PACIS 2023 Proceedings

Pacific Asia Conference on Information Systems (PACIS)

7-8-2023

The Necessary Evil in Mixed-motivational Systems: The Negative Effect of Entropy in Serious Games

Philip Lee
Hong Kong Shue Yan University, tylee@hksyu.edu

Michael Chau
The University of Hong Kong, mchau@business.hku.hk

Richard Lui
The Hong Kong Polytechnic University, cswclui@polyu.edu.hk

The Necessary Evil in Mixed-motivational Systems: The Negative Effect of Entropy in Serious Games

Completed Research Paper

Philip Tin Yun Lee
Hong Kong Shue Yan University
North Point, Hong Kong
tylee@hksyu.edu

Michael Chau
The University of Hong Kong
Pokfulam, Hong Kong
mchau@business.hku.hk

Richard Wing Cheung Lui
The Hong Kong Polytechnic University
Hunghom, Hong Kong
richard.lui@polyu.edu.hk

Abstract

Randomness is common in mixed-motivational system environment. Yet, it is attributable to information deprivation which is not always favored. In this paper, we use the concept entropy to quantitatively capture the rather overlooked influence of randomness embedded in a system. With the use of a serious game, we conducted a study with university students in a classroom setting. We show that entropy has an adverse impact on intention to use. The adverse impact is mediated by perceived control and curiosity. We further demonstrate that people having a strong arousal-avoidance pre-usage state are less prone to the negative effect of entropy. On theoretical implications, the study is among early attempts to examine the negative consequences of information deprivation due to randomness. It shows the mechanisms through which entropy leads to deteriorated intention to use. On practical implications, we suggest that manipulation of pre-usage user states alleviates the adverse impacts of entropy.

Keywords: Mixed-motivational Systems; Serious Games; Randomness

Introduction

Incomplete information in system environments has been considered unfavorable in diagnostic information seeking (e.g., Ho and Bodoff (2014) and Xiao and Benbasat (2007)). However, randomness is a main characteristic of all sorts of plays and games (Costikyan, 2013). Typically, video games with outcomes of certainty cannot keep players for long. Video game players formulate their game strategies in the face of randomness in gaming environments. Efforts to mitigate randomness will be in vain.

Given that functions of typical utilitarian systems are mostly deterministic without much randomness involved, previous relevant literature has paid less attention to the impacts of the embedded randomness of systems in interaction with users. Now that mixed-motivational systems, such as gamified systems (see Liu *et al.*, 2017), serious games (see Boyle *et al.*, 2016) and virtual worlds (see Wasko *et al.*, 2011 and Chau *et al.*, 2013) have emerged in recent years, it is necessary for us to probe deep into the impacts of the randomness which is one of the main exogenous features of hedonic systems and many other mixed-motivational systems (e.g., Cheng *et al.*, 2019; Ortiz-Rojas *et al.*, 2019).

This study is anchored to cognition related to information deprivation in the face of randomness. We examine impacts of randomness that exists in system environments on users' intention to use a system in the context of serious games. Randomness results in information loss in an environment. To measure the information loss due to randomness, we draw on the concept *entropy*, which has been commonly adopted in the studies of the information theory, as a measure of uncertainty that generated by randomness (MacKay, 2003). According to Rényi (1961):

> "The entropy of a probability distribution can be interpreted not only as a measure of uncertainty but also as a measure of information. As a matter of fact, the amount of information which we get when we observe the result of an experiment (depending on chance) can be taken numerically equal to the amount of uncertainty concerning the outcome of information before carrying it out" (p. 553).

We use the concept *entropy* to quantitatively capture the amount of events generated by the randomness that is embedded in a system. Adopting a perspective of information loss, we intend to answer two research questions: (1) how does entropy affect users' intention to use a mixed-motivational system; and (2) does users' pre-usage arousal-avoidance state influence the relationship between entropy and intention to use? The arousal-avoidance state pertains to entropy, since it represents a user's temporary appetite for randomness and adventure right before using a mixed-motivational system. With the use of a serious game, one typical type of mixed-motivational systems, we conducted a study with university student participants in a classroom setting. The participants were required to fill out questionnaires immediately before and after the use of the serious game for measurement of cognitive experience. Their game logs were recorded to measure entropy.

From our data analysis of the survey results, we show that entropy has a negative effect on intention to use. The effect is mediated by perceived control and curiosity of users. We further demonstrate that users at an arousal-avoidance state are less prone to the impacts of entropy on intention to use. Arousal-avoidance users tend to succumb to an illusion of control (Langer, 1975). The illusion of control compensates the loss of cognitive control generated by an increase in entropy.

We aim to make several contributions. On theoretical implications, we draw on the information theory (MacKay, 2003) and introduce the concept entropy to quantitatively capture the impacts of randomness on system usage. Randomness is a main characteristic of hedonic systems and many mixed-motivational systems that features plays and games. The use of quantitative approach of measuring randomness paves the way to further exploration of the influence of randomness on user behavior. Moreover, this study is among the early attempts to delve into the impacts of randomness at different pre-usage states of users. We highlight the importance of pre-usage arousal-avoidance state to user cognitive models of mixed-motivational system usage.

We note that the exogenous impacts of randomness that is embedded in a system have been largely overlooked. Some scholars of gamification over-simplified randomness and assumed that randomness is a sub-construct of challenge (Kapp, 2012; Kim and Lee, 2015). Yet, randomness is distinctive from challenge, since randomness is chance-based and challenge is skill-based. The introduction of the concept, entropy, to scholars of system usage paves the way for future studies to include influence of randomness in studies of mixed-motivational systems and hedonic systems.

On practical implications, we show the possibility of manipulating pre-usage arousal-avoidance state to mitigate the adverse impacts of entropy on user behavioral intention. Given that randomness is commonly involved in mixed-motivation systems, it is not desirable or feasible to take away randomness from system environments. From the perspective of information deprivation, system developers of mixed-motivational systems may consider creating a system-usage environment where users tend to be arousal-avoidant.

Literature Review

Serious Games

Serious games are one typical type of mixed-motivational systems. Mixed-motivational systems are different from utilitarian and hedonic systems in that the mixed-motivational systems are designed for mixed motivations, not primarily for hedonic motivations or utilitarian motivations (Lowry *et al.*, 2015). Users of serious games are both motivated by hedonic and utilitarian purposes. Serious games typically entertain users and concurrently aim to achieve a purpose that is "centred around training and skills development, education or attitudinal and behavioural change" (Moizer *et al.*, 2019, p. 141). A systematic review and effectiveness of these games can be found in Boyle *et al.* (2016). Simulation games are a specific type of serious games. The most distinctive characteristic of simulation games against other serious games is that the nature of simulation enables experiential recreating training situations that involve no substantial real risks and reprisal (Hernández-Lara & Serradell-López, 2018). Randomness should therefore be incorporated into simulation games. A significant number of simulation games in business and engineering education have been developed. Some examples include E-mprende of business management (Pando-Garcia *et al.*, 2016), PMS of software development (Lee *et al.*, 2021) and S-Cube of social enterprise operation (Moizer *et al.*, 2019).

Perceived Control and Illusion of Control

According to Deci's (1975) cognitive evaluation theory, an environmental event provides information and feedback of one's actions from which a person can infer their abilities and competence. The information and feedback may exert pressure on people to induce or coerce them to behave in a certain way. The pressure suppresses or strengthens perceived control of behaviour and thereby affects a person's intrinsic motivation (Deci, 1975; Ryan, 1982). Thus, perceived control is highly influenced by the environment. Csikszentmihalyi's (1975) flow theory also highlights the relationship between perceived control and situational environment in understanding human behaviour in activities. According to the flow theory, perceived control is referred to "a sense that one can in principle deal with the situation because one knows how to respond to whatever happens next" (Nakamura & Csikszentmihalyi , 2009, p. 196).

The role of perceived control in promoting system user behavioural intention has been widely discussed in previous studies of information systems (Lowry *et al.*, 2013; Xu *et al.*, 2012a). A strengthened sense of perceived control is one of the indicators of entering the state of flow (Csikszentmihalyi, 1975). Based on the flow theory, Agarwal and Karahanna (2000) proposed the concept cognitive absorption of which definition is "a state of deep involvement with software" in the context of information systems (p. 665). Perceived control was included as one of the five core dimensions that constitute cognitive absorption which is conducive to intention to use.

In the context of serious games, perceived control has been widely considered as a positive factor of learner outcomes. For example, with the use of a serious game that helps players acquire knowledge of search engine optimization (SEO), Lee *et al.* (2019) showed that learners' perceived control acquired in the game positively influences their self-efficacy of SEO. Martins *et al.* (2023) also found that perceived control in a serious game of entrepreneurship education can lead to a stronger entrepreneurial intention.

An illusion of control was defined as "an expectancy of a personal success probability inappropriately higher than the objective probability would warrant" (Langer, 1975, p. 311). The outcomes of chance activities are largely based on randomness. Thus, chance activities cannot be controlled regardless of a person's capabilities. However, it is difficult for a person to distinguish between chance situations and skill situations. When a person mistaken a chance situation as a skill event, they may be under the illusion that they can control the outcomes. The mistaken thought is considered to be the root of an illusion of control (Langer, 1975). Previous literature suggested a strong tie between a person's state of mind and their tendency to succumb to an illusion of control (e.g., Alloy *et al.*, 1981, Fenton-O'Creevy *et al.*, 2003, Oei *et al.*, 2008).

Curiosity

Curiosity can be defined as "a desire to know, to see, or to experience that motivates exploratory behaviour directed towards the acquisition of new information" (Litman, 2005, p. 793). The reduction of uncertainty, generated possibly by randomness, is rewarding, since acquisition of new environmental information help restore cognitive and perceptual coherence (Berlyne, 1950; Litman, 2005). According to Malone and Lepper's (1987) consolidation of previous literature, curiosity can be interpreted as an intrinsic motivation generated by an informational discrepancy from existing knowledge and expectation (Hunt, 1965; Kagan, 1972; Piaget & Cook, 1952).

Specifically, Loewenstein (1994) viewed generation of curiosity from an information-gap perspective. The information gap was described as the difference between the information an individual possesses and the information one wants to possess. Curiosity reflects a desire to close the gap between one's reference point and one's perceived knowledge possession. The feeling of information acquisition increases with a reducing perceived information gap. Curiosity is generated when an individual perceive that they are closing the information gap (Loewenstein *et al.*, 1992; Loewenstein, 1994). However, accurate feedback mechanisms do not always exist. People make guesses of their information gaps. Underestimation of the information gaps is common, since informational reference point is rather subjective. The underestimation results in an illusionary possession of information (Loewenstein, 1994).

Previous studies have commonly showed that curiosity has a positive influence on user intention to use or purchase a product or service. Hill *et al.* (2016) conducted several online shopping experiments and identified that uncertainty about products can triggers potential consumers' curiosity that is conducive to their purchase intention. On the other hand, Dahabiyeh *et al.* (2021) found that curiosity positively affect gamers' intention to play an online game, However, curiosity can lead to a risky behaviour of playing online games, since curious gamers may be less concerned with cybersecurity risk.

Arousal Avoidance and Arousal Seeking

According to Apter's (1988) reversal theory, people's mind alters between two contrasting states, namely the telic state and the paratelic state. The paratelic state features playfulness and fun, whereas the telic state refers to a serious mind. The former state can also refer to a state that seeks for arousal, and the latter one is a state that avoids arousal. People at an arousal-seeking state tend to develop a sense of "psychological 'protective frame' that tells one (whether accurately or not) that one is safe from consequences" (Apter, 2009, p. 598) of their actions. These arousal-seeking people are pleased by high arousal generated by randomness. On the other hand, people at an arousal-avoidance state are more concerned with outcomes of an action. They prefer more certainty and therefore are less open to unpleasant consequences. The same arousal is therefore interpreted differently by people at different states (Apter, 2001).

Hypothesis Development

We develop a research model of which objectives are to identify: (1) the mechanisms through which entropy influences intention to use, and (2) the condition at which proposed negative impacts of entropy can be ameliorated. The model focuses on information-associated cognitive functions that are direct consequences of entropy. Intention to use was selected as an evaluation of user outcomes. Figure 1 shows the overarching research model of the study.

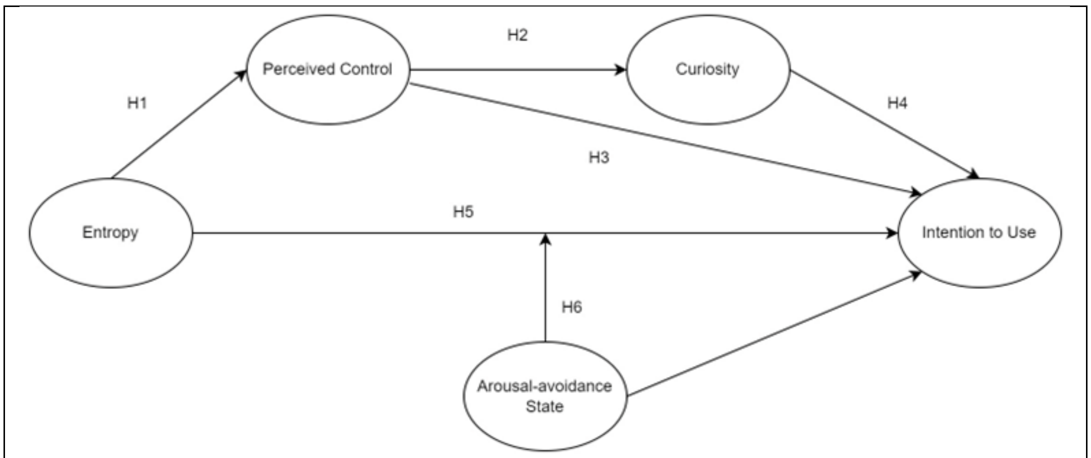

Figure 1. Research Model

Randomness exists everywhere and influences outcomes of numerous human decisions in the reality (Taleb, 2005). Randomness is different from challenge. Challenge refers to an appropriate match between skill and difficulty (Malone & Lepper, 1987). It is skill-oriented, whereas uncertainty generated by randomness is chance-oriented. Regardless of a person's skills, events of randomness are not controllable. Thus, any cognitive efforts on reducing occurrences of the events are vain. The concept entropy is used in this study to quantitatively capture the uncertainty specifically generated by the randomness embedded in our system. Entropy measures the observed quantity of occurrences of the events generated by the embedded randomness. It captures the quantitative amount of information in the environment an individual possess before the randomness has been actualized, given that "the amount of information which we get when we observe the result of an experiment (depending on chance) can be taken numerically equal to the amount of uncertainty concerning the outcome of information before carrying it out" (Rényi, 1961, p. 553).

Randomness leads to deviation of outcomes in system environments from user expectation. An increase of entropy indicates more uncertainty, generated by randomness, faced by users in a system environment. Users can infer from the entropy that they are incapable to foresee the occurrences of the events in the environment. The perceived lack of capabilities in predicting entropy leads to a loss of perceived control (Csikszentmihalyi, 1975; Deci, 1975). We predicted that entropy has a direct negative impact on perceived control of users.

H1: Entropy reduces perceived control.

According to Loewenstein's (1994) information-gap framework, the awareness of the difference between a user's existing knowledge and his preferred informational reference point is the pre-requisite for the experience of curiosity. Events generated by randomness create a gap between perceived knowledge possession and preferred informational reference point, since no human can determine the true value of randomness. Thus, the condition of curiosity generation is fulfilled. Based on Loewenstein (1994), closure of the information gap generates curiosity. The closure requires acquisition of information which reflects strengthened capabilities of understanding the system environment. Thus, an increase of perceived control of the system environment means an increase of perceived acquisition of environmental information. This results in the closure that generates curiosity. We therefore posited that:

H2: Perceived control increases curiosity.

Prior studies have demonstrated that perceived control and curiosity, both of them are core dimensions of cognitive absorption, are conducive to intention to use (Agarwal and Karahanna, 2000). For example, perceived control was found to be a significant factor of intention to use of mobile services (Nysveen *et al.*, 2005). Curiosity was also shown to have direct and positive influence on intention to use of hedonic systems (Lowry *et al.*, 2013). Thus, we predicted that perceived control and curiosity are positively correlated to user intention to use respectively.

H3: Perceived control is positively correlated with user intention to use.

H4: Curiosity is positively correlated with user intention to use.

Overall, we expected that entropy reduces perceived control which is positively correlated with curiosity. We hypothesized that entropy has an overall adverse impact on user outcome:

H5: Entropy adversely affects intention to use.

According to Apter (1988, 2001), individuals at an arousal-avoidance state have a stronger preference to certainty. They therefore have a strong need for cognitive closure and uncertainty clarification (Litman, 2005). The need for cognitive closure is a desire for making sense of the environment. It is a "desire for a firm answer to a question, any firm answer as compared to confusion and/or ambiguity" (Kruglanski, 2004, p. 6). A strong need for cognitive closure drives people to engage in processes that help generate a sense of control (Burger, 1985).

Burger and Hemans (1988) showed that people who have a strong desire for control are more likely to engage in attribution processes which are conducive to gaining perceived control. These people have a stronger tendency to perceive environments with randomness as a skill situation rather than a chance situation. They tend to mistakenly attribute uncertainty generated by randomness as uncertainty that results from lack of relevant knowledge. Since the latter type of uncertainty can be alleviated by acquisition of skills and environmental information, arousal-avoidance people are driven to spend more efforts on the acquisition so as to secure cognitive closure. Hence, because of the strong desire for cognitive closure and control, these people easily fall prey to an illusion of control (Langer, 1975). They develop an overestimated perceived information possession amid the attribution process of uncertainty to controllable factors other than randomness. The illusionary control compensates the loss of perceived control that results from entropy. Thus, the arousal-avoidance state negatively moderates the negative association between entropy and intention to use.

H6: The arousal-avoidance state negatively moderates the negatively correlated relationship between entropy and intention to use.

Research Methods

One hundred and six students (24 females; 82 males) were invited to participate in the study. They were university students who were enrolled in a course related to software development. They used a serious game as an in-class activity. None of them had played the game before. The game simulates the workflow of creation of digital artwork assets in a hypothetical online game development project. It aims to facilitate the learning of Kanban process tools and the tools' applicability in agile project environments. Kanban is a project development approach that features a visual control mechanism to keep track of work flow and processes throughout an entire project cycle, typically using a board with sticky notes. The approach limits Work In Progress (i.e., the number of items possibly in progress) at each state of workflow. It helps ensure predictable project time and reliable deliverables. It also enhances transparency of work flow and processes, and helps identify waste, bottlenecks and variability in delivery cycles (Kniberg & Skarin, 2010).

The game interface is a Kanban board which presented work processes through which an artwork creation will go through, from design, creation, review, testing to deployment. In the game, players work as a project manager and can assign work to two groups of project members: designers and engineers. The designers work on the design, create, review artwork, and the engineers are responsible for testing and project deployment. Similar to real-life software development projects, the simulated project implementation in the game generates defects which hinder project progress. The defects are generated by a random function in the game. The numbers of defects generated were recorded for calculation of entropy for path analysis, and therefore entropy is a formative item in our model. The number of defects were not disclosed to users in the game to avoid direct feedback effects. The use of objective measure of entropy avoids potential common method bias and overestimation of the correlation among constructs measured by questionnaires.

Immediately before and after the game, the participants were required to fill out questionnaires of which questions are adapted from the previous literature including Agarwal and Karahanna (2000), Lowry *et al.* (2013), Hamari *et al.* (2016) and O'Connell and Calhoun (2001). The questions measure users' pre-usage arousal-avoidance states and post-usage cognitive functions. The question items were reflexive items of their corresponding constructs.

Path Analysis

Instrument Validation

The PLS-SEM (partial least squares structural equation modeling) approach was used to analyze the data. The reason for using PLS-SEM is that this study aims to explore the direct impacts on a final user outcome of entropy. The study adopts the perspective of information deprivation, and we do not intend to develop the best model of entropy for behavioral intention, given that examination of randomness in dual systems is relatively new in our field. This study focuses on information-associated constructs. It is exploratory and prediction-oriented. The reasons align with the conditions for using the PLS-SEM outlined by Wong. (2013) and Chin *et al.* (2003). In addition, the PLS-SEM is particularly suitable for small sample sizes (Hair *et al.*, 2019). Three criteria, including the sample size, the convergent validity and the discriminant validity, were checked to justify the use of PLS-SEM.

According to Chin's (1998) suggestion, to ensure a regression heuristic of 10 cases for each predictor, the sample size needs to be at least 10 times more than the largest number of formative indicators of one construct in the model and at least 10 times more than the largest number of structural paths pointing at a particular construct. Thus, based on Chin's suggestion, the minimum sample size for our study is 40. For a typical research study with its significance level at 5%, its statistical power at 80% and its R^2 larger than 0.25, Wong (2013), on the basis of Marcoulides and Saunders' (2006) guidelines, recommended that the smallest required sample size is 65 when the maximum number of arrows pointing at a latent variable in the research model is 4. Bentler and Chou (1987) recommended that the required sample size should be 5 cases per items measured in the research model. Thus, their recommended sample size for our study is 65. Our sample size fulfills the requirements proposed by Wong's (2013), Chin (1998) and Bentler and Chou (1987).

For constructs with reflexive items, average variance extracted (AVE) and heterotrait-monotrait (HTMT) ratios and composite reliability (CR) were used to evaluate their convergent validity and discriminant validity. The AVE for any construct, according to Fornell & Larcker (1981), should be more than 0.5. The square roots of the AVE of one construct should also be higher than the correlation between that particular construct and other constructs in the model (ibid). The comparison aims to verify that measures of one construct are more correlated with the corresponding construct rather than other constructs. Our data fulfilled Fornell and Larcker's (1981) requirements (see Table 1). According to Hair *et al.* (2019), discriminant validity is not present if the HTMT ratios are higher than 0.85. Our data also met Hair *et al.*'s (2019) recommendation (see Table 2).

	AVE	Sqrt (AVE)	Correlation among Constructs						
			EN	PC	Q	AAS	EN*AAS	IU	J
Perceived Control (PC)	0.565	0.752	-0.227	1.000					
Curiosity (Q)	0.766	0.875	-0.167	0.498	1.000				
Arousal-avoidance State (AAS)	0.738	0.959	-0.130	0.299	0.113	1.000			
Entropy*Arousal-avoidance State (EN*AS)	0.873	0.934	0.763	0.027	-0.054	0.498	1.000		
Intention to Use (IU)	0.868	0.931	-0.045	0.570	0.574	0.196	0.149	1.000	
Enjoyment (J)	0.791	0.890	-0.124	0.479	0.728	0.254	0.084	0.550	1.000

Table 1. Details of the Average Variance Extracted, Square of the AVE, and Correlation among the Constructs

	Ratio among Constructs						
	EN	PC	Q	AAS	EN*AAS	IU	J
Perceived Control (PC)	0.272	1.000					
Curiosity (Q)	0.182	0.619	1.000				
Arousal-avoidance State (AAS)	0.146	0.345	0.152	1.000			
Entropy*Arousal-avoidance State (EN*AS)	0.019	0.178	0.105	0.119	1.000		
Intention to Use (IU)	0.067	0.681	0.649	0.204	0.266	1.000	
Enjoyment (J)	0.0094	0.800	0.508	0.144	0.199	0.571	1.000

Table 2. Details of the HTMT ratios among the Constructs

Composite reliability (CR) and Cronbach's alpha (Alpha) were used to measure internal consistency of the constructs for constructs with reflexive items (Werts *et al.*, 1974). CR and Alpha of all constructs in a structural model should be at least more than 0.7 (Bagozzi & Yi, 1988; Wong, 2013). Table 3 shows that our constructs fulfill the requirements of composite reliability and Cronbach's alpha.

Constructs	**Composite Reliability (rho_a)**	**Composite Reliability (rho_c)**	**Cronbach's Alpha (Alpha)**
Perceived Control (PC)	0.752	0.838	0.744
Curiosity (Q)	0.853	0.907	0.847
Arousal-avoidance State (AAS)	1.298	0.847	0.707
Intention to Use (IU)	0.924	0.952	0.923
Enjoyment (J)	0.828	0.834	0.729

Table 3. Details of the Composite Reliability and Cronbach's alpha of the Constructs

Furthermore, following Chin's (2010) recommendation, we compared the loadings for each item with the cross-loadings. Loadings for an item should be higher than its cross-loadings. Items should be more associated with their intended constructs than other constructs. Table 4 shows that our constructs fulfill Chin's requirement.

	EN	**PC**	**Q**	**AAS**	**EN*AAS**	**IU**	**J**
EN	**1.000**	-0.227	-0.167	-0.130	0.763	-0.045	-0.124
PC1	-0.263	**0.722**	0.289	0.145	-0.145	0.320	0.238
PC2	-0.158	**0.702**	0.321	0.176	0.049	0.447	0.363
PC3	-0.166	**0.783**	0.447	0.293	0.061	0.455	0.387
PC4	-0.119	**0.796**	0.421	0.267	0.080	0.472	0.427
Q1	-0.153	0.402	**0.902**	0.115	-0.051	0.492	0.670
Q2	-0.185	0.416	**0.861**	0.035	-0.145	0.463	0.627
Q3	-0.101	0.490	**0.862**	0.142	0.049	0.551	0.613
AAS1	-0.128	0.323	0.132	**0.971**	0.482	0.215	0.280
AAS2	-0.088	0.126	0.017	**0.730**	0.368	0.075	0.091
EN*AAS1	0.737	0.053	-0.035	0.512	**0.988**	0.171	0.107
EN*AAS2	0.722	-0.059	-0.105	0.374	**0.877**	0.055	-0.003
IU1	0.026	0.494	0.529	0.177	0.201	**0.918**	0.507
IU2	-0.051	0.531	0.545	0.197	0.136	**0.958**	0.531
IU3	-0.104	0.569	0.531	0.175	0.075	**0.917**	0.497
J1	-0.117	0.397	0.637	0.274	0.088	0.491	**0.923**
J2	-0.053	0.422	0.679	0.272	0.151	0.508	**0.934**
J3	-0.161	0.457	0.621	0.130	-0.017	0.465	**0.806**

Table 4. *Details of the Composite Reliability of the Constructs*

With the requirements of the sample size, the convergent validity and the discriminant validity fulfilled, we proceeded with data analysis using PLS-SEM. Significance of the relationships between the constructs was evaluated with the use of bootstrapping procedures. The number of bootstrap samples was set at 3000 with no missing values. The analysis was divided into three parts. We first demonstrated the distinctiveness of entropy from enjoyment. Particularly, enjoyment has been considered a highly relevant construct in the context of hedonic systems (van der Heijden, 2004). This aims to evaluate the chance that entropy largely influences system usage via an emotional mechanism instead of a cognitive one. Second, we used a simplified research model without the arousal-avoidance state to validate mechanisms through which entropy influence the user outcome, namely intention to use.

Third, given that entropy is a formative construct, we adopted the two-stage approach proposed by Chin *et al.* (2003) to examine the moderating effect of the arousal-avoidance state on the relationship between entropy and intention to use. Lastly, we put all previously validated paths of significance into one model, and examined the overarching research model (see Figure 1).

Results

The path analysis is divided into 3 parts. In the first part, we demonstrate that enjoyment is not involved in the mechanism through which entropy influences intention to use. As shown in Figure 2 and Table 5, the t-values of the path from entropy to enjoyment and that from entropy and intention to use are lower than 1.645, indicating that the paths are not significant at $p < 0.1$. The results show that enjoyment is not a mediator between entropy and intention to use. The t-value of the path from enjoyment and intention to use is 5.68 at $p < 0.01$. The significant relationship is aligned with prior studies' conclusion that enjoyment is positively associated with intention to use in hedonic settings (van der Heijden, 2004).

Paths	Effects	t-statistics
EN → J	-0.124	1.613
J → IU	0.552	5.680***
EN → IU	0.023	0.418
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$		

Table 5. The Path Coefficients and the t-statistics of the Respective Correlations with Entropy

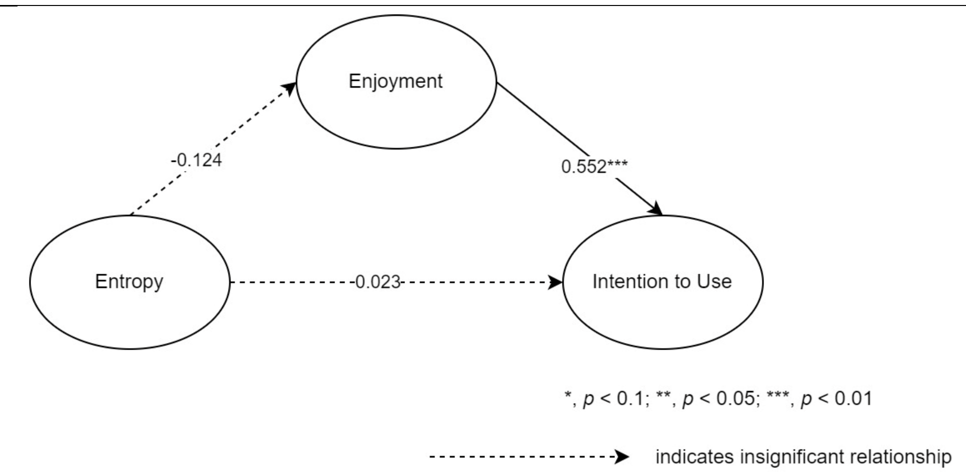

Figure 2. Results of the examination of the mediating role of enjoyment in the relationship between entropy and intention to use.

The second part follows our hypotheses and examines how perceived control and curiosity are involved in the mechanism through which entropy influences intention to use. Figure 3 shows the structural model used and its results of path analysis, and Table 6 presents the path coefficients and the t-values of the model.

Four paths examined in the model are significant at $p < 0.05$. The path from entropy to perceived control is -0.227 at $p < 0.05$, showing that H1 is supported. The path from perceived control to curiosity is 0.049 at $p < 0.01$. This indicates that H2 is supported. The t-value of the path from entropy to curiosity is lower than 1.645. This concurs with our expectation that entropy does not have a direct and negative effect on curiosity. The path from perceived control to intention to use is 0.396 at $p < 0.01$, and the path from perceived curiosity to intention to use is 0.395 at $p < 0.01$. H3 and H4 are supported. Lastly, the t-value of the path from entropy to intention to use is insignificantly at 0.590, showing that the mechanism via perceived control and curiosity fully mediates the relationship between entropy and intention to use.

Paths	Effects	t-statistics
EN →PC	-0.227	2.499**
EN → Q	-0.053	0.590
EN → IU	-0.108	1.475
PC → Q	0.490	4.713***
PC → IU	0.396	4.430***
Q → IU	0.395	4.122***

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 6. The path coefficients and the t-statistics of the mediation model between entropy and intention to use.

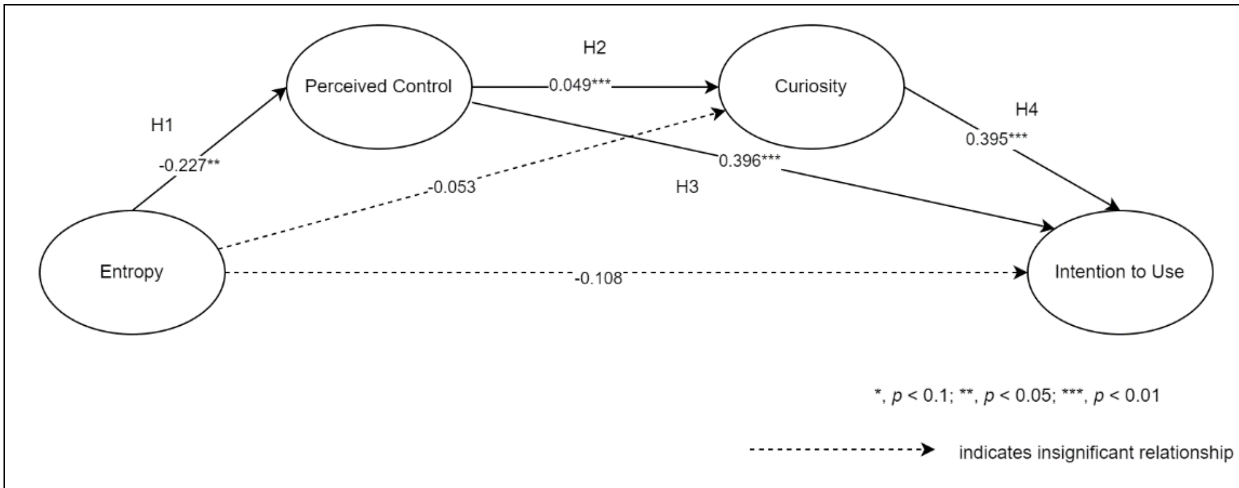

Figure 3. Results of the mediation model between entropy and intention to use.

In the third part, we focus on the moderating role of the pre-usage arousal-avoidance state. Figure 4 shows the structural model to examine the moderating effect and its results of path analysis. Table 7 shows the path coefficients and the t-values of the structural model. The results demonstrate that entropy has an overall negative impact on intention to use. The path from entropy to intention to use is -1.029 at $p < 0.05$. H5 is supported. In line with our prediction, the arousal-avoidance state serves as a significantly negative moderator with $p < 0.05$ in the relationship. H6 is supported. The effect size of inclusion of arousal-avoidance state and its moderating effect is 0.12. According to Chin (2010), the effect size is around moderate. There is also a mild, negative correlation between arousal-avoidance state and intention to use.

Paths	Effects	t-statistics
EN →IU	-1.029	2.456**
AAS → IU	-0.536	1.727*
EN*AAS → IU	1.202	2.246**
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$		

Table 7. The path coefficients and the t-statistics of the structural model with pre-usage state as a moderator.

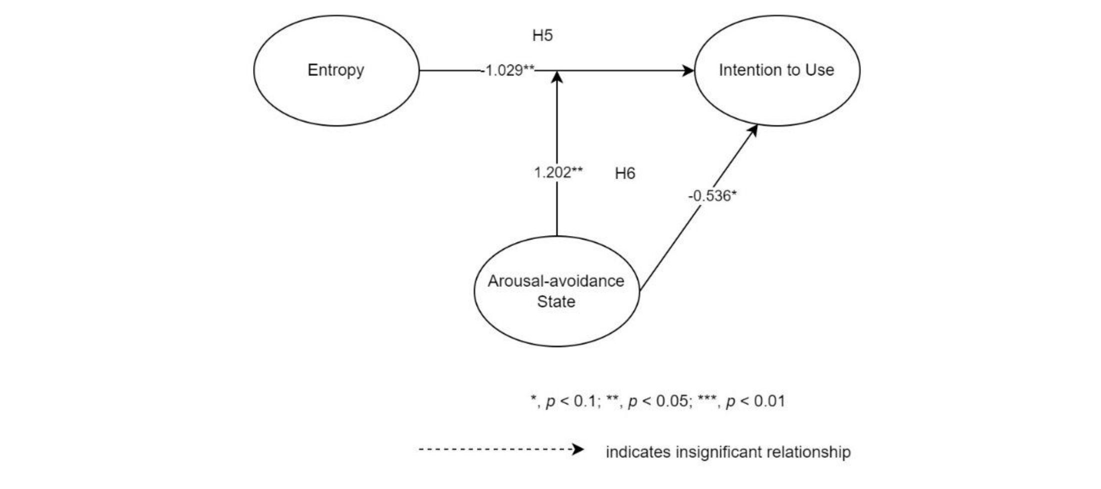

Figure 4. Results of the mediation model between entropy and intention to use.

In the last part, we examine the overarching research model in Figure 1 which is also the integration of significant paths validated in previous two parts. Figure 5 shows path analysis results of the overarching model, and Table 8 shows the path coefficients and the t-values of the model. The entire model contributes to 49% of the variance in intention to use. Variance inflation factors (VIF) of all paths for lateral multicollinearity are shown in Table 8. All VIF values are less than 3, demonstrating that collinearity issues are not critical in the model (Hair *et al.*, 2019).

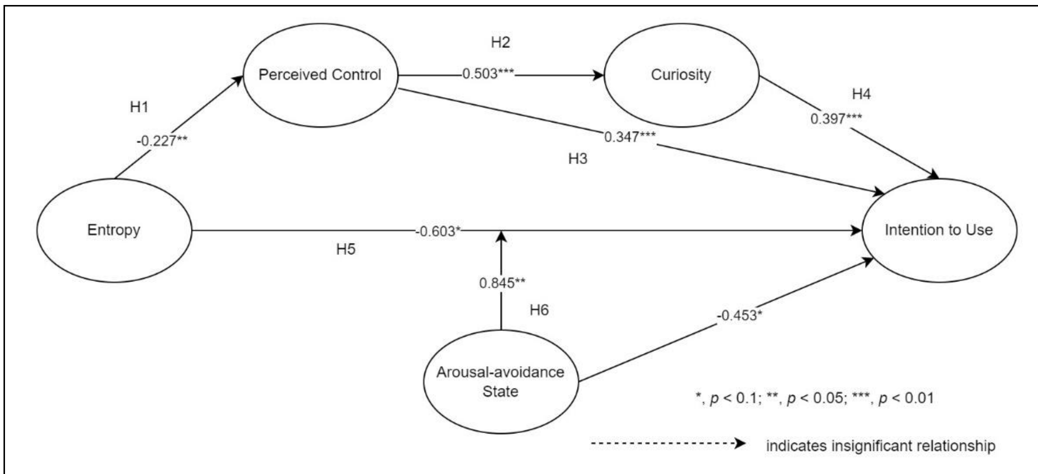

Figure 5. Results of the proposed full model.

Paths	Effects	t-statistics	VIF	Hypotheses
EN → PC	-0.227	2.561**	1	H1 supported
EN → IU	-0.605	1.889*	1.063	N/A
PC → Q	0.503	5.052***	1	H2 supported
PC → IU	0.347	3.871***	1.512	H3 supported
Q → IU	0.397	4.253***	1.346	H4 supported
AAS → IU	-0.453	1.880*	1.133	N/A
EN*AAS → IU	0.845	2.179**	1.039	H6 supported
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$				

Table 8. The path coefficients, the t-statistics and the VIF of the proposed full model.

Table 9 presents the t-statistics of the outer loadings. All the t-statistics are higher than 1.96. The outer model loadings are significant at $p < 0.05$. Relationships among latent variables and their corresponding indicators are validated. The outer model in Figure 5 is significant.

	EN	**PC**	**Q**	**AAS**	**IU**	**EN*AAS**
EN	**N/A**					
PC1		**7.129**				
PC2		**7.547**				
PC3		**14.289**				
PC4		**10.227**				
Q1			**28.444**			
Q2			**11.720**			
Q3			**21.558**			
AAS1				**4.720**		
AAS2				**2.727**		
IU1					**35.034**	
IU2					**80.795**	
IU3					**36.231**	
EN*AAS1						**4.706**
EN*AAS2						**3.819**

Table 9. The t-statistics of the outer loading

Discussion and Implications

Discussion

The results of our quantitative analysis show that entropy has a significantly negative and direct effect on perceived control and a mediated significantly negative and indirect effect on curiosity via perceived control. An increase of entropy means more information loss to users and therefore the users perceive a loss of control of the system environment. They tend to explore the environment to collect information in order to close the gap. The absence of direct effect between entropy and curiosity indicates that entropy generates curiosity mainly through closing an information gap (Loewenstein, 1994). According to Litman and Jimerson (2004), there are two mechanisms of curiosity generation. In addition to closure of information gap, another way to generate curiosity is to stimulate people to anticipate that knowledge discovery in the environment is interesting. Litman and Jimerson (2004) proposed this "feeling-of-interest" mechanism is activated only after individuals close their information gap (i.e., "feeling-of-deprivation" in their words). Our results are aligned with Litman and Jimerson's (2004) thought. Entropy creates information loss and thereby "feeling-of-deprivation", and the condition of activating the "feeling-of-interest" mechanism is not fulfilled in our setting. Thus, there is no direct effect between entropy and curiosity.

In line with previous empirical findings (e.g., Agarwal & Karahanna, 2000), both perceived control and curiosity have significantly positive and direct impacts on intention to use. The influence of perceived control on intention to use is partially, but not fully, mediated by curiosity. This indicates that entropy renders loss of information which results in loss of users' perceived control of the system environment. The reduction of curiosity does not fully capture all negative impact generated by the loss of perceived control on intention to use. This aligns with Agarwal and Karahanna's (2000) findings that both perceived control and curiosity, but not just curiosity, are core components of cognitive absorption which is influential to behavioral intention.

Overall, entropy has a significantly negative effect on intention to use. Prior studies related to games did not delve into the influence of entropy. Some of these studies captured uncertainty generated from interaction with other counterparts in the gaming environment. Liu *et al.* (2013) and Santhanam *et al.* (2016) examined the uncertainty faced by players in competing against different types of competitors. Srivastava and Chandra (2018) drew on the uncertainty reduction theory (Berger & Calabrese, 1974) to explore how to reduce uncertainty among users in a virtual world to foster mutual trust. The uncertainty in focus among these studies is concerned with uncertainty that is mainly attributable to the lack of knowledge about other users' future behavior. This type of uncertainty may pertain more to the "feeling-of-interest" mechanism of curiosity generation. Although randomness existed in user interaction with other players, it was not captured solely in these studies. The negative influence of entropy was not independently examined in previous studies.

Such an adverse consequence of entropy is negatively moderated by the pre-usage arousal-avoidance state of users. The negative moderating effect supports our prediction that the arousal-avoidant users' dislike about uncertainty results in stronger need of cognitive closure of information gap (Loewenstein, 1994). According to Litman's (2005), if an individual dislikes deprivation of environmental information, the need for information due to deprivation may lead to a stronger need for uncertainty clarification and cognitive closure (Webster & Kruglanski, 1994). This irrational need may eventually lead to impulsive approach-oriented behavior such as addiction (Litman, 2005). We argue that this need, if strong enough, may render an illusionary control (Langer, 1975) in the system environment. We suggest that arousal-avoidant users tend to develop an illusory control in the system environment.

The path from entropy to intention to use is fully mediated by perceived control and curiosity. The complete mediation indicates that perceived control and curiosity capture the most important consequences of information loss due to randomness. The R^2 value of the overarching model is 0.49, which is reasonably good. Nevertheless, the model does not explain all variance. For full mediation, future development of a best model of entropy for intention to use may need to explore inclusion of cognitive and affective constructs that are associated with the two mediators in our models, namely perceived control and curiosity.

Theoretical Implications

In this study, we draw on the information theory and introduce the concept *entropy*. We use entropy to quantitatively capture uncertainty generated by randomness in a mixed-motivational system environment. The use of quantitative approach of measuring randomness paves the way to further exploration of the influence of randomness on user behavior. It is noteworthy that "randomness" in some prior studies actually refers to uncertainty results from lack of environmental knowledge (e.g., Srivastava and Chandra, 2018).

This study is among the early attempts to delve into the impacts of uncertainty at different pre-usage state of users. Our results highlight how individuals' pre-usage state of mind may affect their identifying a system. This may subsequently affect their cognitive model of system usage. Some previous studies have revealed this important aspect. With the use of video games, Lowry *et al.* (2013) proposed a technology adoption model specifically for hedonic systems. Interestingly, they found that perceived control has no direct influence on intention to use. Perceived control only has a direct effect on immersion. On the other hand, for users who use goal-oriented services, such as mobile payments, with their mobile devices, Nysveen *et al.* (2005) found that these users' decisions to continuance usage depends largely on the perceived control. Yet, perceived control has a smaller influence on continuance usage if users use playful mobile services.

With the emergence of mixed-motivational systems, we believe in the usefulness of entropy in future studies. Randomness is a common hedonic feature that exists in many hedonic environments. With the use of entropy, researchers can get hold of information loss due to randomness. Contrary to our intuition, information loss has less severe impacts on intention to use of serious-minded users. This indicates that the entropy is less intrusive in the use of a mildly gamified utilitarian system with randomness. Nevertheless, an illusion of control may not always benefit users' serious purpose for using utilitarian systems, if we focus not only on the domain of information loss. The complexity of randomness should be carefully handled. The concept of entropy facilitates future exploration of this aspect.

Practical Implications

The time span between that users try a system and that they decide to continue to use it is rather short. Although system developers can set the embedded randomness in a system, they are unable to control actualized randomness during the short span. Thus, entropy in the time span of first trial is not easily predicted and it may be largely deviated from the long-term expected entropy. Failed adoption and continuance usage of a system merely because of exceedingly large entropy during the first-trial span is disappointing. Yet, randomness is common in hedonic systems, and therefore removal of randomness is not feasible and desirable. To avoid this sad ending, system developers may provide users with a system-usage environment where users tend to be less arousal-seeking. They may also consider lowering user expectation of arousal provided in their systems. A lower expectation of arousal can arguably push down the pre-usage arousal-seeking state of users.

For long, researchers have been concerned with user addictions towards hedonic systems such as gambling websites and video games (Griffiths, 2003, Xu *et al.*, 2012b). These addictive systems are typically associated with high entropy. Our results indicate some potential that we may alleviate addiction via alternation of system-usage environment. We may develop an environment where addictive people tend to seek arousal. The addictive people will then be less prone to illusionary control and tend not to believe that they can control outcomes in the system environments. Based on our proposed model, we may argue that this environment may negatively moderate influence imposed on intention to use by entropy.

Limitations and Future Directions

The study involves a few limitations. First, the approach of this study resembles the approaches of free-simulation experiments of which manipulations are not strict (Gefen *et al.*, 2003; Lowry *et al.*, 2015). The participants' interactions with the system were less controlled than they are in laboratory experiments. Examination of a serious game in classroom setting places stronger emphasis on realism. External validity of our study is strengthened. We did not assume normal distribution of the data and we analyzed the data with PLS-SEM of which the usage requires no such assumption. Nevertheless, future studies may examine entropy in the more extreme conditions, e.g., purely hedonic systems for individuals at strongly arousal-seeking state and purely utilitarian systems for users at a strongly arousal-avoidance state. The laboratory experimental approaches are more suitable for investigation of these two conditions. Second, the study focuses on the trial of a new serious game. In a longer term, it is unclear whether user sensitivity towards uncertainty in a system environment changes. If users are less sensitivity towards uncertainty, impacts of entropy possibly fade out. A longitudinal study that focuses on the interaction between the sensitivity and the entropy is interesting. Lastly, the goal of the study is to explore the direct impacts of entropy on intention to use. We do not intend to develop the best model of entropy. The reasonably good R^2 value in our results indicates that we have captured the most important cognitive functions in our model. Nonetheless, development of the best model for entropy remains a good research direction for future researchers. For future directions, we intend to conduct a qualitative study to further understand system users' perception of information deprivation. Other routes through which entropy may affect intention to use can be found.

References

Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. *MIS Quarterly, 24*(4), 665-694.

Alloy, L. B., Abramson, L. Y., & Viscusi, D. (1981). Induced mood and the illusion of control. *Journal of Personality and Social Psychology*, *41*(6), 1129-1140.

Apter, M. J. (1988). Reversal theory as a theory of the emotions. In *Advances in Psychology* (Vol. 51, pp. 43-62). North-Holland.

Apter, M. J. (2009). Reversal Theory. In R. P. Carlisle (Ed.), Encyclopedia of Play in Today's Society (pp. 597-598). Sage.

Apter, M. J. (2001). *Motivational styles in everyday life: A guide to reversal theory*. American Psychological Association.

Bagozzi, R. P. & Yi, Y. (1988). On the Evaluation of Structural Equation Models. *Journal of the Academy of Marketing Science, 16*(1), 74–94.

Bentler, P. M., & Chou, C. P. (1987). Practical issues in structural modeling. *Sociological Methods & Research*, *16*(1), 78-117.

Berger, C. R., & Calabrese, R. J. (1974). Some explorations in initial interaction and beyond: Toward a developmental theory of interpersonal communication. *Human Communication Research*, *1*(2), 99-112.

Berlyne, D. E. (1950). Novelty and curiosity as determinants of exploratory behaviour. *British Journal of Psychology*, *41*(1), 68-80.

Boyle, E. A., Hainey, T., Connolly, T. M., Gray, G., Earp, J., Ott, M., Lim, T., Ninaus, M., Ribeiro, C., & Pereira, J. (2016). An update to the systematic literature review of empirical evidence of the impacts and outcomes of computer games and serious games. *Computers & Education*, *94*, 178-192.

Burger, J. M. (1985). Desire for control and achievement-related behaviors. *Journal of Personality and Social Psychology*, *48*(6), 1520-1533.

Burger, J. M., & Hemans, L. T. (1988). Desire for control and the use of attribution processes. *Journal of Personality*, *56*(3), 531-546.

Chau, M., Wong, A., Wang, M., Lai, S., Chan, K. W., Li, T. M., & Chu, D. (2013). Using 3D virtual environments to facilitate students in constructivist learning. *Decision Support Systems*, *56*, 115-121.

Cheng, V. W. S., Davenport, T., Johnson, D., Vella, K., & Hickie, I. B. (2019). Gamification in apps and technologies for improving mental health and well-being: systematic review. *JMIR Mental Health*, *6*(6), e13717.

Chin, W. W. (1998). The Partial Least Squares Approach to Structural Equation Modeling. In G. A. Marcoulides (ed.), *Modern Methods for Business Research* (pp. 295–336). New York: Psychology Press.

Chin, W. W., Marcolin, B. L., & Newsted, P. R. (2003). A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. *Information Systems Research*, *14*(2), 189-217.

Chin, W. W. (2010). How to Write Up and Report PLS Analyses. In V. E. Vinzi, W. W. Chin, J. Henseler & H. Wang (eds), *Handbook of Partial Least Squares* (pp. 655–690). Berlin and Heidelberg: Springer.

Costikyan, G. (2013). *Uncertainty in games*. Mit Press.

Csikszentmihalyi, M. (1975). *Beyond boredom and anxiety*. San Francisco: Jossey-Bass.

Dahabiyeh, L., Najjar, M. S., & Agrawal, D. (2021). When ignorance is bliss: The role of curiosity in online games adoption. *Entertainment Computing*, *37*, 100398.

Deci, E. L. (1975). Intrinsic motivation. New York, NY, US.

Fenton-O'Creevy, M., Nicholson, N., Soane, E., & Willman, P. (2003). Trading on illusions: Unrealistic perceptions of control and trading performance. *Journal of Occupational and Organizational Psychology*, *76*(1), 53-68.

Fornell, C. & Larcker, D. F. (1981). Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics. *Journal of Marketing Research*, 18(3), 382–388.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS quarterly*, *27*(1), 51-90.Gottlieb, J., Oudeyer, P. Y., Lopes, M., & Baranes, A. (2013).

Information-seeking, curiosity, and attention: computational and neural mechanisms. *Trends in Cognitive Sciences*, *17*(11), 585-593.

Griffiths, M. (2003). Internet gambling: Issues, concerns, and recommendations. *CyberPsychology & Behavior*, *6*(6), 557-568.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2-24.

Hamari, J., Shernoff, D. J., Rowe, E., Coller, B., Asbell-Clarke, J., & Edwards, T. (2016). Challenging games help students learn: An empirical study on engagement, flow and immersion in game-based learning. *Computers in human behavior*, *54*, 170-179.

Hernández-Lara, A. B., & Serradell-López, E. (2018). Student interactions in online discussion forums: their perception on learning with business simulation games. *Behaviour & Information Technology*, *37*(4), 419-429.

Hill, K. M., Fombelle, P. W., & Sirianni, N. J. (2016). Shopping under the influence of curiosity: How retailers use mystery to drive purchase motivation. *Journal of Business Research*, *69*(3), 1028-1034.

Ho, S. Y., & Bodoff, D. (2014). The effects of Web personalization on user attitude and behavior. *MIS Quarterly*, *38*(2), 497-A10.

Hunt, J. (1965). Intrinsic motivation and its role in psychological development. In *Nebraska symposium on motivation* (Vol. 13, pp. 189-282). University of Nebraska Press.

Kagan, J. (1972). Motives and development. *Journal of Personality and Social Psychology*, *22*(1), 51-66.

Kapp, K. M. (2012). *The gamification of learning and instruction: game-based methods and strategies for training and education*. John Wiley & Sons.

Kim, J. T., & Lee, W. H. (2015). Dynamical model for gamification of learning (DMGL). *Multimedia Tools and Applications*, *74*(19), 8483-8493.

Kniberg, H., & Skarin, M. (2010). *Kanban and Scrum-making the most of both (Enterpresie software development)*. Lulu. com.

Koufaris, M. (2002). Applying the technology acceptance model and flow theory to online consumer behavior. *Information Systems Research*, *13*(2), 205-223.

Kruglanski, A. W. (2004). The psychology of closed-mindedness. New York: Psychology Press

Langer, E. J. (1975). The illusion of control. *Journal of Personality and Social Psychology*, *32*(2), 311-328.

Lee, P. T. Y., Chau, M., & Lui, R. W. C. (2021). The role of attitude toward challenge in serious game design. *Journal of Computer Information Systems*, *61*(4), 383-394.

Lee, P. T., Lui, R. W., & Chau, M. (2019). How does competition help future learning in serious games? an exploratory study in learning search engine optimization. *Journal of Information Systems Education*, *30*(3), 167-177.

Litman, J. (2005). Curiosity and the pleasures of learning: Wanting and liking new information. *Cognition & Emotion*, *19*(6), 793-814.

Litman, J. A., & Jimerson, T. L. (2004). The measurement of curiosity as a feeling of deprivation. *Journal of Personality Assessment*, *82*(2), 147-157.

Liu, D., Li, X., & Santhanam, R. (2013). Digital games and beyond: What happens when players compete?. *MIS Quarterly*, 37(1), 111-124.

Liu, D., Santhanam, R., & Webster, J. (2017). Toward Meaningful Engagement: A Framework for Design and Research of Gamified Information Systems. *MIS Quarterly*, *41*(4), 1011-1034.

Loewenstein, G. (1994). The psychology of curiosity: A review and reinterpretation. *Psychological Bulletin*, *116*(1), 75.

Loewenstein, G., Adler, D., Behrens, D., & Gillis, J. (1992). Why Pandora opened the box: Curiosity as a desire for missing information. *Unpublished manuscript, Department of Social and Decision Sciences, Carnegie Mellon University, Pittsburgh, PA*.

Lowry, P. B., Gaskin, J., Twyman, N., Hammer, B., & Roberts, T. L. (2013). Proposing the hedonic-motivation system adoption model (HMSAM) to increase understanding of adoption of hedonically motivated systems. *Journal of the Association for Information Systems*, *14*(11), 617-671.

Lowry, P. B., Gaskin, J., & Moody, G. D. (2015). Proposing the multi-motive information systems continuance model (MISC) to better explain end-user system evaluations and continuance intentions. *Journal of the Association for Information Systems*, *16*(7), 515-579.

MacKay, D. J. (2003). *Information theory, inference and learning algorithms*. Cambridge university press.

Martins, I., Perez, J. P. P., Osorio, D., & Mesa, J. (2023). Serious Games in Entrepreneurship Education: A Learner Satisfaction and Theory of Planned Behaviour Approaches. *The Journal of Entrepreneurship, 32*(1), 157-181.

Moizer, J., Lean, J., Dell'Aquila, E., Walsh, P., Keary, A., O'Byrne, D., Ferdinando, A. D., Miglino, O., Friedrich, R., Asperges, R. & Sica, L. S. (2019). An approach to evaluating the user experience of serious games. *Computers & Education*, *136*, 141-151.

Malone, T. W. (1981). What makes computer games fun?. *Byte, 6*(12), 258-277.

Malone, T. W., & Lepper M. R. (1987). Making learning fun: A taxonomy of intrinsic motivations for learning. In R. E. Snow, P. A. Federico & W. E. Montague (Eds.) *Aptitude, learning, and instruction* (pp. 223-253). New York: L. Erlbaum Associates.

Marcoulides, G. A., & Saunders, C. (2006). Editor's comments: PLS: a silver bullet?. *MIS Quarterly*, *30*(2), iii-ix.

Moizer, J., Lean, J., Dell'Aquila, E., Walsh, P., Keary, A., O'Byrne, D., Ferdinando, A. D., Miglino, O., Friedrich, R., Asperges, R. & Sica, L. S. (2019). An approach to evaluating the user experience of serious games. *Computers and Education*, *136*, 141-151.

Nakamura, J., & Csikszentmihalyi, M. (2009). Flow theory and research. *Handbook of Positive Psychology*, 195-206.

Nysveen, H., Pedersen, P. E., & Thorbjørnsen, H. (2005). Intentions to use mobile services: Antecedents and cross-service comparisons. *Journal of the academy of marketing science*, *33*(3), 330-346.

O'Connell, K. A., & Calhoun, J. E. (2001). The telic/paratelic state instrument (T/PSI): validating a reversal theory measure. *Personality and Individual Differences*, *30*(2), 193-204.

Oei, T. P., Lin, J., & Raylu, N. (2008). The relationship between gambling cognitions, psychological states, and gambling: A cross-cultural study of Chinese and Caucasians in Australia. *Journal of Cross-cultural Psychology*, *39*(2), 147-161.

Ortiz-Rojas, M., Chiluiza, K., & Valcke, M. (2019). Gamification through leaderboards: An empirical study in engineering education. *Computer Applications in Engineering Education*, *27*(4), 777-788.

Pando-Garcia, J., Periañez-Cañadillas, I., & Charterina, J. (2016). Business simulation games with and without supervision: An analysis based on the TAM model. *Journal of Business Research*, *69*(5), 1731-1736.

Piaget, J., & Cook, M. (1952). *The origins of intelligence in children*. New York: International Universities Press.

Rényi, A. (1961). On measures of entropy and information. In *Proceedings of the Fourth Berkeley Symposium on Mathematical Statistics and Probability, Volume 1: Contributions to the Theory of Statistics*. The Regents of the University of California.

Ryan, R. M. (1982). Control and information in the intrapersonal sphere: An extension of cognitive evaluation theory. *Journal of Personality and Social Psychology*, *43*(3), 450-461.

Santhanam, R., Liu, D., & Shen, W. C. M. (2016). Research Note—Gamification of technology-mediated training: Not all competitions are the same. *Information systems research*, *27*(2), 453-465.

Srivastava, S. C., & Chandra, S. (2018). Social presence in virtual world collaboration: An uncertainty reduction perspective using a mixed methods approach. *MIS Quarterly*, *42*(3), 779-804.

Taleb, N. (2005). *Fooled by randomness: The hidden role of chance in life and in the markets* (Vol. 1). Random House Incorporated.

Van der Heijden, H. (2004). User acceptance of hedonic information systems. *MIS Quarterly, 28*(4), 695-704.

Wasko, M., Teigland, R., Leidner, D., & Jarvenpaa, S. (2011). Stepping into the internet: New ventures in virtual worlds. *MIS quarterly*, *35*(3), 645-652.

Webster, D. M., & Kruglanski, A. W. (1994). Individual differences in need for cognitive closure. *Journal of Personality and Social Psychology*, *67*(6), 1049.

Werts, C. E., Linn, R. L., & Jöreskog, K. G. (1974). Intraclass reliability estimates: Testing structural assumptions. *Educational and Psychological Measurement*, *34*(1), 25-33.

Wong, K. K. K. (2013). Partial Least Squares Structural Equation Modeling (PLS-SEM) Techniques Using SmartPLS. *Marketing Bulletin, 24*(1), 1–32.

Xiao, B., & Benbasat, I. (2007). E-commerce product recommendation agents: use, characteristics, and impact. *MIS Quarterly*, *31*(1), 137-209.

Xu, H., Teo, H. H., Tan, B. C., & Agarwal, R. (2012a). Research note—effects of individual self-protection, industry self-regulation, and government regulation on privacy concerns: a study of location-based services. *Information Systems Research*, *23*(4), 1342-1363.

Xu, Z., Turel, O., & Yuan, Y. (2012b). Online game addiction among adolescents: motivation and prevention factors. *European Journal of Information Systems*, *21*(3), 321-340.