms of play bound by rules and goals) over playing (i.e., free forms of play that is open, expressive, and exploratory) (Deterding et al., 2011). This definition is valuable in probing gamification as a system because it creates a reasonable conceptual boundary. Nonetheless, this conceptualization evolves in later years fuzzing out the boundaries between gameful and playful design. The distinction between the two does not seem to matter as long as the main argument remains the same; gamification should relate to "play" and invoke "fun", which is joyful experience (Deterding et al., 2013; Nacke & Deterding, 2017). From this view, gameful design that includes playful design enlarges the potential of gamification. This is because the purpose of gamification does not end in achieving artificially created goals such as obtaining badges and defeating opponents. The main purpose of it lies on achieving the instrumental goals such as completing tasks (Koivisto & Hamari, 2019; Liu et al., 2017). The proxy view of gamification helps identify the most important aspect of this construct, which is eliciting enjoyable user experience. However, the current conceptual definition has been reduced and simplified to an abstract form creating a surplus of interpretations among scholars for the discourse on gamification.

On a positive note, the abstract conceptualization of gamification – the use of game like design in non-gaming contexts (Deterding et al., 2011) – has been adopted and revamped by researchers that take the tool view of IT artifact. As a result, the meaning of gamification expanded as an enabler of motivational information system that aims to increase its utility through experiencing fun (Koivisto & Hamari, 2019). This conceptualization frames gamification as emotionally motivating design that enhances both experiential (e.g., sense of enjoyment) and instrumental (e.g., completing tasks) outcomes (Koivisto & Hamari, 2019; Liu et al., 2017). These outcomes are the analogue of psychological and behavioral outcomes. The mélange of these two outcomes demonstrates how gamification as an IT artifact evolved to include both hedonic and utilitarian views (Baptista & Oliveira, 2019; Koivisto & Hamari, 2019). To illustrate this integrated view, we explain the case of Fitbit, a company that sells wearable devices such as activity trackers. This company uses gamification to enable users not only achieve their tasks (i.e., exercise regularly) but also experience enjoyment and satisfaction. The gamification features used by this company includes but not limited to presenting colorful graphs that show the level of user achievements, calling for challenges with other app users, and rewarding badges when users achieve small tasks.

Integrating the tool view with the proxy view of gamification undoubtedly has improved our understanding of gamification. Liu et al. (2017) defined gamification as *"the incorporation of game design elements into a target system while retaining the target system's instrumental functions"* (Liu et al., 2017, p. 1013). This definition highlights the property of gamification as game design elements and the outcomes as instrumental functions. Koivisto and Hamari (2019) describe gamification as *"designing information systems to afford similar experiences and motivations as games do, and consequently, attempting to affect user behavior"* (p. 191). This definition highlights the property of gamification as games affording similar experience and motivation and the outcomes as affecting user behavior. Nevertheless, the way in which researchers have conceptualized gamification is still too simple. Whether this IT artifact is regarded as a tool or perceived to be measured as a proxy, both views take a stance that gamification is *"single, seamless, stable and the same every time and everywhere"* (Orlikowski & Iacono, 2001, p. 131). This rigid view may attribute to the systematic reviews on gamification (Koivisto & Hamari, 2019; Liu et al., 2017; Schöbel et al., 2020) to find inconsistent results and lack of theoretical arguments in empirical studies.

To overcome the simplistic conceptual definition of gamification that either takes a tool or proxy view, this study applies an ensemble view. This view considers IT artifact as an assembly of components that extends the meaning of technology by adapting factors relevant to socio-economic activity (Orlikowski & Iacono, 2001). For instance, technology can be represented as a development project, production network, embedded system or structure (Orlikowski & Iacono, 2001). Following this logic, this study considers gamification as a structure "*in which technology is enmeshed in the conditions of its use"* (Orlikowski & Iacono, 2001, p. 127). To explicate gamification as such, this research analyzes gamification as a multidimensional construct applying the framework of typology to better understand how gamification comes to be and to be used. More specifically, this study conceptualizes gamification by integrating playfulness of the technologies and seriousness of the tasks. Based on the configuration of these subdimensions this study proposes six ideal types that may maximize user engagement on digital platforms. Thus, we explicitly theorize gamification as an IT artifact, instead of taking it for granted. This enables us to understand *"the meanings, capabilities and uses of IT artifacts, their multiple, emergent, and dynamic properties, as well as the recursive transformations occurring in the various social worlds in which they are embedded*" (Orlikowski & Iacono, 2001, p. 133). Based on our discussion, we define gamification as *the use of gamified design in information systems that assimilates the playful experience of games into non-gaming contexts to achieve instrumental outcomes*. This definition synthesizes conceptual definitions established based on tool and proxy views. This definition is explicated further as a multidimensional construct to reflect the ensemble view that takes into consideration of how this construct is situated in its use.

User Engagement as Gamification Outcome

User engagement is a term widely used in both academia and practice to describe user experience relevant to information systems in digital era (O'Brien, 2016). This construct has been conceptualized and operationalized in various ways depending on the theoretical stance of the research (O'Brien, 2016). Research in the IS field has considered user engagement as a context specific measurement that shows frequency and intensity of system use such as the number of posted comments, likes, shares, click-throughs as well as user efforts and contribution (Chen et al., 2018; Goes et al., 2016; Gu et al., 2022; Lee et al., 2018; Zhang et al., 2019). Research in Human-Computer Interaction (HCI) has conceptualized user engagement as a process of engagement that changes over time through the experience that touches upon emotion, cognition and behaviors of users (O'Brien & Toms, 2008). This understanding is echoed in the marketing research where user engagement is perceived as an analogue of customer engagement. Customer engagement is found to be a multidimensional construct that has both psychological and behavioral concerns accompanied by specific outcomes that may have economic implications (Brodie et al., 2011; Gu et al., 2022). Synthesizing the discourse of the prior literature, this study defines user engagement as *user cognitive, emotional, and behavioral interaction with information systems bound with its frequency and intensity*.

As the outcome of gamification, studies conceptualize and operationalize user engagement in various ways depending on the focus of the studies and their contextual boundaries. Some gamification studies explain user engagement as the path from psychological to behavioral outcomes (Koivisto & Hamari, 2019). Others describe it as meaningful engagement to accentuate simultaneous achievement of both experiential (e.g., sense of enjoyment and satisfaction) and instrumental outcomes (Liu et al., 2017). Either way, user engagement has been studied often in relation to gamification to describe and explain the effectiveness of gamification in empirical analyses (Koivisto & Hamari, 2019). For instance, prior studies examined the impact of gamification on user engagement as cognitive absorption (Santhanam et al., 2016), user responses (Burtch et al., 2018; Huang et al., 2019), improved learning (Bai et al., 2021; Landers et al., 2017; Leung et al., 2022), user contributions (Chen et al., 2018; Goes et al., 2016; Liu et al., 2022; Wang et al., 2020), and weight loss (Bojd et al., 2022).

Theoretical Model Development

Before introducing our theoretical model, we state our underlying assumptions to set the boundary conditions (Busse et al., 2017; Rivard, 2014). First, we consider gamification as a design strategy applied on digital platforms to enhance user engagement. Second, we view gamification as a multi-dimensional construct made up of two subdimensions – technology playfulness and task seriousness. Third, we assume that the technology playfulness and task seriousness are orthogonal, so the degree of each variable is assumed to exist independent of each other. Fourth, we build our theory through the lens of task-technology fit applied in gamification design principles (Liu et al., 2017). Fifth, we develop our research model using typology as a theory, which guides to create *"conceptually derived interrelated sets of ideal types"* (Doty & Glick, 1994, p. 232) of gamification that have a positive impact on user engagement.

In the following we first describe the type of theory that we aim to develop, then explain the key elements of our theoretical model – technology playfulness and task seriousness. This is followed by creating a typology of gamification that is comprised of six ideal types that may positively affect user engagement on digital platforms.

Typology Theory

Typology is a way of constructing a concept using theory-driven arguments. Doty and Glick (1994) describe typology as "conceptually derived interrelated sets of ideal types" (p. 232) that show a unique combination of attributes that may have impact on the relevant outcomes. From this perspective, we consider typology a theory as it explains and predicts the causal relationship between the main construct and the outcome variable. However, unlike a typical theory that focuses on the relationship between independent and dependent variables, typology focuses on theorizing the main construct that is multidimensional and unique. The constructed ideal types are non-exhaustive nor mutually exclusive, but still, they have clear implication to their outcome variable (Doty & Glick, 1994). These characteristics differentiate typology from classification or taxonomy, which are "classification systems that categorize phenomena into mutually exclusive and exhaustive sets with a series or discrete decisions rules" (Doty & Glick, 1994, p. 232). Unlike typology these classification systems do not have the implication to a dependent variable.

We use typology to establish a parsimonious theoretical framework that describes the forms of gamification and their causal relationship with user engagement that enables empirical testing. In terms of forms, gamification is theorized to have interrelated sets of ideal types that are comprised of a unique combination of first-order constructs – technology playfulness and task seriousness. These ideal types are non-exhaustive nor mutually exclusive because they represent theory-driven types not the categories (Doty & Glick, 1994). In terms of casual relationship, the identified forms of gamification are theorized to explain and predict user engagement. This causal relationship differentiates typology from classifications or taxonomies (Doty & Glick, 1994).

Applying typology as a theoretical framework has an advantage of clarifying the conceptual definition of an IT artifact (i.e., gamification). Researchers have argued theorizing IT artifacts is indispensable to advance the discourse of IT and IS research (Grover & Lyytinen, 2015; Orlikowski & Iacono, 2001). Grover and Lyytinen (2015), for example, shed light on the potential of developing new theories when explicating competing reference theories and assumptions within poorly developed IT artifacts. Accordingly, they suggest developing and advancing *"contextual theories and sound typologies of IT and information"* (Grover & Lyytinen, 2015, p. 287). In the IS field, collective IS use has been explicated using typology, which conceptualized the emergent process of individual-level task, user and system interdependence (Negoita et al., 2018). Similarly, obsessive technology use has been theorized using typology in which the ideal types have been contextualized in the online social gaming setting (Gong et al., 2021). Therefore, we apply typology to conceptualize gamification in the hope that it will advance the discourse on gamification. An in-depth analysis of gamification as an IT artifact answers the concern of needing to develop theory-driven research, which is often raised in the reviews on gamification studies (Koivisto & Hamari, 2019; Liu et al., 2017; Nacke & Deterding, 2017). Disentangling the two competing assumptions of gamification - useful and playful - may yield new theories that would advance the discourse on gamification.

Technology Playfulness

Playfulness is a concept studied in relation to information systems over 30 years tracing back to 90s. Webster and Martocchio (1992) defined microcomputer playfulness as a situation-specific trait of individuals that describes *"the degree of cognitive spontaneity in microcomputer interactions"* (p.201). This motivational trait describes spontaneous, inventive, and imaginative tendency of individuals when interacting with information systems (Webster & Martocchio, 1992). This concept accentuated intellectual playfulness of adults (Barnett, 1991; Lieberman, 1977). However, over time microcomputer playfulness has evolved by applying the concept of flow (Nakamura & Csikszentmihalyi, 2014). Flow describes the state wherein individuals are completely absorbed to the activities that they are involved in (Nakamura & Csikszentmihalyi, 2009, 2014). This construct cannot be explained with rational reasonings as it is not motivational or intentional. Thus, applying this concept to cognitive spontaneity enabled researchers to shed light on a state of playfulness. For instance, flow was applied as a measure of playfulness to capture a state of playful and exploratory experience (Webster et al., 1993). Others developed new constructs and models such as cognitive absorption *"as a state of deep involvement with software"* (Agarwal & Karahanna, 2000, p. 673) and an integrative model of playfulness that combines playful trait and flow state that has time bound emotional arousal stemming from optimal challenges and enjoyment (Woszczynski et al., 2002). The development of playfulness in the IS field shows that our understanding of playfulness has evolved to consider not only the trait to but also the state of individuals.

In gamification research, playfulness has been either implied or actively excluded. Studies that implied playfulness discussed it in relation to motivation by emphasizing the mediating role of experiencing enjoyment to achieve utilitarian outcomes (Hamari, 2013; Koivisto & Hamari, 2019). This view is actively reflected in the meaningful engagement, which describes achieving both experiential and instrumental outcomes (Liu et al., 2017). Experiential outcomes refer to emotional satisfaction such as perceived enjoyment while instrumental outcomes refer to practical goals (Liu et al., 2017). These studies draw meaningful insight of playfulness by highlighting the psychological aspect of human in relation to gamification. On the other hand, studies that actively excluded playfulness emphasized that gamification is not about playing - a free form of play that is exploratory. This argument accentuates gaming (as opposed to playing) that is a structured form of play typically governed by predetermined rules and goals (Deterding et al., 2011; McGonigal, 2015). This approach argues that playing misses the core aspect of gaming and signals games to be childlike (i.e., not serious). However, we argue that gamification is different to games in that the context in hand (i.e., tasks) is outside of a game universe. Thus, following the game rules may or may not be effective for achieving those tasks. Further, these tasks are likely to already have their own rules stemming from relevant reality. Thus, providing additional layers of rules may backfire their effectiveness. From this point of view, technology playfulness in gamification should include both free and structured forms of play given the focus of gamification is to bring joyful experience. Regardless of the stance, evoking joyful experience in non-gaming context seems to be the common understanding of the role of gamification.

By synthesizing prior research, we define technology playfulness as *the degree of spontaneity evoked by the play structure of information systems*. What this conceptualization suggests is that the degree of technology playfulness describes the scale that moves from playful (i.e., free form play that is open, expressive, and exploratory) to gameful (i.e., structured play bound by rules and goals) design. To develop this subdimension of gamification, we first clarify the conceptual boundary. We consider gamification research as the study of designing information systems that motivate users to achieve both experiential and instrumental outcomes (Koivisto & Hamari, 2019; Liu et al., 2017). Then, we use the accumulated knowledge of playfulness from the IS field in which it accentuates immersive experience and emotion such as flow (Agarwal & Karahanna, 2000; Webster & Martocchio, 1992; Webster et al., 1993; Woszczynski et al., 2002). We apply this knowledge to the conceptualization of gamification of Deterding et al. (2011). Then, we expand the scope of gamification to include both gameful and playful design as part of playfulness. To sum up, we consider technology playfulness as a trait of technologies in gamification that evokes a state of playfulness. Higher degree of technology playfulness indicates more playful design (i.e., free form play that is open, expressive, and exploratory) while the lower degree of technology playfulness indicates more gameful design (i.e., structured form play bound by rules and goals) (Deterding et al., 2011).

The definition of technology playfulness enables us to distinguish gamification that has explicit and clear rules such as leaderboard system from exploratory and free formed design such as avatar system. With this conceptualization, we can interpret gamification with a nuanced understanding. For instance, we can think of a badge rewarding system as gamification applied in an online community where users are freely exchanging their opinions. In this case, the technology playfulness describes the degree that this gamification enables emotional excitement and enjoyment of the users that is bound by certain rules that exist only within the universe of the referred online community. Table 1 summarizes our discussion on the different degrees of technology playfulness. On the third column of the table, we use a continuum scale to showcase gamification elements identified in the gamification literature (Koivisto & Hamari, 2019) from being playful to being gameful.

Technology Playfulness	**Description**	**Gamification Elements**
Playful	Free forms of play that are spontaneous, inventive, and imaginative	Avatar, character, virtual identity Virtual world, 3D world, game world, simulation Narration, storytelling, dialogues, theme Social networking features, multiplayer, role play Assistance, virtual helpers Motion tracking Reminders, cues, notifications, annotations Progress, status bars, skill trees Assistance, virtual helpers Warnings
Gameful	Structured forms of play that are rule bound, less inventive, and specific	Check-ins Quizzes, questions Timer, speed Health points, health Collective voting Challenges, quests, missions, tasks, clear goal Points, score, XP Badges, achievements, medals, trophies Leaderboards, ranking, levels Real world or in-game rewards (virtual currency)

Table 1 Gamification Technology Playfulness

Task Seriousness

In gamification research, tasks are rarely analyzed (Liu et al., 2017). They are generally described as given within the context of the research setting. For instance, some of the tasks described in gamification studies include asking and answering questions to increase online contribution (Goes et al., 2016), conducting self-regulated learning activities to enhance online learning (Leung et al., 2022), leaving reviews and votes to signal competent reviewers (Wang et al., 2020), participating in challenges to lose weight (Bojd et al., 2022) and participating in challenges to increase healthy behaviors (Liu et al., 2022). Among these studies Bojd et al. (2022) paid attention to different tasks for losing weight and found that gamification such as leaderboards that induce social comparison may have different effects on physical activity and dietary activity. They explained the main difference of these two tasks are the underlying motivational mechanisms where physical activity is intrinsically motivated while dietary activity is extrinsically motivated (Bojd et al., 2022). Although insightful, this attribute of tasks relies on prior empirical analysis. Thus, it is not suitable for our study since we cover broader range of contexts beyond weight-loss community.

To enrich our understanding of tasks in gamification we conceptualize tasks as serious matters that pertain complexity owing to the number of users involved in tasks and their interdependence owing to the structure of goals and rewards of tasks. Tasks are typically explained by their outcomes and their inputs (e.g., required acts and the information cues created during this process) (Campbell, 1988; Wood, 1986). Some describe tasks as the "*networks of events, where an event is an action performed by some actor at some moment in time"* (Hærem et al., 2015, p. 452). Given this understanding, tasks become more complex as more actors are included and related to the events. This is because information cues are generated by the events, which exponentiate the number of paths toward achieving the task outcomes (Hærem et al., 2015) In other words, increased users and their interdependence in tasks increases the number of steps required to complete a task (i.e., component complexity), the interdependence between those steps (i.e., coordinative complexity) and their dynamics (Wood, 1986).

For example, in the educational domain, the degree of task complexity differs between individual assignments and group activities. Individual assignments require only one actor that needs to follow clearly defined linear steps that create information cues that are followed by the same actor. On the other hand, group activities involve multiple actors that take reciprocal steps that create information cues that may affect other actors' actions. The difference in complexity would require different degrees of nudges (i.e., gamification in our study), which would change user cognitive, emotional, and behavioral interaction with information systems bound with its frequency and intensity (i.e., degree of user engagement). Consequently, as user interdependence increases in tasks more serious the tasks. We label this as task seriousness to indicate that the impact of a task becomes more serious as user interdependence increases.

We formally define task seriousness as *the degree of network of events shaped by the user interdependent structure within a task.* We use this as a subdimension of gamification and divide it into three levels through two steps. First, we consider the number of actors of a task either one or multiple. The task that requires multiple actors is relatively complex compared to the task that requires only one actor (Campbell, 1988; Hærem et al., 2015; Wood, 1986). Then, we consider user interdependence to further divide the task with multiple actors. We apply user interdependence conceptualized in collective IS use, which explains that the degree of interdependence changes depending on the goals and reward structure (Negoita et al., 2018). When individual goals and rewards are accentuated, the user interdependence is low because individuals will focus on their achievements while working for a group task (Negoita et al., 2018). On the other hand, when the goals and rewards are determined by the group work, the user interdependence is high because individuals will be dependent of the actors involved in the task (Negoita et al., 2018). From this, we can infer that when a task involves multiple actors working for a collaborative task for collaborative rewards, the user interdependence will be high because there will be increased number of acts required (i.e., component complexity), interdependence among those acts (i.e., coordinative complexity), and information cues to process among the involved actors (Hærem et al., 2015). Table 2 summarizes the three level of task seriousness.

Task Seriousness	Description	Examples
Very high	Tasks with high network of events (i.e., include multiple actors) that require high user interdependence	Cooperative tasks that require coordination among members - Generating ideas to create a logo for organizations, Online discussions
High	Tasks with high network of events (i.e., include multiple actors) that require low user interdependence	Cooperative tasks that underscore individual competence by identifying individual goals and rewards
Low	Tasks with low network of events (i.e., include only one actor) that require no user interdependence	Individual tasks carried out independent of others - Learning a language, Exercising

Table 2 Gamification Task Seriousness

A Typology of Gamification

We propose a typology of gamification that integrates the degree of technology playfulness and the degree of task seriousness. We use the framework of task-technology fit (Goodhue & Thompson, 1995; Zigurs & Buckland, 1998) to create and evaluate ideal types of gamifications. The use of this framework is justified following a general gamification design principle that suggests *"game design elements incorporated in a target system must match the intended purpose of the system"* (Liu et al., 2017, p. 1018). Among various gamification design principles derived from Liu et al. (2017), we focus on the task congruence principle. This principle emphasizes the importance of the complementarity between the task and the gamification design elements. For example, when a task requires large amount of feedback, the gamification design should be able to provide this. This principle suggests that the gamification design and the task characteristics (e.g., a knowledge-sharing task or a weight-loss task) must be matched (Liu et al., 2017).

There are couple of reasons for choosing this particular gamification principle for our study. The focus of our study is the design of gamified system, so task congruence principle (Liu et al., 2017) falls into the boundary of our discussion. Further, our study assumes that users are inseparable from tasks, so we analyze the practice emerging from the interactions between the two (i.e., tasks and users) rather than focusing on personalizing the gamification design. Finally, we use the term technology very broadly that includes gamification as part of information systems. We take this broad view because our conceptualization focuses on creating abstract ideal profiles of gamification through the lens of task-technology fit. Thus, we do not concern about identifying granular variables through technology affordance that affect the probability distribution of user engagement.

According to Doty and Glick (1994) there are two ways of specifying ideal types – theoretical approach and empirical approach. We take a hybrid approach that combines both theoretical and empirical approaches to create gamification ideal types since it is relatively a nascent topic. Studying new topics creates some concerns as theoretical understanding may overlook common practices of gamification. With regards to the theoretical approach, we reviewed the extent gamification literature to better understand how researchers have described gamification (refer to the "gamification as a construct" under the section of theoretical background and literature review). Then, we derived two important concepts for gamification - technology playfulness and task seriousness – which we have combined and analyzed through the lens of task-technology fit (Goodhue & Thompson, 1995; Zigurs & Buckland, 1998). With regards to the practical approach, we investigated organizations that successfully engaged users in their platforms of which applied a few to many gamification elements. We identified some of the tasks that they try to achieve along with the applied gamification elements (refer to Appendix A. Various Tasks and Gamification Applied on Digital Platforms). Through this process, we identified emerging patterns from empirical evidence that approximate theoretical ideal types that may maximize user engagement as shown in Figure 1.

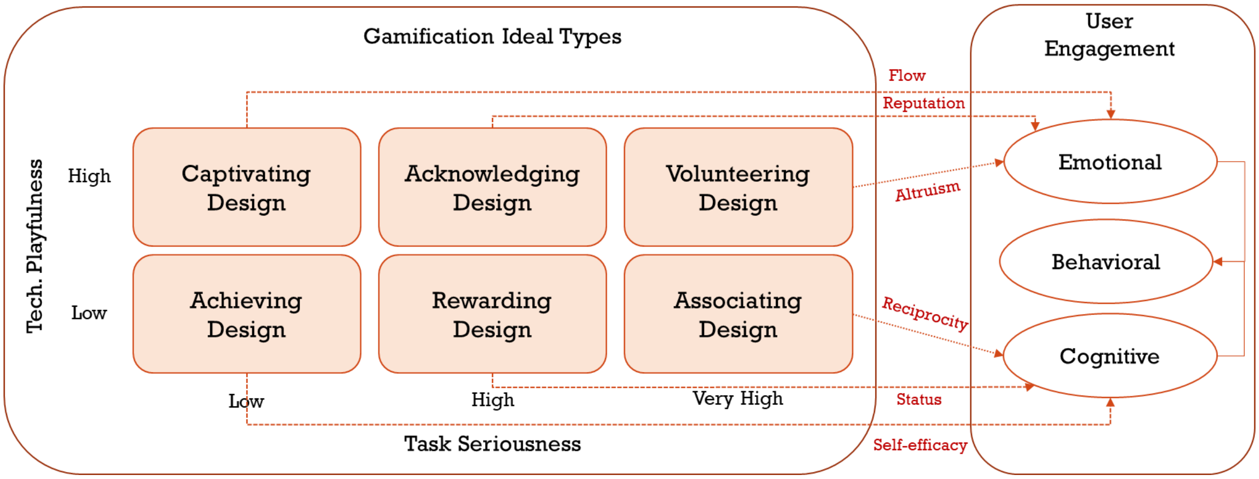

Figure 1 Six Ideal Types of Gamification Design

Table 3 shows six ideal types of gamifications with detailed explanations. The first column shows the label of each ideal type. The second and third columns show the degree of the subdimensions that constitute the ideal types (i.e., technology playfulness and the task seriousness). The fourth column shows the main effect of the dependent variable (i.e., user engagement), and the sixth column provides a brief explanation of each ideal type.

Ideal Types	Technology Playfulness	Task Seriousness	User Engagement	Explanation
Volunteering Design	High	Very High	Emotional and Behavioral Effects	This gamification design is suitable for the seekers of **altruism** who are happy to help others in a collaborative environment without expecting anything in return. Thus, providing a way to show that they are happy to help through communicative tools (e.g., avatar, messaging, social networking features, etc.) would increase enjoyable experience.
Acknowledging Design	High	High	Emotional and	This gamification design is suitable for the seekers of **reputation** who are sensitive to

			Behavioral Effects	what others thinks about them. Thus, providing a way to show their achievements (e.g., badges, avatar, points, etc.) would increase enjoyment.
Captivating Design	High	Low	Emotional and Behavioral Effects	This gamification design is suitable for the seekers of **flow** who are happy to be immersed to what they are doing. Thus, providing gamification such as narrative, story building, and virtual world would increase enjoyable experience.
Associating Design	Low	Very High	Cognitive and Behavioral Effects	This gamification design is suitable for the seekers of **reciprocity** who put great value on fairness. Thus, providing a clear structure and rules in a collaborative environment such as team leaderboards and points would increase enjoyable experience.
Rewarding Design	Low	High	Cognitive and Behavioral Effects	This gamification design is suitable for the seekers of **status in social hierarchy**, who put great value on being at higher positions than others. Thus, providing a clear structure in a competitive environment would increase enjoyable experience such as leaderboard, ranks etc.
Achieving Design	Low	Low	Cognitive and Behavioral Effects	This gamification design is suitable for the seekers of increased **self-efficacy**. Thus, providing clear feedback and structured forms of play would help them move forward such as progress bar, missions, badges etc.

Table 3 A Typology of Gamification with Explanation

Volunteering design refers to the type of design that has high degree of playfulness and very high degree of task seriousness. The idea of this gamification design is to create a digital environment that induces spontaneous, explorative, and imaginative experience to the users who are involved in a collaborative task with high user interdependence. In terms of tasks seriousness, individuals use a shared platform where their task is shared among multiple users in which their achievements are dependent of others' actions. In terms of technology playfulness, the design of this gamification type does not impose strict rules or structure of games but encourages excitement and enjoyment through free forms of play such as vibrant colors and design, virtual identities (like avatars) and objects, multiplayer environment, and animated messaging tools.

This ideal type would be particularly helpful for those who value altruistic motives to engage in digital platforms. For example, Stack Exchange is an online Questions and Answers (Q&A) platform that provides an online space for people to ask questions and find answers[6]. This website is run by voluntary contributors who are willing to share their time and knowledge for strangers without any financial compensation. Researchers have wondered how and why the voluntary engagement occurs in online platforms (Bateman et al., 2011; Chen et al., 2018; Goes et al., 2016; Huang et al., 2019; Ma & Agarwal, 2007; Von Krogh et al., 2012; Wasko & Faraj, 2005). Some researchers suggested that altruism is human nature (Fehr & Fischbacher, 2003; Feigin et al., 2014; Von Krogh et al., 2012) and thus voluntary engagement in online communities should be understood as a social practice where ethics and virtue play important roles (Von Krogh et al., 2012). From this perspective, the volunteering design would work best for the seekers who are happy to help others in a collaborative environment without expecting anything in return. Thus,

[6] For further information on Stack Exchange refer to https://stackexchange.com/about

providing a way to show that they are pleased to collaborate (e.g., easy communicative tools such as avatar, messaging, social networking features etc.) would likely to increase enjoyable experience, and subsequently the user engagement on digital platforms.

Acknowledging design refers to the type of design that has high degree of playfulness and high degree of task seriousness. The idea of this gamification design is to create a digital environment that induces spontaneous, explorative, and imaginative experience to the users who are involved in a collaborative task with low user interdependence. In terms of tasks seriousness, individuals use a shared platform where their task is shared among multiple users, but their rewards are not dependent of others' actions and their actions are recognized at the individual level rather than be hidden at the collective level. In terms of technology playfulness, like the volunteering design type, the acknowledging design type does not impose strict rules or structure but encourages excitement and enjoyment through free forms of play. However, the examples of gamification elements included in this ideal type would be more specific such as vibrant colors and design of badges, virtual identities (like avatars) and objects that can be highlighted by votes or points, and multiplayer environment that accentuates individual achievements.

This ideal type would be particularly helpful for those who find reputation as their motivation to engage in digital platforms. Researchers have constantly found that reputation is an effective motivation for knowledge contribution in online communities (Chen et al., 2018; Wasko & Faraj, 2005). Some researchers explain reputation as a way to get peer-recognition (Chen et al., 2018), to present self-image (Chen et al., 2018; Ma & Agarwal, 2007) and to signal competence (Wang et al., 2020). Others consider reputation as the evolutionary origins that signals trustworthiness of individuals (Fehr & Fischbacher, 2003; Gross & De Dreu, 2019). Illustrating this point, Stack

Overflow, a Q&A platform often studied in academia, uses “reputation score” as an optional function to “roughly measure how much the community trusts you”[7]. Users can earn reputation scores by receiving votes from others for their questions, answers, and edits. The rules for voting up is straightforward and not stringent, allowing users to simply vote if they like any questions, answers, and edits. Although greater reputation scores unlock other privileges that can be used in this online space, the main attraction of the reputation score is reputation. Similar types of scores can be found in sharing economy (e.g., Uber driver ratings) and review websites (e.g., TripAdvisor helpful votes). From this perspective, the acknowledging design would work best for the reputation seekers who are concerned about what others think about them. Thus, providing a way to show their achievements or their self-image (e.g., badges, avatar, votes, etc.) may increase enjoyment, and eventually the user engagement on digital platforms.

Captivating design refers to the type of design that has high degree of playfulness and low degree of task seriousness. The idea of this gamification design is to create a digital environment that induces immersive experience to the users who are involved in individual tasks. In terms of tasks seriousness, individuals use a shared platform where their tasks are achieved by themselves. In terms of technology playfulness, like the previous two design types, the captivating design type does not impose strict rules or structure but encourages excitement and enjoyment through free forms of play. This type of gamification is geared toward individuals who are happy to be absorbed to what they are doing. Researchers extensively have studied about the positive aspect of flow state when using information systems (Agarwal & Karahanna, 2000; Nakamura & Csikszentmihalyi,

[7] For further information on reputation score used in Stack Overflow refer to https://stackoverflow.com/help/whats-reputation

2009; Webster et al., 1993), and highlighted the value of emotion and feelings to explain the outcomes that go beyond the rationally calculated behaviors (De Guinea & Markus, 2009).

This ideal type would be particularly helpful for those who seek for immersive experience to engage in digital platforms. For example, Duolingo, a language learning platform, uses playful characters and a mascot to captivate users[8] for a self-directed journey of learning a language. The mascot of this platform, Duo the owl, is used to remind users of various activities and news such as regular exercises, receiving bonuses, unlocking new stories, and checking current progress. Further, this platform uses Duo the owl and other several friendly characters to be present on each page of exercise so that translating a sentence, filling in the blanks, or finding the right words can be encouraged and celebrated by the animated characters. This creates a sense of being part of a community even though the task is done by an individual, and these characters are just objects that are part of the design. From this perspective, the captivating design would work best for the seekers of flow who are happy to be immersed to what they are doing. Thus, providing gamification such as narrative, story building, and virtual world would likely to increase enjoyable experience, which would lead to increased user engagement on digital platforms.

Associating design refers to the type of design that has low degree of playfulness and very high degree of task seriousness. The idea of this gamification design is to create a digital environment that brings enjoyable experience shaped by the structured forms of play to the users who are involved in a collaborative task with high user interdependence. In terms of tasks seriousness, individuals use a shared platform where their task is shared among multiple users in which their achievements are dependent of others' actions. In terms of technology playfulness, the design of

[8] For further information on Duolingo refer to https://www.duolingo.com/

this gamification type imposes rules and structure of games to encourage excitement and enjoyment through gamification elements such as team leaderboards, challenges and missions for multiplayer environment, and progress based on team points.

This ideal type would be particularly helpful for those who put great value on reciprocity. Reciprocity describes the behaviors in response to perceived kindness and unkindness, which are conditioned by fairness and fairness intentions (Falk & Fischbacher, 2006). Researchers found that reciprocity plays an important role to transfer user motivation from low to medium in online communities (Chen et al., 2018). In the context of health digital platforms, reciprocity significantly increases the amount of exercise performed by users compared to the users incentivized by their self-interest (Liu et al., 2022). Given the appreciation of fairness in reciprocity, using gamification that implements clear and fair rules and a strong sense of online community would benefit collaborative work performed online. For instance, Kaggle, an online community for data science and machine learning, launches regular team competitions to solve problems using given data set[9]. This platform provides challenges with clear guidelines and rules in which they are evaluated. It also provides easy to use discussion boards where users can freely upvote comments. Finally, but not least, their leaderboards are designed to inform users with not only immediate feedback (i.e., public leaderboard) but also final evaluation scores of their solutions at the end of the competition (i.e., private leaderboard). The two-tier leaderboards system encourages teams to find the model with best accuracy but at the same time discourages teams to overfit the sample data. This system increases the fairness of evaluation for the submitted project. All these gamification elements are geared toward fairness in using the platform and competing as a team, so encourage users to

[9] For further information on Kaggle refer to https://www.kaggle.com/

collaborate while achieving both experiential (i.e., have fun) and instrumental outcomes (e.g., improve machine learning skills, win Kaggle merchandises, sponsor appreciation, and financial prizes). From this perspective, the associating design would work best for the seekers who cherish fairness in performing their tasks. Thus, providing a way to show feedback of collective achievement (e.g., team leaderboards, collective progress bars etc.), or ways to appreciate fairness (e.g., badges and points, online discussion boards with votes etc.) may increase enjoyment, and consequently user engagement on digital platforms.

Rewarding design refers to the type of design that has low degree of playfulness and high degree of task seriousness. The idea of this gamification design is to create a digital environment that brings enjoyable experience shaped by the structured forms of play to the users who are involved in a collaborative task with low user interdependence. In terms of tasks seriousness, individuals use a shared platform where their task is shared among multiple users, but their achievements are recognized independently. In terms of technology playfulness, the design of this gamification type imposes rules and structure of games to encourage excitement and enjoyment through gamification elements such as leaderboards, ranks, points, badges, and individual missions.

This ideal type would be particularly helpful for those who seek for status in social hierarchy as their motivation to engage in digital platforms. Status hierarchy is an agreed upon rank order of individuals or groups by the amount of respect (Magee & Galinsky, 2008). This nature makes individuals to yearn for obtaining higher status as they are perceived as competence (Magee & Galinsky, 2008). In gamification literature, researchers have studied status in relation to incentive hierarchy in which predefined milestones create artificial status that extrinsically motivate users to engage in digital platforms (Goes et al., 2016; Wang et al., 2020). For instance, a typical badge rewarding system uses different levels of badges (e.g., gold, silver, copper badges) as artificially created status that are valued within specific online communities (Goes et al., 2016; Von Rechenberg et al., 2016). These badges do not convey any practical value outside of the given communities, but peers recognize them and confer respect. From this perspective, the rewarding design would work best for those who value status even in an artificially created community. These users are likely to put great value on being at higher positions than others in terms of incentive hierarchy. Thus, providing a way to achieve the status that they want to be at through a clear competitive structure (e.g., leaderboards, ranks, badges etc.) would increase enjoyable experience, and subsequently the user engagement on digital platforms.

Achieving design refers to the type of design that has low degree of playfulness and low degree of task seriousness. The idea of this gamification design is to create a digital environment that brings joy to the individual tasks through structured forms of play. In terms of tasks seriousness, individuals use a shared platform where their tasks are achieved independent of others. In terms of technology playfulness, this design imposes strict rules or structure to encourages excitement and enjoyment such as daily goals, progress bars, missions, badges and personalized leaderboards.

This ideal type would be particularly helpful for those who value self-efficacy as motivation to perform their tasks through engaging in digital platforms. Self-efficacy concerns with *"judgments of how well one can execute courses of action required to deal with prospective situations"* (Bandura, 1982, p. 122). This notion differs from having the intention or knowledge of what to do but emphasizes on the generative nature of capability (i.e., cognitive, social, and behavioral skills) that manifests as integrative courses of actions, which are found to increase the performance accomplishments (Bandura, 1982). Thus, the type of gamification that achieving design proposes is geared toward increasing perceived self-efficacy. Duolingo, a language learning app, uses various gamification elements that support users to increase their self-efficacy. For instance, Duolingo enables users to set goals such as visiting the app every day to do lessons for 30 consecutive days. Setting the goal helps users to control their prospective situation. Further, each time that the daily goal is achieved, the app marks the accomplishment very clearly by marking the day in a calendar. This allows users to have positive self-appraisal of operative capabilities. Another gamification feature that helps increasing self-efficacy is “streak freeze”. This feature enables users to miss a day if needed, thus giving a possibility of dealing with unforeseen circumstances (i.e., missing a day due to busy schedule). From this perspective, the achieving design would work best for the seekers of increased self-efficacy. Thus, providing a clear structure that enables users to self-control their tasks in the given environment or to positively assess their capabilities would likely to increase enjoyable experience, and consequently the user engagement on digital platforms.

Summary and Caveat

We identified and explained six ideal types of gamifications. Each of them demonstrates the unique combination of different degrees of technology playfulness and task seriousness. These ideal types are built upon theoretical arguments and supported by the approximation of the real examples. It is noteworthy that they are not mutually exclusive nor mutually exhaustive. Further, some types may exist, but some may not because these are theoretically derived ideal profiles that may maximize user engagement on digital platforms.

To conclude we make couple of inferences about the relationship between ideal types and user engagement on digital platforms. Intuitively, as a task gets more complex and has greater user interdependence (i.e., higher degree of task seriousness), aligning it with higher degree of technology playfulness would be more impactful on user engagement. This is because when users perform a complex task with high user interdependence, they use high cognitive efforts. Thus, aligning with free forms of play, which has close to no structure, would reduce cognitive overload (Kirsh, 2000) compared to aligning with structured forms of play. On the other hand, for a task that is relatively simple that only involves one actor, aligning the task with the lower level of technology playfulness would be more effective. This is because structured forms of play would make the task more challenging, so increases user efforts to engage in the activities (Nakamura & Csikszentmihalyi, 2014; Santhanam et al., 2016). Therefore, we infer that volunteering, acknowledging, and achieving design may have greater task-technology fit to increase user engagement compared to the fit of the associating, rewarding, and captivating design as shown in Figure 2.

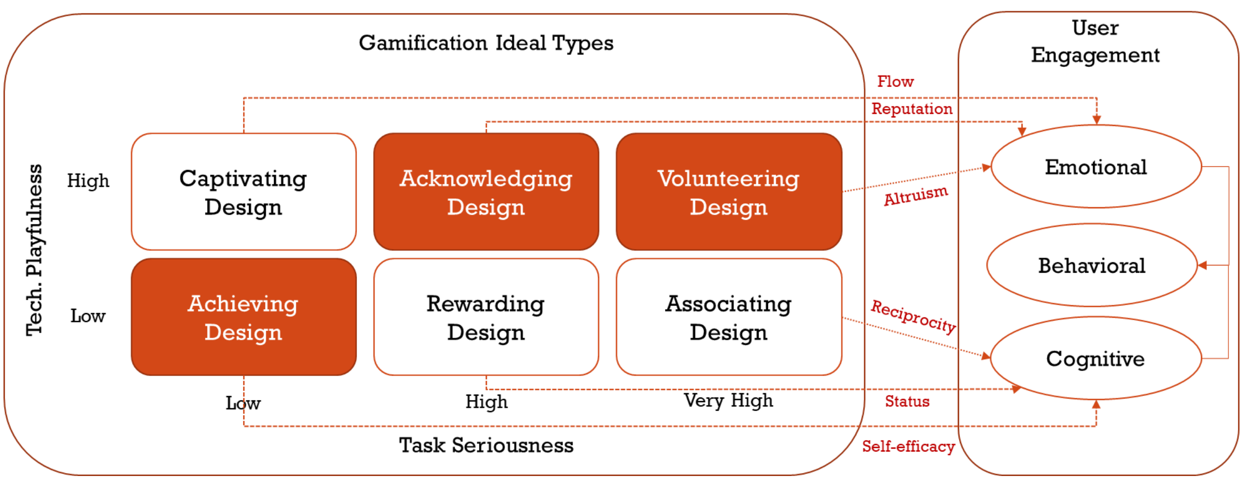

Figure 2 Impact of Cognitive Overload on Ideal Types

However, this inference needs cautious interpretation as each user is unique. Gamification studies have underlined the importance of individual differences (Klock et al., 2020; Leung et al., 2022; Liu et al., 2017) and discussed player types as a considerable factor to create personalized gamification (Hamari & Tuunanen, 2014; Klock et al., 2020). Further, individuals pertain various social values that manifest as either pro-social or prof-self behaviors when interacting with others (Balliet et al., 2009). The diversity of users means that it is not possible to pinpoint the most impactful ideal types, especially when types are abstract. However, the value of typology comes from identifying the ideal patterns derived from theories and evidence. Thus, our typology provides a guidance to create an adequate gamification that matches technology playfulness and task seriousness. As a caveat, researchers should account for the different characteristics of users, and organizations should account for the user composition in their digital platforms.

Discussion and Conclusion

This section describes the theoretical contribution of our study. To make our argument as clear as possible, we explain how the eight ions of theory construction (Rivard, 2014) are reflected in this research. The eight elements that make a theory reasonable are clarifying and explaining motivation, definition, erudition, imagination, explanation, presentation, cohesion and contribution (Rivard, 2014). Then, we conclude our discussion by explaining practical contribution and opportunities for future research.

Theoretical Contribution

In terms of motivation, we answer the call for theory driven research in gamification studies (Koivisto & Hamari, 2019; Liu et al., 2017). Our study applies the lens of task-technology fit (Goodhue & Thompson, 1995; Zigurs & Buckland, 1998) that has been reflected in the task congruence principle of gamification (Liu et al., 2017). Through this framework we theorize gamification as a multidimensional construct. In the process of developing subdimensions of gamification – technology playfulness and task seriousness - we use accumulate knowledge on microcomputer playfulness (Agarwal & Karahanna, 2000; Webster & Martocchio, 1992; Webster et al., 1993; Woszczynski et al., 2002) and task complexity (Campbell, 1988; Hærem et al., 2015; Wood, 1986).

Furthermore, one of the motivations of our study is to clarify conceptual definition of gamification. Researchers have emphasized the importance of theorizing IT artifacts to advance the discourse in IS research and developing new theories (Grover & Lyytinen, 2015; Orlikowski & Iacono, 2001; Rivard, 2014). However, gamification researchers lamented that gamification has been described as a simple concept that is dependent on research contexts (Schöbel et al., 2020). Thus, they collectively suggested to conduct in-depth studies on “what gamification is, why we need it, and how it works” (Schöbel et al., 2020, p. 30). Our study uses the framework of typology to answer these concerns. We explain gamification as a multidimensional construct, identify six gamification ideal types that may maximize user engagement, and explain how these ideal types work and why they are needed.

The final motivation of this study is to challenge assumptions made in gamification research. We point out the limitation of excluding playfulness when defining gamification (Deterding et al., 2011), and only focusing on gamification as a tool or proxy. We propose gamification as an ensemble, which considers IT artifact as an assembly of components that extends the meaning of technology by adapting factors relevant to socio-economic activity (Orlikowski & Iacono, 2001). Thus, task-technology fit plays an important foundation to explicate gamification as an IT artifact that includes both gameful and playful design, which is mapped with tasks that are inseparable with users.

In terms of definition, we provide conceptual definitions for all the core constructs used in our study. Gamification is defined as *the use of gamified design in information systems that assimilates the playful experience of games into non-gaming contexts to achieve instrumental outcomes.* We define technology playfulness, one of the subdimensions, as *the degree of spontaneity evoked by the play structure of information systems*. The other subdimension, task seriousness is defined as *the degree of network of events shaped by the user interdependent structure within a task*. Although less discussed, as an important construct in the equation of gamification study, we defined user engagement as *user cognitive, emotional, and behavioral interaction with information systems bound with its frequency and intensity*.

Rivard (2014) explains that definitional clarity means to clarify not only the definitions of constructs but also "the phenomenon of interest, the boundary of the theory and its underlying assumptions, and the type of theory one aims to develop." (p. vi). As clarified at the beginning of the research model development section, we state that our phenomenon of interest is to conceptualize gamification through the lens of task-technology fit. We consider gamification as design strategy applied on digital platforms to enhance user engagement. Further, we view gamification as a multi-dimensional construct made up of two subdimensions – technology playfulness and task seriousness – which are assumed to be orthogonal. Most importantly, our study aims to develop a typology of gamification.

In terms of erudition, our study demonstrates the depth of gamification studies. We synthesize overall gamification research to identify gaps in the conceptual definition of gamification. Then we discuss in-depth gamification as a construct to clarify the scope of our study. We find that gamification as a construct has rarely studied using an ensemble view. This understanding enables us to disentangle the simple construct into a multidimensional construct. We review the literature on microcomputer playfulness and task complexity. This is followed by conceptualizing technology playfulness and task seriousness. These two are configured to create six ideal types of gamifications built upon the framework of task-technology fit.

In terms of imagination, throughout our study we follow one of the heuristics suggested by Jaccard and Jacoby (2019) and introduced by Rivard (2014) to explain the ions of theory construction. This heuristic is to alternate between abstractions and specific instances when creating theories. We illustrate this heuristic by explaining each ideal type (i.e., abstraction) with a real example (i.e., specific instance). For instance, we use Duolingo to explain some of their gamification elements that encourage self-efficacy for a simple task. From this explanation we describe how the achieving design that emerges from the configuration of low technology playfulness and low task seriousness can be realized as an ideal type.

In terms of explanation, our study explains causality by connecting the dots between ideal types and user engagement. Since the focus of this study is creating ideal profiles, the relationships between independent and dependent variables are presented briefly. However, we acknowledge the significance of this relationship because the causality is the raison d'etre of our typology. Thus, we provide couple of theoretical backgrounds for the causal relationships. Firstly, we identify three ideal types - volunteering, acknowledging, and achieving design – to have greater task-technology fit, which may increase user engagement due to decreased cognitive overload (Kirsh, 2000) for complex tasks and increased challenges (Nakamura & Csikszentmihalyi, 2014) for simple tasks. Secondly, we put a caveat on our interpretation because our ideal types are identified to work best for users who value different things when carrying out different types of tasks. Given that each user is unique and holds different social value when interacting with others, we suggest accounting for individual differences when applying this typology of gamification for empirical analysis.

In terms of presentation, our study followed the outline introduced by Rivard (2014) as an ideal type of a theory manuscript. This outline suggests three main sections. Section 1 asks for justifying the study of proposing a new theory based on in-depth analysis of previous thoughts. Our study provides theoretical background and literature review that includes synthesis of gamification research as background, followed by gamification as a construct and user engagement as gamification outcome. Through this process we identify the gaps and clarify the scope of the research. Section 2 asks for explanation of new theoretical development. We devote our efforts to this section by first clarifying our assumptions and describing the type of theory that we aim to develop (i.e., typology). Then, we explain the key elements of our theoretical model – technology playfulness and task seriousness. These dimensions are presented along with figures and tables. Finally, we present a typology of gamification with a table that shows how the two dimensions are combined. The outcome of our conceptualization is six gamification ideal types that may maximize use engagement. These ideal types are volunteering, acknowledging, achieving, associating, rewarding, and captivating design of gamification. They are theorized to best work when users value altruism, reputation, flow, reciprocity, status hierarchy, and self-efficacy, respectively. Finally, section 3 asks for explaining the implication of new theoretical development. For this we use the eight ions of theory construction from motivation to contribution (Rivard, 2014) to discuss in-depth the implications and the theoretical contribution of our study.

In terms of cohesion, this study walks through different ideal types of gamifications using real and imaginative scenarios. Since we build a typology that is not mutually exclusive nor exhaustive, we do not expect to cover all possible scenarios available under the sun. Further, as we are creating ideal types, some types simply may not exist. However, we make sure that our scenarios make sense within the boundary that we set (e.g., cohesion with foundational theories, cohesion between subdimensions and our typology). We provide specific scenarios for different ideal types derived from digital platforms (e.g., Stack Overflow, Kaggle and Duolingo). We provide imaginary scenarios for conceptualizing subdimensions derived from empirical gamification studies.

Finally, and most importantly, in terms of contribution, our theoretical model is novel and different from the previous studies because it conceptualizes gamification as a multidimensional construct that integrates playfulness and seriousness. The degree of playfulness is conceptualized as a characteristic of technology. We take a broad view of technology where the design of information systems is part of technology. The degree of seriousness is conceptualized as a characteristic of tasks in which we combine the concepts of task complexity and user interdependence. Our theoretical model is unique in that we expand the conceptual horizon of gamification by clarifying what it means to be playful outside of games (i.e., free and structured forms of play) while maintaining the purpose of information systems in hand (i.e., performing serious tasks). We take an ensemble view of gamification and explain it as a structure "*in which technology is enmeshed in the conditions of its use"* (Orlikowski & Iacono, 2001, p. 127). A typology of gamification that our study creates configures different sets of technology playfulness and task seriousness. This process enables us to define six gamification ideal types that may maximize user engagement and to better understand how gamification comes to be and to be used. We believe that explicitly theorizing gamification enables us to understand *"the meanings, capabilities and uses of IT artifacts, their multiple, emergent, and dynamic properties, as well as* *the recursive transformations occurring in the various social worlds in which they are embedded*" (Orlikowski & Iacono, 2001, p. 133).

Our work extends and deepens the task congruence principle of gamification design (Liu et al., 2017) derived from the framework of task-technology fit (Goodhue & Thompson, 1995; Zigurs & Buckland, 1998). We concur with the overall idea of the task congruence principle, which posits that *"to be effective, gamification design elements must be congruent with the target task"* (Liu et al., 2017, p. 1019). This principle has laid the groundwork for our study. We further investigate into what it means to focus on a targeted task. Given the diversity of tasks that users perform on digital platforms, we argue simply explaining gamification as being impactful does not take us far in advancing our knowledge on gamification. Although gamification restructures tasks by providing feedback, clear goals, meaningful narratives, and visible social networking (Koivisto & Hamari, 2019), without understanding the nature of tasks we will be uncertain why certain gamification works (or not work). Thus, we develop the notion of tasks being serious as a meaningful characteristic on digital platforms by combining task complexity and user interdependence. Highlighting tasks as a degree of seriousness explain why certain gamification elements would fit or not fit to maximize user engagement.

Our work also extends the conceptual definition provided by Deterding et al. (2011). Their conceptualization has been well received but with some limitations because the concept draws the line between gameful (i.e., structured forms of play) and playful design (i.e., free forms of play). We argue that playful design is also part of gamification by connecting the construct developed and successfully used in information systems – microcomputer playfulness (Webster & Martocchio, 1992). Expanding the range of play in gamification design enables us to explain much broader scenarios that use gamification in non-gaming contexts. It is notable that to integrate the idea of playfulness into our typology, we consider design of information systems as part of technology. Our broad view differs from the technology described in the principles of gamification design (Liu et al., 2017). Our view is necessary because we study gamification as a structure rather than an additional tool to the information systems. By doing so, we create the notion of technology being playful as a characteristic and accentuate this dimension more clearly to explicate gamification.

We believe that our study contributes to the gamification research, which is a nascent field of study with great amount of interest from both practice and academia. We provide an in-depth analysis of gamification as a construct using the framework of typology. Instead of only focusing on the relationship between gamification and user engagement, we went back to basic, the IT artifact. We explore the meaning of gamification using the lenses of task-technology fit, microcomputer playfulness, and task complexity. Although our explanation is not the only way to analyze gamification, we hope that our synthesis and conceptualization adds value to the community of gamification research and encourage more diverse views and discourses.

Our study also adds value to the user engagement research. Myriad of studies analyzed gamification in relation to user engagement in digital platforms (Bojd et al., 2022; Chen et al., 2018; Goes et al., 2016; Huang et al., 2019; Landers et al., 2017; Leung et al., 2022; Liu et al., 2022; Santhanam et al., 2016). Our study fits into this discourse by explaining that the forms of gamification that we identify with the framework of typology explain and predict user engagement. Further, our study contributes to the digital platforms research. One of the topics discussed in the digital platforms research is the design aspect (Asadullah et al., 2018). Our study falls into this category as gamification lend itself to improve the design of this innovative virtual spaces that facilitate effective and efficient interactions among users. We believe that gamification has a great potential to expand our understanding about how to manage and design digital platforms. For example, technology playfulness could enable less stressful access to information systems through enjoyment and lower the barrier of accessing to information systems by being less serious from the outset while conducting serious business.

Practical Contribution

From the practical perspective, this study provides a theoretical explanation for gamification design that is typically implemented through a trial-and-error basis. Theoretical understanding is valuable because gamification affects human minds and behaviors. Our study is also meaningful as it responds to the current change of working environment from in-person to hybrid form. In the hybrid environment, organizations expect to have strategies to increase user engagement in virtual spaces. A typology of gamification could provide a practical guidance to organizations that leverage digital platforms. For instance, our typology could describe clear use case scenarios for each gamification design. This would help organizations to have accessible strategies to motivate users, which in turn, may increase the usability of digital platforms.

Another important aspect to note is the flexibility that a typology of gamification brings to the table. A typology of gamification improves the explanatory power of gamification elements applied in various contexts. This means that it enables organizations to adapt to dynamic changes in digital platforms caused by technological advancement or growing number of digital natives. Digital natives grow up interacting with computers through playing video and mobile games. Thus, they are likely to have different sets of communicating tools that are playful such as using emoticons, short-lived messages, sound effects, colorful backgrounds, and moving pictures. Although it is not realistic to think that gamification can reduce the differences between the digital natives and non-digital natives on digital platforms, using our typology as a template may help reduce digital divide that may appear from the evolution of digital platforms.

Opportunities for Future Research

Our typology of gamification provides sets of propositions manifested as six ideal types that may maximize user engagement. Thus, the nature of this study is theoretical. Our study creates numerous opportunities for future research including but not limited to examining our theories as a whole or as a part as well as extending our theoretical model with additional perspectives. For example, an experiment could be designed to test the causal relationship between volunteering design and user engagement. This gamification type has been theorized to work best for the users with altruistic motivation. Thus, researchers should observe increased user engagement in this experiment for those who identify themselves as altruistic or showing altruistic behaviors before any intervention. Another experiment example would be comparing the average effect of the two types of gamifications (e.g., volunteering design vs. associating design) to test if cognitive load has the impact in maximizing user engagement, and if so how. According to our study, volunteering design has greater impact on user engagement compared to the impact of associating design due to the change in cognitive load. However, we cannot confirm our theory without testing it and accounting for individual differences.

Our study used many different examples to illustrate each ideal type that aligns technology playfulness and task seriousness. However, the emergent process of each ideal type has not described in detail. This can be a great opportunity for future research. A case study that investigates into some of the listed digital platforms or platforms of different characteristics (e.g., e-commerce platforms vs. online community platforms) could be beneficial as case studies that involve interviews and surveys give in-depth insights on why certain gamification elements work or not work in practice.

Further, estimating the fit between ideal types and real cases would be a fascinating avenue for future research. An empirical study that collects large amount of data on gamification elements, related types of tasks, and user engagement on those digital platforms would enable calculating the distance between the ideal types and the real case scenarios. Depending on the degree of success of the real cases, the ideal types can be revised and improved to reduce the gap between the theories and realities.

As an effort to create theory driven research in gamification studies, we took the task congruence principle (Liu et al., 2017) as a guideline to develop our typology of gamification. Future research could explore other principles of design as well as other frameworks of gamification design. For instance, Leung et al. (2022) applied the personalization principle – match of gamification elements with users' characteristics (Liu et al., 2017) – to analyze gamification in a self-regulated online learning environment. Hamari and Tuunanen (2014) used user-centered design to create different gamification player types, and Harms et al. (2014) used mechanics-dynamics-aesthetics framework (Hunicke et al., 2004) to design gamification on online survey. We believe all these efforts and perspectives expand and advance the discourse on gamification.

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Appendix A. Various Tasks and Gamification Applied on Digital Platforms

Examples	Tasks	Gamification Elements
Duolingo (language learning)	Perform lessons regularly	Milestones, daily goals, daily streaks
	Perform as much lessons as possible	Weekly leaderboard, points (XP)
	Perform as much lessons as possible in a short period of time	Special challenges (XP ramp-up, timer boost)
	Continue learning lessons without being discouraged	Streak Freeze
	Build a long-term habit of taking lessons	Challenges, monthly badges, points
	Learn languages with others	Badges, celebrating messages, sharing, following, followers
	Complete set goals	Progress bars (daily and monthly)
	Complete a full lesson	Mascot, characters, encouraging messages
	Complete a set of lessons	Circle progress bar, crowns
	Unlock bonus skills, add extra time, equip streak freeze	Gems
	Review mistakes	Images, progress bars (timed weekly)
Fitbit (health tracking)	Exercise regularly	Notification, daily and weekly goals
	Exercise as much as possible	Progress circles (e.g., active minutes, steps, distance, and calories)
	Move 250 + steps every hour	Notification, feedback message (e.g., 1 of 9 hours)
	Exercise more effectively	Colored progress bar (e.g., heart rate zone of peak, cardio, fat burn, below zones), Images (e.g., moving heart)
	Exercise with others	Add friends, create groups, encouraging messages (cheers, taunt, message), challenges with others
	Build a long-term habit of exercise	Badges, challenges, scores, images (e.g., running man, sleeping moon)
	Complete set goals	Progress circles, colored circles, encouraging messages (e.g., you did it! Try hitting 10,000 steps a day!)
	Lose weight	Set goals, progress circle, encouraging messages (e.g., you did it! nice job! It’s a big deal to reach a goal)
	Sleep better	Images (e.g., smiley faces, stars), messages (e.g., fair, good, excellent), progress circles, sleep scores, benchmark bars)

	Drink more water	Images (e.g., filling water glass), set goals, numerical feedback, log history
Kaggle (data science and machine learning online community)	Participate in competition	Images (card stack with clear info such as reward and number of participating teams), rewards, leaderboard
	Continue participating in competition	Progress bar, team leaderboard, discussion boards, medals
	Finding information	Discussion board, votes, images
	Contribute to discussions	Medals, ranks, votes
	Build a long-term habit of contributing	Performance tiers (novice, contributor, expert, master, and grandmaster), medals (gold, silver, bronze), points (decay over time), Kaggle rankings
	Connect with others	following, followers
	Take lessons	Progress bars, discussions, images (tutorial, exercices)
	Publish and share datasets	Medals, ranks, upvotes
	Share notebooks	Medals, ranks, upvotes
	Unlock privileges	Performance tiers, medals
Stack Overflow (Q&A for programmers)	Ask questions	Votes, reputation scores, avatar
	Answer or edit questions	Votes, reputation scores, avatar
	Write quality answers	Votes, reputation scores, accepted image
	Visit the website regularly	Challenges, badges
	Appreciate questions and answers	Votes
	Be part of community	Avatar, badges, trophies, tags
	Find content easily	Tags
	Increase interactions with companies	Collectives recognized members, votes, images
	Contribute more	Reputation leagues, leaderboard (weekly, monthly, quarter, yearly, all time), badges
	Unlock privileges	Reputation score

POSITIONING OF ESSAY 2

Essay 2 presents an empirical study that extends the discussion of the first essay. It investigates competitive structures represented as gamification on digital platforms in the context that involves multiple users simultaneously. This essay hypothesizes that different competitive structures represented as leaderboards (i.e., local vs. global leaderboards) have different effects on user engagement on Q&A platforms. To guide the theoretical arguments, it builds upon earlier studies in gamification that use self-determination and goal-setting theories (Goes et al., 2016; Landers et al., 2017; Santhanam et al., 2016), and argues that gamification design that incorporates availability heuristics and anchoring heuristics guides users to make better decisions (i.e., increased user engagement). Formally, this essay answers the following research question: *Does the competitive structure represented as leaderboards increase the level of user engagement on digital platforms? If so, how do leaderboards that present different competitive structures impact user behavior?*

Earlier studies consider competitive structures of gamification within the contexts of one-on-one matching (Santhanam et al., 2016), or fixed status hierarchy system (Goes et al., 2016). These studies provide in-depth insights of gamification design by underling the perceived differences of competitive structures. However, their findings and explanations cannot explain the contexts where the tasks involve multiple users, and the status of users changes by the actions of self and others. Thus, we design and compare two types of competitive structures that incorporate these contexts (i.e., dynamic inventive hierarchy system) using leaderboards and examine which leaderboard (either local or global) is more effective to increase user engagement on digital platforms.

The results from two field experiments suggest that competitive structures that incorporates dynamic aspect of competition increase user engagement on digital platforms. The degree of user engagement is further strengthened when the information on competition is salient to individual users through local leaderboards. Thus, the second essay provides empirical evidence that the visual cues of leaderboards have impact on user engagement for the tasks that involve multiple users simultaneously.

IV. HOW AM I DOING? THE IMPACT OF LOCAL LEADERBOARDS ON USER ENGAGEMENT ON DIGITAL PLATFORMS

Abstract

User engagement has been widely discussed as a critical factor for the success of digital platforms. Among various mechanisms for increasing user engagement, of particular interest are gamification techniques. In this study, we focus on competition and use a behavioral economics lens to investigate how competitive structures presented to users in the form of leaderboards affect user engagement. We construct a novel leaderboard design, which we refer to as "local leaderboards", to create competitive structures unique to each user by showing the competitors around them and compare this design against the traditional "global leaderboards", which typically show only the top ranked users. Our field experiments that use randomized block design suggest that the localized leaderboards are more effective than the traditional leaderboards in increasing the level of user engagement. Our findings are reinforced by the generalized linear regression models with fixed effects, which provide further insights.

Keywords: Competition, gamification, leaderboards, user engagement, randomized field experiment, digital platforms, behavioral economics

Introduction

In digital economy, organizations increasingly leverage digital platforms, which are innovative virtual spaces that facilitate efficient and effective interactions among users, to increase customer engagement and facilitate effective communication with their partners and employees (Sebastian et al., 2020). Accordingly, improving user engagement becomes a critical issue for the operation and growth of organizations. Illustrating this point, a vast number of successful technology-led businesses such as Facebook and YouTube use digital platforms as their main medium of operation, and measure and publish daily active users in their platforms as a key performance indicator. To actively increase user engagement, these organizations devise a wide variety of tactics. They proactively design and develop tools, features, and interfaces to maximize user engagement, which may lead to increased retention, greater loyalty, and improved revenue (Gu et al., 2021; Sebastian et al., 2020). For example, popular social networking sites such as Instagram and YouTube encourage users to react to the content posted on their platforms and to engage in peer-to-peer messaging.

Among various mechanisms to increase user engagement, of particular interest are gamification techniques. We define gamification as *the use of gamified design in information systems that assimilates the playful experience of games into non-gaming contexts to achieve instrumental outcomes*. This construct has been touted as an effective means to motivate users in digital environments (Blohm & Leimeister, 2013; Koivisto & Hamari, 2019; Liu et al., 2017). In practice, we observe a plethora of gamification tools applied to digital platforms on a trial-and-error basis (Burke, 2014) while overlooking the underlying mechanism of gamification. Aggravating our understanding on gamification, in academia we observe few theory-driven research mainly focused on examining the sheer number of gamification techniques and often these techniques are lumped together, thereby making it impossible to tease out the impact of each technique (Koivisto & Hamari, 2019; Liu et al., 2017). Therefore, the current gamification literature provides a limited understanding of how gamification works on digital platforms. This creates the need for better theorization and research design that can elucidate not only the effect of gamification but also the effective design of gamification that can improve its outcomes.

Our study focuses on one important and commonly discussed mechanism of gamification: competition (Koivisto & Hamari, 2019). What we know about the role of competition in gamification is rather limited. Earlier research on this stream found that people perceive competitive structures differently depending on the skill levels of opponents in a one-on-one matching (Santhanam et al., 2016). Although this study explicates the intricate nature of competition on digital platforms, this explanation does not consider situations wherein users are challenged with multiple competitors simultaneously, which would be more common in large online platforms. Other researchers have considered peer recognition as tightly linked to competition and explored the role of badges as status to compete in digital platforms in motivating user behaviors (Goes et al., 2016; von Rechenberg et al., 2016). However, their findings are restricted to the context of using fixed goals (i.e., going up to higher status), and cannot be generalized to situations in which goals change dynamically owing to the actions of other users. To fill these gaps, we study leaderboards, a gamification technique that present dynamic competitive structures to users. Leaderboards show multiple users simultaneously competing for a moving target that is a function of user interactions. Specifically, we address the following research questions: *Does the competitive structure represented as leaderboards increase the level of user engagement on digital platforms? If so, how do leaderboards that present different competitive structures impact user engagement?*

Leaderboards are one of the most popular gamification designs representing competition that influences the motivation and engagement of users (Chou, 2019). Typically, leaderboards display a ranked list of users according to their relative performance on a set of specified criteria. Such relative ranking acts as a competitive indicator of progress and induces social comparison among users. However, due to various constraints, primarily space limitations, most platforms keep the size of leaderboards small by displaying a limited number of top performers (e.g., top 10 or 100 users). Thus, many users cannot assess, or at least must incur significant efforts to assess, their performance against those who are comparable to them based on the leaderboard ranking criteria. We consider this a weakness of the commonly employed "global leaderboards" and propose a new leaderboard design that can alleviate this issue. In so doing, we use a lens of behavioral economics, which posits that people make decisions under uncertainty using heuristics by taking the cues from salient information accessible to them.

Given that the motivational effect of competition is likely to function when users perceive their competitive goals to be attainable, user contribution will be greater when users can better visualize their competition with others at a similar performance level (Landers & Landers, 2014; Santhanam et al., 2016). To test this premise, we propose a novel leaderboard design, which we refer to as "local leaderboard," and empirically examine its efficacy. Specifically, we construct local leaderboards to create competitive structures unique to each user by showing the competitors around them and compare this design against the traditional "global leaderboard". By doing this, our research examines whether and how the design of leaderboards (global vs. local) presented to users affects the degree of user engagement on digital platforms.

Our study contributes to the growing literature on gamification and user engagement by providing theoretical explanations and empirical evidence regarding how the way competition is presented to users (in terms of leaderboard design) affects user engagement. More specifically, this study delves into an in-depth discourse regarding how to enhance user engagement when there is significant uncertainty associated with competition presented on leaderboards. This uncertainty stems from the fact that various levels of skilled users are presented simultaneously on leaderboards and user ranks change constantly, which leads to a dynamic incentive hierarchy system. We apply a behavioral economics lens to highlight the importance of framing and anchoring for saliency of information in the presence of uncertainty regarding competition and find support for our argument that the use of localized leaderboards may lead to a greater increase in user engagement compared to the use of traditional global leaderboards. Our findings suggest that the salience of information matters when designing competitive structure using gamification on digital platforms, which also contributes to the research stream on digital platforms. Applying our theoretical understanding to practice, we believe that blindly implementing a commonly adopted gamified design reflecting competition (i.e., global leaderboards) on digital platforms may not be an effective strategy especially when competition is dynamic and uncertain. From this point of view, our findings can provide insights and actionable guidance to practitioners concerning how to implement gamification with various types of competitive structures on digital platforms to increase user engagement.

Literature Review

Our research questions concern the design of competitive structure represented as leaderboards. This line of inquiry is congruent with one of the gamification design principles – dynamism principle – which proposes "gamification design elements must match desired user-system interactions" (Liu et al., 2017, p. 1027). As a way of applying dynamism principle, this study implements gamification design that encourages competition among users, which is user-user interactions through a system that induces social comparison (Liu et al., 2017). In the following section, we first discuss prior studies relevant to the gamification design incorporating competition and highlight studies that use leaderboards on digital platforms. Then, we describe the gaps in the literature followed by our theoretical framework that shapes our arguments and research design of this study.

Competition as Gamification Design

Competition is a rivalry among two or more parties striving for something that not everyone can gain (Vickers, 1995). In the gamification literature, researchers have examined competition as rivalry over victory or superiority (Chen et al., 2018; Goes et al., 2016; Landers et al., 2017; Liu et al., 2013; Santhanam et al., 2016). For instance, in the context of one-on-one matching technology-mediated training programs, when users are matched against equally skilled competitors, they engage more compared to when they compete against higher or lower skilled competitors (Santhanam et al., 2016). The key finding of this study is that users perceive competition differently depending on competitive structures that they are exposed to (Santhanam et al., 2016). This finding is in line with an earlier study on competition, which examined the degree of users' efforts in the context of open-source games. Although this study concerns games rather than gamification, it reached the same conclusion that users tend to put more efforts when they compete against users with similar skill levels (Liu et al., 2013). One of the explanations for these observations is that when users compete against similarly skilled users, they completely immerse in their use of IT and thus are in a flow state (i.e., cognitive absorption) (Santhanam et al., 2016). Interestingly, in a setting of technology-mediated training programs, individuals have been found to learn better when competing against lower-skilled competitors due to self-efficacy (Santhanam et al., 2016). Thus, we can assume that creating a competitive structure on digital platforms that considers competitors of similar or of lower skill levels would work either to engage or satisfy users. However, this would work only when users can assess their skill levels against others by assuming that they can identify a clear winner in the competition that they are in and perceive competition as a fixed entity matched by the similar skill levels of competitors. Unfortunately, these assumptions are too rigid, and cannot be applied in most cases in digital platforms. For example, these assumptions would not hold in a situation where users concurrently face several competitors with diverse skill levels because users in that situation will struggle to make a clear judgement on where they are relative to others and what they want in terms of competition (e.g., goals).

Some researchers have studied competition in relation to reputation, which is a social construct reflecting peer recognition through a status hierarchy system (Chen et al., 2018; Goes et al., 2016; Wang et al., 2020). For instance, a typical badge conferring system on digital platforms uses status hierarchy to create different levels of badges and make their values hierarchical, thus creating artificial status (Goes et al., 2016) or competence (Wang et al., 2020). These artifacts are recognized by peers within the digital platforms that they are involved in. Although badges do not convey any practical value outside of a specific context, they incentivize users as users perceive them as implicit goals that they could achieve by exerting their efforts especially when they are close to those goals (Goes et al., 2016; von Rechenberg et al., 2016). Nevertheless, badges have a limitation as a gamification technique for competition because the hierarchical structure may not be obvious to users. Typical badge design does not show numbered orders, and, therefore, only the users with keen interest in obtaining badges in a given platform will clearly understand the hierarchical differences between the rainbow badges and the plain colored badges, for instance. Corroborating this point, a study by Chen et al. (Chen et al., 2018) theorized that badges are the reflection of self-image rather than implicit goals that can be recognized by others; instead, this study illustrated that a voting system is a peer recognition mechanism that positively affects users with in diverse motivational states.

Our study combines the ideas from the findings of aforementioned studies that users behave differently depending on given competitive structures (Liu et al., 2013; Santhanam et al., 2016) and care about incentive hierarchy system owing to peer recognition (Chen et al., 2018; Goes et al., 2016; Wang et al., 2020). Our study differs from prior research in that we consider users with diverse skill levels concurrently (as opposed to one-on-one matching of competitors) in a dynamic incentive hierarchy system (ranks on leaderboards) as opposed to a static incentive hierarchy system (badges). We argue that compared to a static incentive hierarchy system where users simply progress to the next level of badges, a dynamic incentive hierarchy system illustrates much more realistic competition because ranks move up and down depending on the behaviors of the focal users and others. This characteristic makes decision-making process much more complex and uncertain since users need to adjust their uncertain preferences (i.e., implicit goals) in the ever-changing competitive environment. Therefore, we expect users to shape their behaviors using the visual cues available to them on leaderboards, which may help them make better judgment about where they are and what strategies to choose to move forward in an uncertain competitive environment.

Leaderboards as Gamification Technique

Leaderboards are gamification design that simultaneously display the users at different levels of skills by showing their position in a hierarchy system. Typically, leaderboards induce social comparison through the displayed information such as ranks and scores, which may create a sense of peer recognition. This gamification design is one of the most widely applied techniques along with points and badges on digital platforms (Burke, 2014; Chou, 2019). Despite its functionality and popularity, researchers paid little attention to the competitive structures of leaderboards. They explained leaderboards as a feedback tool that assists individuals to make decisions on their progress through goal metrics (Koivisto & Hamari, 2019; Landers et al., 2017). This may be because intuitively information on leaderboards such as ranks or scores enable users to compare themselves to others as motivating force, but at the same time leaderboards seem to create ambiguous emotional effects depending on the amount of disclosed information (Lemus & Marshall, 2021) and the overall position of the users in a hierarchy system (e.g., high or low) (Bai et al., 2021).

Most research on leaderboards have found that the use of leaderboards positively affect user behaviors on digital platforms such as increased user performance and engagement (Landers et al., 2017; Landers & Landers, 2014; Mekler et al., 2017). These studies built their arguments based on the frameworks of goal-setting theory (Landers et al., 2017; Landers & Landers, 2014) and self-determination theory (Mekler et al., 2017). Goal-setting theory explains the role of implicit goals promoted by leaderboards, which may motivate users to self-regulate their actions to achieve their goals (Landers et al., 2017; Landers & Landers, 2014). Self-determination theory describes leaderboards as external incentives that may increase the competence of users and subsequently increase their motivation and their performance (Mekler et al., 2017). Although these studies provide theoretical explanation and empirical evidence of why leaderboards work and posit that leaderboards may assist individuals to set their target goals to top or near-top (Landers et al., 2017), they rely on an assumption that users have clear implicit goals that they can pursue, and thus treating the role of leaderboards as a mere personal feedback tool. If we were to capture the full picture of competition, our explanation should go beyond describing personal progress and explain how users behave when they interact with other users by observing the information revealed on leaderboards. Through the interactions with others, users will face situations in which they have to deal with dynamic goals where their ranks continuously change by both their actions and those of others, which could pose greater uncertainty when making decisions on digital platforms.

Despite the paucity of theory-driven studies on leaderboards, we find interesting empirical studies that discuss competitive structures of leaderboards through social comparison (Bai et al., 2021), and the choice of information disclosure (Lemus & Marshall, 2021). The study that uses social comparison theory, which describes human tendency of comparing themselves to others to evaluate themselves, finds that top-ranked users in leaderboards show greater motivation compared to medium or low ranked users (Bai et al., 2021). However, the results of this study should be interpreted with caution because its research design included maximum of 8 users for each experiment group, and the leaderboard design combined various gamification techniques (i.e., ranks, badges, profile photos and names, total scores, and progress bars) making it difficult to isolate the effect of leaderboards (Bai et al., 2021). Notwithstanding its weakness, this study is meaningful because it investigates into the competitive structure of leaderboards by comparing enjoyment and performance of users among high, medium and low ranked groups (Bai et al., 2021). Further, this study examines both absolute (i.e., typical leaderboards that display all users) and relative leaderboards (i.e., smaller leaderboards that display five immediate neighbors), to understand how users feel about the competition through surveys and interviews (Bai et al., 2021). This study did not compare between the absolute and relative leaderboards, but this line of thought is worth to explore further because it gives us a good opportunity to observe how users shape their behaviors when different competitive structures or information is presented to them. Another study focused on the choice of information disclosure as an important element and examined if the outcomes of competition improve when disclosing others' performance in the dynamic tournament platforms (Lemus & Marshall, 2021). The finding of this study suggests that leaderboards showing additional information such as cost-to-prize ratio and the variance of the score distribution may improve quantity and quality of solution submissions in these platforms because participants can make informed decisions whether to quit or continue their competition (Lemus & Marshall, 2021). Although this study has very specific context, which is an online machine learning competition that entails financial incentives, it gives us insight that competition can be modeled with right information.

From reviewing empirical studies that investigated the effect of leaderboards and their competitive structure, we conclude that on average leaderboards have positive impact on user engagement (e.g., reduced time to tasks, greater engagement and scores, increased quality and quantity of submissions). However, as noted by many researchers, gamification may be context-specific in such a way that what works in one setting might not be effective in another setting (Koivisto & Hamari, 2019). This may be why we observe ambiguous leaderboards effects such as lower motivation and performance (Hanus & Fox, 2015). We also believe that inconsistencies arise due to lack of theory-driven research. For instance, the effect of ranks on leaderboards can be ambiguous because ranks may affect motivations differently depending on the user positions on leaderboards (i.e., high vs. low) (Bai et al., 2021; Lemus & Marshall, 2021), contexts (Nebel et al., 2016) and the type of disclosed information (Lemus & Marshall, 2021; Leung, 2019). Research on leaderboards suffer from fragile experiment design such as lumping together various gamification techniques (Koivisto & Hamari, 2019; Liu et al., 2017) and insufficient data analysis that do not identify and deal with confounders. Thus, to acquire robust results, we design our research based on a strong theoretical framework (i.e., behavioral economics), focusing on one gamification element (i.e., leaderboards) and using identification strategy that can deals with confounders (i.e., adding other techniques as control variables when conducting data analysis).

To sum up, our review of the leaderboard literature exposed some gaps that we need to fill. From the current accumulated knowledge, we cannot explain situations with greater uncertainty. That is, we do not have a solution for explaining user behaviors when various levels of skilled user are simultaneously displayed on leaderboards. Further, our knowledge is limited in explaining user behaviors against the constant change of ranks, which creates dynamic implicit goals on leaderboards. Another obstacle in the literature is that most research assumes that users can process all information given to them via leaderboards. However, this might not be the case if we consider users as bounded in computational power, willpower, and self-interest (Camerer & Loewenstein, 2011). Thus, which and how much information to disclose will matter greatly when designing leaderboards because those decisions may reduce the uncertainty and nudge users to make better decisions under competition.

Research Model Development

Behavioral Economics as Theoretical Framework

Behavioral economics taps into the idea that people do not always make rational choices but use heuristics when making decisions under uncertainty (Tversky & Kahneman, 1974). This is because people have limited capacity in processing information caused by human limitation (i.e., bounded rationality) and complication (i.e., dependence on beliefs, emotions and heuristics) (Angner & Loewenstein, 2012; Mullainathan & Thaler, 2000). Numerous experiments have shown evidence for the anomalies of human behaviors, which can be modeled as systematic biases (Kahneman et al., 1991).

Our research uses these assumptions about human behaviors to examine the impact of two types of leaderboards that show different competitive structure on digital platforms. We argue that competitive structure in leaderboards pertains to high uncertainty due to simultaneously displaying different skilled level users and constantly changing ranks. Thus, it creates the needs to identify heuristics that can help users to make better choices under this highly uncertain environment. To do so, we apply the notion of the salience of information as an important cue for using heuristics. More specifically, we leverage availability heuristics and anchoring heuristics to frame and anchor competitive structure displayed to users.

Availability Heuristics

Availability heuristics refer to people's judgment on the plausibility of an event based on information that is easily accessible (Tversky & Kahneman, 1974). People fall prey to drawing conclusion that some events happen more often than others because they can imagine them more easily, not because they are statistically more likely. Similarly, when users receive "global leaderboards”, which only includes participants who are far from their own ranks (although this is not the case if the focal users are in top ranks), they may need to think hard to calculate how much effort they must make to be on the leaderboards. However, this type of leaderboards may impede users from knowing where they are and thus make them feel uncertain about their choices. Thus, these users are likely to look for cues that help them make judgements on what to do. In other words, they will use availability heuristics. If users do not find any clear cues, they may be discouraged from engaging actively in digital platforms because they may assume that it would require significant efforts to be in the leaderboard. In contrast, if users receive “local leaderboards”, which show participants close to their own ranks, they will take that information as cues and may feel more confident about their choices. Compared to the earlier scenario, users may figure out with greater ease what they need to do to move up because they clearly see where they stand on a leaderboard. This salience of information will encourage users to engage more actively in digital platforms. More specifically, explicitly showing achievable goals that users could attain may help them set their implicit goals, which is in line with prior studies suggesting that high-ranked users perceive competition more clearly than the lower ranked users when a typical leaderboard is available to users (Bai et al., 2021; Lemus & Marshall, 2021; Nebel et al., 2016).

Anchoring Heuristics

Anchoring heuristics describe that people make judgement based on suggested reference points. For instance, if a person is told that many households in South Korea own two to three cars, then is asked how many traffic accidents would happen daily in Korea, the person might answer this question with some number around five, but no more than 10. However, according to the report from the Korean police, 209,654 cases of traffic accidents occurred in 2020[10] making on average 574 traffic cases a day. Now we apply the idea of information anchoring to our case. First, we assume that in a dynamic incentive hierarchy system such as leaderboards, users do not have clear preferences for their ranks, which increases uncertainty from the users' perspective. Then, we presume that the decisions in the dynamic incentive hierarchy system require more thinking than in a static hierarchy system since users consciously or unconsciously decide on their level of engagement based on their current and future ranks, which are difficult to predict as users need to consider the ranks and behaviors of others at the same time. Therefore, users may consider any visible ranks on leaderboards as a reference point for their decisions on engagement. Simply put, users are overloaded with complex information, and thus will use anchoring heuristics to find an easier path in their cognitive processes.

Anchoring heuristics are like availability heuristics in that given information is salient to users but differ from the latter in that the information is anchored to a certain point so that users unconsciously regard this information as the basis for their future decisions. For example, if users receive local leaderboards, the uncertainty of their status may decrease because they can see their status more clearly. However, the role of reference (i.e., implicit achievable goals) through anchoring heuristics is that users may set their implicit goals based on the provided rank information. Then, we may see increased motivation of users because losses or gains close to the reference points are perceived much greater in value than those far from the reference points. This logic has been examined in prior research: users exert their efforts when their implicit goals are in close proximity due to loss aversion, which explains that users perceive the value of loss to

[10] Visit https://www.police.go.kr/eng/statistics/statisticsSm/statistics05.jsp for further information.

be greatest just before reaching their closest reference points such as ranks (Goes et al., 2016; von Rechenberg et al., 2016). Figure 1 graphically demonstrates what we have discussed as a diagram of theoretical model.

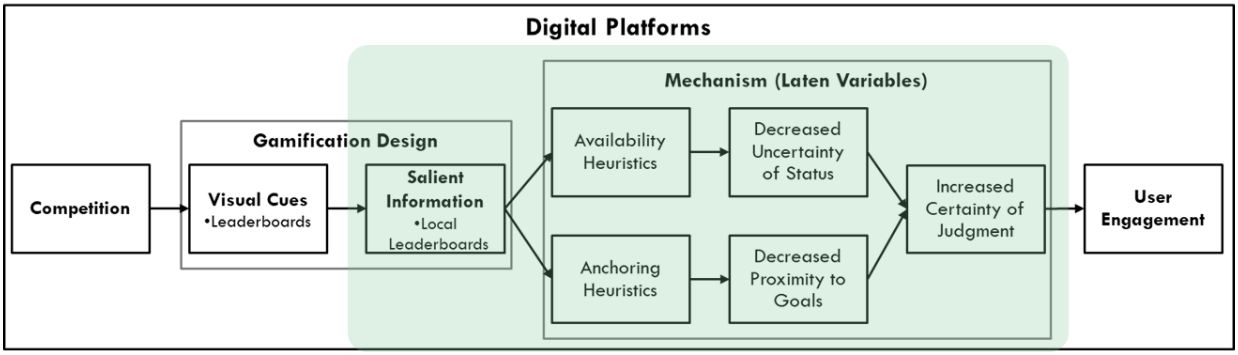

Figure 1 Theoretical Model Highlighting Our Contribution

Research Model

Discussions so far suggest that both heuristics are susceptible to visual cues because “some thoughts come to mind much more easily than others” (Kahneman, 2003, p. 697). From these principles of heuristics, we argue that users in digital platforms, when challenged with multiple competitors via leaderboards, will try to find visual cues that may give them rationale to make proper judgments and choices. Thus, we conjecture that user will exhibit a greater degree of engagement when they receive local leaderboards, compared to when they receive global leaderboards. That is, competitive structure presented with more salient information (i.e., local leaderboards) may increase the level of user engagement more on digital platforms, compared to the competitive structure with less salient information (i.e., global leaderboards). Figure 2 graphically represents the research model of this study.

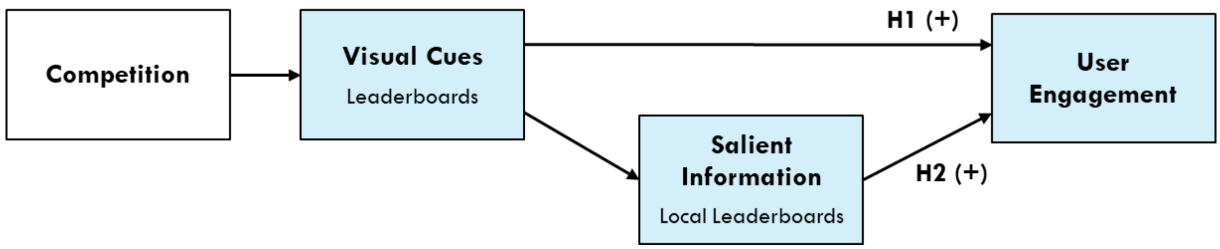

Figure 2 Research Model

Research Methods

To validate our theoretical prediction, we conducted two randomized field experiments in the context of university courses. We conducted our main experiment in an undergraduate course and an additional experiment in a graduate course. For brevity, we only provide the details of the main experiment in the section 4.1.

Controlled experiments are common in gamification (Koivisto & Hamari, 2019) as they allow researchers to precisely estimate the causal effects of treatment, but they are criticized for lacking generalizability. For this reason, we conducted field experiments where we randomly assign our subjects into two groups and observed their behaviors in a naturally occurring context to benefit from both internal and external validity (Baldassarri & Abascal, 2017). For our data analysis, we applied two strategies: non-parametric tests and generalized linear regression models. In the following we first describe the details of how we collected our data using experimental design; then we explain our data in depth, followed by the results of our data analysis using non-parametric tests and generalized linear regression models with time fixed effects.

Data Collection

For our main experiment we recruited 50 subjects from two sections of an undergraduate course that taught Python and SQL for 13 weeks. This course was offered completely online owing to the lockdown measures put in place during the pandemic in 2021. This situation gave us a great opportunity to test our research model while minimizing the confounding factors that could arise from physical interactions among subjects during our experiment. Out of 81 students enrolled in this course, 50 agreed to take part in our experiment, and two students dropped the course after the first week, leaving us total of 48 subjects. To overcome the issue of small sample size (N), we conducted our experiment for the entire semester, which enabled us to create a panel dataset with large time period (T).

The instructor of this course used an online Q&A platform to promote discussions among students. This digital platform was independent of the university-wide learning management system, and students could easily access the platform via online or a mobile application reducing any barriers to access. The instructor expected students to visit the platform every week and asked students to use the platform as a medium for discussions by asking and answering questions, leaving comments, and reacting to others' comments.

Design of Experiment

Our experiments followed the basic principles of experimental design: replication, randomization, and local control. Replication refers to repeating intervention to experimental units (in our case each human subject) to reduce the measurement error and the degree of freedom to improve the accuracy of statistical test and testing power, respectively. To follow this principle, we analyzed the proper sample size for our experiment, and intervened our subjects every week. The result of our power analysis in which we combined standard levels of statistical power (i.e., 1-β at 80% and significant level α at 5%) and the medium effect size (d at .5) showed that the right number of sample size is around 36 (for a one-tailed test).

The second principle that we followed for our experiment was randomization, the random assignment of subjects in each group. Randomization reduces confounding of our results by removing selection bias, which may create systematic error in our analysis. Thus, we transformed the systematic error into the random error following randomization principle, which set our control group as counterfactual of the treatment group. Thanks to randomization, we can estimate the difference of the probability of user engagement between the treated and the controlled groups without worrying about other confounding factors as we can assume that the two groups are comparable, and they are not systematically different in any other factors other than our intervention. We included some tests and discussions on this matter later in the data analysis.

Our third principle in conducting the field experiment was the use of local control. Local control is an experimental technique that treats systematic errors originating from specific experimental space or time as factors. Since we recruited our subjects from two sections of one course, we expected that the discussion dynamic between these two groups may differ over time. To deal with this issue, we used local control technique called blocking design in our experiment as it allowed us to control for their variation by randomly assigning our subjects from each section to either the controlled or the treated groups. Our randomized block design theoretically gives us credible results for our experiment given that the two groups are exposed to the same conditions except for our intervention. However, our experiment continued for a whole semester with human subjects adding complexity in their behaviors over time. This led us contemplate on our research design because simply comparing the average level of user engagement of the two groups might not reveal the full extent of our experiment results. Thus, we decided to add more details in our experimental design and investigate the changes of user engagement over time in micro-level (i.e., daily user engagement) using statistical tools that can give us much greater range of meaningful interpretation in our analysis.

With this in mind, we applied within-subjects design to our study to examine the baseline of our experiment: leaderboards vs. no leaderboards. We tested if there was any statistical difference before and after we sent leaderboards to our subjects. This pre- and post-tests conducted for within-subjects design reinforced our assumption that receiving leaderboards indeed increase the level of user engagement within our context and further supported that our treatment - sending localized leaderboards - was more salient to participants in terms of its availability and design.

For our main experiment we applied between-subjects design, which we followed randomized blocked design. We examined the treatment effect on user engagement by randomly assigning subjects to either control (global leaderboard; 24 subjects) or treatment groups (local leaderboard; 24 subjects). We designed our treatment - the salience of competition represented as a local leaderboard – as a scoreboard that showed five participants close to the rank of the focal subject. On the other hand, we designed our control – the traditional global leaderboards – as a scoreboard that showed only the top five participants regardless of the focal subject’s scores or ranks.

Design of Leaderboards

We developed the design of our leaderboards after reviewing various examples of leaderboards used in practice. Although on digital platforms the design of leaderboards seems to change quite often and its development tend to take a trial-and-error approach, we can gain insight from some of these available designs as companies implicitly understand unknown mechanism that motivate users. The closest design that we could find in practice to test our theory was an app called Sololearn[11], which is an online code learning platform. As shown in Figure 3, this app uses leaderboards that show both the top five learners with the most points and ten learners around the app user, which is highlighted in dark color.

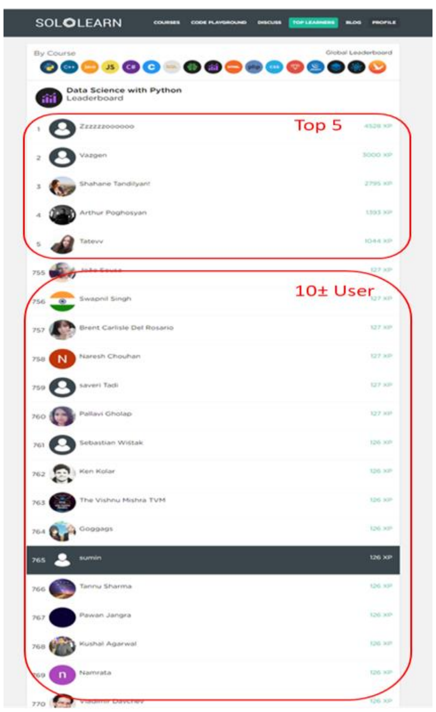

Figure 3 An Example of Leaderboard Design

[11] Visit https://www.sololearn.com for further design information on this app.

Building on the design ideas from practice, we created two types of leaderboards: the “local leaderboards” that exhibit the competitors around them and the traditional “global leaderboards”, which show only the top-ranked users. We simplified the aesthetic of our leaderboards to minimize the influence of any irrelevant factors. As Figure 4 illustrates, each subject could see their ranks, names, and their scores. To control for the confounders that could arise owing to social network of the subject (e.g., feeling more competitive when acquaintances’ or friends’ names are on leaderboards), we masked the names of the users on leaderboards except for the focal subject. Further, to avoid any conflict or disagreement between our subjects and the instructor of the course in relation to participation points, we added a warning message at the bottom of the leaderboards indicating that the class participation assessment and the scores that they see on their leaderboards may differ.

Figure 4 Leaderboards on Screen

Implementation of Experiment

We next explain how we implemented our experiment in chronological order (refer to Table 1)

Week	Dates	Days	Activities
1-2	Jan. 11 - 25	15	Recruitment and receipt of consent forms
3-4	Jan. 26 – Feb. 7	13	Sending emails with a link of demographic survey
5-11	Feb. 8 – Mar. 28	49	Randomization and sending emails with a link of leaderboards (global vs. local)

12-13	Mar. 29 – Apr. 11	14	Switching groups and sending emails with a link of leaderboards
14-15	Apr. 12 - 23	12	Sending emails with a link of post-experiment survey, debriefing our experiment to our subjects, and randomly selecting subjects for gift vouchers

Table 1 Experiment Process

At week 1, we recruited participants of our experiment via course platform and collected their consent forms. At week 3, we sent our subjects an email with a link asking for demographic information such as age, gender, and school year. At week 5, we began sending weekly emails with a link to their leaderboards, which were customized for each individual based on their participation level and the assignment of their group. Participants could access their leaderboards as many times as they wanted in any day at any time except for one or two hours on Monday morning when we updated their leaderboards. At week 12, we switched the types of leaderboards that each group received as we felt that seven weeks were sufficient for observing the treatment effect and decided to use the last two weeks of data as out-of-sample to check the predictability of our model. At week 14, we asked our subjects to complete a post-experiment survey from which we administered manipulation checks to validate our treatment effect and collected participants' perception of our experiment using survey questions from relevant literature (refer to Appendix 1). Once our experiment was complete, we held an online debrief session and randomly drew five participants to award 20 CAD gift vouchers.

Data Analysis

We applied two strategies for our data analysis: non-parametric tests and generalized linear models. First, we chose non-parametric methods to confirm the causal relationship between our treatment and user engagement. Our outcome variable, user engagement, is a non-negative count variable measured during a fixed period, one day in our case, so it does not follow normal distribution and violates assumptions for more commonly used statistical tests such as t-test or ANOVA. Given this limitation, we employed Wilcoxon signed-rank test and Wilcoxon rank-sum test for within-subjects design and between-subjects design, respectively. Although non-parametric tests allowed us to make statistical inference without assuming normal distribution of our sample, we could not interpret our test results in depth as the tests could only estimate the differences between matched pairs or two independent samples. Thus, we added another strategy for our data analysis - generalized linear models - to explain nuanced meaning of the degree of our treatment effect while controlling for other factors.

Randomization Check

As our first step of data analysis, we checked if we can statistically confirm the randomized assignment of the groups. Table 2 shows the mean and the standard deviation of the collected variables accompanied by student t-tests between the two groups. The section variable indicates the course section number that our subjects registered for (either 1 or 2). We also collected their gender (1 for male an and 2 for female), their school year (from year 1, 2, 3, and 4+), their ethnicity of which they could select more than one category, their age group divided by five years between 18 to 38, their school major concentration, and their familiarity with the online discussion platform measured by 5-point Likert scale (1 being very familiar and 5 being very unfamiliar). All t-test results suggest that the two groups are statistically not different and thus they are comparable.

Groups (# of Subjects)	Local Group (24)	Global Group (24)	# Levels	t-value	p-value
Section (1 or 2)	1.42 (0.50)	1.42 (0.50)	2	0	1
Gender (0 or 1)	1.33 (0.48)	1.58 (0.50)	2	1.76	0.09
School Year (1 to 4+)	2.67 (0.76)	2.83 (0.82)	4	0.73	0.47
Ethnicity (6 categories)	4.25 (1.98)	3.52 (1.97)	6	-1.26	0.21
Age (6 categories)	1.00 (0.00)	1.08 (0.28)	6	1.45	0.16
Major (14 concentrations)	7.04 (3.14)	6.62 (2.79)	14	0.49	0.63

Familiarity (1 to 5)	2.21 (0.83)	2.25 (1.03)	5	0.15	0.88

Table 2 Comparison of Two Groups

Descriptive Statistics

Although our groups are comparable, our sample size for each group is smaller than the suggested size of 36 according to the power analysis given that our treatment has medium effect on user engagement. To overcome this issue, we expanded our sample to create a panel data set that records daily user engagement for each subject over the semester assuming that each subject on each day is independent and they consider their customized leaderboard whenever they engage in online discussion.

From our experiment of 48 subjects that lasted for 91 days, we collected a total of 4,368 data points of which 1,344 data points are from week 1 to 4 (i.e., before our intervention), 2,352 data points are from week 5 to 11 (i.e., during our intervention), and 672 data points are from the last two weeks when we switched the control and the treatment groups. The reason for collecting the first four weeks of data without any intervention is to ensure that all subjects are on the same page by familiarizing with the designated online discussion platform and course materials. Further, this period gave us enough time to collect consent forms and demographic information via online and minimize the mortality rate of our sample as the school deadline for dropping the course was until week 4. We collected the last two weeks of data by switching the intervention between the treated and controlled groups so that we use them as out-of-sample data to test the predictability of our regression model.

Table 3 shows our descriptive statistics of the data between week 5 and 11. We measured our main dependent variable, daily user engagement, as the total number of posts, replies and reactions of each subject for each day without any weight. We divided this variable into more nuanced variables for further analysis. For example, we measured daily engagement concerning only the comments because we considered leaving comments such as posts and replies would require more cognitive efforts compared to leaving reactions such as pressing thumbs-up or like buttons. We used these additional dependent variables to cross-validate our regression models.

	Local (Treatment) Group					Global (Control) Group				
	Obs.	Mean	SD	Min	Max	Obs.	Mean	SD	Min	Max
Daily Engagement	1,176	0.40	1.94	0	40	1,176	0.32	2.25	0	54
Daily Engagement (Posts and Replies)	1,176	0.13	0.51	0	5	1,176	0.08	0.40	0	5
Daily Engagement (Reactions)	1,176	0.27	1.69	0	38	1,176	0.24	2.12	0	54
Local Leaderboard (LL) (0 or 1)	1,176	1.00	0.00	1	1	1,176	0.00	0.00	0	0
Adj. LL (0 or 1)	1,176	1.00	0.00	1	1	1,176	0.09	0.29	0	1
Section # (1 or 2)	1,176	1.42	0.49	1	2	1,176	1.42	0.49	1	2
Gender (1 or 2)	1,176	1.33	0.47	1	2	1,176	1.58	0.49	1	2
School Year (1 ~ 5)	1,176	2.67	0.75	2	4	1,176	2.83	0.80	1	4
Ethnicity (1 ~ 6)	1,176	4.25	1.94	2	6	1,127	3.52	1.93	1	6
Ages (1 ~ 6)	1,176	1.00	0.00	1	1	1,176	1.08	0.28	1	2
Major (1 ~ 14)	1,176	7.04	3.08	1	14	1,176	6.62	2.74	1	13
Familiarity (1 ~ 5)	1,176	2.21	0.82	1	4	1,176	2.25	1.01	1	5
Ranks (1 ~ 28)	1,176	8.88	6.25	1	28	1,176	10.55	6.85	1	28
Cumulated Scores	1,176	20.40	24.18	1	144	1,176	14.53	20.12	0	114
Link Access (0 ~ 3)	1,176	0.12	0.40	0	3	1,176	0.10	0.39	0	3

Table 3 Descriptive Statistics

Our main independent variable, Local Leaderboard, was coded 1 if the subject received local leaderboards, and 0 otherwise. As described in the design of leaderboards section, we differentiated the design of the local and global leaderboards; the local leaderboard recipients saw their names highlighted in the middle of the screen along with two users before and after them, while the global leaderboards recipients always saw the five top-ranked participants and their highlighted names at the bottom of their screen. Yet, there were a few cases where the subject happens to be between rank 1 to 3 while receiving global leaderboards, and thus perceiving their leaderboards as if they are local leaderboards (i.e., the same bin issue). To account for these cases, we created an adjusted local leaderboard variable where those cases were coded as local leaderboards; as a result, 105 data points were from the global leaderboard group to the local leaderboard group. We used this variable to cross-validate our regression models.

For control variables, we collected demographic information explained above. We also collected data on ranks displayed on customized leaderboards where 1 indicates the highest rank and 28 is the lowest rank. Since each section of the course had 38 to 45 students, theoretically the lowest rank could have been 45, but there were a lot of students who scored the same points and, in those cases, they were given the same rank, so the lowest rank in our context was 28. Other collected variables include the accumulated number of engagements of each subject on each day (i.e., accumulated scores), which were presented in their customized leaderboards, and the number of times that our subjects accessed the links to their leaderboards each day, which ranged from 0 to 3.

Non-parametric Tests

We designed our experiment as between-subjects, having two independent samples where the treatment group received local leaderboards while the control group received global leaderboards. We compared these two independent samples using Wilcoxon rank-sum test to examine if our treatment, the local leaderboards, caused the differences in user engagement between these two groups.

To test the validity of our randomization, we conducted Wilcoxon rank-sum tests and found that there were no significant differences in engagement intensity between the two groups before our intervention (W=218,507, p>0.01). Then, we tested if the treatment group was different from the control group after the subjects began to receive emails with links to their leaderboards. Based on the test results, we rejected the null hypothesis that the two groups were from an identical distribution at 1% level (W=653,628, p<0.01), indicating that our leaderboards design caused a significant difference in user engagement between these two groups. Table 4 shows the summary of our results.

	Global vs. Local (Before Treatment)	Global vs. Local (After Treatment)
W	218,507	653,628
p-value	0.05715	0.00046

Table 4 Between- Subjects Wilcoxon Rank Sum Tests

To support our results from the between-subjects design, we also tested the impact of receiving the first leaderboard in both groups to set our baseline by comparing the user engagement level between the subjects that received leaderboards and those received no leaderboard. Because the objective of the test was to ensure that both treatment and control groups were on the same baseline at the beginning of our intervention, we examined the variance between pre- and post-intervention levels of user engagement of our sample. It is worth noting that we had to restrict the range of time for our pre-post analysis because unlike between-subjects design, within-subjects design is susceptible to the time factor, as observing the same sample in later time may alter user behaviors (i.e., learning effect). For our within-subjects analysis, we employed Wilcoxon signed rank tests, which compared the matched pairs (i.e., the same sample before and after a certain point) to assess if the median of user engagement level for our sample was significantly greater than 0 after the first leaderboard was sent to our subjects. Specifically, we compared 10 days before and after we sent the first leaderboard to our participants and found that receiving leaderboards compared to not receiving leaderboards may lead to significant changes in user engagement ($V=2754$, $p<0.01$). This test was also valid when we conducted pre-post tests for control and treated groups separately.

In summary, our within-subjects analysis suggests that receiving leaderboards, which visualize competition, may incentivize users to engage more in digital platforms; and our between-subjects analysis suggests that receiving local leaderboards, which represents competition with more salient information, may lead to significantly greater increase in the level of user engagement compared to receiving global leaderboards.

Generalized Linear Models with Fixed Effects

Although Wilcoxon rank-sum tests showed statistical significance of the treatment effect, these tests provide little information on how much or to which direction localized leaderboards affect user engagement. Further, while randomization theoretically takes care of both observed and unobserved variations of our sample, environmental factors could generate errors that decrease the accuracy of statistical tests, especially when conducting a field experiment. For these reasons, we employ generalized linear models to further scrutinize the treatment effect.

As observed in Figure 5, our dependent variable, daily user engagement, follows Poisson distribution with its level ranging from 0 to infinity, and this shape justifies the choice of using Poisson regression models that use logarithm as a link function. We also investigate negative binomial regression models by relaxing the assumption of the shape of our expected counts to have different variance to the mean value; and zero-inflated Poisson models by assuming that overdispersion happens due to a separate mechanism that creates more 0s in our data.

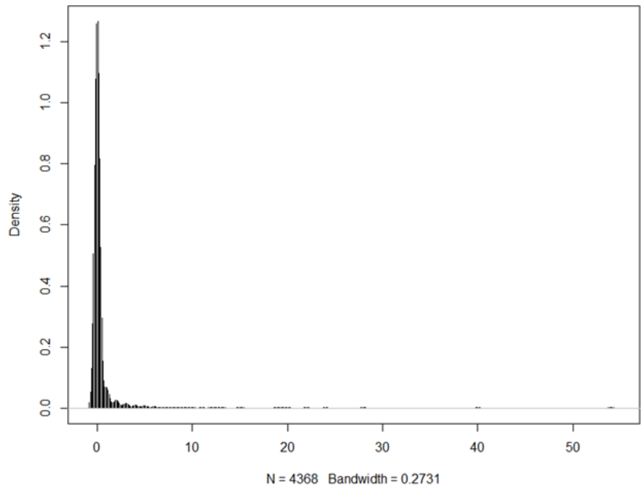

Figure 5 Probability Density Function of User Engagement

Since we are analyzing panel data where the unit of randomization was individual *i* not individual *i* at time *t*, we considered five types of potential confounders and controlled for them in our regression models. First, to account for the fact that user engagement is measured across time periods and each subject is likely to be associated with their own self of past and future, we clustered standard errors at individual level. Second, we used time-fixed effects in our regression models to account for the unobserved time-specific factors that may affect our estimation. Third, we added control variables in our regression models to improve the accuracy of our estimate. We first compared the demographic variables (refer to Table 2) between the treated and controlled groups using t-test on the individual-time data, and found that the gender, the school year, the ethnicity, the age, and the major concentration variables were statistically different between these two groups. Then, we estimated generalized variance inflation factors (VIF) in our base regression model to identify any multicollinearity, which led us to remove the age and the ethnicity variables as they generated very high generalized VIFs. Among the rest of variables, we adjusted the school major concentration variable into two-level category: concentrations within the major that the course was offered (i.e., management in our case) and concentrations from outside of management school as we presumed that subjects majoring in management would be more familiar with the materials offered in the course. As an additional control variable, we included the number of times that a subject accessed the link to their leaderboards each day as we assumed that subjects who accessed their leaderboards more each day might have different characteristics (e.g., more conscious about their leaderboards), compared to the subjects with fewer clicks to their leaderboards.

Our next adjustment deals with the section variable. When we designed our experiment, we had assumed that the two sections may have different dynamic, so we applied randomized block design. Yet, we needed to consider that our subjects voluntarily registered for their sections, meaning their choices between section 1 and 2 were not random and it may reflect systematic differences in their characteristics. For instance, we conjecture that the subjects registered for section 1 are likely to have stronger motivation for learning the course topics compared to the subjects in section 2 for two reasons. First, the university offered section 1 on Mondays while offering section 2 on Wednesdays. Since Monday is the beginning of a week, registering the course for Mondays as opposed to Wednesdays may indicate stronger will to learn the topics of the course. Further, section 1 is more likely to be the first choice of registration for many students compared to section 2 owing to the order of their numbers (i.e., 1 comes before 2), and this typically leads section 1 to satisfy earlier the minimum required number of students, giving more certainty of offering the course to the registered students in section 1. In a similar vein, section 1 may reach the maximum number of students allowed in the course earlier than section 2, creating some urgency to students for registration. From these train of thoughts, we deduced that students register for section 1 are more likely to have greater zeal to pursue the course compared to the students register for section 2. To test this assumption, we ran a simple regression that compared the two sections before any intervention (i.e., week 1 – 4) and found that section 1 on average engaged 1.57 times more than section 2 when controlled for dates and previous day achievements (represented as ranks). To control for any systematic differences across sections, we include the section fixed effects in our regression models.

Finally, we control for the other information presented on the leaderboards: each user's accumulated scores and relative ranks (1-28) calculated based on those scores. Although visible ranks and scores on leaderboard are communicating similar information to users, users may perceive them differently probably because ranks are relative measures while scores are absolute measures. In other words, ranks stand for the dynamic dimension of the hierarchy system of competition while scores show individual progress by accumulated efforts. Thus, we cannot rule out the moderating effect of ranks on different types of leaderboards as they are closely related to competition. Consequently, we added an interaction term in our model to capture the effect of dynamic competitive structure through the localized leaderboards on user engagement.

Based on the discussion so far, we formally write the following equation to estimate:

$$\log_e(\mathbf{Y_{ict}}) = \boldsymbol{\alpha_c} + \boldsymbol{\tau_t} + \boldsymbol{\rho}\mathbf{LL_{ict}} + \boldsymbol{\gamma}\mathbf{R_{ict}} + \boldsymbol{\delta}(\mathbf{LL_{ict}} * \mathbf{R_{ict}}) + \boldsymbol{\beta}\mathbf{X'_{ict}} + \boldsymbol{\varepsilon_{ict}}$$

where we log-transform our user engagement ($\mathbf{Y_{ict}}$) for individual *i* in section *c* on day *t* as a linear function of our treatment effect ($\mathbf{LL_{ict}}$), our treatment effect moderated by lagged normalized rank ($\mathbf{R_{ict}}$), a vector of control variables ($\mathbf{X'_{ict}}$), and section fixed effects ($\boldsymbol{\alpha_c}$) and daily time fixed effects ($\boldsymbol{\tau_t}$). Based on this model, we estimated $\boldsymbol{\rho}$ our treatment effect along with $\boldsymbol{\gamma}$ the coefficient or normalized rank, $\boldsymbol{\delta}$ the interaction effect of the treatment and ranks, and $\boldsymbol{\beta}$ the matrix of coefficients for controlled variables (i.e., lagged normalized scores, gender, school year, major, and access of link). ε_{it} is included in our model to represent the random error term.

As our baseline specification we first estimated Poisson regressions with and without the interaction term. Then, we estimated the same models using negative binomial regressions by relaxing the assumption of Poisson model that takes only one parameter to describe the mean and variance of distribution. Next, we cross-validated our results with two alternative models: one with the adjusted local leaderboard variable that dealt with the same bin issue (i.e., transferring samples in rank 1-3 in the global leaderboards group to the local leaderboards group); and the other with the dependent variable that only considered posts and comments (i.e., removing reactions from daily user engagement). Table 5 shows the results of our regressions.

	Poisson Models		Negative Binomial Models			
	(1) W/O Interaction	(2) W. Interaction	(3) W/O Interaction	(4) W. Interaction	(5) Cross - Validation	(6) Cross- Validation
Dependent Variable	Daily User Engagement (DUE)					DUE excl. Reactions
Local Leaderboard (LL)	**0.192* (0.084)**	**0.463* (0.201)**	**0.539** (0.164)**	**0.534** (0.171)**		**0.455** (0.168)**
Adj. LL					**0.700*** (0.161)**	
Normalized Rank (Lagged)	**1.402*** (0.128)**	**1.665*** (0.254)**	**1.441*** (0.129)**	**1.430*** (0.162)**	**1.114*** (0.171)**	**0.854*** (0.146)**
Normalized Scores (Lagged)	0.035 (0.054)	0.041 (0.058)	0.097 (0.122)	0.097 (0.121)	0.106 (0.119)	0.005 (0.090)
Male	0.337** (0.122)	0.309** (0.114)	0.593** (0.181)	0.594** (0.181)	0.559** (0.174)	0.427* (0.167)
School Year	0.158** (0.049)	0.104. (0.058)	0.134 (0.101)	0.135 (0.102)	0.088 (0.097)	0.255* (0.117)
Management Major	-0.373*** (0.088)	-0.441*** (0.069)	-0.555 (0.396)	-0.556 (0.398)	-0.402 (0.377)	-0.395 (0.370)
Access to Links	0.081 (0.166)	0.079 (0.159)	0.499* (0.245)	0.500* (0.246)	0.495* (0.245)	0.443. (0.238)
LL x Normalized Ranks		-0.451 (0.293)		0.021 (0.2377)		0.094 (0.212)
Adj. LL x Normalized Ranks					0.365 (0.226)	

Fixed-Effects (Date & Section)	Yes	Yes	Yes	Yes	Yes	Yes
S.E.: Clustered	by: Name	by: Name	by: Name	by: Name	by: Name	by: Name
Observations	2,208	2,208	2,208	2,208	2,208	2,016
Squared Cor.	0.462	0.474	0.19	0.19	0.243	0.063
Pseudo R2	0.448	0.450	0.161	0.161	0.165	0.149
BIC	3,445.90	3,442.60	**2,474.20**	**2,481.90**	**2,471.80**	**1,609.10**
Over-dispersion	--	--	0.166	0.180	0.180	0.323
Significant Codes	. p<0.1; * p<0.05; ** p<0.01; *** p<0.001.					

Table 5 Poisson and Negative Binomial Regression Models

The results suggest that on average receiving the local leaderboards has a greater positive effect on user engagement compared to receiving the global leaderboards. For instance, model (1) shows that on average the female subject who receive the local leaderboard in a particular section in a particular day engages 1.21 times (i.e., $e^{0.192}$) more than the female subject who receive the global leaderboard with the same condition. Our estimate improves from 1.21 times to 1.71 times (i.e., $e^{0.539}$) when we use Negative binomial model (see model (3)). In Model (3), the over-dispersion coefficient of 0.166 suggests that the negative binomial model might be better than the Poisson model as the coefficient is $\rightarrow 1$ rather than $\rightarrow \infty$; also, the comparison of the Bayesian Information Criteria also suggests that the negative binomial model predicts user engagement better than the Poisson model (model (1): 3,445.90 < model (3): 2,474.20).

Models (2) and (4) show the results of the full model including the interaction term between local leaderboards and normalized ranks, and their estimated local leaderboards coefficients reinforce our results from model (1) and (3). The moderating effect of ranks on local leaderboards seems to change the estimate of local leaderboards greatly from 1.21 times to 1.59 times for Poisson models, but not so much for the negative binomial regression models from 1.71 times to 1.70 times. Given the value of information criteria (BIC), we could assume that the negative binomial regression models explain our data better compared to the Poisson models.

It is noteworthy that our regression models indicate that the normalized rank variable has the largest effect on user engagement as shown in Figure 6. According to the negative binomial regression models, one standard deviation increase in ranks (i.e., around 6.6 ranks) adds 4.18 (i.e., exponential of 1.4) more daily user engagement when female users receive global leaderboard, and all other factors are set to their means or 0. This implies that increased ranks motivate users to engage more in digital platforms.

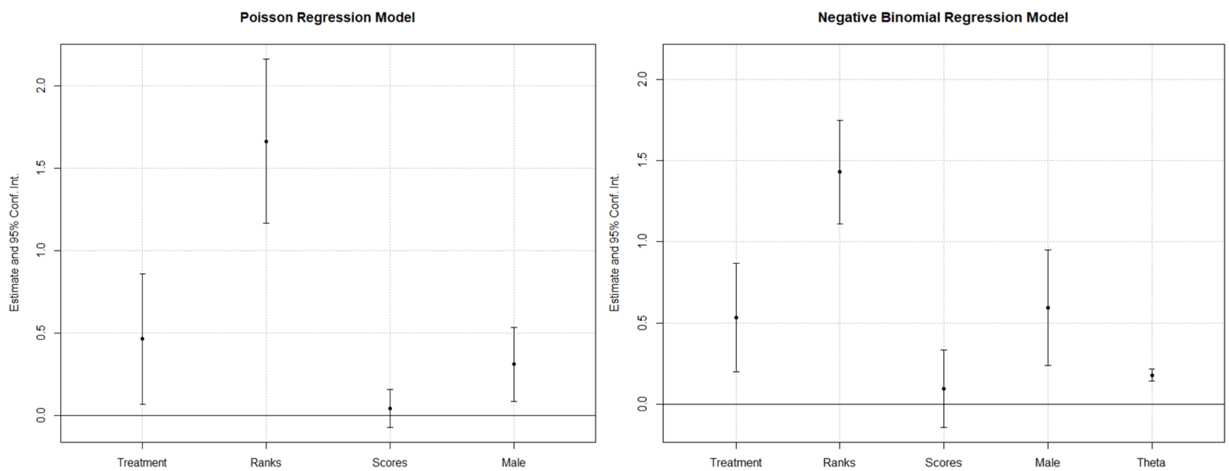

Figure 6 Selected Coefficients with Confidence Intervals

To cross-validate our results we ran our full model in two versions: in model (5) we used the adjusted local leaderboards variable; and in model (6) we used an alternative dependent variable that only accounted for posts and replies while excluding the number of reactions as they require less cognitive efforts compared to leaving comments on discussion platforms. Our estimates of the effect of local leaderboards in these models are positive and significant, thus reinforcing our findings from our main model.

So far, we assumed that our models generated user engagement in one way. However, our data has many 0s and it is reasonable to think that all 0s are not equal, meaning that some 0s are created in a different way. For instance, some 0s may have been produced because our subjects are enjoying weekends, or just finished submitting their assignments or quizzes and they are taking time off. Isolating the generating process of these excess 0s might provide clearer implication to our count model. To this end, we employ zero-inflated Poisson models and zero-inflated negative binomial models, which estimate binomial logit model for estimating the 0 generating process followed by a count model. Since we are isolating certain days to explain how certain 0s are generated, we cannot use time-fixed effects anymore as it may produce multicollinearity. Thus, in our count models we used week time-fixed effects to control for week-specific confounders, and added weekends, assignments due and quiz submission as the independent variables of the zero inflation models (refer to Table 6).

	Zero-Inflated Poisson Models		Zero-Inflated Neg. Binomial Models	
	(7) Base	(8) Cross-Validation	(9) Base	(10) Cross-Validation
Dependent Variable	Daily User Engagement	DUE w. Comments only	Daily User Engagement	DUE w. Comments only
Count Model Coefficients (w. Log Link):				
Local Leaderboard	**0.375. (0.207)**	**0.444** (0.166)**	**0.547** (0.188)**	**0.489** (0.180)**
Zero-Inflation Model Coefficients (Binomial with Logit Link):				
Intercept	1.326*** (0.123)	0.903*** (0.140)	-1.141 (2.034)	0.229 (1.330)
Weekends	**0.907*** (0.225)**	**1.095*** (0.316)**	1.775 (1.280)	**1.267 * (0.524)**
Assignments Due	-0.416 (0.337)	-0.505 (0.466)	-0.215 (1.354)	-0.695 (1.164)
Quiz Submission	**-0.724* (0.356)**	-0.157 (0.473)	**-10.055** (3.558)**	-0.306 (0.832)
Fixed-Effects (Week & Section)	Yes	Yes	Yes	Yes
S.E.: Clustered	by: Name	by: Name	by: Name	by: Name
Observations	2,352	2,352	2,352	2,352
BIC	2,593.22	**1443.30**	**2,310.31**	**1,443.16**
Over-dispersion	--	--	0.225	1.101
Significant Codes	. p<0.1; * p<0.05; ** p<0.01; *** p<0.001.			
Notes	For brevity we omit control variables and interaction terms in this table.			

Table 6 Zero-Inflated Poisson and Negative Binomial Models

The base Zero-inflated regression result suggests that the negative binomial model has better predictive power for user engagement compared to the Poisson model as model (9) shows smaller BIC value compared to model (7). Our cross-validation models, which used daily user engagement that only include comments as their dependent variable, show even greater predictive power, suggesting that the impact of localized leaderboards is not only limited to simple tasks that do not require much cognitive efforts such as leaving reactions, but also works for tasks that require more efforts such as leaving comments.

The estimates of the effect of local leaderboards from models (9) and (10) in Table 6 are similar to those from models (4) and (6) in Table 5, demonstrating that accounting for 0-generating processes does not significantly alter our findings. Taken together, these results provide support for our hypothesis 2 - users who receive local leaderboards may increase the degree of user engagement more in digital platforms, compared to those receiving global leaderboards.

Extended Analysis

Cross-Validation using a Graduate Course

As illustrates in Figure 7, we conducted an additional experiment for this study. This experiment maintains the same experimental design as the first one, but some details change. The course was offered during summer completely online like it was the case for the main experiment. However, the course was prepared for graduate students, the duration of the course halved, and all students were put in one section instead of two sections. Out of 89 students we recruited 36 students but at the end 3 students dropped the class, so we ended up with total of 33 students for 42 days.

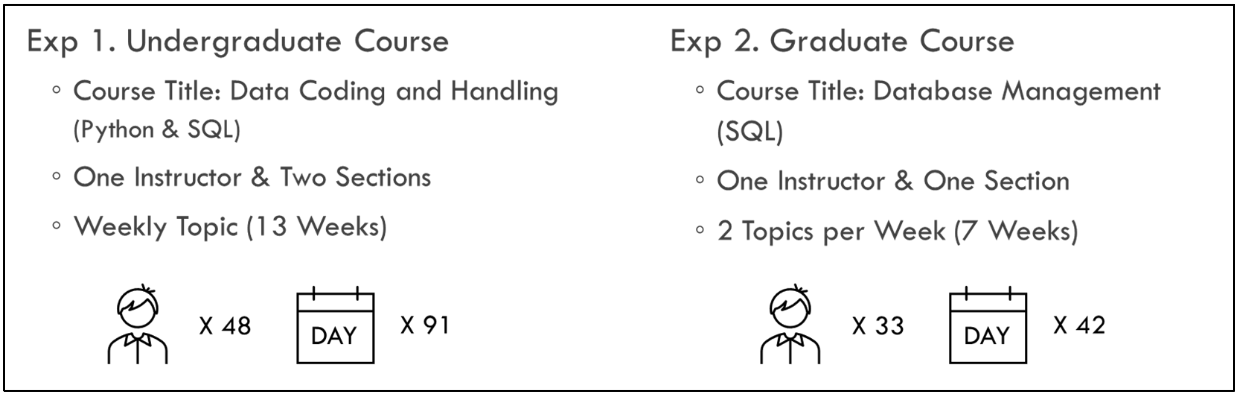

Figure 7 Experiment Environments

The additional experiment provides couple of insights to our study. First, as shown in Table 7, the results from the additional experiment (models (12) and (15)) corroborate the findings from our main experiment (models (2) and (4)). This means that the local leaderboards are effective for not only undergraduate students but also graduate students. We think that graduate students are likely to be more motivated compared to the undergraduate students due to an opportunity cost for pursuing education at the graduate level. Thus, the positive significant effect of the local leaderboards in both experiments suggests that our theoretical arguments may apply to user with different levels of motivation.

Another interesting insight from additional experiment is the role of the age variable. Unlike the main experiment, the age range is wider in the graduate course, so we could create a binary variable for age instead of school years. We coded 1 for the graduate students between the age of 18 and 22, and 0 for the graduate students above 23 years old. Then, we interacted the age variable with the local leaderboards to see if this gamification design plays a stronger role to younger generation. The results of our findings are shown in models (13) and (16) of the Table 7. As expected, younger people (i.e., 18-22 years) seem to respond more actively to the local leaderboards compared to the less young people (i.e., 23 years +). The difference is quite striking. The coefficients that we get from the interaction terms are 1.66 and 1.35 for Poisson model (13) and negative binomial model (16), respectively. These coefficients tell us that given all other variables constant when users receive local leaderboards, those who are in the age between 18 and 22 engage more than 8.5 times (exp(1.66+0.49) from model (13)) in the activities on digital platforms than those who are in the age of 23 or above. This difference is much greater than the difference between receiving the global and local leaderboards, which in this same context around 2.4 times (exp(0.88) from model (15)).

	Poisson Models			Negative Binomial Models		
	(2) Undergraduate w. Interaction	(12) Graduate w. Interaction	(13) Graduate Age Interaction	(4) Undergraduate w. Interaction	(15) Graduate w. Interaction	(16) Graduate Age Interaction
Dependent Variable	Daily User Engagement (DUE)					
Local Leaderboard (LL)	**0.463* (0.201)**	**0.782* (0.337)**	**0.498. (0.279)**	**0.534** (0.171)**	**0.882*** (0.230)**	**0.687** (0.246)**
Normalized Rank (Lagged)	**1.665*** (0.254)**	**0.727* (0.282)**	**0.949** (0.292)**	**1.430*** (0.162)**	**0.713** (0.248)**	**0.807** (0.282)**
Normalized Scores (Lagged)	0.041 (0.058)	0.100 (0.143)	0.017 (0.180)	0.097 (0.121)	0.148 (0.183)	0.139 (0.212)
Male	0.309** (0.114)	-0.048 (0.255)	0.049 (0.233)	0.594** (0.181)	-0.016 (0.258)	0.029 (0.232)
School Year or Age (18-22 == 1; 23-28 or 28-32 == 0)	0.104. (0.058)	0.414 (0.511)	-0.317 (0.210)	0.135 (0.102)	0.434 (0.345)	-0.176 (0.289)
Management Major	-0.441*** (0.069)	-	-	-0.556 (0.398)	-	-
Access to Links	0.079 (0.159)	-0.002 (0.044)	-0.002 (0.045)	0.500* (0.246)	-0.032 (0.067)	-0.033 (0.064)
LL x Normalized Ranks	-0.451 (0.293)	-0.405. (0.241)	-0.531* (0.227)	0.021 (0.2377)	-0.240 (0.193)	-0.333. (0.201)
LL x Age	-	-	**1.660*** (0.253)**	-	-	**1.348*** (0.261)**
Fixed-Effects (Date & Section)	Yes	Yes	Yes	Yes	Yes	Yes
S.E.: Clustered	by: Name	by: Name	by: Name	by: Name	by: Name	by: Name
Observations	2,208	690	690	2,208	690	690
Squared Cor.	0.474	0.172	0.221	0.19	0.104	0.063
Pseudo R2	0.450	0.235	0.26	0.161	0.125	0.149
BIC	3,442.60	1,313.30	**1,289.60**	**2,481.90**	**1,104.90**	1,609.10
Over-dispersion	--	--	--	0.180	0.347	0.323

Significant Codes	. p<0.1; * p<0.05; ** p<0.01; *** p<0.001.

Table 7 Comparison between Undergraduate and Graduate Courses

Out-of-Sample Test for Robustness Check

To further ensure the robustness of our analysis, we conducted out-of-sample test using the last two weeks of collected data from the main experiment wherein we switched the controlled and the treated groups. We used negative binomial regression (model (4)) that incorporated all controls and the interaction term to predict our model. Nevertheless, to run our prediction with out-of-sample, we had to adjust our time fixed-effects from date to something more generalizable such as days of a week because model (4) created different intercept for each day that did not exist in our out-of-sample data and thus would be impossible to run our prediction. Thus, we replaced dates to days by assuming that each day would have specific characteristics that affect our dependent variable. The advantage of this change is fitting our out-of-sample to model (4) with increased variability while keeping to certain degree our assumption of time-specific intercepts as we had assumed when we established our analytical model.

Before running our prediction, we checked if our adjusted model (17) produced similar results to model (4); and our results showed that substituting days instead of dates slightly reduced the degree of our treatment effect but increased our observation numbers and the predictability of our model (refer to Table 8). Thus, we test our out-of-sample using the adjusted model (17) without much concern.

	(4) Main Model	(17) Adj. Model
Dependent Variable	Daily User Engagement	Daily User Engagement
Local Leaderboard (LL)	**0.534** (0.171)**	**0.4816** (0.1756)**
Family	Negative Binomial	Negative Binomial
Fixed-Effects (Section)	Yes	Yes
Fixed-Effects (Date or Day)	**Date**	**Day**
S.E.: Clustered	by: Name	by: Name

Observations	2,208	2,352
BIC	**2,481.90**	**2,398.50**
Over-dispersion	0.180	0.09869
Significance Codes	. p<0.1; * p<0.05; ** p<0.01; *** p<0.001.	
Notes	For brevity, control variables are omitted in this table.	

Table 8 Comparison between Model (4) and Adjusted Model (17)

Our prediction using the adjusted model (17) and out-of-sample suggest that the effect of the local leaderboards is greater compared to the effect of the global leaderboards on user engagement; and the moderating effect of the ranks on the local leaderboards predicts greater user engagement compared to its effect on the global leaderboards (refer to Figure 8). Thus, we conclude that our out-of-sample test supports our main hypothesis that the local leaderboards may be more effective than the global leaderboards in motivating users to engage in digital platforms.

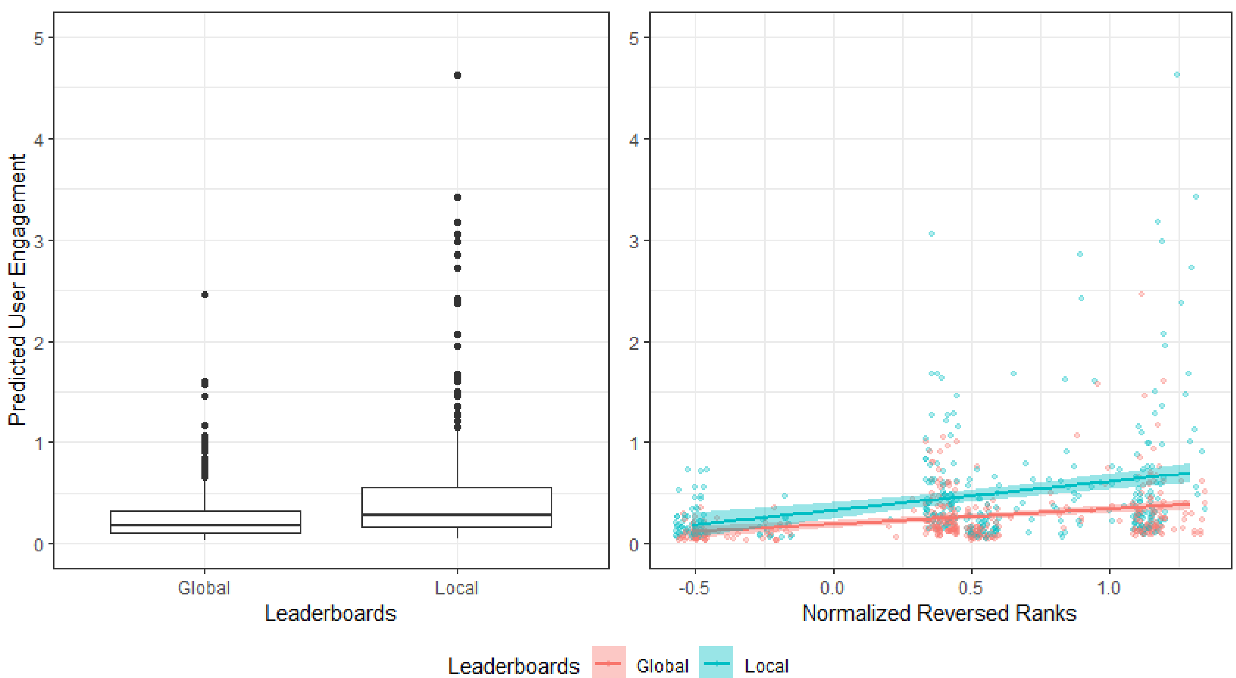

Figure 8 Predicted User Engagement using Out-of-Sample

Exploratory Analysis on the Role of Pre-Intervention Motivation

The type of data that we collected and used for our analysis give us an opportunity to explore about the role of leaderboards on the users with different level of intrinsic motivation. Since the selection of the course was not random, we assumed that students who chose the section offered on Mondays may have higher motivation compared to the students who chose the section offered on Wednesdays. Then, we conducted an exploratory analysis that investigates the role of intrinsic motivation in the relationship between competition and user engagement.

Researchers have studied the relationship among extrinsic incentives, intrinsic motivation, and performance for a long time, and the meta-analysis of the 40 years of psychology studies on this topic suggest that intrinsic motivation and extrinsic incentives jointly predict performance (Cerasoli et al., 2014) while in a long-term, extrinsic incentives could undermine the intrinsic motivation, which is the behaviors derived from self-enjoyment and satisfaction (Benabou & Tirole, 2003). As an exploratory analysis, we wondered if we could empirically assess the interactive effect of intrinsic motivation and extrinsic incentive to predict the level of user engagement in digital platforms using our data as we had assumed that the two course sections may be systematically different regarding their intrinsic motivation.

We have argued that students in section 1, which was offered on Mondays, would have greater intrinsic motivation on learning the course subjects compared to the students in section 2, which was offered on Wednesdays, because section 1 would be filled with students earlier than section 2, so it would create urgency and more certainty of offering the course. Put differently, the choice of section shows the students' intention of registering for a particular section based on uniformly given information; and students in section 1 shows greater motivation due to greater benefits that section 1 entails in terms of certainty. To test this idea, we ran a simple regression model that can differentiate the level of user engagement between the control and the treatment group before introducing any intervention (i.e., leaderboards). The result of the regression suggests that given all other variables constant users who registered for section 1 engaged 1.53 times more (i.e., exp(0.425)) than users who registered for section 2 before any intervention was in place, meaning from week 1 to 4. Thus, statistically, we can argue that participants in section 1 might have been more motivated group compared to the participants in section 2.

Figure 9 graphically compares the level of user engagement before and after our intervention by dates and by subjects. According to this comparison before our intervention section 1 seems to have subjects with marginally greater daily and weekly engagement with greater range compared to the subjects in section 2. This tendency seems to strengthen after our intervention. From the figure before the intervention, we can induct that the subjects in section 1 is more motivated compared to section 2, which is in accordance with our statistical test. However, making inference from the figures after the intervention is not easy due to the big ranges happening in daily and weekly user engagement, so we run our negative binomial regression model adding the interaction term between the treatment variable and the section variable.

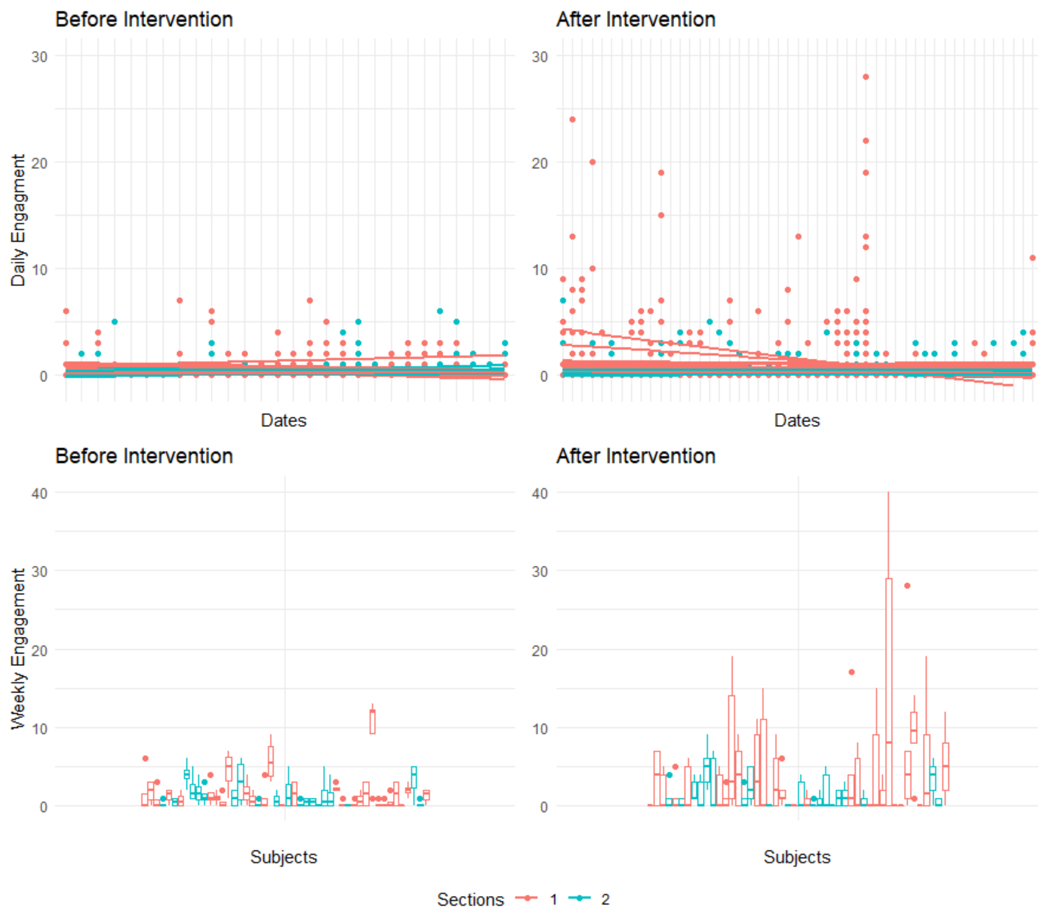

Figure 9 User Engagement Comparison between Sections

The results of our regression that included section interaction term suggests that on average less motivated section (i.e., section 2) engage less to online discussion compared to more motivated section (i.e., section 1) when receiving global leaderboards, which can be inferred from the coefficient estimate of the section 2 variable of model (18) (-1.26***). This implies that the external incentive that is not salient to all individuals would benefit more intrinsically motivated users. However, when the local leaderboards are presented to the subjects in the less motivated section (i.e., section 2), they engage two times more (estimated from exponential of 0.702) compared to the subjects who received local leaderboards in more motivated section (i.e., section 1). This implies that the salient extrinsic motivator that provide more meaningful information to individuals such as localized leaderboards benefit more the intrinsically less motivated users compared to the intrinsically more motivated users. However, this does not imply that intrinsically more motivated users (i.e., section 1) will not benefit from the salient extrinsic motivator such as localized leaderboards. The coefficient of the local leaderboards shows marginally significant result to the positive direction, which means that the local leaderboards recipients in section 1 engage 1.3 times more (estimated from exponential of 0.301) compared to when they receive global leaderboards. Table 9 shows the results of our regression with section interaction effect (i.e., model (18)) compared with the main model (4).

Variables	(4) Main Model	(18) W. Section Interaction
Local Leaderboard (LL)	0.534** (0.171)	0.301. (0.162)
Section 2	Fixed effects	-1.256*** (0.301)
LL x Section 2	-	0.702* (0.338)
F.E. (Date)	Yes	Yes
F.E. (Section)	Yes	No
Family	Neg. Bin.	Neg. Bin.
S.E.: Clustered	by: Name	by: Name
Observations	2,208	2,208
BIC	2,481.90	2,486.40
Over-dispersion	0.180	0.183
Significance Codes	. p<0.1; * p<0.05; ** p<0.01; *** p<0.001.	
Notes	For brevity, control variables are omitted in this table.	

Table 9 Additional Models with Sections and Access Interactions

In summary, both groups of users benefit from local leaderboards, but less motivated group is more likely to benefit further. However, when presenting global leaderboards less motivated users will suffer more to engage in the platform compared to more motivated users. We show the effect of this interaction term in

Figure 10 where we plotted the mean and confidence interval of daily user engagement as well as predicted daily user engagement of two sections divided by different types of leaderboards. Our results support that intrinsic motivation and external incentives jointly predict performance (Cerasoli et al., 2014), and implies that external incentives when presented with more salience they may have a greater effect on the intrinsically less motivated users because they may undermine the motivation of the group with greater intrinsic motivation (Benabou & Tirole, 2003).

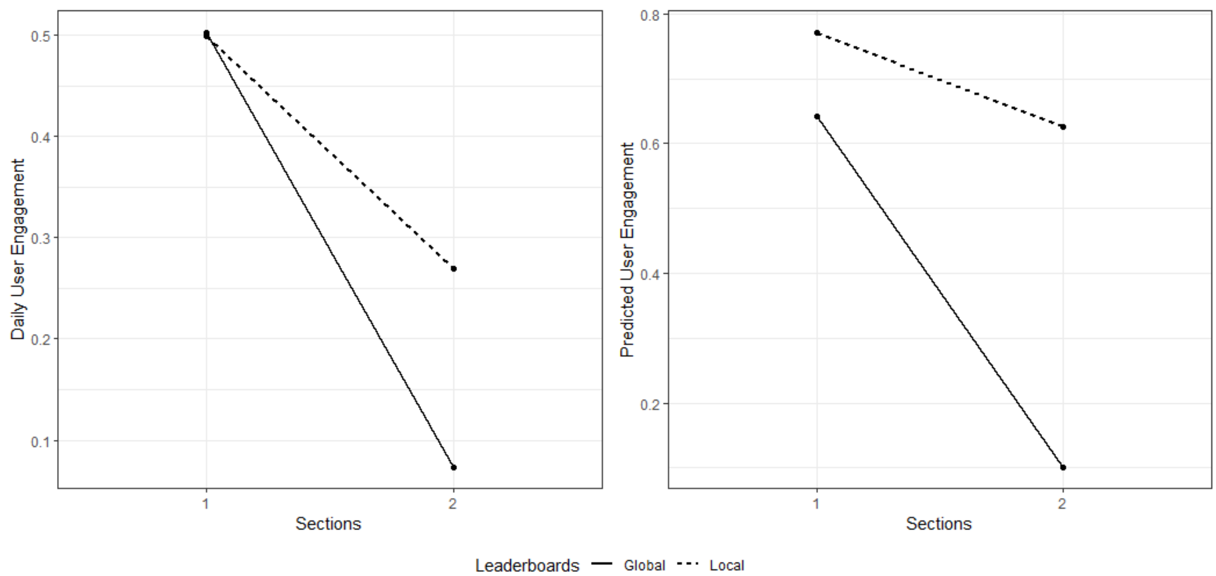

Figure 10 Comparison of Daily User Engagement between Different Motivational Groups

Discussion

The main finding of this study is that competitive structure that incorporates the dynamic aspect of competition may increase user engagement on digital platforms, especially when the information of competition is more salient to individual users. We established our hypotheses by borrowing a lens of behavioral economics, which posits that people when making decisions under uncertainty use heuristics taking the cues from salient information accessible to them. To test our hypotheses, we conducted randomized field experiments, where we created a novel leaderboard design to motivate competitive structures unique to each user by showing the competitors around them (i.e., local leaderboards) and compared this design against the traditional leaderboards, which typically show only the top ranked users (i.e., global leaderboards). We used two statistical strategies to analyze our collected data: non-parametric tests and generalized linear models.

Our results suggest that the localized leaderboards may be more effective than the traditional leaderboards in influencing the level of user engagement on digital platforms. More specifically, we found the use of local leaderboards lead to a significantly greater increase in user engagement compared to the traditional global leaderboards. Our results were robust to employing various model specifications (Poisson regressions, negative-binomial regressions, and zero-inflated version of those regressions), using an alternative dependent variable that considered only the comments, and using an alternative independent variable that dealt with the same bin issue.

As for the extended analysis, we cross validated our results using an additional experiment conducted with graduate students, which not only reinforced our main arguments but also offered additional insight regarding the role of age. We also tested our results with out-of-sample, which we used the last two weeks of experiment data that switched the treatment and the control groups. Lastly, but not least, we explored the possibility of the interaction effect between intrinsic motivation and extrinsic incentives of leaderboards on user engagement. We found that the localized leaderboards may help both low and high intrinsically motivated users, but less motivated users may benefit more.

The theoretical contributions of this study are threefold. First, our study contributes to the stream of research that investigates the relationship between competition and performance in the context of gamification and user engagement. We used leaderboards as a gamification tool that represents competition and explored its role as a competitive mechanism, providing novel insights to the literature that mostly treated leaderboards as a feedback mechanism. We extended previous studies that looked into one-on-one matching competition (Santhanam et al., 2016) and status (static) incentive hierarchy system (Goes et al., 2016; von Rechenberg et al., 2016) by incorporating competitive structures that consider simultaneous multiple competitors competing for a dynamic goal owing to user interactions. Thus, we extend discussions on the design of digital platforms by highlighting the impact of gamification when multiple users compete and their ranks change dynamically (i.e., a dynamic incentive hierarchy system).

Second, we applied a theoretical lens of behavioral economics to broaden the scope of inquiry on the role of competition in digital platforms. Our theory-driven discussions on gamification design relaxes the commonly held assumption that people are not bounded in rationality or willpower. Although we do not challenge the idea that people use information technology with rational intentions and make choices accordingly, we recognize that these intentions are affected by emotional and social factors that incite heuristics, which may cause systematic biases. Our findings suggest that we need to consider these biases when studying gamification in digital platforms. Thus, we contribute to the gamification and user engagement research by integrating behavioral economics as its foundational lens, thereby providing an additional perspective on how users make decisions when their willpower and rationality is bounded. More specifically, we contribute to the gamification literature by explaining decision making process as a process of using heuristics that reduces uncertainty via visual cues.

Lastly, we contribute to the literature on user engagement by providing empirical evidence that shows heterogenous effects of gamification that focus on competition. By conducting long-term field experiments to examine the impact of different types of competitive structure on digital platforms, we add values to the empirical analysis of user engagement, which are typically conducted as a short-term experiment. As a further extension of empirical analyses, other types of gamifications such as ranks could be considered for in-depth study, or large scale leatherboards and different contexts of digital platforms may be useful to investigate further.

On a practical front, our findings provide insights to practitioners regarding how to apply gamification on digital platforms in such a way that increases user engagement. Particularly, our findings can provide actionable guidance for implementing various types of competitive structures in their digital platforms using the idea of gamification. Although a trial-and-error approach is useful for companies, in most cases changing one particular aspect of gamification design and observing its impact would be impractical and may create confusion among the users of their platforms. Specifically, our theoretical discussion and empirical evidence suggest that digital platform owners and designers need to consider implementing leaderboards that emphasize local competition surrounding each focal user rather than blindly adopting global leaderboards that show top-ranked users only, as doing so can help them increase user engagement, which can ultimately help improve the long-term viability of their platforms.

Conclusion

Like any research, we acknowledge that our study has limitations. First, the interpretation of our results is bounded to our context, which is a university course. Given that users are greatly affected by their academic goals, applying the same research design to another context might not produce the same outcomes. However, we argue that our study could be applied in a broader context since we applied a setting similar to the Q&A online platforms, which are an online space where users ask questions and answer questions raised by others. We used a separate online platform that students had to access with their individual credentials, which we believe created a similar environment that users face when visiting Q&A platforms; therefore, we believe that our context might be generalizable beyond the educational context we examined. Nevertheless, we do not think that localized leaderboards could solve the problem of motivating users from 0 level of initial engagement to some engagement; rather they could encourage users from little engagement to greater engagement on digital platforms given the platform has some active users.

Second, our leaderboards design accommodates a small number of competitors, and applying the same design to a larger scale (e.g., 100 or more users) might have different effect as users may perceive their relative positions differently. However, it is unclear whether showing a large number of competitors on the leaderboards would be effective if we consider the limited capacity of human cognition, which has been reported to have working memory of seven plus or minus two (Miller, 1956). Therefore, displaying too much information on leaderboards possibly will lead to unreliable results.

Lastly, in our data analysis we assumed a linear relationship between competition and user engagement, but we acknowledge that gamification has a dynamic and cyclical nature (Koivisto & Hamari, 2019) that cannot be divorced from the bidirectional relationships between users and digital platforms. Exploring the dynamic, non-linear relationship between competition and user engagement would be an interesting avenue for future research.

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POSITIONING OF ESSAY 3

Essay 3 presents an empirical study that extends the discussion of the first essay. This study uses gamification to encourage cooperation of the free riders on digital platforms. It examines team tasks performed on digital platforms that requires active collaboration among involved members, who are incentivized to cooperate due to the reward structure that depends on the efforts from self and others (i.e., very high degree of task seriousness). We argue that virtual collaboration can be undermined by the free riding behaviors; so, we motivate their contribution by using team leaderboards (i.e., low degree of playfulness).

Team leaderboards as a cooperation-based gamification element, has been studied to increase user engagement on digital platforms. This gamification element helps free riders in teams recall their team goals and understand their current state as a team. The visibility of tasks through team leaderboards increases the user engagement of free riders, ultimately reducing free riding behaviors. However, not all free riders hold the same view about collaboration. Some rely on self-assessment and determination; and others consider social factors in their equation of free riding behaviors.

Our model theorizes that designing team leaderboards that accentuate task visibility along with varied individual performance feedbacks that accentuate the meaning of task is essential to improve the user engagement of free riders. Our arguments are guided by the following research questions: *Can we solve the free-rider problems in digital environments by using gamification? How does the gamification that accounts for both team and individual performance feedback affect different types of free riders in virtual collaborative environments?*

The following essay describes and explains how we established our hypotheses to answer our research questions and how we examined them through online lab experimentation. Based on the analysis of our evidence, we discuss the implications of our study and conclude our arguments by suggesting some future research avenues.

V. EXAMINING THE IMPACT OF TEAM LEADERBOARDS ON FREE RIDERS IN VIRTUAL ENVIRONMENTS

Abstract

Organizational free riders can negatively impact productivity. While organizations employ free riding mitigation strategies in traditional operations, these may not be sufficient in modern digitally focused hybrid work environments. Virtual workspaces allow enlarged teams, the greater distance between users and to engender the dehumanization of peers, resulting in free riding behaviors becoming more prevalent. This study proposes a gamification design to alleviate free riding behaviors through internalizing extrinsic motivation while accommodating the diverse social values of the free riders. Through online lab experiments we find that providing simple team leaderboards are not effective in changing the behavior of free riders. However, team leaderboards that incorporate individual performance feedback increase the user engagement of free riders. In particular, free riders that receive injunctive social norm messages along with team leaderboards engage more compared to those receiving within-team leaderboards that identify and assess individual inputs using competitive mechanism. We contribute to gamification literature by increasing the understanding of cooperation-based design in the context of group and individual level feedback and diverse free rider types. Further, we provide a practical implementation for free riding issues on virtual collaboration platforms in the era of hybrid working environments.

Keywords: free riders, social loafing, cooperation, gamification, team leaderboards, user engagement, lab experiment

Introduction

Most of tasks conducted in organizations are collaborative work. Performing collaborative work requires the coordination of many parties. However, not all parties are on the same page in terms of their expectations. Among many challenges, free riding is a well-known phenomenon that shows a tendency of people extracting benefit from collective work without paying a proportional share of the costs (Albanese & Van Fleet, 1985). This can negatively affect firm performance (Albanese & Van Fleet, 1985). The prevalence of this behavior in collaborative environments demonstrates the difficulty of executing collaborative work in organizations.

Organizations use various strategies to mitigate free riding behaviors. For instance, organizations may reduce the size of work units to increase control in collaborative environments (Albanese & Van Fleet, 1985; George, 1992; Karau & Williams, 1993). Other strategies include providing group level feedback to make the collective tasks salient, using rewards and punishment to identify and incentivize individual contributions to the group performance, and increasing the interaction among the members to make the collective tasks meaningful (Albanese & Van Fleet, 1985; George, 1992; Karau & Williams, 1993). All these strategies, however, face limitations because they are contingent on specific contexts that cannot always be managed (Karau & Williams, 1993).

Virtual collaborative environments present particular challenges as the nature and potential benefits of the environment contradicts these mitigative strategies. The size of collaborating units is theoretically infinite, as are the physical distances between involved parties, and the lack of direct social contact permits greater dehumanization of colleagues (Alnuaimi et al., 2010; Chidambaram & Tung, 2005; Gilson et al., 2015).

There are some remedies presented by prior work to facilitate collaboration in virtual environments. Studies have indicated that increasing the sense of being part of online community or virtual teams (Chang et al., 2020; Shiue et al., 2010; Zhang et al., 2021) or identifying and evaluating individual inputs using IT artifacts (Bryant et al., 2009; Chidambaram & Tung, 2005; Gilson et al., 2015) may reduce free riding behaviors. These strategies have typically been examined by means of survey questionnaire rather than by observed behaviors, and they are rarely implemented on digital platforms. Considering the hastened transition of collaborative environments from physical to virtual spaces, the lack of understanding in implementing these strategies creates an urgent need for research supporting the design of digital platforms that ease virtual collaboration.

As a motivational tool, gamification is considered to be an effective means to improve user engagement (Koivisto & Hamari, 2019). Gamification can be defined as the use of gamified design in information systems that assimilates the playful experience of games into non-gaming contexts to achieve instrumental outcomes. As the definition suggests, gamification presents a unique value by motivating users of digital platforms as a result of increasing intrinsic motivation such as joy and excitement (Koivisto & Hamari, 2019) or internalizing extrinsic motivators such as reputation, and reciprocity (von Krogh et al., 2012; Chen et al., 2018). This is distinct from the traditional motivation mechanisms of rewards and penalties that incur either direct financial costs or indirect costs in the form of employee resistance or rejections.

Earlier study has shown that for a collaborative task, the gamification design element of team leaderboards increases user engagement when compared to individual leaderboards (Morschheuser et al., 2019). This finding was explained by highlighting the positive impact of gamification on intrinsic motivation such as enjoyment through social interactions. Following this finding, the review on cooperative gamification literature suggests that gamification can motivate social dynamics and cooperative activities (Riar, 2020). Considering that team leaderboards make group tasks visible and enable to share group level feedback, we expect this design element to increase the user engagement of free riders in virtual collaborations.

However, the degree of effectiveness of this gamification is unclear given the various types of free riders. Free riders may exhibit exploitative behaviors for different reasons depending on their social values (i.e., collaborative or individualistic tendencies) and their given circumstances. Consequently, we can expect that simply applying team leaderboards would not be sufficient to eliminate the free riding issue in virtual collaborative environments. We suggest that by adding varied individual performance feedback on team leaderboards to accommodate free riders of diverse social values some of these limitations may be overcome.

In order to better understand the impact of gamification and specific design elements on free riders on digital platforms we propose the following research questions:

- Can we solve the free-rider problems in digital environments by using gamification?
- How does the gamification that accounts for both team and individual performance feedback affect different types of free riders in virtual collaborative environments?

We propose a study using online lab experimentation to observe behaviors directly and avoid issues related to the self-reporting of socially undesirable behaviors and measurement by proxy. As our study is primarily concerned with behavior, we feel that this method provides the greatest fidelity.

Our study extends the literature on virtual teams that accentuates the importance of acknowledging individual performance on alleviating free riding behaviors (Chidambaram & Tung, 2005). We differentiate our contribution in six significant ways. We integrate the concepts of gamification as a motivational tool (Koivisto & Hamari, 2019) in virtual collaborative environments that use digital platforms. We re-examine the relationship between task visibility, task uniqueness and free riding (George 1992) in virtual collaborative environments by means of internalizing extrinsic motivation through IT artifacts on digital platforms (von Krogh et al, 2012; Chen et al, 2018). We apply a lens of social psychology that differentiates individualistic and collective social values in team performance (Wagner III, 1995) from individual performance feedback for free riders. Through this process, we expand the use case of gamification design by inclusion of mechanisms directed towards different types of users such as free riders. Further, we provide insight on how to build gamification features for virtual collaboration and explain how the non-economic extrinsic motivators can turn into sources of intrinsic motivation. In practice, we provide guidance for practitioners on the application of gamification to digital platforms in such a way that decreases free riding behavior and increases user engagement.

Literature Review

In this section, we first review studies discussing free riding behaviors in virtual collaborative environments. This is followed by the identification of different reasons for observing these behaviors along with some strategies studied in prior studies. The section concludes by discussing gamification design that focuses on collaboration or cooperation.

We include in our review studies examining this phenomenon from the perspective of social psychology which employs the parallel concept of social loafing behaviors, which describes the tendency of individuals to put in less effort for collective work compared to that which they would when working individually (Karau & Williams, 1997). We note that within a virtual environment, where user engagement is often measured as a function of communication, the complications of observing communications effort of an isolated individual for comparative purposes results in social loafing research tending to measure similar factors to that of research on free riders. Consequently, we consider the findings on social loafing behavior to be relevant to the understanding of free riders.

Free Riding in Virtual Environments

In virtual environments, free riding is typically studied in either the context of virtual teams or online communities. In the context of virtual teams, it has been shown that increases in team size are linked to increases in social loafing behaviors (Chidambaram & Tung, 2005; Gilson et al., 2015). Further, increased geographical dispersion among the members in virtual teams was identifying as intensifying social loafing behaviors due to the dehumanization of colleagues and the diffusion of responsibility (Alnuaimi et al., 2010). In online communities, weak social ties among users and the perceived social risks of online communications were shown to increase social loafing behaviors (Shiue et al., 2010). Furthermore, a decreased sense of being part of community may also contribute to free riding behaviors (Chang et al., 2020; Zhang et al., 2021).

To better understand the reason behind exhibiting free riding behaviors in virtual environments, we categorize free riders into three types, as illustrated in Table 1. This categorization, however, is not exhaustive nor mutually are the categories exclusive. At an individual level users may have different rationales for their involvement in social loafing behaviors.

Types of Users	Relevant Strategies
(1) Users that care less about others, being highly rational agents (Albanese & Van Fleet, 1985)	**Clear goals** and **task uniqueness** may alleviate social loafing behavior in online communities (Ling et al., 2005) **Mixed-incentive reward structure** (team and individual reward) and richer technology medium (both visual and audio medium) may decrease social loafing in a virtual team environment (Bryant et al., 2009) **Self-feedback** may alleviate social loafing behaviors (Suleiman & Watson, 2008)
(2) User whose environment makes them care less about others (Alnuaimi et al., 2010; Chidambaram & Tung, 2005)	**Strong social ties** and **weak perceived risk** may decrease social loafing in online communities (Shiue et al., 2010) **Cooperatively framed performance** feedback is effective at user contribution by touching upon users' altruistic intent in User Generated Content (UGC) context (Huang et al., 2019) **Affective community commitment** decreases social loafing behaviors in online brand communities (Zhang et al., 2021) **Enjoyment and community identification** may alleviate social loafing behaviors in online travel communities (Chang et al., 2020)
(3) Users that make wrong judgments about their actions (Hall & Buzwell, 2013; Kruger & Dunning, 1999; Ross and Sicoly, 1979)	**Information sharing** may increase team performance (Mesmer-Magnus & DeChurch, 2009) **Salient information** may reduce the uncertainty of individual contribution thus enabling users to make better decisions (Kahneman, 2003)

Table 1 Types of Users that Exhibit Free Riding Behaviors

Some users appear to be purely rational agents that do not care much about others' actions. These agents are motivated by self-interest and consequently, where they are able to maximize their personal utility by reducing effort and receive the same benefits they will do so (Albanese

& Van Fleet, 1985). For these users, an incentive system where each member is rewarded for their actions or is recognized for their performance within groups is of great importance (Albanese & Van Fleet, 1985). In the context of virtual teams, self-feedback (Suleiman & Watson, 2008) and mixed-incentive reward schemes (i.e., groups and individuals) are helpful as they increase task visibility (Bryant et al., 2009). In online communities, both providing clear goals and highlighting the uniqueness of tasks are helpful as they increase the meaningfulness of individual contributions (Ling et al., 2005).

The second type of users are affected by the digital environments that they are exposed to. Thus, these users are conditioned to act as rational agents, regardless of their social inclination. For example, virtual environments may make some users care less about others by dehumanizing them (Alnuaimi et al., 2010) or submerging themselves in groups (Chidambaram & Tung, 2005). The free riding behaviors of these users may be alleviated by increasing social ties through cooperatively framed feedback (Huang et al., 2019), affective community commitment activities (Zhang et al., 2021), and accentuating the enjoyment from helping others (Chang et al., 2020).

The last type of users makes wrong judgments due to being ignorant of their environment. Some users are simply not good at reading the dynamics in virtual collaborative environments, so underestimate their ability. This leads to performing involuntary free riding behaviors owing to uncertainty emerging from feelings of inadequacy or incompetence when conducting collective tasks (Hall & Buzwell, 2013). Other users suffer from egocentric biases in availability of information, so overrate their contribution to the collective tasks (Ross & Sicoly, 1979). The tendency of overestimating their ability can lead to free riding behaviors due to perceiving the reality as being the case where others could take an advantage of their contribution in the joint work. Whether the free riding behaviors appear from underrated or overrated competence and contribution, both cases show that these users make inadequate judgment for being unintentionally ignorant of their environment (Kruger & Dunning, 1999). Consequently, these users need an appropriate design of digital platforms that put on information sharing practice commonly applied in teams (Mesmer-Magnus & DeChurch, 2009). Presenting salient information may also reduce the uncertainty of individuals' contributions enabling users to make better judgement of their current state (Kahneman & Tversky, 2013; Kahneman, 2003).

To summarize, the first type of free riders are intentional free riders who are well aware of their environments and their actions. The second and the third types of free riders are unintentional free riders that are strongly influenced by their environments or simply are not good at evaluating their own contribution. Considering that the causes of free riding behaviors appear to vary between individuals working through digital platforms, we suggest considering these differences in the feedback mechanism design of those platforms.

Cooperation-based Gamification

Gamification is a motivational tool that enables to design digital platforms to increase user engagement that differs from the traditional incentives such as rewards and punishment. We define gamification as *the use of gamified design in information systems that assimilates the playful experience of games into non-gaming contexts to achieve instrumental outcomes*. This concept has gained popularity for motivating users to engage in activities on digital platforms (Blohm & Leimeister, 2013; Koivisto & Hamari, 2019; Liu et al., 2017). In particular, studies on cooperation-based gamification design have shown the positive impact of gamification in increasing user engagement with positive psychological (e.g., fun, enjoyment) and behavioral outcomes (e.g., participation, performance) (Koivisto & Hamari, 2019; Riar, 2020). For instance, team leaderboards, a common gamification design element, have been shown to have a positive effect on user contribution by increasing intrinsic motivations, such as enjoyment through social interactions (Morschheuser et al., 2019). Other gamification design elements such as points, rewards, and badges have been shown to encourage collaboration through immediate performance feedback at individual and group levels in the context of education (Hasan et al., 2019). Other types of gamification design such as voting and 'likes' have been linked to greater cooperation by adding social dynamics that require input from others (Morschheuser et al., 2019; Wang et al., 2020).

The social dimension of cooperation-based gamification relates closely to activities that require collaboration. Team-leaderboards, for example, are used quite commonly in video games to encourage within-team cooperation while competing against other teams. This design provides group level feedback by simultaneously displaying teams at different positions based on a given hierarchy system. The unique characteristic of team leaderboards, which is the combination of competition and cooperation, makes them superior in terms of psychological outcomes (i.e., enjoyment) over other gamification design that either focuses on purely competition (i.e., leaderboards at individual level) or cooperation (i.e., feedback on team progress without being compared with other teams) (Morschheuser et al., 2019). Thus, we expect that the application of team leaderboards as a gamification design element would be effective to reduce free riding behaviors.

However, despite the advantage of the team leaderboards in promoting collaboration, it is doubtful that this design would mitigate free riding behaviors effectively as the reasons behind these behaviors may vary. For instance, simply applying team leaderboards may not be sufficient for the highly rational users as team leaderboards do not recognize individual input. Thus, incorporating a design that combines both individual and group level feedback could be more effective. This thought is in line with the review of cooperative gamification literature where the review highlighted the hybrid form of gamification as more enjoyable and preferable in increasing cooperation (Riar, 2020).

This review acknowledged the difficulties of implementing a hybrid form of gamification and recommended aligning personal and group goals through creating competition at group level while encouraging cooperation within-group level (Riar, 2020). We expand this design approach by detailing the gamification design elements that encourage cooperation within-group level. Given the importance of acknowledging individual performance in mitigating social loafing behaviors (Chidambaram & Tung, 2005) and the positive effect of providing individual performance feedback on user engagement (Bryant et al., 2009; Gilson et al., 2015; Huang et al., 2019), we consider creating feedback mechanisms that can account for both group and individual level contribution as well as varied types of free riders.

Research Model and Hypotheses

In this section, we first describe our research model that provides a framework that enables our main constructs (i.e., task visibility and task uniqueness) to be represented using gamification design elements. Then, we discuss two main hypotheses that link the gamification design elements and free riding behaviors within virtual collaborative environments.

Research Model

To develop our hypotheses, we visualize our research model as shown in Figure 1 using theoretical lenses from management and social psychology. These disciplines present the problem of free loading as a function of motivation, which may be generated internally (intrinsic) or received from external sources (extrinsic).

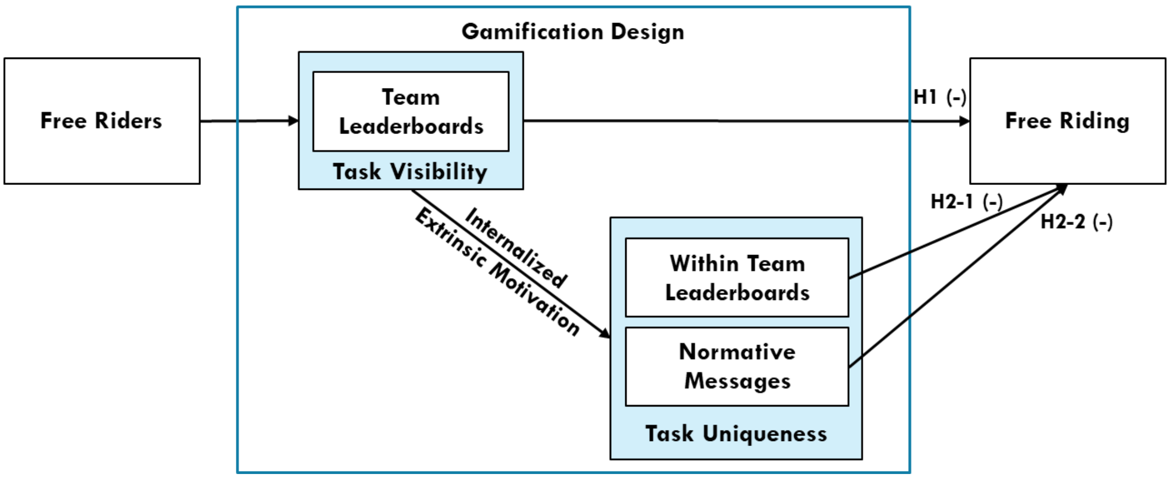


Figure 1 Research Model

Management literature has shed light on free loaders by studying the constructs of task visibility and task uniqueness in collaborative environments (Albanese & Van Fleet, 1985; George, 1992). Task visibility is the degree to which the task and its performance is clear to the individual. Task uniqueness is the degree of importance of a particular task to an individual. Both constructs are found to be effective in reducing free riding behaviors (George, 1992). For example, greater degree of task visibility increases extrinsic motivation such as identifying goals that are likely to provide direct benefits to the team, and consequently to the individual. Greater degree of task uniqueness increases intrinsic motivation such as satisfaction and enjoyment in achieving team tasks. This explanation led to suggest that the interaction effect of task visibility and task uniqueness is negative (i.e., negatively moderating effect of task uniqueness); the effectiveness of extrinsic motivator decreased when users are motivated intrinsically in a collaborative setting in organizations (George, 1992).

We argue that the interaction effect may differ in virtual collaborative environments as the IT artifacts of digital platforms have been theorized to be capable of transforming of external factors into intrinsic motivators; enabling users to self-regulate their behavior and consequently increase user engagement (Chen et al., 2018; Von Krogh et al., 2012). Thus, our research model suggests that the interaction effect of task visibility and task uniqueness is positive. The effectiveness of extrinsic motivator increases when users are motivated intrinsically (i.e., positively mediating effect of task uniqueness).

To represent our argument, our model includes individual level gamification elements on team leaderboards as a mediator of the relationship between task visibility and free riding. Our model presents gamification as a factor influencing free riding behavior, in particular by altering task visibility as an external source of motivation and by altering the perception of task uniqueness by either collectivistic appeals or individualistic appeals.

The communication of effective task performance is an important aspect of task visibility. The gamification design element of team leaderboards presents collective goals and performance against other teams, which incorporates signaling for the purposes generating both within-team cooperation and across-team competition. Task visibility has been shown to have an impact on free riding (Albanese & Van Fleet, 1985; George, 1992). As team leaderboards make task performance visible and thus explicitly share group level feedback, they may decrease free riding.

The communication of individual efforts in task is an important aspect of task uniqueness. The individual performance feedback to team leaderboards presents the identification and self-assessment of individual input within the group. An increase in the task associated intrinsic motivation of individual users by means of increased task uniqueness has been shown to result in a reduction in free riding (George, 1992; Ling et al., 2005). The addition of individual performance feedback to team leaderboards in a manner that saliently confers the unique meaning or significance of tasks to an individual may decrease free riding.

Social psychology research offers potential for a greater understanding of free riders in group environments by distinguishing between individualistic and collective types (Wagner III, 1995). Individualistic types ignore group interests where they see conflicts with their personal desires, while collectivistic types put the group interests before their personal desires or needs (Wagner III, 1995). Free riders can fall into either individualistic or collectivistic types given that free riders can be either intentional or unintentional depending on their circumstances. Individualistic free riders are likely to be competitive when their personal desires conflict with group interests or others, while collectivistic free riders are likely to be cooperative when their personal desires conflicts with group interests.

Gamification that integrates social aspect can be categorized either competitive or cooperative. Competitive design promotes social comparison, which enables users to compare their achievements or progress against other users or themselves. This type of design would benefit free riders that value competition (i.e., to win over others). On the contrary, cooperative design promotes social norms, which enables users to better understand the acceptable behaviors or actions within the community that the users are part of. This type of design would benefit free riders that value cooperation (i.e., to work with others).

Consequently, within-team leaderboards, which present information in such a manner so as to provoke social comparison among team members would likely more greatly encourage those with individualistic tendencies to engage more in team activities. Conversely, information presenting emotive feedback, or injunctive normative messages that emphasize social norms would better encourage free riders with collectivistic tendencies. Thus, it is fair to assume that each user would find meaning in their tasks differently depending on their orientation towards either individualistic or collective values. These value types have therefore been added to the model within the task uniqueness factor; as forms of individual performance feedback: within-team leaderboards and injunctive normative messages (i.e., normative messages that shows the approval of the actions).

To conclude, our research model demonstrates that team leaderboards increase the user engagement of free riders through increasing the degree of task visibility, which works as an extrinsic motivator that shares group level feedback that positively affects team performance (Mesmer-Magnus & DeChurch, 2009). Individual performance feedbacks increase the user engagement of free riders through increasing the degree of task uniqueness, which works as intrinsic motivators that enables individuals to enjoy contribution by either competing or cooperating. The interaction effect of team leaderboards and individual performance feedback further increases the user engagement of free riders by internalizing extrinsic motivators that enable free riders to self-regulate their behaviors. These internalized extrinsic motivators would be reputation in case of the interaction with within-team leaderboards and reciprocity in case of the interaction with injunctive normative messages.

Hypotheses

As a consequence of the developed research model, we set forth the following hypotheses.

We expect that cooperative gamification design elements, such as team leaderboards, would reduce free riding behaviors as a result of increased task visibility. We would expect this outcome irrespective of the social value of the free riders.

> Hypothesis 1 (H1). *Team leaderboards may reduce free riding in virtual collaborative environments.*

Team leaderboards are hypothesized to encourage free riders to contribute on digital platforms by sharing information that helps identify collective performance. However, the grouped presentation of performance leaves free riders uncertain about their individual contribution. This can be problematic as they may misjudge their current contribution and thus could choose to contribute less. Further, if their motivation is low, seeing team performance may do little or could backfire with free riders preferring to hide in the crowd (Chidambaram & Tung, 2005). More direct or personalized information sharing would increase task uniqueness, and positively impact these problems. Thus, individual performance feedback should be added to team leaderboards to accentuate task uniqueness. Consequently, individual performance feedback decreases free riding.

Hypothesis 2 (H2). *Individual performance feedback along with team leaderboards negatively affects free riding in virtual collaborative environments.*

The presentation of individual performance feedback may have an impact on how effective it is at motivating free riders depending on their social value orientation. When it comes to cooperation, users can be either individualistic or collectivistic (Wagner III, 1995). Given these types, we examine the impact of gamification design individual performance feedback elements that act upon both social comparison and social norms by the formulation of the following sub-hypotheses.

For social comparison, we examine within-team leaderboards as individual performance feedback. Leaderboards typically display a ranked list of users according to their relative performance on a set of specified criteria. Relative ranking acts as a competitive indicator of progress and induces social comparison among users, which is likely to stimulate the contribution of free riders with individualistic social value inclinations. Within-team leaderboards presents salient information to free riders by narrowly framing only the activities of members that are directly affecting the results, which tends to stimulate competition even more.

Hypothesis 2-1 (H2-1). *Within-team leaderboards along with team leaderboards may reduce free riding behaviors more than team leaderboards alone.*

For social norm, we examine injunctive normative messages as gamification design element providing individual performance feedback. Social norms are the expected behaviors of individuals in certain contexts and they have been found to increase user engagement in online platforms (Burtch et al., 2018). However, it is important to note that in non-virtual contexts, normative messages that only show the information on the average behaviors (i.e., descriptive normative messages) have suffered from boomerang effects (Schultz et al., 2007). Thus, we suggest that injunctive normative messages (i.e., conveying social approval or disapproval), such as by means of an 'emoticon' showing a happy or sad face to indicate the expected (or approved) contribution in virtual collaborative environments. This approach would be more appropriate for the free riders with collectivistic social value inclination. Thus, we expect providing injunctive normative messages with emotive messaging (i.e., emoticons) as individual performance feedback to decrease free riding.

> Hypothesis 2-2 (H2-2). *Injunctive normative messages along with team leaderboards may reduce free riding behaviors more than team leaderboards alone.*

Data Collection

To examine our hypotheses, we conducted an online lab experiment. We chose this research method as we were interested in examining the behavioral changes of free riders when subtle design changes occur on digital platforms. Online lab experiments enable us to control the environment of the study and observe the changes in behavior in response to our interventions. Using this research method also increases the degree of internal validity of our study compared to other data collection methods (Karahanna et al., 2018). In the following section we describe our experimental design in detail including the type of experiment, treatments, tasks, and the procedure.

Experiment Design

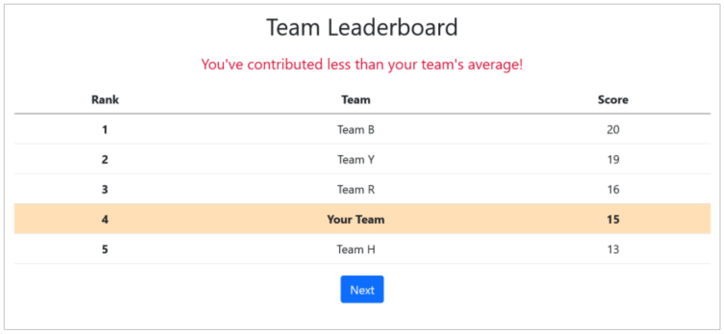
For our online lab experiment, we applied a 2x3 factorial design. This design enabled us to examine the effects of two independent variables simultaneously, those of team leaderboards and individual performance feedback. For the team leaderboards, we compared the user engagement of free riders for collaborative tasks before and after our intervention (i.e., pre-test vs. post-test). For the individual performance feedback, we compared the user engagement of free riders under three conditions. Participants were presented with either team leaderboards with no individual performance feedback, team leaderboards with individual performance feedback that enables the comparison of engagement with others' (i.e., social comparison), or team leaderboards with individual performance feedback that enables the assessment of engagement relative to expected engagement (i.e., injunctive social norms). Table 2 below presents the group assignments in our experiment.

		Individual Performance Feedback		
		No	Social Comparison	Social Norms
Team Leaderboards	No (pre-test)	Group 1	Group 2	Group 3
	Yes (post-test)	Group 4	Group 5	Group 6

Table 2 Group Assignments

Treatments

To examine the impact of gamification on free riding, we designed our treatment to reflect the three different types of team leaderboards. The first type of team leaderboard simply displayed the ranks and the scores of the teams as shown in Figure 2.



Team Leaderboard

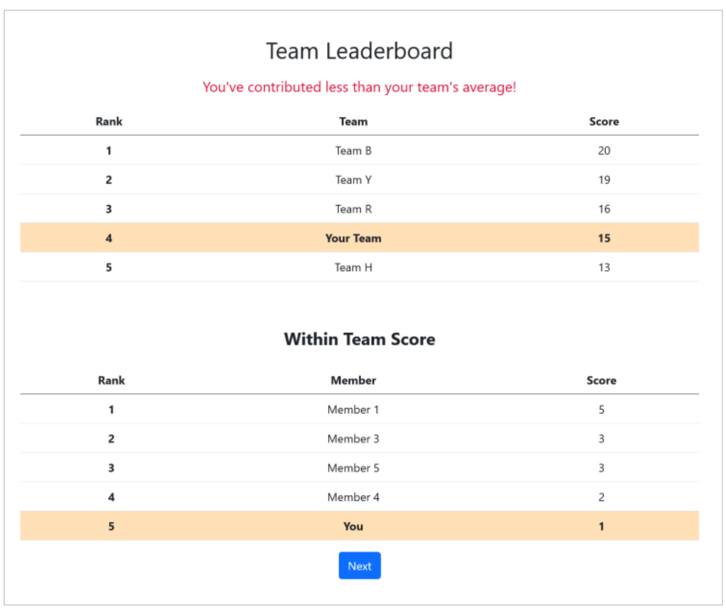
You've contributed less than your team's average!

Rank	Team	Score
1	Team B	20
2	Team Y	19
3	Team R	16
4	**Your Team**	**15**
5	Team H	13

Next

Figure 2 A Simple Team Leaderboard

The second type of team leaderboards displayed the team leaderboards with individual performance feedback that enabled individuals to compare their current state against other team members using a within-team scoreboard as shown in Figure 3. This scoreboard showed the ranks and the scores of team members. However, it did not disclose the names or nicknames of team members to avoid any confounding effects stemming from being familiar with any members.



Team Leaderboard

You've contributed less than your team's average!

Rank	Team	Score
1	Team B	20
2	Team Y	19
3	Team R	16
4	**Your Team**	**15**
5	Team H	13

Within Team Score

Rank	Member	Score
1	Member 1	5
2	Member 3	3
3	Member 5	3
4	Member 4	2
5	**You**	**1**

Next

Figure 3 A Team Leaderboard with Within-Team Scoreboard

The third type of team leaderboard displayed the team leaderboards with individual performance feedback that enabled individuals to compare their current engagement against the average contribution of the team members using a contribution scoreboard, as shown in Figure 4. This scoreboard showed an emoticon depicting a facial expression next to the focal user score to indicate the expected degree of engagement within team for the given collaborative tasks. For example, the sad face next to the focal user score shown in the figure provides an injunctive social norm message to free riders.

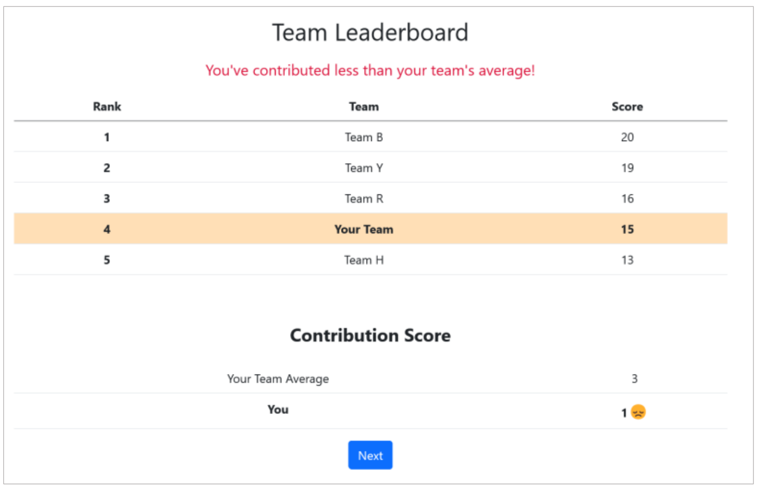


Figure 4 A Team Leaderboard with Contribution Scoreboard

Common to all leaderboards was the presentation to all participants of their effort as being below the average for their group. We wanted to make all participants to perceive themselves as free riders because our research interests lie in observing the user engagement of free riders. As discussed in the literature review section, while some free riders are intentional others do so by accident. Thus, making all participants to believe that they are free riders would provide the opportunity observe not only the deliberate free riders but also the free riders by their surroundings. For example, we could consider a situation where team members do not intend to free ride in their team tasks, but they happen to be in a team with extraordinary performers, so they become accidental free riders.

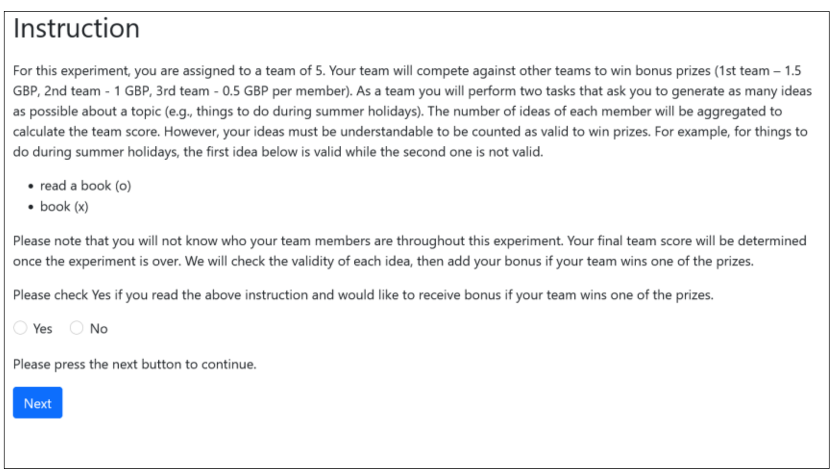
The ‘free rider’ status of participants was enforced by a message at top of all team leaderboards that read “You’ve contributed less than your team’s average!”. This placement was based on digital platforms design practice best practices which suggest that placing important messages at the top of leaderboards is more effective (refer to Appendix A for an example) as users are likely to read information from top to bottom (Ruiz et al., 2021). Including this message was critical for our experiment because it enabled us to account for both intentional and accidental (or unintentional) free riders, making our data analysis and discussions more insightful.

Tasks

In order to design the team tasks in our experiment, we had to consider various factors. First, given the nature of our experiment, which was a short-term one-time experiment, we had to create a team task that could motivate individuals to engage actively in digital platforms as a team. Secondly, the team task had to be not too cognitively complex, because complex team tasks would be highly correlated to the experience or the level of education of the participants. For instance, participants with more experience or education are likely to better solve cognitively challenging tasks as they are trained or learnt to break down complex tasks into smaller chunks.

Given these considerations, we asked participants to perform a simple team task of generating as many ideas as possible for a given topic (e.g., things to do during summer holidays). All participants were provided with a basic renumeration of one dollar. To provide a clear incentive to perform the team tasks, we randomly assigned participants to a team of five and informed them that they would compete against other teams to win three prizes based on team scores. The set prizes were bonuses of $1.50, $1 and $0.50 paid to each member of the first, second and third placed teams, respectively. We informed participants that their team scores would be calculated by aggregating the number of contributions of each member in a team.

Limitations were placed on the manner in which the tasks were performed, with relevant instructions being provided to the participants for reasons of experiment reliability. First, we emphasized that their ideas must be written in a way to make them understandable in order to be counted as valid contributions, as shown in Figure 5. We also explained that the final team scores will be determined once the experiment is over, and we will check the validity of each written idea. We hoped that this would eliminate attempts to manipulate results by simply putting many words or nonsensical texts in order to win bonuses. Secondly, we informed participants that they would not know the members of their team for the entire experiment. We hoped that this would remove confounding effects that could arise from seeing acquaintances' names on within-team scoreboards.



Instruction

For this experiment, you are assigned to a team of 5. Your team will compete against other teams to win bonus prizes (1st team – 1.5 GBP, 2nd team - 1 GBP, 3rd team - 0.5 GBP per member). As a team you will perform two tasks that ask you to generate as many ideas as possible about a topic (e.g., things to do during summer holidays). The number of ideas of each member will be aggregated to calculate the team score. However, your ideas must be understandable to be counted as valid to win prizes. For example, for things to do during summer holidays, the first idea below is valid while the second one is not valid.

- read a book (o)
- book (x)

Please note that you will not know who your team members are throughout this experiment. Your final team score will be determined once the experiment is over. We will check the validity of each idea, then add your bonus if your team wins one of the prizes.

Please check Yes if you read the above instruction and would like to receive bonus if your team wins one of the prizes.

Yes No

Please press the next button to continue.

Next

Figure 5 Experiment Instruction Page

Procedure

The procedure of our online lab experiment required many steps as diagrammed in Figure 6.

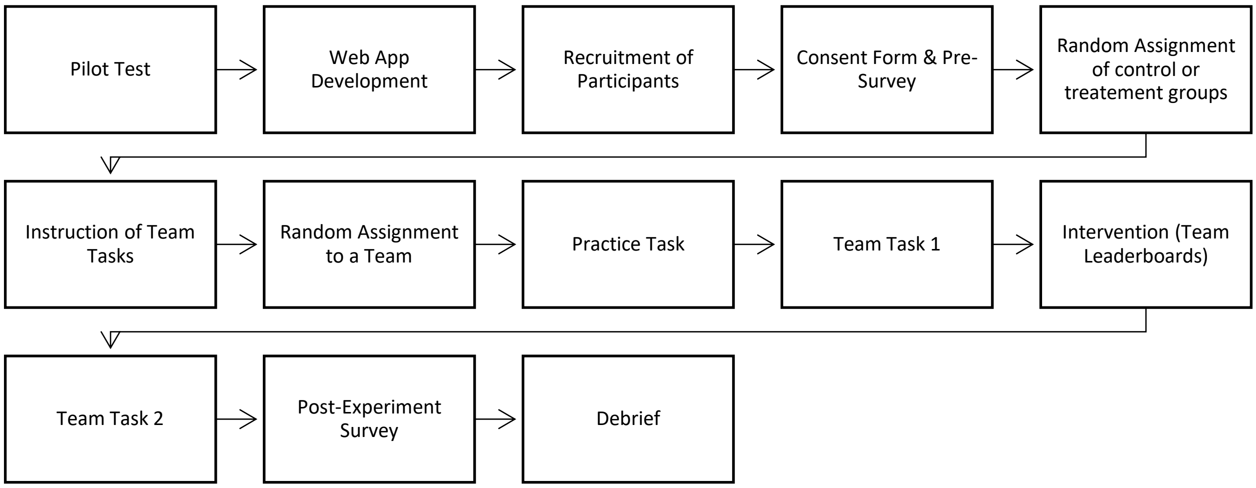


Figure 6 Experiment Procedure

Before conducting our experiment, we pilot tested the experimental design to identify team tasks that were comparable throughout our experiment. As we planned to ask participants to generate as many ideas as possible for a given topic (e.g., things to do during summer holidays), we tested various topics with PhD students in management school. We asked six PhD students to generate ideas for two randomly selected topics out of a set of seven topics that were common in lists of discussion topics online. We asked them to rate the level of difficulties of the topics on a 5-point Likert scale, where 1 indicated very easy and 5 indicated very difficult. We also asked them to rate the difficulty of the five topics that they did not use to generate ideas and asked them to suggest any other comparable topics with assigned difficulty levels. Through this process, we identified and selected two topics of comparable difficulty for the experiment, “things to do to protect the environment” and “things to do to improve your community”.

The lab experiment was conducted on a customized web app. the web app was developed using ‘oTree’, an open-source framework for experiments and surveys (Chen et al., 2016). Within the developed web app, we created a scenario that enabled participants to navigate through our experiment in a predetermined order.

Then, we recruited our participants from Prolific[12], which is a crowdsourcing platform dedicated to uses for academic research. We announced our experiment on this platform in June 2022 requesting for the total of 150 participants. From the Prolific page, participants needed to click a button to access our web app that had our online experiment setting. Then, they were directed to the consent form page where they had to click a checkbox to agree the use of data for academic purposes. Once they were linked to the web app, they were randomly assigned to either the control or treatment groups. Once they agreed to the consent form, they could access to the next page where they were asked to read an instruction. They had to check ‘yes’ to indicate that they read and understood the instructions. If participants checked ‘no’ or proceeded to next step without checking anything, we regarded them as paying little or no attention (i.e., attention check). To proceed, they then needed to click a button labelled ‘next’, which randomly assigned participants into different teams that would compete to win bonuses.

At the beginning of the main experiment, participants were provided with practice task to complete within one minute. This task provided a measure of their base level of commitment to the experiment and provided similar level of familiarity to all participants. They were then directed to a break page where they could rest before starting the first team task. For team task 1,

[12] For further information on Prolific refer to https://www.prolific.co/

they were given two minutes to write as many ideas as possible on the theme ‘things to do to protect the environment’. Participants were given the option of progressing to the next task early by clicking a button at the bottom of the page.

Following the task, participants were directed to different team leaderboards depending on their randomly assigned groups. All team leaderboards presented the participants as ranked at fourth place out of five teams, irrespective of the actual results. Participants who received a team leaderboard with within-team scores were shown their rank as being the lowest among the members in their team regardless of actual performances. Their scores however reflected their actual contributions (i.e., the scores given to them based on the number and length of ideas) so as to appear consistent with participant experiences, lending legitimacy to the results. Participants who received a team leaderboard with a contribution scoreboard were shown that their actual contribution but always as two points less than the team average score. Their scores were accompanied by a sad face emoticon. Once participants had seen their leaderboard, they had to click the ‘next’ button to move on to the second team task. Once again, participants were given maximum of two minutes to write as many ideas as possible, this time on the theme “things to do to improve their community”.

After the experiment, we administered an exit survey principally as a manipulation check, but also to gather additional data relevant to the experiment. We used manipulation check to ensure that we were effectively measuring the treatment effects of our experiment and the dependent variable. We used the user engagement scale adapted from prior literature (Agarwal & Karahanna, 2000; O’Brien et al., 2018) to measure cognitive, emotional and behavioral engagement. Our exit survey also included attention checks. Following the post-experiment survey, participants were debriefed and asked to press the ‘next’ button on the bottom of the page to complete the experiment, as an additional attention check. The expected duration for the experiment was a maximum of ten minutes. For more information on the experimentation refer to the appendices of this document. Appendix B provides the overall information about the experiment and appendix C has the table that provides the detail procedures of our experiment.

Data Analysis

In the following section, we first explain how we processed the collected data to remove any errors stemming from failing attention checks or from exaggerated behaviors due to the nature of the online lab experimental setting. This discussion is followed by descriptive statistics, measurements and randomization check. Then, we provide detail analysis of our data including the main results derived from the multivariate regression models applied to our collected data.

Data Cleaning

Before beginning the analysis, we first checked to see if there is any indication of inattention or exaggerated engagement due to cheating in our data. The reason that we were concerned about attention and cheating was because of some characteristics of online lab experiments. Online lab experiments could attract ‘professional’ participants that are economically driven and attempt to maximize their revenue by completing experiments quickly without paying attention to the tasks or by intentionally slowing down at strategic points to maximize the time taken, as some crowdsourcing platforms (including Prolific) enforce remuneration minimum based on time. Although the crowdsourcing platform that we chose for our experiment has expertise and designed incentives to provide reliable participants, we decided to investigate our data as our experiment offered a bonus in addition to participating compensation. Although the team bonus could inflate the engagement of users in our experiment, their engagement results cannot be excessive as we set time limit for each team task.

A total of 159 people participated in our experiment. Fourteen participants were rejected for failure to accept the consent form or due to not completing the experiment. An additional participant was rejected due to failing the attention check on the instruction page, that is, they failed to check ‘yes’, to indicate they had read and understood the instructions. We checked the participants for those that spent too much time on the first page of our experiment, (i.e., the consent form). Given that participants must provide their consent in order to proceed to the online lab experiment, dwelling too long on this page without checking either ‘yes’ or ‘no’ may indicate that they are not paying sufficient attention to the task. We dropped four people who lingered on this page for more than three standard deviations of the median time spent on the consent form page without proceeding to the main experiment. As shown on Appendix D, these people spent more than 10 minutes (600 seconds) on this page, when the median spent time on the page was just 47 seconds. Finally, we examined the number of ideas and the length of answers of team tasks. Given that each team task was timed at maximum of two minutes, we assumed that there are human limitations on the number of ideas that participants could produce without cheating. We removed data points that exceeded more than three standard deviations from the median user engagement of performing either of the team tasks. Through this step we removed five participants who may have copied and pasted answers from the internet. The process of cleaning our data left us with 135 participants.

Descriptive Statistics

Table 3 provides descriptive statistics of our data. User engagement scores based on the number of ideas shows that on average participants wrote about 7 ideas with standard deviation of 2.7. The ranges of user engagement indicates that the minimum number of ideas was 1 while the maximum was 14. On average, participants took about 9.7 minutes to complete the experiment with the ranges from 3.3 minutes to 17.8 minutes. The average age of participants was 26.6 years old with the ranges from 19 to 61 years old. The average employment status indicates that the participants were starting a new job in the coming months, or they were part-time workers when they completed the experiment. The average technology usage shows that the participants used technology once or more every day when this experiment was conducted.

Variables	**N**	**Mean**	**S.D.**	**Min.**	**Max.**
User Engagement before intervention (ideas of team task 1)	135	6.98	2.74	1	14
Team Task 1 Abort	135	0.32	0.47	0	1
Time Taken (in minutes)	135	9.73	2.51	3.33	17.86
Platform Experience (number of joined studies)	135	126.47	111.09	8	991
Age	135	26.61	6.99	19	61
Sex (Female is 1)	135	1.49	0.5	1	2
Individualism Index (higher the score more individualism)	135	40.74	18.14	18	90
Education Level	135	2.3	1.25	0	5
Employment Status (from full income to no income)	130	3.16	1.86	0	5
Technology Usage at Work	135	3.67	2.39	0	6
Technology Device Usage	135	1.41	0.68	0	2

Table 3 Descriptive Statistics

Measurements

Measures were designed to provide proxy indicators for the constructs in our research model. Free riding behavior was measured through the user engagement of participants. If user engagement increased, we interpreted it as a decrease in free riding behaviors. Table 4 describes how we measured our dependent variable, independent variable, and control variables that we used for our analysis.

Types	Variables	Descriptions
Dependent Variable	User Engagement (Ideas)	Number of Ideas from team task 2 (e.g., 'Plant a tree' = 1)
Independent Variable	Treatment	0 = control (team leaderboard), 1 = treatment 1 (team leaderboard + within-team leaderboard) 2 = treatment 2 (team leaderboard + individual-team average comparison board)
Control Variables	Pre-Test User Engagement (Ideas)	Number of ideas from team task 1 (team task conducted before any intervention)
	Task 1 Abort	1 = subject proceeded to the next activity before time (2 min.), 0 = subject used full time allocation
	Time Taken (in minutes)	Length of time that a subject took to complete the experiment; the maximum time for performing all team tasks is 5 min. (automatic time out)
	Platform Experience	Number of studies completed by the subjects in Prolific; this variable measures the level of familiarity of using this online platform
	Age	Age (Years)
	Sex	1 = female 0 =male
	Individualism Index Value (IDV)	IDV of the current country of residence, this index compares countries by the degree of individualism and higher the score greater the individualism[13]

[13] refer to https://www.hofstede-insights.com/fi/product/compare-countries/

	Education Level	0 = not applicable 1 = secondary education or high school diploma 2 = technical/community college 3 = undergraduate degree 4 = graduate degree 5 = doctorate degree
	Employment Status	0 = other 1 = not in paid work (e.g., homemaker', 'retired or disabled) 2 = unemployed 3 = due to start a new job within the next month 4 = part-time 5 = full-time
	Technology Usage at Work	0 = not at all 1 = less than once a week 2 = about once a week 3 = 2-3 times a week 4 = 4-6 times a week 5 = about once a day 6 = more than once a day
	Technology Device Usage	0 = 2-6 times a week, 1 = every day, and 2 = multiple times every day.

Table 4 Variables

Dependent variable

We measured the user engagement of the second team task as our dependent variable. The second team task was performed after participants received treatments, so we could observe the changes in behaviors of the free riders after our intervention. We operationalized user engagement in three ways to cross-validate our results. The main dependent variable was measured by the number of ideas. Additionally, we measured the length of ideas in words to capture engagement expressed as verbose descriptions of ideas (total number of words from team task 2; e.g., ‘Plant a tree, Eat an egg’ = 6). We also created a variable that provided the number of ideas adjusted by a weight derived from the number of words of those ideas (adjusted number of ideas = (Number of Ideas + Number of Words/3) -1; e.g., ‘plant a tree’ = 1)

To better understand our dependent variable, we created their density plots as shown in Appendix E. The normal distribution of our dependent variable confirmed that we could use ordinary least square (OLS) regression models for our data analysis without transforming our dependent variable or applying link functions to our regressions.

Independent variable

For our independent variable, we created a categorical variable to indicate the types of team leaderboards that the participants had received. The group that received team leaderboards without any individual performance feedback (i.e., the control group) was coded as 0. The group that received team leaderboards with individual performance feedback of social comparison was coded as 1 (i.e., treatment 1). Finally, the group that received team leaderboards with individual performance feedback of social norms was coded as 2 (i.e., treatment 2).

Control variables

We collected various control variables in our experiment. We randomly assigned our participants into three groups to remove selection bias. As our design included both between-subject along with within-subject comparisons we collected control variables to enable the statistical control of confounding factors stemming from the characteristics of our participants. We included measures of age, sex, education level, employment status, Individualism Index Value (IDV), technology platform specific experience, technology usage at work and technology device usage. We also measured variables that indicate the context in which our participants undertook the experiment, such as time taken to complete, time taken to complete team task 1 as well as the number of contributions of team task 1. By measuring user engagement for team task 1, which is the pre-test of our dependent variable, we are able to adjust for and control the unobserved variability in our randomized experiment (Trochim & Donnelly, 2001).

Randomization Checks

Despite we randomly assigned our subjects to different groups, we examined the randomness of our samples using statistical measures to check the reliability of our data. We performed a one-way ANOVA test for each variable in our data before any intervention as shown on Table 5. The p-values of the ANOVA test indicate that the three groups in our data are randomized. Thus, we could compare these groups as they were statistically the same in all measures.

			Team Leaderboard (45)		**Ind. Leaderboard (43)**		**Norm Leaderboard (47)**		**ANOVA test**
Variables	**min.**	**max.**	**mean**	**s.d.**	**mean**	**s.d.**	**mean**	**s.d.**	**Pr(>F)**
User Engagement Score of Team Task 1 (pre-test)	1	14	6.93	2.61	7.77	2.91	6.3	2.55	0.26
Team Task 1 Abort	0	1	0.38	0.49	0.28	0.45	0.3	0.46	0.42
Time Taken (in minutes)	3.3	17.9	10.09	2.62	9.78	2.53	9.34	2.39	0.15
Platform Experience (number of joined studies)	8	991	136.29	98.03	116.91	80.64	125.81	143.68	0.66
Age	19	61	28.04	6.85	25.28	5.07	26.45	8.39	0.28
Sex (Female is 1)	1	2	1.42	0.5	1.56	0.5	1.49	0.51	0.53
Individualism Index (higher the score more individualism)	18	90	38.76	17.63	40.33	18.41	43.02	18.5	0.26
Education Level	0	5	2.38	1.25	2.19	1.26	2.34	1.27	0.89
Employment Status (from full income to no income)	0	5	3.28	1.8	3.31	1.81	2.91	1.96	0.35
Technology Usage at Work	0	6	4.24	2.14	3.47	2.42	3.32	2.53	0.06
Technology Device Usage	0	2	1.51	0.55	1.28	0.83	1.45	0.65	0.67

Table 5 Descriptive Statistics with ANOVA tests

Main Results

We analyzed our data using multivariate regression models with three variations of the dependent variable to cross-validate our results. We first examined our data using within-subjects analysis to compare the average user engagement before and after our intervention (i.e., team leaderboards). For this analysis we compared the control group in pre-test (group A*a*) and the groups in post-test (group A*b*) as shown on Table 6. Then, we examined our data using between-subjects analysis to compare the average user engagement of different types of team leaderboards, which compared the user engagement of group B*b* and group *Cb* against group A*b*. Finally, we analyzed the interaction effects between the pre-test and treatments to determine the impact of individual performance feedback on different types of free riders.

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="3">Individual Performance Feedback (Between-Subjects)</td></tr>
<tr><td>No (Control)</td><td>Social Comparison</td><td>Social Norms</td></tr>
<tr><td rowspan="2">Team Leaderboards (Within-Subjects)</td><td>Pre-Intervention</td><td>Group Aa</td><td>Group Ba</td><td>Group Ca</td></tr>
<tr><td>Post-Intervention</td><td>Group Ab</td><td>Group Bb</td><td>Group Cb</td></tr>
</table>

Table 6 Selected Group for Analysis

Within-Subjects Analysis

We used within-subjects analyses to compare the average user engagement of free riders before and after our intervention (i.e., no team leaderboards vs. team leaderboards). For these analyses we used hierarchical regression models that accounted for individual differences. The dependent variable was measured as user engagement of team task 1 (before the intervention), and the user engagement of team task 2 (after the intervention). Our full estimated model is written as follows:

$$\mathbf{Y_i = \beta_0 + \beta_1 L_i + \beta_2 X_i' + \varepsilon_i}$$

where we estimated expected user engagement ($\mathbf{Y_i}$) for an individual *i* as a linear function of team leaderboards ($\mathbf{L_i}$). We added a vector of control variables ($\mathbf{X_i'}$) to account for individual differences. Using this model, we estimated our treatment effect $\boldsymbol{\beta_1}$ and the matrix of coefficients for control variables $\boldsymbol{\beta_2}$ (i.e., age, sex, education level, employment status, frequency of technology usage at work, frequency of technology device usage, platform experience, the degree of individualism in the current country of residence, and time taken to complete the experiment). We modeled our constant as $\boldsymbol{\beta_0}$ and used $\boldsymbol{\varepsilon_i}$ as our random error term.

Before running our model, we standardized independent variables where it was applicable. Then, we tested the validity of the assumptions necessary to run linear regression models and found that we did not violate any of the assumptions[14].

The result of our main regression model, Model (2), appears to support our first hypothesis that team leaderboards reduce free riding behaviors in virtual collaborative environments (i.e., increase user engagement of free riders). These findings are in accordance with the findings of the prior literature that examined the impact of task visibility on free riding behaviors in the context of in-person collaboration (George, 1992). Our findings suggest that prior findings are applicable to the virtual context as well.

	Dependent Variable: User Engagement			
	frequency		**frequency + length**	**length**
	(1)	(2)	(3)	(4)
Team Leaderboards	1.000* (0.539)	1.116** (0.529)	1.256 (1.211)	0.395 (2.284)

[14] Refer to Appendix E to check the results on the tests of the homogeneity of variance of residuals, the normality assumptions of residuals, the multicollinearity of variables, and the correlation among included independent variables in our model

Technology Device Usage		1.353***	3.583***	6.487***
		(0.485)	(1.109)	(2.092)
Age		0.574*	1.406*	2.402
		(0.335)	(0.767)	(1.446)
Constant	5.933***	5.821***	12.807***	21.813***
	(0.381)	(0.454)	(1.039)	(1.959)
Observations	90	86	86	86
R2	0.038	0.224	0.214	0.207
Adjusted R2	0.027	0.120	0.110	0.101
Residual Std. Error	2.558 (df = 88)	2.455 (df = 75)	5.617 (df = 75)	10.591 (df = 75)
F Statistic	3.440* (df = 1; 88)	2.160** (df = 10; 75)	2.045** (df = 10; 75)	1.953* (df = 10; 75)

Note: Other control variables omitted for brevity *p~0.1;* p<0.05, *** p<0.01

Table 7 Within-Subjects Analysis Results

However, our findings are limited to the main model that user engagement measured as the number of ideas as the dependent variable Model (2). When we cross-validated our findings against user engagement measured as the number of words per idea, we could not find enough evidence to support hypothesis 1 as shown as Model (3) and (4) in Table 7 above. This result suggests that team leaderboards as an extrinsic motivator encourage free riders to focus on the quantity of ideas expressed over the quality of idea expression. Although more words used to communicate an idea does not always mean that these are better ideas, the greater description suggests more application to conferring meaning and consequently applied effort. For example, ‘plant a fast-growing tree’ conveys more meaning than ‘plant a tree’ as an idea to protect our environment. We speculate that after receiving the team leaderboards, participants may have decided to write shorter ideas in order to increase the number of contributions while sacrificing the length of each idea, which could be interpreted as lower quality answers. While this could be an interesting avenue for future research, it is beyond of the scope of the current study.

Also of interests is the relationship between the frequency of using technological devices and the age of participants which has a positive impact on user engagement. Model (2) suggests that 1 standard deviation increase in the usage of technological devices leads users to generate 1.35 more ideas when team leaderboards are not presented to them. From this, we might suggest that organizations could benefit from providing easy to use computers and tablets to employees when they need to have active virtual collaboration. Further, 1 standard deviation increase in age leads users to generate 1.12 more ideas when the team leaderboards are not presented to them. This finding suggests that in virtual collaborative environments organizations could leverage younger users to encourage other members to collaborate virtually. These factors could be explored further in future research to better understand their relationship with the user engagement of free riders in virtual collaborative environments.

Between-Subjects Analysis

We used between-subjects analysis to examine the impact of individual performance feedback on team leaderboards. For this analysis, we employed hierarchical multivariate regression models to account for systematic differences emerging from demographic factors as well as the pre-test user engagement scores. Pre-test user engagement scores indicate the user engagement tendency of free riders before any intervention. Including such pre-test variable is recommended to reduce the noise from observation when analyzing experimental data (Trochim & Donnelly, 2001). We modeled our regression as follows:

$$\mathbf{Y_{ic} = \beta_0 + \beta_1 T_{ic} + \beta_2 U_{ic} + \beta_4 X'_{ic} + \varepsilon_{ic}}$$

where we estimated expected user engagement ($\mathbf{Y_{ic}}$) for individual *i* in group *c* as a linear function of our treatment effect ($\mathbf{T_{ic}}$), controlled by the pre-tested user engagement scores ($\mathbf{U_{ic}}$), and a vector of control variables ($\mathbf{X}'_{\mathbf{ic}}$). Using this model, we estimated our treatment effect $\boldsymbol{\beta_1}$ along with $\boldsymbol{\beta_2}$, the coefficient of the pre-tested user engagement scores, and $\boldsymbol{\beta_4}$, the matrix of coefficients for control variables (i.e., age, sex, education level, employment status, frequency of technology usage at work, frequency of technology device usage, platform experience, the degree of individualism in the current country of residence, time taken to complete the experiment, and task 1 early completion). We modeled our constant as $\boldsymbol{\beta_o}$ and our random error term as $\boldsymbol{\varepsilon_{ic}}$. Before running our model, we standardized most independent variables to have a mean of 0 and a standard deviation of 1.

Table 8 shows the results of our regression models, which support our second hypothesis. The second hypothesis theorized that team leaderboards with individual performance feedback are negatively associated with free riding behaviors. Model (1) suggests that free riders who received team leaderboards with individual performance feedback generated 0.89 more ideas compared to free riders who received team leaderboards with no individual performance feedback. This result is consistent with Model (2) that included all demographic information as control variables. Model (3) and (4) cross validated Model (2). Our findings are in line with a prior study that examined the impact of task uniqueness on free riding behaviors in the context of in-person collaboration (George, 1992). We employed gamificiation elements that incorporated individual perfromance feedback to accentuate the uniqueness of tasks (i.e., the meaning or signficance of the tasks), indicating that the prior findings are applicable to the virtual context as well.

	Dependent variable: User Engagement			
	frequency		**frequency + length**	**length**
	(1)	**(2)**	**(3)**	**(4)**
Ind. Leaderboard	0.852*	0.884*	2.167*	4.006*

	(0.493)	(0.527)	(1.185)	(2.251)
Norm Leaderboard	0.883*	1.222**	3.127***	5.824***
	(0.481)	(0.513)	(1.154)	(2.191)
Task Engagement (Pretest)	1.774***	1.956***	4.140***	6.576***
	(0.203)	(0.234)	(0.527)	(1.000)
Constant	5.962***	5.625***	12.415***	21.199***
	(0.342)	(0.436)	(0.980)	(1.861)
Observations	135	130	130	130
R2	0.392	0.439	0.434	0.376
Adjusted R2	0.378	0.376	0.370	0.306
Residual Std. Error	2.296 (df = 131)	2.286 (df = 116)	5.140 (df = 116)	9.761 (df = 116)
F Statistic	28.156*** (df =3; 131)	6.972*** (df = 13; 116)	6.829*** (df = 13; 116)	5.383*** (df = 13; 116)

Note: Control variables omitted for brevity *p<0.1; *p<0.05; ***p<0.01*

Table 8 Between-Subjects Analysis Results

Our full models (Model (2), (3), and (4)), which included all control variables, enabled us to differentiate the impact of two types of individual performance feedback. Model (2) shows that when free riders received individual performance feedback that enabled them to compare their scores to others (i.e., social comparison), they generated about 0.88 more ideas compared to receiving team leaderboards without individual performance feedback. When free riders received individual performance feedback that enabled them to assess expected team engagement (i.e., social norms), they generated 1.22 more ideas compared to those receiving team leaderboards without individual performance feedback. These differences become wider as we interpret the results from Model (3) and (4) that considered the length of ideas in formulating the dependent variable. From these results, we infer that individual performance feedback that provides injunctive social norm messages induces more engagement from free riders when compared to individual performance feedback that provides within-team scoreboards. The cross-validation of our results suggests that the impact of individual performance feedback goes beyond increasing the number of ideas. Unlike the impact of task visibility, task uniqueness encouraged free riders to generate not only many ideas but also more lengthy explanations of those ideas.

Our results also provide some evidence that supports the mediating role of task uniqueness between task visibility and free riding behaviors. We theorized that the relationships between task visibility and task uniqueness are additive. Our coefficients that represent task visibility (i.e., team leaderboards) and task uniqueness (i.e., individual performance feedback) are all significant and positive in relation to the user engagement of free riders. Thus, adding the two will lead to greater positive user engagement. To examine based on Model (2), the average expected user engagement when free riders receive team leaderboards without individual performance feedback is 5.63 ideas (the constant of the model), and the average expected user engagement when free riders receive team leaderboards with individual performance feedback of social comparison is 6.51 (the constant of the model + the coefficient of Ind. Leaderboard variable).

Exploratory Analysis

As our final analysis, we used interaction effects that allowed us to study the impact of different individual performance feedback (i.e., social comparison vs. social norms) on different types of free riders (intentional vs. accidental). We wrote our analytical model as follows:

$$\mathbf{Y_{ic} = \beta_0 + \beta_1 T_{ic} + \beta_2 U_{ic} + \beta_3 (T_{ic} * U_{ic}) + \beta_4 X'_{ic} + \varepsilon_{ic}}$$

where we added an interaction term between the treatments and the pre-test user engagement scores ($T_{ic} * U_{ic}$) to the earlier analytical model used in the between-subjects analysis. Then, we estimated coefficient β_3 to find out if there is any difference between individual performance feedback on different types of free riders.

The results of our regression models suggest that the increase in the user engagement before any intervention (i.e., the presentation of a gamification element) is positively affected by team leaderboards with injunctive social messages to decrease free riding behaviors. More specifically, Table 9 shows that 1 standard deviation increase of the pre-tested user engagement scores makes free riders to generate 4.12 more ideas when receiving injunctive normative messages compared to receiving team leaderboards without individual performance feedback. This result enables us to infer that the free riders with a greater tendency to engage would benefit from receiving team leaderboards with social norm messages. However, we are limited in interpreting the effect of team leaderboards presenting a within-team scoreboard as the interaction term was not significant.

	Dependent variable: User Engagement			
	frequency		**frequency + length**	**length**
	(1)	**(2)**	**(3)**	**(4)**
Ind. Leaderboard	0.884*	0.908*	2.113*	3.767*
	(0.527)	(0.519)	(1.179)	(2.259)
Norm Leaderboard	1222**	1.421***	3.427***	6.099***
	(0.513)	(0.507)	(1.152)	(2.208)
Task1 Engagement (Pretest)	1.956***	1.277***	2.686***	4.340***
	(0.234)	(0.372)	(0.846)	(1.622)
Ind x pretest		0.646	1.793	3.354
		(0.493)	(1.120)	(2.147)
Norm x pretest		1.423***	2.557**	3.210

		(0.505)	(1.149)	(2.202)
Constant	5.625***	5.606***	12.358***	21.086***
	(0.436)	(0.425)	(0.967)	(1.854)
Observations	130	130	130	130
R2	0.439	0.475	0.459	0.393
Adjusted R2	0.376	0.406	0.387	0.313
Residual Std. Error	2.286 (df = 116)	2.230 (df = 114)	5.069 (df = 114)	9.717 (df = 114)
F Statistic	6.972*** (df = 13; 116)	6.881*** (df = 15; 114)	6.437*** (df = 15; 114)	4.911*** (df = 15; 114)

Note: Control variables omitted for brevity *p<0.1; **p<0.05; ***p<0.01*

Table 9 Results of Interaction Effects

For a more nuanced understanding of our exploratory analysis, we drew an interaction term plot, as shown in Figure 7. The interaction plot shows the effectiveness of different types of individual performance feedback in relation to the pre-tested user engagement scores. A User engagement score of 0 indicates that the participant shows average user engagement for conducting cognitively simple team tasks. In our experimental setting, all participants were presented information in such a way as to perceive themselves as free riders. However, some are intentional free riders (i.e., free riders who are consciously not contributing much to team tasks) and others are accidental free riders. From the plot, the intentional free riders are likely to be located on the space to the left of the red vertical dotted line because without being informed of their relative performance, their engagement level was already lower than the overall average. On the other hand, the accidental free riders are likely to be located on the space to the right of the red vertical line as their engagement is greater than the overall average.

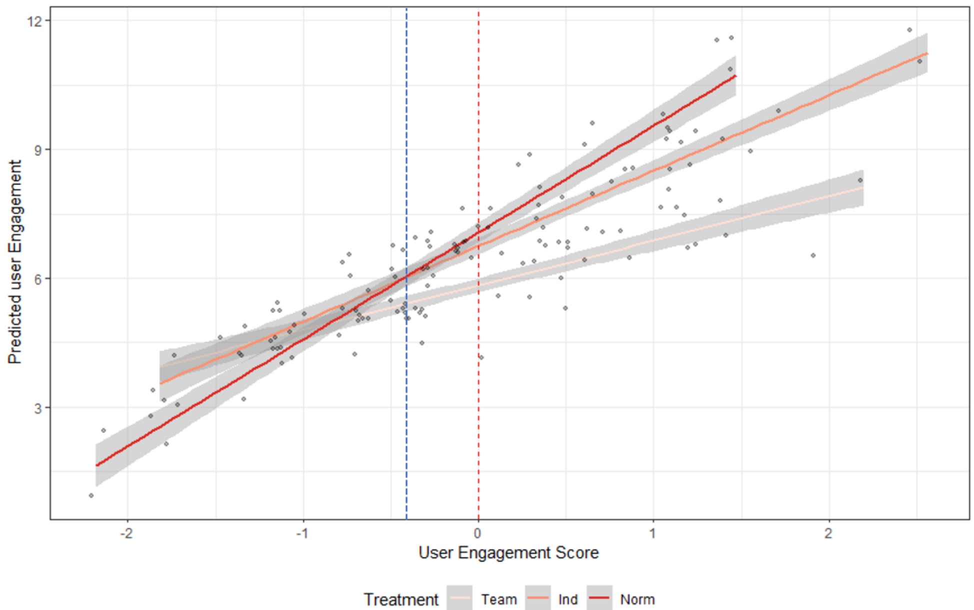


Figure 7 Interaction Effects on User Engagement (Interaction Model)

Our plot shows that team leaderboards with injunctive normative messages have the largest effect in increasing the user engagement of free riders compared to other types of team leaderboards for it has the steepest slope. However, for pre-test user engagement scores of -0.4 or less, these team leaderboards are not as effective as other team leaderboards. For those free riders, team leaderboards with within-team scoreboards work better. From the observations of our plot, we conclude that the intentional free riders are likely to increase their engagement when they receive team leaderboards with within-team scoreboards. On the other hand, the accidental or unintentional free rides, who engage actively but still contribute less than other users, are likely to increase their engagement when they receive team leaderboards with social norm messages.

Discussion

This study demonstrated cooperation-based gamification that reduces free riding behaviors in virtual collaborative environments. We developed our theories from both management and social psychology perspectives resulting in models of gamification that combined both group and individual level feedback while incorporating collective or individualistic distinctions in free rider social values. The results of our online experiment show that team leaderboards work as an extrinsic motivator to decrease free riding. Further, individual performance feedback works as an intrinsic motivator that makes tasks unique resulting in less free riding behaviors. Finally, our experiment suggested that the relationship between team leaderboards and individual performance feedback is additive in virtual collaborations, making individual performance feedback a mediator that could further improve the user engagement of free riders.

The results of our study suggest that team leaderboards on average are effective in reducing free riding behaviors. This finding is in line with earlier studies that found sharing information increases user engagement and team performance (Mesmer-Magnus & DeChurch, 2009), and making tasks visible decreases free riding behaviors in physical collaboration contexts (George, 1992). Team leaderboards on digital platforms work as a tool that makes team tasks visible, working as an extrinsic motivator that helps reduce free riding behaviors in virtual environments.

Although team leaderboards seem to work in virtual contexts and for both general users and free riders, we noticed that simple team leaderboards tend to encourage free riders to focus on generating large number of ideas rather than more elaborate ideas. In virtual collaboration, this tendency could create a problem because this gamification element could lead free riders to focus on low hanging fruit. In a long-term collaboration, this could create friction with other collaborators who are contributing greater efforts to solve complex issues.

The findings of our second hypothesis suggests that individual performance feedback along with team leaderboards increases the user engagement of free riders. We theorized that individual performance feedback represents the uniqueness of tasks, which conveys the particular meaning of tasks to each individual. This seems to play an important role in the change the behaviors for free riders through making their experience emotional. Once they receive individual performance feedback, regardless of whether the messaging was designed for competitive or cooperative free riders, their engagement transforms from merely ‘winning the game’ by increasing the number of ideas to making their ideas significant by increasing the elaboration of their ideas.

Our study provides additional insight that distinguishes two types of individual performance feedback from the perspective of social psychology. Our findings suggest that free riders respond better to individual performance feedback that compares their contribution against the team’s average (i.e., social norms) rather than within-team scoreboards (i.e., social comparison). Seeing more users with collaborative inclinations is in line with earlier studies that consistently found that social norms have positive impact on changing people’s behavior (Schultz et al., 2007), and that peer information can be framed as social norm in a competitive environment (Li et al., 2021). Free riders by definition are individuals that do not appreciate the collaborative value of work as much as others. We reason that for free riders within-team scoreboards may not be as effective as the injunctive normative messages because of the contradicting effect of the leaderboards on these users. Leaderboards may positively affect high ranked users but negatively affect low ranked users (Lemus & Marshall, 2021) such as free riders.

It is worth discussing the results of our exploratory analysis, which differentiated free riders as being either intentional or accidental. From the beginning of this study, we argued that free riders can results from not only an informed calculation of the cost-benefit analysis of the task but also due to surroundings that are uncertain and unclear. Accordingly, we think that anybody can become a free rider without intention. For example, an average performer could, by chance be assigned to a team that has only extreme performers, making the person a free rider. Other users can assess the situation of virtual collaboration differently to others, so resulting in making a lower contribution than the average. Our experimental setting enabled us to explore the effectiveness of individual performance feedback on these two types of free riders. Our analysis suggests that team leaderboards with within-team scoreboards appeal more to intentional free riders, while team leaderboards with injunctive normative messages are more effective at motivating accidental free riders. This finding underscores the importance of understanding the virtual collaborative environments of organizations in order to implement digital platforms that are appropriate for the context.

Our study adds value to the literature on virtual collaboration. We found that some of the strategies used to reduce free riding behaviors in physical collaboration can be applied in online settings. Further to the established positive impact of task visibility and task uniqueness in reducing free riding behaviors (George, 1992), we found that strategic implementation of gamification can shape motivation drivers to be additive rather than subtractive in virtual collaborative environments. For example, gamification designs including elements that increase tasks visibility, such as team leaderboards can be strengthened to decrease free riding behaviors when complementary elements that can make tasks unique, such as within-team leaderboards or social norm messages are added to the design.

Our study also contributes to the gamification and user engagement literature by detailing the motivational effects that could reduce the issue of free riding. We provide specific instances that demonstrate the power of gamification as a motivational tool, which deepens the academic discourse on gamification. More specifically, this study provides results that are easily translatable to real world uses of gamification by analyzing the user engagement of free riders on a digital platform. It indicates that incentivization though gamification works to change the behaviors of free riders even though it does not entail direct or indirect financial implications to individuals.

From a methodological perspective, our study presents a set of techniques that can be used to both theorize and examine different elements of gamification simultaneously. This study examined gamification elements in a granular fashion examining the precise triggers that encouraged collaboration among users through a system that induced competition and cooperation designed team leaderboards. The dynamism principle of gamification design, which states that "gamification design elements must match desired user-system interactions" (Liu et al., 2017, p. 1027), requires that the impact of each of those elements be very well understood as well as their effect in concert with other included elements. We expand this to logically include their effect on the particular users of the system based on their characteristics and context. Our research technique provides a valuable tool towards implementing gamification effectively as our unique experimental design enabled us to examine organization-level collaboration (digital platform environment), group-level competition (team leaderboards), and individual-level competition and collaboration (individual performance feedback) enabling us to understand the impact of particular elements at multiple levels and on both collaborative and competitive actors within those systems.

In practice, our findings underscore the importance of good design of digital platforms to increase virtual collaboration. Our result implies that organizations should avoid transferring the responsibility for free riding to collaborators but actively find ways to assess the design of digital platforms that encourage free riders to engage more. Although intentional free riders may not respond well to the injunctive social norm messages, we found that they would respond to the gamification element that induces competition or social comparison. Accordingly, implementation of gamification could be tuned depending on the characteristics of free riders to realize improvements in engagement by appropriately matching elements to users.

Conclusion

As with all studies, our results are presented with limitations. First, our findings are bound to our experimental setting. Although using an online lab experiment guarantees high internal validity the method is limited in its generalizability. For example, our team tasks are not complex and do not require engagement over long periods. Consequently, it may not be as applicable in virtual environments for complex tasks (e.g., such as finding bugs and issues in programs). Further, our results may not interpret well for long-term collaboration, where collaborators have better understanding of each other, and their communication manners may change accordingly. While these are limitations in the current research, they do provide clear avenues for the advancement of research in this area.

Despite the limitations inherent to the experimental method, we believe that our design provides a nuanced explanation that can be easily applicable in real setting. For instance, we differentiate the impact of team level and individual level feedback, as well as the social value of free riders (i.e., cooperative or competitive). Further, our setting included both intentional and accidental free riders, which is realistic for virtual collaborative environments.

For future research, an experimental design that incorporates different types of tasks and different sizes of teams would be beneficial. Further, more research investigating different types of free riders would offer useful implications for better understanding and designing virtual collaborative environments. the understanding of this area would be furthered by research using field experiments. Conducting field experiments in different contexts (e.g., for profit organizations, non-profit organizations, educational settings) may result in different findings as being a free rider in an educational setting may have less of an impact to an individual compared to being a free rider in a private company. Finally, conducting sentiment analysis of team tasks, interviewing or surveying participants for in-depth analysis of their behaviors, creating tasks of different difficulties or complexity, and looking into the free riders in long-term projects would benefit our understanding on the free riders in virtual collaborative environments.

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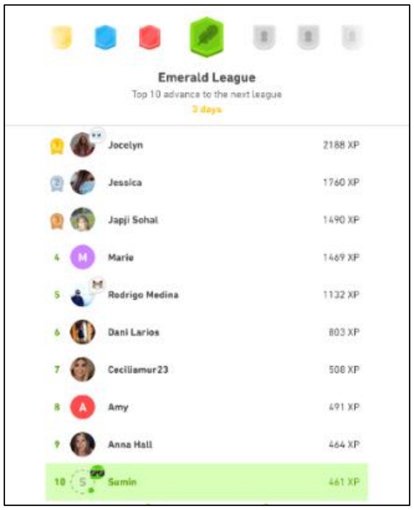
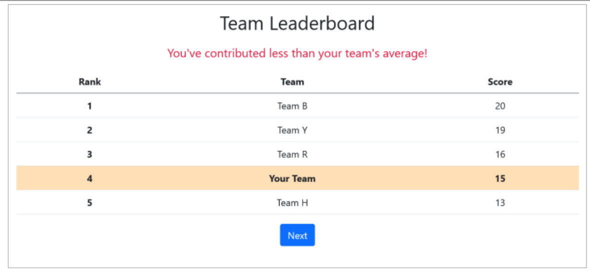
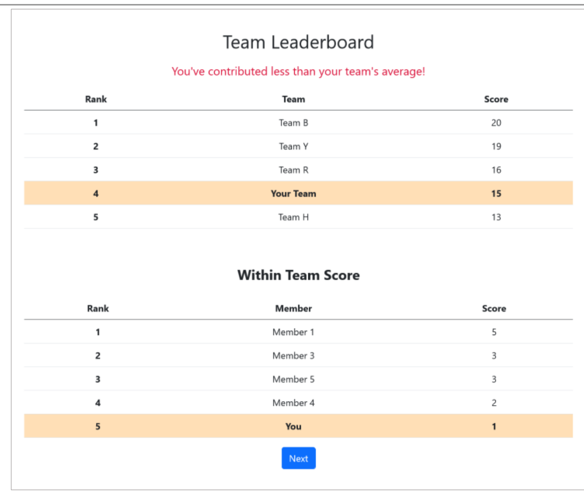
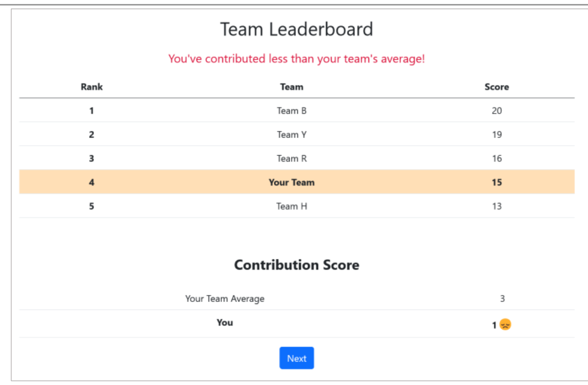
Appendices

Appendix A. A Leaderboard with Important Messages on Top



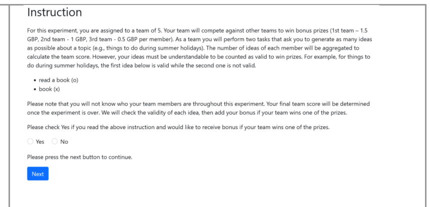
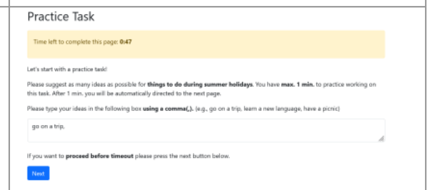
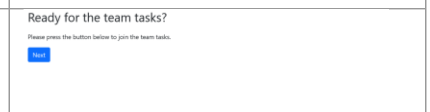
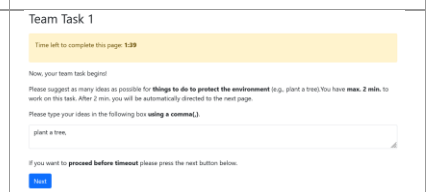
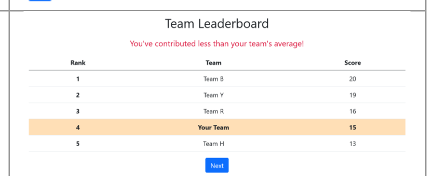
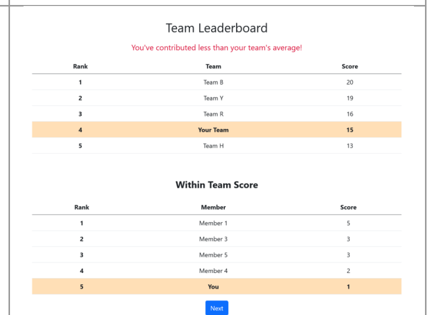
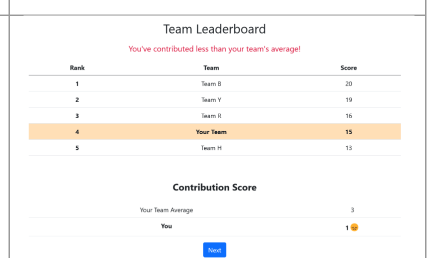
Appendix B. Experiment Overall Information

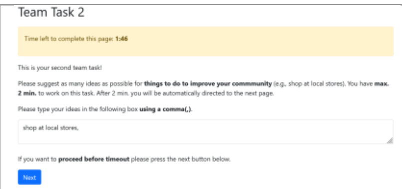
Items	Details
Method	Online Lab Experiment
Implementation Date	June 21, 2022
No. of Recruitment	145 (Requested recruitment: 150; Attempted subjects: 159; Returned (either rejected to consent or dropped after the instruction page): 10; Timed out subjects: 4)
Online Lab Setting	· oTree, a framework that enables to create a web app (online platform) · Heroku, a cloud server that enables web hosting and managing Postgres database · Prolific, a crowdsourcing platform that recruits online subjects and manages their payments
Environment	A web app accessed from the web page of Prolific via any web browser (e.g., Chrome, Safari, Firefox, Edge) and any device (i.e., desktop, mobile)
No. of Samples	140 (Attention check fail: 5)
No. of Groups	Control (48), Treatment 1 (44), Treatment 2 (48)
No. of Teams	30 Teams

<table>
<tr><td rowspan="3">Intervention</td><td>Control: Team Leaderboard</td><td>
</td></tr>
<tr><td>Treatment 1: Team Leaderboard + Within Team Leaderboard</td><td>
</td></tr>
<tr><td>Treatment 2: Team Leaderboard + Within Team Comparison Board with an injunctive message</td><td>
</td></tr>
</table>

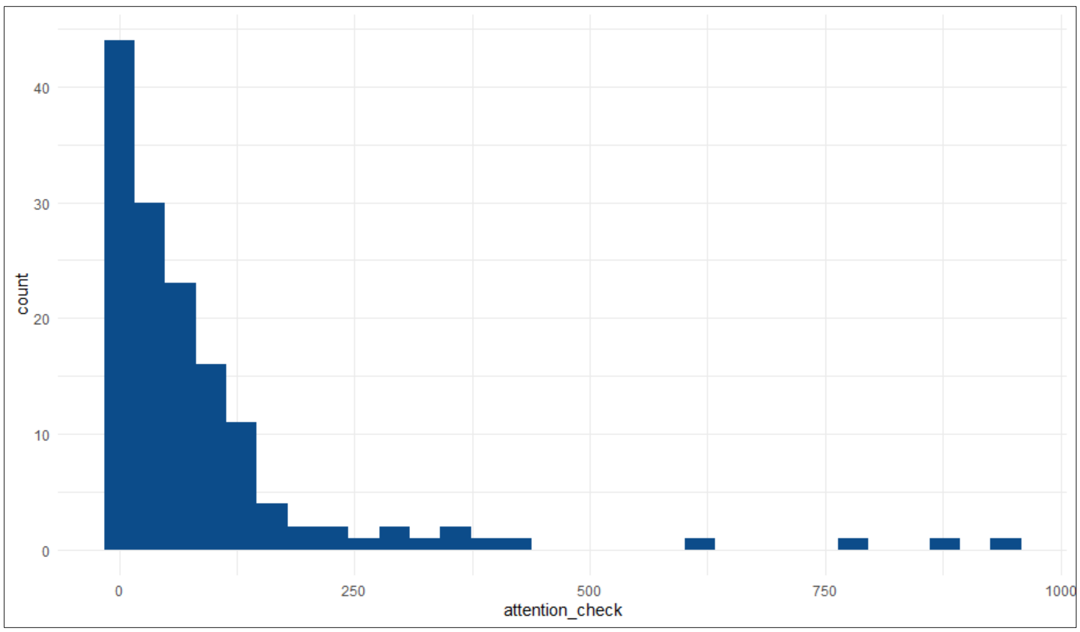
Appendix C. Detailed Experiment Procedures

#	Title	Detail	Screen
1	Recruitment	Participants must click the next button to access the online experiment link.	Prolific Page
2	Consent Form	Participants must click a checkbox to agree the consent form. Only then, they can go to the next page to begin the experiment.	-
3	Demographic Survey	Prolific provided basic demographic information of participants, so this page was excluded in our experiment.	-

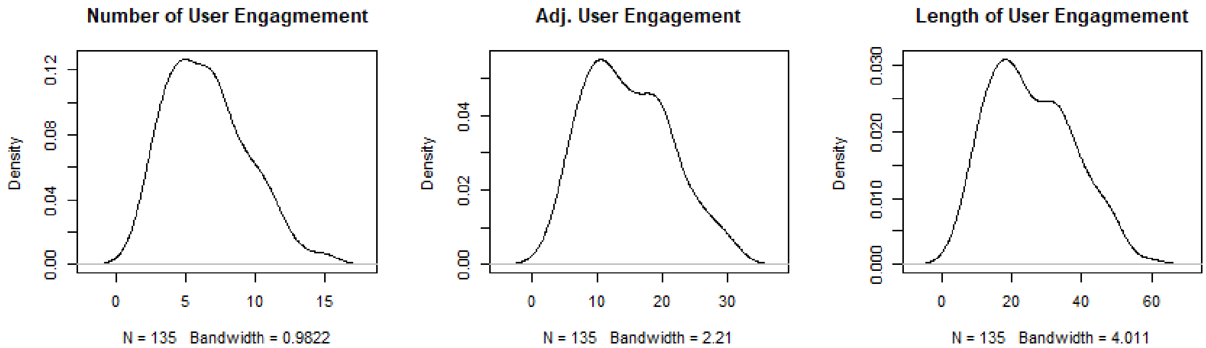
<table>
<tr><td>3</td><td>Instruction</td><td>Participants were asked to read the instruction then check yes if they read and understood the instruction (i.e., attention check).</td><td>
</td></tr>
<tr><td>4</td><td>Practice Task</td><td>This page was created to provide a clear instruction as to what participants were expected to do for the team tasks. They were given maximum of 1 min. to practice.</td><td>
</td></tr>
<tr><td>5</td><td>Break</td><td>After 1 min. participants were directed to the break page where they could take a break before starting the experiment.</td><td>
</td></tr>
<tr><td>6</td><td>Team Task 1</td><td>Participants were given maximum of 2 min. to write as many ideas as possible for things to do to protect the environment (e.g., plant a tree).</td><td>
</td></tr>
<tr><td rowspan="3">7</td><td rowspan="3">Leaderboard</td><td>Participants were directed to a team leaderboard page depending on the group that they were randomly assigned.
- Control group received a statement e.g., "You have contributed less than their team's average" with their team leaderboard. This team leaderboard was manipulated to show participants to be on the fourth place out of five top ranked teams.</td><td>
</td></tr>
<tr><td>- Treatment 1 group received team leaderboards with within-team scoreboard. This scoreboard was manipulated to show participants that they were at the bottom. However, the number of ideas that they contributed were reflected on the team leaderboard as-is to make the circumstance as real as possible.</td><td>
</td></tr>
<tr><td>- Treatment 2 group received the team leaderboards with contribution scoreboard that showed the average of the team being greater than the contribution of the participants. We also added an emoticon that showed a sad face next to the contribution number of the participants.</td><td>
</td></tr>
</table>

	Team Task 2	Participants were given maximum of 2 min. to write as many ideas as possible for things to do to improve your community (e.g., shop at local stores).	
	Exit Survey	Participants were asked to answer the post-experiment survey that asked how they felt about performing team tasks after receiving gamified feedback. This survey was conducted mainly as a manipulation check and to gain additional insight of the experiment.	-
	Debrief	Participants were debriefed and asked to press next button to complete the experiment (i.e., additional attention check).	-

Appendix D. Time Taken to Complete the Consetn Form

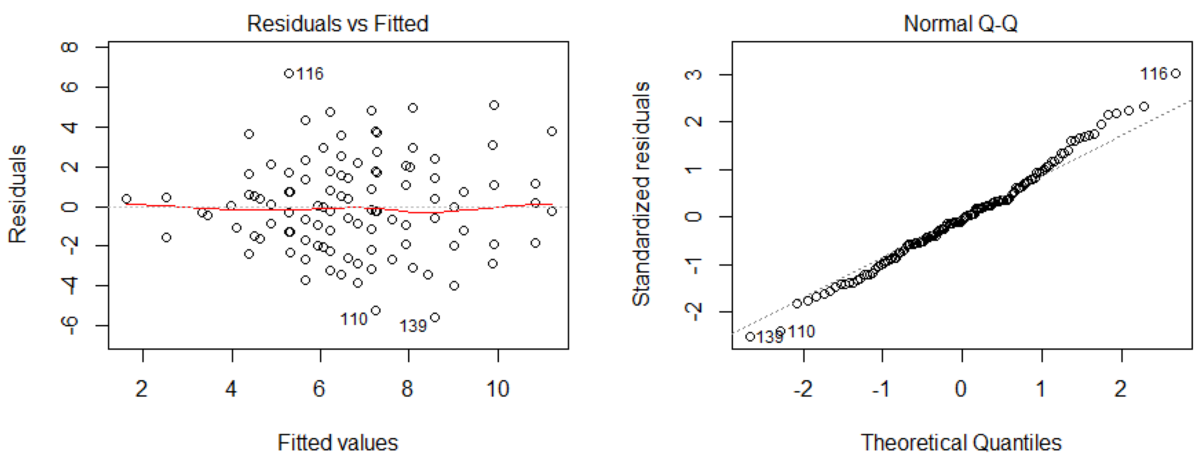


Appendix E. Density Plots of the User Engagemetn of Free Riders



Appendix F. Assumptions Checks

Check homogeneity of variance assumption & normality assumption (visual checks)

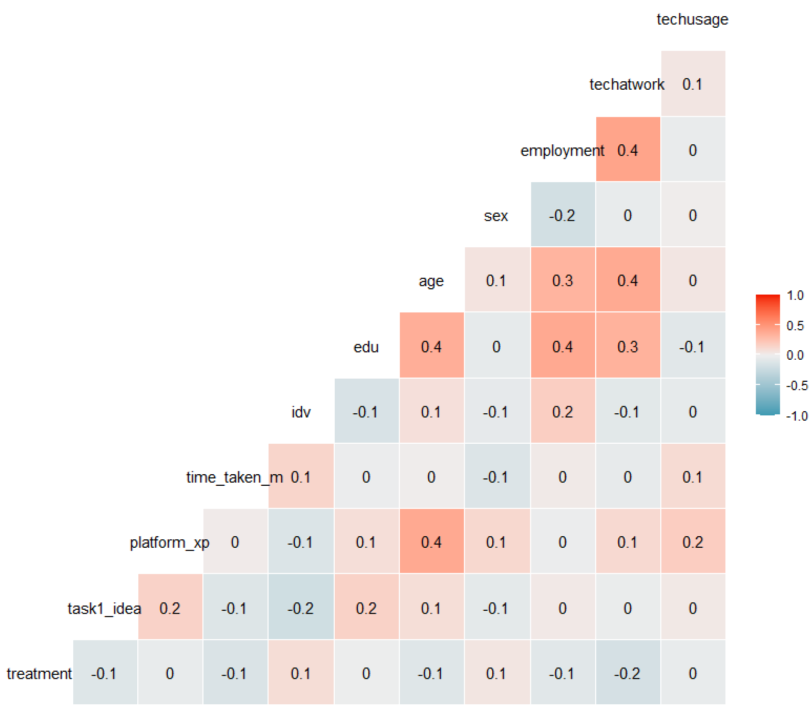


Check multicollinearity

Variables	GVIF	Df	GVIF^(1/(2*Df))
User Engagement Score (pre-test)	1.362726	1	1.167359
Platform Experience	1.459937	1	1.208279
Technology Usage at Work	1.485585	1	1.218846
Technology Device Usage	1.121499	1	1.059009

Age	1.821109	1	1.349485
Sex	1.131193	1	1.063575
Education	1.519485	1	1.232674
Employment	1.589157	1	1.260618
Individualism Index Value	1.334793	1	1.155333
Task 1 Early Completion	1.30689	1	1.143193
Time Taken (in minutes)	1.19225	1	1.091902

Check correlation



VI. DISCUSSION

The main contribution of this thesis is laying the foundation for the development of theory-based gamification research. The three essays included in this dissertation borrow frameworks from management, psychology, behavioral economics, and social psychology. These perspectives shed light on different aspects of gamification. For example, the first essay explores gamification as a multidimensional construct using the framework of task-technology fit, then creates a typology that integrates seriousness of tasks and playfulness of technologies. The second essay applies the assumptions of behavioral economics and accentuates how users make decisions via availability and anchoring heuristics in a competitive environment. The third essay integrates the views from management, psychology and social psychology to explain the change in behaviors of free riders in virtual collaborative environments when presented with gamification design that combines collective and individual feedback that contains competitive and cooperative structures. Table 1 shows a summary of the main findings from each essay.

Essay #	Main Findings
Essay 1	- Theorizing gamification as a multidimensional construct that contains subdimensions of task seriousness and technology playfulness - Creating six ideal types of gamification design that maximizes user engagement on digital platforms
Essay 2	- Identifying effective competition-based gamification design that increases user engagement on digital platforms - Providing theoretical explanations using a lens of behavioral economics to describe why localized leaderboards are more effective than traditional leaderboards for increasing user engagement
Essay 3	- Identifying effective cooperation-based gamification design that increases user engagement of the free riders on digital platforms - Providing theoretical explanations using a lens of social psychology to describe why individual performance feedback matters for cooperative gamification design

Table 1 Summary of Study Main Findings

The first essay contributes to improving the theory of gamification using the lens of task-technology fit (Goodhue & Thompson, 1995). This study explores the concept of gamification as an IT artifact of a multidimensional construct. Using the framework of task-technology fit, this study conceptualizes task seriousness and technology playfulness as subdimensions of gamification. These subdimensions are combined to theorize six ideal types that may maximize user engagement. These ideal types are volunteering design, acknowledging design, captivating design, associating design, rewarding design and achieving design. The first essay expands the discourse on the gamification research by proposing a typology that integrates utilitarian and hedonic motivation in the use of information systems. Consequently, it improves our understanding on how gamification comes to be and is used. The created abstract ideal types provoke new research avenues for future empirical analysis that deal with specific instances. Further, they provide practical guidance on how to apply gamification to tasks of different natures that involve various user characteristics.

The main findings of the first essay are (1) theorizing gamification as a multidimensional construct that contains subdimensions of task seriousness and technology playfulness, and (2) identifying and explaining six ideal types of gamification design that maximize user engagement on digital platforms. Each ideal type demonstrates the combination of different degrees of technology playfulness and task seriousness. However, these ideal types are not mutually exclusive nor mutually exhaustive. Further, it is noteworthy that some types may exist in practice, but others may not because these are theoretically derived ideal profiles.

We make inferences about the relationship between ideal types and user engagement on digital platforms. Intuitively, as a task gets more complex and has greater user interdependence (i.e., higher degree of task seriousness), aligning it with higher degree of technology playfulness (i.e., free forms of play that is open, expressive, and exploratory) would be more impactful on user engagement. This is because when users perform a complex task with high user interdependence, they use higher amounts of cognitive effort. Thus, aligning with free forms of play, which has close to no structure, would reduce cognitive overload (Kirsh, 2000) compared to aligning with structured forms of play that is bound by rules and goals. On the other hand, for a task that is relatively simple that only involves one actor, aligning the task with a lower level of technology playfulness (i.e., structured forms of play bound by rules and goals) would be more effective. This is because structured forms of play would make the task more challenging, and so increase user efforts to engage in the activities (Nakamura & Csikszentmihalyi, 2014; Santhanam et al., 2016). Therefore, we infer that volunteering, acknowledging, and achieving design may have greater task-technology fit to increase user engagement compared to the fit of the associating, rewarding, and captivating design.

However, this inference needs cautious interpretation as each user is unique. Gamification studies have underlined the importance of individual differences (Klock et al., 2020; Leung et al., 2022; Liu et al., 2017) and discussed player types as a considerable factor to create personalized gamification (Hamari & Tuunanen, 2014; Klock et al., 2020). Further, individuals have various social values that manifest as either pro-social or prof-self behaviors when interacting with others (Balliet et al., 2009). The diversity of users means that it is not possible to pinpoint the most impactful ideal types, especially when the types are abstract. However, the value of a typology comes from identifying the ideal patterns derived from theories and evidence. Thus, our typology provides a guidance to create adequate gamification that matches technology playfulness and task seriousness. As a caveat, researchers should account for the different characteristics of users, and organizations should account for the user composition in their digital platforms.

Overall, the first essay contributes to gamification research and expands our understanding of how to design and manage effective digital platforms. Our conceptual framework underlines the multidimensionality of gamification by demonstrating the degree of technology playfulness and the degree of task seriousness. In particular, this study highlights the significance of playfulness in enabling less stressful access to information systems through enjoyment that lowers the barrier of completing serious tasks. Further, this study expands the discourse on the gamification design principles (Liu et al., 2017) by creating a typology of gamification that follows the task congruence principle. This principle emphasizes the importance of the complementarity between the task and the gamification design elements. Through the process of conceptualizing ideal types of gamifications, this study sheds light on a mechanism of gamification that may maximize user engagement. The increased understanding of gamification design helps respond to the rapid advancement of technologies and ever-expanding user base, which may drastically change information systems applied on digital platforms and add complexity to their use. Thus, creating a typology of gamification offers accessible strategies for motivating users, which increase the usability of digital platforms and helps reduce digital divide that may appear from the evolution of digital platforms.

From the practical perspective, this study provides a theoretical explanation for gamification design that is typically implemented on a trial-and-error basis. Theoretical understanding is valuable because gamification affects human minds and behavior. Our study is also meaningful as it responds to the current change of working environment from in-person to hybrid forms. In a hybrid environment, organizations expect to have strategies to increase user engagement in virtual spaces. A typology of gamification could provide a practical guidance to organizations that leverage digital platforms. For instance, our typology could describe clear use case scenarios for each gamification design. This would help organizations to have accessible strategies to motivate users, which in turn, may increase the usability of digital platforms. Another important aspect to note is the flexibility that a typology of gamification brings to the table. A typology of gamification improves the explanatory power of gamification elements applied in various contexts. This means that it enables organizations to adapt to dynamic changes in digital platforms caused by technological advancement or the growing number of digital natives. Digital natives grow up interacting with computers through playing video and mobile games. Thus, they are likely to have different sets of communicating tools that are playful such as using emoticons, short-lived messages, sound effects, colorful backgrounds, and animated pictures. Although it is not realistic to think that gamification can reduce the differences between the digital natives and non-digital natives on digital platforms, using our typology as a template may help reduce digital divide that may appear from the evolution of digital platforms.

The second essay focuses on competition and uses a behavioral economics lens to investigate how competitive structures presented to users in the form of leaderboards affect user engagement. We construct a leaderboard design, which we refer to as “local leaderboards”, to create competitive structures unique to each user by showing the competitors around them and compare this design against the traditional “global leaderboards”, which typically show only the top ranked users. Our field experiments that use randomized block design suggest that the localized leaderboards are more effective than the traditional leaderboards in increasing the level of user engagement. Our findings are reinforced by generalized linear regression models with fixed effects, which provide further insights.

The main findings of the second essay are (1) identifying effective competition-based gamification design that increases user engagement on digital platforms (i.e., local leaderboards), and (2) providing theoretical explanations by using the lens of behavioral economics to describe why localized leaderboards are more effective than traditional leaderboards in increasing user engagement.

Leaderboards are one of the most popular gamification designs implemented on digital platforms to show competition that influences the motivation and engagement of users (Chou, 2019). Typically, leaderboards display a ranked list of users according to their relative performance on a set of specified criteria. Such relative ranking acts as a competitive indicator of progress and induces social comparison among users. However, due to various constraints, primarily space limitations, most platforms keep the size of leaderboards small by displaying a limited segment of top performers (e.g., top 10 or 100 users). Thus, many users cannot assess, or at least must incur significant efforts to assess, their performance against to those who are comparable to them, subject to the leaderboard ranking criteria. We considered this a weakness of the commonly employed "global leaderboards" and propose another way of presenting information on leaderboards. In so doing, we applied a lens of behavioral economics, which posits that people make decisions under uncertainty using heuristics by taking cues from the salient information accessible to them.

Given that the motivational effect of competition is likely to function when users perceive their competitive goals to be attainable, user contribution will be greater when users can compete with others at a similar performance level (Landers & Landers, 2014; Santhanam et al., 2016). Hence, we constructed localized leaderboards to create competitive structures unique to each user by showing the competitors around them and compared this design against the traditional "global leaderboard". We argue that a novel leaderboard design, which we refer to as "local leaderboard", could better leverage the potential of leaderboard mechanism. To this end, our research examined whether and how the design of leaderboards (global vs. local) presented to users affects the degree of user engagement on digital platforms.

The results of this essay suggest that gamification design that incorporates dynamic competitive structure (i.e., leaderboards) increases user engagement on digital platforms. This is especially true when competitive information is more salient to individual users. The study established hypotheses by borrowing assumptions from behavioral economics, which posit that people when making decisions under uncertainty use heuristics taking the cues from salient information easily accessible to them (Kahneman, 2003; Tversky & Kahneman, 1974). To examine these hypotheses, this study conducted randomized field experiments and analyzed collected data using non-parametric tests and generalized linear models with fixed effects.

The theoretical contributions of this study are threefold. First, we add value to the literature on gamification and user engagement by providing empirical evidence that shows the difference between local and global leaderboards on digital platforms. This essay finds that the use of local leaderboards leads to a greater increase in user engagement compared to that of global leaderboards. We theorized the differential effects of local and global leaderboards based on a lens of behavioral economics and provided evidence of the differential effects.

Second, we broaden the scope of inquiry on the role of competition on digital platforms. Competition in gamification research has typically seen as self-determined actions that aim for achieving explicit or implicit goals (Goes et al., 2016; Landers et al., 2017; Mekler et al., 2017; Santhanam et al., 2016). While this line of thought is reasonable given that users on digital platforms use information technology with rational intentions and make choices accordingly, our theoretical approach relaxes this commonly held assumption and recognizes that these intentions are affected by emotional and social factors that involve heuristics, which may cause systematic biases. This essay finds that the use of local leaderboards leads to a significantly greater increase in user engagement when compared to traditional global leaderboards. These findings suggest that the decisions that users made with given information is biased by how the information is presented to them. In our study, we applied gamification design to frame competition in a way that anchors users to think and aim differently between global and local leaderboards. Thus, we need to consider these biases when studying gamification applied on digital platforms. We contribute to gamification research by adding another perspective that bounds rationality and willpower when explaining the change of behaviors on digital platforms. More specifically, we explain user engagement on digital platforms as a result of using heuristics that reduce uncertainty via visual cues triggered by gamification.

Finally, this study contributes to the stream of research that investigates the relationship between competition-based gamification and performance, such as user engagement. This study considered leaderboards as a gamification design that represents competition and explored its role as a competitive mechanism, adding novel insights to the extant literature that mostly treated leaderboards as a feedback mechanism. Further, our study extends previous studies that looked into one-on-one matching competition (Santhanam et al., 2016) and a status incentive hierarchy system that applied a static competition (Goes et al., 2016; Von Rechenberg et al., 2016). In our study, we considered multiple competitors (as opposed to one-to-one matching) concurrently competing for a dynamic goal (as opposed to static competition) created due to constant user interactions. Thus, this study highlights the impact of a gamification design that represents a dynamic incentive hierarchy system, which describes multiple users competing against each other when their ranks or positions change dynamically depending on their actions and the actions of others.

On a practical front, our findings provide insights for practitioners regarding how to apply gamification on digital platforms in such a way that increases user engagement. Particularly, our findings can provide actionable guidance for implementing various types of competitive structures in their digital platforms using the idea of gamification. Although a trial-and-error approach is useful for companies, in most cases changing one particular aspect of gamification design and observing its impact would be impractical and may create confusion among the users of their platforms. Specifically, our theoretical discussion and empirical evidence suggest that digital platform owners and designers need to consider implementing leaderboards that emphasize local competition surrounding each focal user rather than blindly adopting global leaderboards that show top-ranked users only, as doing so can help them increase user engagement, which can ultimately help improve the long-term viability of their platforms.

The final essay focuses on gamification design that deals with cooperation and collaboration in virtual environments. The main contribution of this essay is to examine gamification design that motivates collaboration among different types of users by combining both cooperative and competitive nudges. In particular, we focus on free riders, which are those users that take advantage of work performed by the collective without paying a proportional share of the costs (Albanese & Van Fleet, 1985). Given that performance feedback is effective for user engagement (Huang et al., 2019) and information sharing has positive effect on team performance (Mesmer-Magnus & DeChurch, 2009), this study suggests adding individual performance feedback to team leaderboards as a gamification design that incorporates both competition and cooperation.

The main findings of the third essay are (1) identifying effective cooperation-based gamification design that increases user engagement of the free riders on digital platforms, and (2) providing theoretical explanations by integrating a view from social psychology to describe why individual performance feedback matters for cooperative gamification design. Through theorizing and analyzing a mechanism of gamification design that encourages collaboration, this essay finds that simple team leaderboards are not effective in changing the behaviors of free riders. However, team leaderboards that incorporate individual performance feedback increase user engagement of free riders. In particular, when free riders receive injunctive social norm messages along with team leaderboards, they engage more compared to receiving within-team leaderboards that identify and assess individual inputs.

This study contributes to an increased understanding of the varied cooperative structure applied in gamification. In particular we examine a cooperation-based gamification design that not only encourages collaboration but also reduces social loafing behaviors in virtual environments. The results of our online experiment suggest that the combination of team leaderboards and individual performance feedback decreases social loafing behaviors. From this we can infer that for free riders acknowledging individual inputs and making their task meaningful is of great importance (Albanese & Van Fleet, 1985; George, 1992; Karau & Williams, 1993). In particular, as individual performance feedback, the injunctive normative messages have larger positive effects on user engagement of free riders in comparison to the effects of within-team leaderboards. We have designed injunctive normative messages as the messages that show the approval of individuals' behaviors compared to social norm using facial expression such as smiley or sad face. We have designed within-team leaderboards as the leaderboards that compare the positions of members within a team. This gamification design is found to be more effective than the injunctive normative messages when intentional free riders engage very little.

It is important to note that our study do not find any evidence to support the proposition that the team leaderboards increase user engagement of free riders. This result is the opposite of what has previously been found in non-virtual collaborating environments where task visibility is negatively associated with social loafing behaviors (George, 1992). Previous research suggested that team leaderboards are more effective than individual leaderboards due to increased enjoyment (Morschheuser et al., 2019). Thus, we can presume that free riders do not perceive group level feedback to be as enjoyable as non-free riders in a virtual setting.

To summarize, individual performance feedback matters for cooperation-based gamification design. At a group level, gamification design such as team leaderboards increases task visibility. However, at an individual level, gamification design that underlines task visibility turns into an internalized extrinsic motivator, which when combined with task uniqueness (i.e., individual performance feedback), increases intrinsic motivation of free riders. Individual performance feedback is further delineated by using the social dimension of gamification design such as social norm messages or social comparison leaderboards, which account for the differences of individuals in relation to their social values. Thus, these perspectives provide interesting insights that touch upon both group and individual levels of gamification design. Further, examining users with varied social tendencies enables us to discuss gamification designs that incorporate both competition and cooperation with greater variability.

Another contribution of this study is to continue the discussion of gamification design principles. This study applies the dynamism principle, which suggests that "gamification design elements must match desired user-system interactions" (Liu et al., 2017, p. 1027). In so doing, this study creates and implements a gamification design that encourages collaboration among users through a system that induces competition and cooperation. As a solution for mitigating different types of users who exhibit social loafing behavior on digital platforms, we first create team leaderboards to increase the collaboration among team members, which may induce social comparison against other teams and create a sense of group level peer recognition. We then add individual performance feedback, which stimulates different types of users and ultimately encourages free riders to participate more in the cooperative activities by satisfying their needs at the individual level.

On a practical front, our approach helps the imaging and design of better gamified features that better solve the issue of free riding and increase user engagement. The findings of this study show a use case of gamification design and provides a practical solution for free riding issues in virtual collaboration in the era of hybrid working environments. Further, the unique experimental design that shows collaboration within competition (i.e., team leaderboard) through individual performance feedback helps platform owners diversify their gamification strategies to increase not only their user engagement but also the revenue derived from their platforms.

VII. CONCLUSION

The objective of this thesis is to better understand the role of gamification on digital platforms in solving issues relevant to user engagement from the perspective of competition and cooperation. This thesis has presented three essays. The first essay conceptualized gamification using a typology theory that maximizes user engagement. The second essay examined gamification design that motivates competition, and the third essay examined gamification design that motivates cooperation on digital platforms. Through the process of examining gamified information systems and explaining their impact on user engagement, this thesis found that gamification has a great value as a solution that calls for further scrutinization of its mechanisms.

At its core, this thesis has revealed that gamification plays an important role as a design strategy to increase user engagement on digital platforms. The impact of gamification is found to be positive whether users are motivated by competition or cooperation. These findings are nuanced and explained from a perspective that accounts for a limited human rationality, constrained by either cognitive resources or emotion. The empirical evidence of the second essay shows that competitive structures presented using gamification design are processed differently due to the use of heuristics. The empirical evidence of the third essay shows that collaborative structures presented using gamification design are processed differently due to the use of social values.

On a practical front, our enhanced understanding of gamification provides guidance to firms and organizations to assess the gamified features of their digital platforms. Therefore, it helps avoid ineffective, inefficient, or ethically problematic design use on digital platforms. Given the current transition of working environment toward a hybrid form, this study of gamification presents great potential for future research avenue. This thesis is the beginning of a new chapter for future endeavors.

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