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Gamified Digital Intervention to Reduce Online Game Gambling Tendency among Youth: A TAM–SDT Evaluation

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Abstract

The rapid growth of online gaming has raised concerns about addictive behaviors among young people, particularly with the emergence of loot boxes that resemble gambling mechanisms. This study aims to examine the effectiveness of a gamification-based application as a preventive intervention for online gambling game addiction and to evaluate user acceptance through an extended Technology Acceptance Model (TAM). The research was conducted in two stages. In the pre-test phase, 588 respondents aged 15–25 completed a questionnaire measuring impulsivity, Internet Gaming Disorder (IGD), and loot box exposure. The results identified 169 individuals (28.7%) with addictive tendencies. In the intervention phase, 86 respondents from this group participated in a gamified stimulation program using a specially designed application. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The measurement model met reliability and validity requirements. Structural model analysis confirmed the classic TAM relationships: perceived ease of use significantly influenced perceived usefulness ($\beta = .559$, $p < 0.001$), perceived usefulness influenced attitude toward use ($\beta = .385$, $P= 0.001$), and attitude influenced behavioral intention ($\beta = .461$, $p < 0.001$). In addition, Self-Determination Theory (SDT) significantly affected both attitude ($\beta = .360$, $P= 0.003$) and behavioral intention ($\beta = .166$, $P= 0.038$). However, Affective Visual Design (AVD) was not significant, and behavioral intention did not reduce addictive behavior ($\beta = -0.109$, $P= 0.386$). The model demonstrated predictive relevance for PU, ATT, and BI ($Q^2 > 0$), whereas ABT showed no predictive relevance ($Q^2 = –0.003$), indicating limited short-term behavioral predictability. This study contributes theoretically by extending TAM with SDT in the context of digital health interventions and practically by demonstrating the potential of gamification as a preventive tool. However, the short intervention period and limited sample size constrained its effectiveness in reducing addiction. Longer-term interventions and broader contextual factors are recommended for future research.

Keywords: Gamification, Internet Gaming Disorder, Gambling, Technology Acceptance Model, Self-Determination Theory, Adolescent, Young Adult

1. Introduction

The rapid advancement of digital technology has significantly driven the growth of the online gaming industry over the past two decades. Online games have evolved beyond entertainment, becoming platforms for socialization, competition, and even sources of income. However, this phenomenon also poses risks of addictive behavior, especially among young people [1]. One of the most highlighted aspects is the emergence of loot boxes and chance-based features that resemble gambling, where players purchase virtual items in hopes of obtaining rare rewards [2]. Recent studies have revealed a strong association between loot box purchases, impulsivity, and problem gambling tendencies [3]. Loot box mechanisms may lead to compulsive behaviors similar to traditional gambling patterns because they involve elements of uncertainty and random rewards [4].

In addition, excessive playing time often disrupts academic, occupational, and social activities, as categorized under Internet Gaming Disorder (IGD) in the DSM-5 [5]. The tendency toward online gaming addiction has been associated with factors such as impulsivity [6], self-control [7], and engagement in loot box mechanisms [8]. Studies across

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countries show that the prevalence of addictive gaming behavior among young people ranges between 5% and 30%, depending on the instruments used [9]. In Indonesia, the increasing penetration of the internet and the popularity of mobile games underscore the urgency of examining this issue from a local perspective.

One preventive approach that has gained increasing attention is gamification, defined as the application of game elements (points, levels, badges, feedback, and leaderboards) in non-game contexts to enhance motivation and behavior change [10]. Gamification has proven effective in various domains such as education [11], health [12], and organizational management [13]. However, the application of gamification as a preventive intervention for online gambling game addiction remains relatively underexplored. To understand user acceptance of digital interventions, this study integrates the Technology Acceptance Model (TAM) [14] with additional constructs such as Self-Determination Theory (SDT), which emphasizes intrinsic motivation [15], and Affective Visual Design (AVD), which assesses the aesthetic and comfort aspects of application design [16]. Thus, this study not only evaluates the effectiveness of gamification as a stimulant but also analyzes the extent to which the application can be accepted by users.

This study offers novelty in several aspects that distinguish it from previous works. First, it focuses on young people in Indonesia, where international literature on online gambling game addiction has rarely addressed perspectives from developing countries. This is important because cultural characteristics, levels of digital literacy, and gaming patterns in Indonesia may differ from findings in developed nations. Second, the study combines two main stages: mapping respondents with addictive tendencies through a pretest and implementing an intervention program using a specially developed gamification application. This approach not only identifies risk levels but also directly tests the effectiveness of a technology-based intervention. Furthermore, this study examines TAM in a relatively new context, namely the prevention of online gaming addiction. Most previous research has applied TAM in education, e-commerce, or general technology adoption. By incorporating constructs from SDT and AVD, this research enriches the understanding of factors influencing user acceptance of digital applications designed for preventive purposes. This demonstrates an integration of technology acceptance theory with motivational and design aesthetics theories, thereby providing broader theoretical contributions.

This study provides a novel contribution by examining online gambling game addiction among Indonesian youth within a distinct socio-cultural setting. Unlike studies in East Asia that link gaming disorder to academic pressure [7] or Western studies emphasizing psychological traits such as impulsivity [4], [17], this research situates the phenomenon within Indonesia's collectivist culture and rapidly expanding mobile gaming environment shaped by gacha and loot box systems. This contextual focus extends current literature by highlighting how cultural norms and motivational patterns influence digital gaming behavior in a non-Western population

Although studies on online gaming addiction have grown rapidly in recent years, several research gaps remain. First, most studies on IGD and addictive gaming behaviors have focused on developed countries such as the United States, Europe, or East Asia. Research in developing countries, including Indonesia, remains limited, even though internet and mobile gaming use in these regions has shown significant growth [18]. Differences in social and cultural contexts and digital literacy levels may result in different patterns of addictive behavior, which warrant further exploration. Second, prior research has largely emphasized descriptive aspects of the negative impacts of gaming addiction, such as academic disruption, social problems, or mental health issues [1], [9].

Preventive strategies and technology-based interventions remain underexplored. This raises an important question: how can technology, often associated with the cause of the problem, be leveraged as part of the solution? Third, while gamification has been widely used in education and health, its application to prevent online gambling game addiction is still scarce [4]. Most interventions are still based on traditional counseling or general education, without utilizing the motivational potential of gamification mechanisms. Fourth, research on the acceptance of technology-based interventions has mostly applied TAM in productivity or learning contexts [14], [18]. Few studies have examined TAM in digital health interventions, particularly in the context of gaming addiction. Moreover, the combination of TAM with motivational theories such as SDT and design factors such as AVD remains rarely explored.

Based on these gaps, this study addresses the need for empirical research that not only maps the prevalence of gaming addiction but also evaluates the effectiveness of a specially developed gamification intervention and examines its acceptance through the integration of TAM, SDT, and AVD. This study extends the TAM by integrating constructs from the SDT and AVD to provide a more comprehensive understanding of user acceptance and behavioral engagement. While TAM explains cognitive evaluations such as PU and ease of use, SDT introduces motivational elements—autonomy, competence, and relatedness—that are critical for sustained use of health-related gamified applications. The addition of AVD captures the affective and aesthetic aspects influencing emotional connection and enjoyment during interaction. Together, these frameworks represent cognitive, motivational, and affective dimensions that jointly determine how users accept and engage with digital interventions designed to reduce addictive gaming behaviors

2. Method

2.1. Study Design

This study employed a quantitative explanatory approach with a pretest–posttest design. In the first stage, a pretest was conducted to identify respondents with tendencies toward online gaming addiction using a questionnaire developed based on the IGD indicators in DSM-5, impulsivity [6], and involvement in loot box or gacha mechanisms [19].

The second stage involved an intervention using a specially designed gamification application as a stimulant program to reduce addictive tendencies. Gamification was implemented in the form of an educational game application containing knowledge-based questions designed to raise awareness of the harmful impacts of online gaming addiction. The knowledge content was organized into several aspects: impulsivity (addressed with questions on healthy behavior), gaming duration (addressed with questions on time management), and exposure to loot boxes (addressed with questions about gambling risks in online games and the importance of self-control).

This research design enabled the researchers to: (1) identify at-risk (addictive) respondents through the pretest; (2) deliver a gamification-based intervention to minimize addictive behavior; and (3) examine application acceptance using the TAM [14] extended with constructs from SDT [15] and AVD [16] in the posttest stage.

2.2. Participants

The study population comprised young people aged 15–25 years who were active online gamers. A total of 588 respondents participated in the pretest stage. Analysis identified 169 respondents (28.7%) as having addictive tendencies based on a cut-off of Duration/IGD ≥ 3 and Impulsivity or Loot Box Exposure ≥ 3 [16], [20]. The cutoff values were determined based on the DSM-5 IGD framework [5], where three or more indicators suggest moderate-to-severe risk. This approach is consistent with prior studies by King and Rockloff [20], [21], which used similar thresholds to classify participants with problematic gaming behavior. Accordingly, the present study adopted the same criteria to ensure methodological consistency with established practices.

For the intervention stage, purposive sampling was applied to select 86 respondents from the addictive group to participate in the gamification-based stimulant program. This sample size was consistent with minimum recommendations for Partial Least Squares Structural Equation Modeling (PLS-SEM), which suggests a sample size of at least 10 times the number of indicators of the construct with the largest number of outgoing arrows [22].

2.3. Intervention

The intervention was conducted using the gamification application designed with elements such as missions, points, badges, and notifications, which served as reminders and behavioral reinforcements. The intervention was delivered through a mobile gamified application featuring short educational missions across three behavioral domains: impulsivity, play duration, and loot box exposure. The intervention was implemented over a two-week period, during which participants interacted with the application daily to complete the assigned educational missions. Each mission used interactive quizzes, brief reflective tasks, and instant feedback supported by game elements such as points, badges, and level progression. The learning content promoted self-control, time management, and awareness of gambling-like game mechanics to reduce excessive gaming behavior. The procedure consisted of three stages:

Pretest: questionnaires were distributed to 588 respondents to identify addictive tendencies. Analysis identified 169 respondents meeting addiction-prone criteria [4], [23]. Intervention: 86 respondents from the addictive group participated in the stimulant program through the gamification application. Respondents were instructed to use the app according to guidelines, with the aim of increasing awareness and self-control over gaming behavior. Posttest:

respondents who completed the intervention filled out a questionnaire measuring addiction tendencies after the program, as well as an evaluation questionnaire on application acceptance based on TAM, SDT, and AVD.

2.4. Measures

The research instruments consisted of two main clusters. The first cluster measured addictive tendencies during the pretest stage, consisting of three constructs assessed on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). The first construct, Impulsivity, captured the tendency to act without consideration in gaming contexts [6], with indicators such as spontaneous play, difficulty controlling urges, and impulsive reactions to gaming triggers. The second construct, Duration/IGD, represented behavioral indicators related to IGD [5], including playing for more than three hours per day, skipping tasks, losing track of time, feeling anxious when not playing, and experiencing difficulty stopping. The third construct, Loot Box Exposure, assessed the intensity of interest in or purchasing loot boxes, as well as emotional responses to random in-game outcomes [2], [4]. Example indicators included interest in opening loot boxes, purchase frequency, feelings of euphoria when obtaining rare items, disappointment when receiving low-value rewards, and spending personal money on these randomized features [22], [24].

The second cluster evaluated application acceptance during the intervention stage using the extended TAM framework, also measured on a 5-point Likert scale. This cluster included Perceived Ease of Use (PEOU), which captured the perceived ease of interacting with the application [14]. Perceived Usefulness (PU) assessed how useful the application was perceived to be for managing gaming behavior [14]. Attitude Toward Use (ATT) measured the affective and cognitive evaluations of using the application [18], whereas Behavioral Intention (BI) referred to the intention to continue using the application [18]. SDT assessed intrinsic motivation—including autonomy, competence, and relatedness—experienced during application use [15]. AVD captured users' perceptions of aesthetics and comfort in the application's design. This construct was operationalized through indicators related to color harmony and visual balance, clarity of layout and navigation, and the emotional appeal or comfort experienced during interaction, emphasizing affective responses rather than functional usability [16]. Finally, measurement quality was evaluated following established PLS-SEM guidelines [22]. Reliability and validity criteria included Cronbach's $\alpha \geq 0.70$, Composite Reliability (CR) ≥ 0.70, and Average Variance Extracted (AVE) ≥ 0.50 [25], while discriminant validity was assessed using the HTMT threshold of ≤ 0.85 or 0.90 [26]. Items that reduced reliability or validity were removed based on theoretical justification.

2.5. Statistical Analysis

Data were analyzed using PLS-SEM with SmartPLS version X [22]. Reliability, convergent validity, and discriminant validity were tested using Cronbach's α, CR, AVE, and HTMT thresholds. Path coefficients, significance levels, and predictive relevance (Q^2) were assessed to evaluate the structural model. The structural model was assessed using the bootstrapping procedure with 5,000 resamples to estimate path significance. Model fit was evaluated using the Standardized Root Mean Square Residual (SRMR), which yielded a value of 0.061—well within the recommended threshold of 0.08—indicating an acceptable overall model fit.

2.6. Proposed Model

The proposed model integrated TAM with SDT and AVD in the context of gamification-based addiction prevention interventions (figure 1). Conceptually, PEOU increases PU (the easier the system is to use, the more useful it is perceived). PU influences ATT, which in turn drives BI to continue using the application [14], [18]. SDT was positioned as a motivational driver reinforcing ATT and directly influencing BI [15]. AVD was assumed to increase BI through positive visual experiences [16]. Ultimately, BI was hypothesized to reduce Addictive Behavior Tendencies (ABT), since continuous use of the application facilitates self-control (cognitive bias education, time management, and cool-down mechanisms. Based on the integration of the TAM, SDT, and AVD, this study formulated seven hypotheses grounded in prior theoretical explanations. First, H1 posits that PU positively influences ATT of the gamification system, consistent with TAM's central proposition that usefulness shapes user attitudes [14].

In relation to system usability, H2 proposes that PEOU positively affects ATT [18], while H3 states that PEOU positively influences PU [14], reflecting the TAM assumption that ease of use enhances perceptions of usefulness. Concerning behavioral intention, H4 suggests that a positive ATT increases BI to continue using the application [18].

Beyond cognitive beliefs, aesthetic evaluation is examined in H5, which states that AVD positively influences ATT [16]. From a motivational standpoint, H6 proposes that intrinsic motivation derived from SDT—including autonomy, competence, and relatedness—positively affects BI [15]. Finally, H7 posits that BI negatively influences ABT, assuming that stronger intentions to use the intervention reduce the likelihood of engaging with addictive gaming mechanisms such as loot boxes [2], [4]. The proposed research framework integrating TAM, SDT, and AVD is illustrated in figure 1.

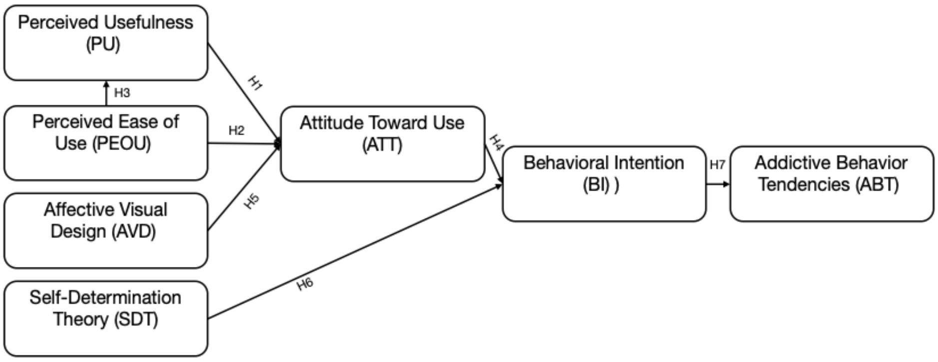

Figure 1. Proposed Model

3. Result

3.1.Participant Characteristics

The initial stage of the study was conducted by distributing questionnaires to 588 respondents. Descriptive analysis showed that the average impulsivity score was 3.07 (SD = 0.81), the average duration/IGD score was 2.53 (SD = 1.05), and the average loot box exposure score was 2.94 (SD = 1.22) on a 1–5 scale. Reliability testing with Cronbach's alpha showed adequate results: impulsivity ($\alpha = 0.724$), duration/IGD ($\alpha = 0.871$), and loot box exposure ($\alpha = 0.908$), which means that all three constructs had good internal consistency [22], [27]. Based on the DSM-5 cut-off for IGD [5], respondents with an average Duration/IGD score ≥ 3 were categorized as potentially addictive. As a result, 177 respondents (30.1%) met the initial criteria. To strengthen the addictive category, a combined requirement was added, namely Duration/IGD ≥ 3 as well as Impulsivity ≥ 3 or Loot Box Exposure ≥ 3. With this combined criterion, 169 respondents (28.7%) were categorized as having stronger addictive tendencies. Demographic analysis showed that this group was dominated by males (77%) compared to females (23%) [28].

3.2. Intervention Using Gamified Application

From the 169 addictive respondents, 86 were selected to participate in the intervention using the specially designed gamified application. The application included features such as daily missions, point systems, achievement badges, and reminder notifications. The aim was to stimulate healthier behavior, such as limiting playtime, reducing impulsive urges, and raising awareness of loot box risks. During the intervention period, respondents were directed to use the application in their daily activities. After the intervention, a post-test was conducted to reassess addictive tendencies and to test application acceptance using the TAM model. Of the 86 participants who began the gamified intervention, 78 completed the post-test stage, indicating a dropout rate of approximately 9.3%.

3.3. Measurement Model Evaluation (Outer Model)

The results of the outer model evaluation showed that most constructs met the criteria for reliability and validity. The values of Cronbach's alpha and CR for all constructs were above 0.70, while the AVE values were above 0.50, indicating that the instruments were valid and reliable [22]. Some items, such as PEOU1, AVD1, and ATT1, were removed to improve discriminant validity. After modification, the model was deemed suitable for further analysis. Table 1 below presents the validity and reliability test results [29], [30].

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Table 1. Validity and Reliability Test Results

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
BI	0.769	0.770	0.896	0.812
ABT	0.856	0.992	0.930	0.869
PU	0.893	0.896	0.949	0.904
SDT	0.825	0.826	0.895	0.740

The final structural model estimation using SmartPLS 4.0 is presented in figure 2.

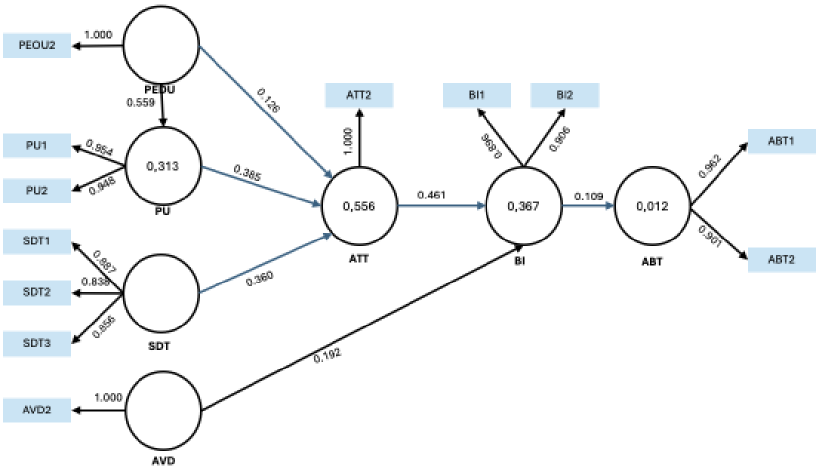

Figure 2. Final Model in SmartPLS 4.0

Reliability testing of constructs was carried out using Cronbach's alpha and CR, while convergent validity was evaluated through AVE. The results showed that all constructs met the recommended criteria [22], namely Cronbach's alpha and CR above 0.70 and AVE above 0.50 [30], [31]. The BI construct had a Cronbach's alpha value of 0.769, CR (rho_a) of 0.770, and CR (rho_c) of 0.896, with an AVE of 0.812. This indicates that the instrument used to measure BI had good internal consistency and could explain more than 81% of the variance in its indicators. The ABT construct also showed very strong reliability with a Cronbach's alpha of 0.856, CR (rho_a) of 0.992, rho_c of 0.930, and an AVE of 0.869. These results indicate that ABT indicators had very high consistency and excellent convergent validity [25], [32].

The PU construct showed superior reliability with a Cronbach's alpha of 0.893, rho_a of 0.896, and rho_c of 0.949. Its AVE was 0.904, indicating that almost all of the variance of its indicators could be explained by the PU construct. The SDT construct had a Cronbach's alpha of 0.825, CR (rho_a) of 0.826, and rho_c of 0.895, with an AVE of 0.740. This proves that the SDT construct had adequate reliability and good convergent validity, with more than 74% of the indicator variance explained. Overall, the results confirmed that all constructs in the model met the required standards. The instruments were therefore valid and reliable for measuring research constructs, and suitable for proceeding to the structural model analysis stage [26], [33]. The HTMT test results after several items were removed can be seen in table 2 below.

Table 2. HTMT Results

	ATT	AVD	BI	ABT	PEOU	PU	SDT
ATT							
AVD	0.658						
BI	0.669	0.567					
ABT	0.176	0.346	0.135				
PEOU	0.504	0.545	0.446	0.225			
PU	0.711	0.672	0.687	0.107	0.592		

SDT	0.712	0.748	0.838	0.224	0.498	0.699

Discriminant validity was tested using the Heterotrait-Monotrait Ratio of Correlations (HTMT). Discriminant validity is achieved when the HTMT values between constructs are below the threshold of 0.90 (or 0.85 for stricter criteria). The HTMT results after deleting some items showed that all constructs met this criterion. The HTMT values between the ATT construct and other constructs ranged from 0.504 to 0.711. For example, the correlation of ATT with PU was 0.711 and with SDT was 0.712, both still below the tolerance limit of 0.85. This indicates that the ATT construct had adequate discriminant validity with other constructs. The AVD construct showed the highest HTMT value with SDT at 0.748 and with PU at 0.672. Nevertheless, all values were still below 0.85, meaning that AVD could be clearly distinguished from other constructs. The BI construct had relatively high HTMT values with SDT (0.838) and PU (0.687), but still below 0.90. This indicates that BI had a close relationship with SDT but could still be distinguished conceptually. The ABT construct had low HTMT values with other constructs, ranging from 0.107 to 0.346. This confirms that ABT stood as an independent construct distinct from technology acceptance constructs. The PEOU construct showed HTMT values with PU at 0.592 and with AVD at 0.545, while the highest with SDT was 0.498. These values reinforce that PEOU had good discriminant validity. Overall, the HTMT results proved that all constructs in the model had adequate discriminant validity, so each construct could be considered unique and not excessively overlapping with others. Thus, the research model was feasible to proceed to structural evaluation.

Discriminant validity was also evaluated using the Fornell–Larcker criterion, where the square root of the AVE on the main diagonal must be higher than the correlations between constructs in the respective rows and columns [25]. The test results showed that all constructs met this criterion as seen in table 3.

Table 3. Results of the Fornell Larckel Test

	ATT	AVD	BI	ABT	PEOU	PU	SDT
ATT	1.000						
AVD	0.658	1.000					
BI	0.588	0.496	0.901				
ABT	-0.153	-0.305	-0.109	0.932			
PEOU	0.504	0.545	0.390	-0.209	1.000		
PU	0.673	0.636	0.571	-0.069	0.559	0.951	
SDT	0.649	0.682	0.665	-0.170	0.453	0.604	0.861

The square root of AVE values shown on the diagonal were above 0.85 for all constructs, namely ATT = 1.000; AVD = 1.000; BI = 0.901; ABT = 0.932; PEOU = 1.000; PU = 0.951; and SDT = 0.861. These values were consistently higher than the correlations between constructs. For example, the square root of AVE for PU was 0.951, greater than its correlations with ATT (0.673), AVD (0.636), BI (0.571), and SDT (0.604). Similarly, the BI construct had a diagonal value of 0.901, higher than its correlations with ATT (0.588), AVD (0.496), and SDT (0.665). In addition, the ABT construct showed a diagonal value of 0.932, much higher than its correlations with other constructs, all of which were low or even negative (e.g., with ATT = -0.153; BI = -0.109). This emphasized that ABT stood as a separate construct with very good discriminant validity compared to technology acceptance constructs.

Overall, the Fornell–Larcker results supported that each construct in the research model had adequate discriminant validity. Thus, both HTMT and Fornell–Larcker consistently showed that the constructs were conceptually and empirically distinct, so the measurement model could be declared valid and suitable for further structural analysis [5]. Discriminant validity was also tested using the cross-loading criterion, by comparing each indicator's correlation with its intended construct to its correlations with other constructs. According to [30], discriminant validity is met if the loading value of an indicator is higher on its intended construct than on other constructs, as seen in table 4.

Table 4. Cross Loading

	ATT	AVD	BI	ABT	PEOU	PU	SDT
ATT2	1.000	0.658	0.588	-0.153	0.504	0.673	0.649
AVD2	0.658	1.000	0.496	-0.305	0.545	0.636	0.682

BI1	0.471	0.487	0.896	-0.198	0.391	0.461	0.627
BI2	0.586	0.409	0.906	-0.003	0.314	0.565	0.574
ABT1	-0.114	-0.244	-0.119	0.962	-0.200	-0.024	-0.102
ABT2	-0.191	-0.354	-0.075	0.901	-0.189	-0.128	-0.252
PEOU2	0.504	0.545	0.390	-0.209	1.000	0.559	0.453
PU1	0.671	0.626	0.548	-0.099	0.531	0.954	0.583
PU2	0.606	0.582	0.537	-0.030	0.532	0.948	0.565
SDT1	0.535	0.572	0.612	-0.154	0.409	0.509	0.887
SDT2	0.598	0.619	0.533	-0.159	0.383	0.578	0.838
SDT3	0.537	0.563	0.576	-0.124	0.377	0.464	0.856

The results showed that all indicators had the highest loading values on their corresponding constructs. For example, ATT2 had a loading of 1.000 on the ATT construct, higher than its loadings on other constructs (e.g., PU = 0.673 or SDT = 0.649). Similarly, AVD2 had a loading of 1.000 on AVD, greater than its correlations with other constructs (PU = 0.636; SDT = 0.682). For the BI construct, BI1 and BI2 indicators had loadings of 0.896 and 0.906 on BI, respectively. These values were much higher than their loadings on other constructs, confirming BI's discriminant validity. Likewise, the ABT construct showed loadings of 0.962 and 0.901 for ABT1 and ABT2, both higher than their correlations with other constructs. The PEOU2 indicator had a loading of 1.000 on the PEOU construct, much higher than its loadings on other constructs (e.g., PU = 0.559 or ATT = 0.504). For PU, PU1 and PU2 had loadings of 0.954 and 0.948 on PU, higher than their loadings on other constructs. Finally, SDT1, SDT2, and SDT3 had their highest loadings on SDT with values of 0.887, 0.838, and 0.856, respectively. These values were higher than their loadings on other constructs, confirming the discriminant validity of SDT. Overall, the cross-loading results showed that all indicators loaded more strongly on their intended constructs than on others. This reinforced the findings of HTMT and Fornell–Larcker, confirming that all constructs in the model had good discriminant validity.

3.4.Structural Model Evaluation (Inner Model)

Structural model evaluation was conducted to assess the strength of relationships between constructs within the extended TAM framework. The results showed that PEOU significantly influenced PU with a path coefficient $\beta = .559$, $t = 7.773$, and $p < 0.001$. The magnitude of this path effect was reflected in an f^2 value of 0.455 (large effect), and the contribution of PEOU to PU was shown by R^2 PU = 0.313, indicating that 31.3% of PU variance was explained by PEOU. The summary of the structural model evaluation results, including R^2, f^2, and Q^2 values for each endogenous construct, is presented in table 5.

Table 5. Summary of R^2, f^2, and Q^2

Construct / Path	R^2	f^2 (Effect Size)	Q^2	Interpretation
PU (influenced by PEOU)	0.313	0.455 (large)	0.279	Ease of use has a large effect on usefulness; moderate predictive power
ATT (influenced by PU, PEOU, AVD, SDT)	0.556	PU→ATT = 0.178 (medium); SDT→ATT = 0.180 (medium); AVD→ATT = 0.033 (small)	0.502	The model is fairly strong in explaining attitude
BI (influenced by ATT, SDT)	0.367	ATT→BI = 0.191 (medium); SDT→BI = 0.041 (small)	0.274	The model is moderate in explaining behavioral intention
ABT (influenced by BI)	0.012	BI→ABT = 0.012 (very small)	-0.003	Very weak prediction, not significant

The significance of the direct effects among constructs in the structural model is summarized in table 6.

Table 6. Significance of Direct Effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
ATT → BI	0.461	0.455	0.130	3.556	0.000
AVD → BI	0.192	0.219	0.204	0.942	0.346
BI → ABT	-0.109	-0.144	0.126	0.867	0.386

PEOU → ATT	0.126	0.140	0.116	1.091	0.275
PEOU → PU	0.559	0.562	0.072	7.773	0.000
PU → ATT	0.385	0.377	0.119	3.243	0.001
SDT → ATT	0.360	0.353	0.121	2.982	0.003

Furthermore, PU significantly influenced ATT (β = .385, t = 3.243, P= 0.001), with $f^2 = 0.178$. Together with SDT, these constructs explained R^2 ATT = 0.556, meaning that 55.6% of variance in ATT was explained by PU, PEOU, and SDT. ATT then significantly influenced BI (β = .461, t = 3.556, p < 0.001), with $f^2 = 0.191$. BI itself had $R^2 = 0.367$, indicating that 36.7% of variance in BI was explained by ATT, PU, SDT, and AVD.

Intrinsic motivation (SDT) also played an important role, significantly influencing ATT (β = .360, t = 2.982, P= 0.003; $f^2 = 0.180$) and BI (β = .166, t = 2.078, P= 0.038). These findings show that intrinsic motivation not only enhanced positive attitudes but also directly drove behavioral intention. However, although statistically significant, the SDT → BI path (β = 0.166) indicates a modest effect. This suggests that intrinsic motivation contributes to behavioral intention but with limited strength, functioning as a supportive rather than dominant predictor. This aligns with previous research showing that motivational factors typically complement cognitive determinants like PU and attitude in explaining technology adoption behavior. Conversely, AVD had no significant effect on BI (β = .192, t = 0.942, P= 0.346), although its effect size was small ($f^2 = 0.033$). This suggests that application aesthetics were not a primary determinant of behavioral intention.

Finally, the path between BI and ABT was not significant (β = -0.109, t = 0.867, P= 0.386; $f^2 = 0.012$). The ABT construct had an R^2 of only 0.012, indicating that the model explained just 1.2% of variance in addictive behavior, reinforced by a negative Q^2 ABT = -0.003, showing no predictive relevance for reducing addictive tendencies. Overall, the model demonstrated good predictive relevance for PU ($Q^2 = 0.279$), ATT ($Q^2 = 0.502$), and BI ($Q^2 = 0.274$), but failed to provide predictive relevance for ABT. The low R^2 (0.012) and negative Q^2 (-0.003) values for ABT indicate that the model had limited predictive power in explaining behavioral change. This outcome suggests that although the intervention improved user attitudes and intention toward healthier gaming behavior, these psychological changes did not yet manifest in observable behavior within the two-week period. The short intervention duration and lack of external reinforcement likely constrained the practical impact, emphasizing that behavioral transformation requires sustained engagement over time.

3.5.Indirect Effects Analysis

In addition to testing direct effects, the study also evaluated indirect effects between constructs using PLS-SEM. The results showed that some mediation paths were significant, while others had no meaningful effects, as shown in table 7.

Table 7. Indirect Effects Results

Path	β (O)	t-value	p-value	Description
ATT → ABT	-0.050	0.780	0.436	Not significant
AVD → ABT	-0.021	0.416	0.677	Not significant
PEOU → ATT	0.215	3.005	0.003	Significant
PEOU → BI	0.158	2.224	0.026	Significant
PEOU → ABT	-0.017	0.667	0.505	Not significant
PU → BI	0.178	2.331	0.020	Significant
PU → ABT	-0.019	0.714	0.475	Not significant
SDT → BI	0.166	2.078	0.038	Significant
SDT → ABT	-0.018	0.711	0.477	Not significant

First, PEOU had a significant indirect effect on ATT through PU. This mediation path was significant with β = .215, t = 3.005, P= 0.003. This means that applications perceived as easy to use were also perceived as more useful, ultimately enhancing positive attitudes toward their use. Second, the indirect path from PEOU to BI through PU and ATT was also significant (β = .158, t = 2.224, P= 0.026). Thus, respondents who found the application easy to use were more likely to intend to use it, primarily because they perceived its usefulness and developed positive attitudes. Next, PU showed an indirect effect on BI through ATT, with β = .178, t = 2.331, P= 0.020. This indicates that the perceived benefits of the application increased behavioral intention mainly because they positively influenced attitudes. Meanwhile, SDT demonstrated an indirect effect on BI through ATT, with β = .166, t = 2.078, P= 0.038. This confirms that intrinsic motivation influenced attitudes, which in turn strengthened behavioral intention. However, the indirect paths from ATT, PEOU, PU, and SDT to ABT were not significant. For example, ATT → ABT had β = -0.050, t = 0.780, P= 0.436. These findings suggest that although mediation paths contributed to behavioral intention, they did not translate into significant changes in addictive behavior. Overall, the indirect effects analysis showed that gamification acceptance was explained through significant mediation mechanisms, particularly PEOU → PU → ATT → BI and SDT → ATT → BI. However, mediation mechanisms toward ABT were not significant, highlighting the limitations of the application's effectiveness in directly reducing addictive tendencies.

4. Discussion Principal Findings

4.1. Principal Findings

The results of this study provide several important findings regarding the acceptance of a gamified application as a preventive intervention against online gambling game addiction tendencies among young people. First, the main pathways in the TAM were confirmed to be significant. H1, which states that PU positively affects ATT, was supported (β = .39; P= .001). Likewise, H3 was also well supported, in which PEOU positively influenced PU (β = .56; $p < .001$). This means that applications that are easy to use are perceived as more useful, and that usefulness in turn increases positive user attitudes. However, H2, the direct effect of PEOU on ATT, was not found to be significant, although the coefficient direction was positive. This indicates that ease of use does not directly shape attitude, but rather works indirectly through PU as a mediator. In other words, the PEOU–ATT relationship is stronger when mediated by perceived usefulness. Furthermore, H4, which states that a positive attitude ATT influences the intention to use the application (BI), was significantly supported (β = .46; $p < .001$). This finding is consistent with the TAM model that attitude is an important factor in shaping behavioral intention [21]. Although the path BI → ABT was not significant, this outcome reflects the limitation of short-term exposure to the intervention. The result indicates that while user acceptance was achieved, behavioral change requires longer intervention duration and stronger reinforcement. Thus, this finding is interpreted as a methodological limitation rather than an inconsistency in the model.

4.2. Comparison With Prior Work

Contrary to the initial assumption, H5, which emphasized the effect of AVD on ATT, was not confirmed (β = .19; P= .346). The non-significant effect of AVD on behavioral intention may reflect the secondary role of visual aesthetics in preventive gamification contexts, where cognitive and motivational factors (e.g., usefulness and intrinsic motivation) are more influential in sustaining user engagement than aesthetic appeal alone. A further explanation for the nonsignificant role of AVD may relate to gender-based differences in aesthetic preference. Research indicates that male and female users differ in how they respond to color balance, layout composition, and emotional tone. Given that this study's sample was predominantly male, this demographic imbalance could have reduced the variability in affective responses to design features, thereby attenuating the statistical effect of AVD. Future work should consider a more gender-balanced sample or design customization to account for these perceptual differences. This result highlights that in the context of digital health intervention applications, respondents place more emphasis on practical benefits and intrinsic motivation than on visual aspects. This finding differs from web design or commercial application studies, where aesthetics is often a critical factor [34], [35].

Meanwhile, H6, which states that motivational elements from SDT positively influence BI, was significantly supported (β = .17; P= .038). Intrinsic motivation in the form of autonomy, competence, and social relatedness was shown to increase respondents' intention to continue using the gamification application. In fact, SDT also influenced ATT (β = .36; P= .003), reinforcing the motivational role in shaping both attitude and intention. Finally, H7, which states that BI negatively affects the tendency to use addictive features (ABT), was not confirmed (β = –.11; P= .386). Although respondents demonstrated good acceptance of the application, such intention did not significantly reduce addictive behavior. The low R^2 for ABT (.012) and the negative Q^2 (–.003) show the model's limited predictive ability for addictive behavior. This is consistent with the behavior change literature, which emphasizes that digital interventions require longer duration and deeper strategies to achieve tangible impact [36].

4.3. Implications

Overall, this study confirmed that most hypotheses were supported (H1, H3, H4, H6), some were only confirmed through indirect effects (H2), and some were not supported (H5, H7). These findings imply that acceptance of gamified applications has been achieved, but their effectiveness in reducing addictive tendencies remains limited within a short-term intervention phase. The theoretical contribution of this research is to extend the application of TAM into the context of preventing online game addiction, emphasizing the importance of integrating SDT to understand the role of intrinsic motivation. Its practical contribution is to demonstrate the potential of gamification as a preventive strategy, although it needs to be complemented by real-time feedback mechanisms, behavioral reminders, cognitive education modules, and social reinforcement to enhance long-term effectiveness. The results of the hypothesis testing, including supported and unsupported hypotheses, are summarized in table 8.

Table 8. Summary of Hypothesis Testing Results

Code	Hypothesis	β (Coef.)	p-value	Status
H1	PU → ATT: Perceived Usefulness positively affects Attitude Toward Use	.39	.001	Supported
H2	PEOU → ATT: Perceived Ease of Use positively affects Attitude Toward Use	n.s.	> .05	Not directly supported (indirect via PU)
H3	PEOU → PU: Perceived Ease of Use positively affects Perceived Usefulness	.56	< .001	Supported
H4	ATT → BI: Attitude Toward Use positively affects Behavioral Intention to Use	.46	< .001	Supported
H5	AVD → ATT: Affective Visual Design positively affects Attitude Toward Use	.19	.346	Not supported
H6	SDT → BI: Motivational elements (SDT) positively affect Behavioral Intention to Use	.17	.038	Supported
H7	BI → ABT: Behavioral Intention negatively affects the tendency to use addictive features	–.11	.386	Not supported

5. Conclusion

This study aimed to examine the effectiveness of a gamification-based application as a preventive intervention against online gambling game addiction tendencies among young people, while also testing the TAM extended with constructs from SDT and AVD. The pre-test results from 588 respondents showed that 169 individuals (28.7%) had addictive tendencies based on indicators of play duration, impulsivity, and loot box exposure. From this group, 86 respondents participated in the stimulation program using the gamification application. Model evaluation indicated that the application was positively received in terms of usability and motivational engagement, Although the application achieved favorable levels of perceived usefulness, ease of use, and positive attitudes, the description of 'well accepted' has been refined to reflect a more balanced interpretation. Acceptance was primarily driven by cognitive and motivational factors rather than aesthetic appeal, indicating that usability and intrinsic motivation played a stronger role than visual design in shaping user intention. The classical TAM pathways were confirmed, where PEOU increased PU ($\beta = .559$, $p < 0.001$), perceived usefulness increased attitudes ($\beta = .385$, $P= 0.001$), and attitudes increased the intention to use the application ($\beta = .461$, $p < 0.001$).

Furthermore, intrinsic motivation SDT played an important role in shaping attitudes ($\beta = .360$, $P= 0.003$) and usage intention ($\beta = .166$, $P= 0.038$). However, the application did not show a significant effect on reducing addictive behavior tendencies (BI → ABT; $\beta = -0.109$, $P= 0.386$). The R^2 value for ABT was only 0.012, and Q^2 was negative (-0.003), indicating that the model lacked predictive relevance for changes in addictive behavior. Thus, although the application was positively accepted, its effectiveness in reducing addiction was not proven within the short intervention period. In relation to the research hypotheses, most were confirmed: H1, H3, H4, and H6 were supported; H2 was only confirmed indirectly through PU; while H5 and H7 were not supported. This indicates that gamification application acceptance is primarily determined by perceived usefulness, ease of use, positive attitudes, and intrinsic motivation, whereas visual aspects and direct effects on addictive behavior have not shown significant results. This study contributes theoretically

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by extending TAM into the context of online game addiction prevention and highlighting the importance of integrating motivational constructs from SDT.

Practically, it demonstrates that gamification has potential as a preventive strategy, but to achieve full effectiveness, interventions must be longer in duration, more intensive in educational content, and supported by adequate social reinforcement. Future research is recommended to extend the intervention period, increase sample size, and consider external factors such as family roles, social environments, and gaming industry regulations. With these steps, it is expected that gamification applications will not only be positively accepted but also truly effective in reducing online gambling-related game addiction among young people.

5.1. Limitations of the Study

This study has several limitations that should be noted for interpreting the results and guiding future research. First, the intervention duration was relatively short, so the impact of the gamification application on reducing addiction tendencies was not fully observed. Addictive behavioral changes, especially those related to impulsivity and loot box engagement, require a longer period and consistent reinforcement. Second, the intervention sample size was limited, with only 86 respondents out of 169 individuals with addictive tendencies. Although this number met the minimum requirement for PLS-SEM analysis [22], a larger and more diverse sample would provide stronger external validity and improve generalizability. The gender distribution of participants was uneven, with male respondents comprising approximately 77% of the sample. This skew reflects the general demographic of online gamers in Indonesia but limits the generalizability of the findings to female users. The smaller female subgroup also prevented reliable subgroup or multigroup analyses.

Future research should strive for a more gender-balanced sample or explore gender-based differences in acceptance and behavioral responses to gamification interventions. Third, this study focused on psychological variables and application acceptance through TAM, SDT, and AVD frameworks. However, external factors such as family support, social environment, gaming industry regulation, and economic accessibility were not analyzed, even though they may influence addictive behavior and intervention success. Fourth, the study used self-report questionnaires, which are prone to social desirability bias and inaccuracies in reporting play duration and loot box purchases. Using objective data such as in-app usage tracking or digital activity logs would strengthen the reliability of the findings. Fifth, the AVD variable may not have been measured in sufficient depth. The instrument relied on general perceptions of aesthetics. Visual design in gamification contexts may require more specific indicators, such as color elements, navigation, animations, or comprehensive user experience design.

Another limitation of this study is the absence of a control group, which restricts causal interpretation of the intervention's effect. The pre–post design used in this study primarily aimed to assess feasibility, user acceptance, and short-term behavioral responses. Future research should include a randomized control group and longer follow-up period to validate the findings and more accurately determine the intervention's effectiveness. Considering these limitations, future research should extend the intervention duration, increase the sample size, integrate external factors, and use data triangulation methods to obtain stronger results. Additionally, a small proportion of participants did not complete the post-test, which introduces a potential attrition bias. Future studies should implement strategies to enhance adherence, such as reminder systems or incentive mechanisms.

5.2. Implications

This study provides several important implications, both theoretical and practical. From a theoretical perspective, the findings reinforce the relevance of classical pathways in the TAM, where PEOU influences PU, PU increases attitudes, and attitudes drive behavioral intention. However, the finding that AVD did not have a significant effect provides a new nuance: visual aesthetics are not always determinants of technology acceptance, particularly in the context of digital health intervention applications. Conversely, the role of intrinsic motivation through SDT proved important for both attitudes and behavioral intentions, thereby expanding TAM with motivational dimensions often overlooked in studies of technology adoption.

The practical implications of this research relate to the development of gamification applications for addiction prevention. Applications should emphasize core functions that enhance real usefulness for users, such as playtime

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management features, reminder systems, or educational modules about loot box risks. Motivational elements should also be explicitly designed, for example, by providing autonomy in setting goals, feedback that enhances a sense of competence, and social interaction features that foster relatedness. While visual aspects remain relevant as supportive elements, they should not take precedence over practical benefits and intrinsic motivation. For educational institutions and counseling practitioners, this application can be used as a screening and early intervention tool, especially for young people who show addictive tendencies. These findings also provide insights for policymakers that online gaming addiction prevention cannot rely solely on formal regulation but must also be supported by technology-based interventions that are engaging and accepted by users. Meanwhile, for the gaming industry and digital service providers, the results highlight the importance of transparency regarding high-risk features such as loot boxes, as well as opportunities to collaborate in creating a healthier gaming ecosystem.

From a methodological perspective, this study also demonstrates the need for objective indicators, such as in-app usage logs or loot box transaction frequencies, to complement questionnaire data that may be influenced by social desirability bias. Additionally, longer intervention periods with follow-up evaluations would provide a clearer picture of the long-term effectiveness of gamification applications. This study evaluated the gamified intervention as a unified system without isolating the effects of individual game mechanics such as missions, points, and badges. Consequently, it was not possible to determine which specific gamification elements contributed most to user motivation or behavioral outcomes. Future studies should adopt a comparative design to test the differential impact of each game mechanic, enabling a more granular understanding of effective engagement strategies. Thus, this study opens pathways for more comprehensive future research, including larger sample sizes, testing moderators such as gender or game genre, and comparing different gamification designs to determine which are most effective in reducing addictive tendencies.

5.3. Future Research Directions

This study opens wide avenues for further research on gamification-based prevention of online game addiction. One important direction is extending the intervention duration, as this study showed that although the application was well accepted, its impact on addictive behavior was not significant. Complex behavioral changes such as addiction require longer periods and repeated evaluations; therefore, future studies should include follow-up periods to observe more stable changes. Furthermore, future research should involve objective data such as in-app usage logs, playtime duration, and loot box transaction histories to complement questionnaire data, which are prone to perception biases. With more concrete data, the findings will be more trustworthy and valid.

Testing moderator and mediator variables is also important. Factors such as gender, preferred game genre, baseline impulsivity, and social support from the surrounding environment may influence both acceptance and effectiveness of the application. Likewise, mediation mechanisms such as user engagement can be further explored to understand more comprehensive pathways of influence. Subsequent studies can also compare variations in gamification design. This study used missions, points, and badges, while other approaches such as competitive, cooperative, or gain/loss framing strategies may have different impacts on reducing addictive tendencies. Equally important, integrating external contexts such as family support, educational policies, and gaming industry regulations should be considered, as social and structural factors can strengthen or weaken intervention effectiveness. By considering these research directions, it is expected that gamification interventions will not only stop at the level of application acceptance but also deliver real, sustainable impacts in reducing tendencies toward online gambling-related game addiction among young people.

6. Declarations

6.1. Author Contributions

Conceptualization: Y. and E.K.; Methodology: D.H. and F.Y.; Software and Data Analysis: E.K. and F.Y.; Validation and Interpretation: Y. and D.H.; Writing Original Draft Preparation: Y.; Writing Review and Editing: D.H. and E.K.; Supervision and Project Administration: Y.; All authors have read and approved the final version of the manuscript.

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6.2. Data Availability Statement

The data supporting the findings of this study are not publicly available due to privacy and ethical restrictions involving participant information. However, anonymized data can be made available from the corresponding author upon reasonable request and with permission from the Research Ethics Committee of Universitas Kuningan.

6.3. Funding

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6.4. Institutional Review Board Statement

This study was conducted in accordance with the ethical standards of research involving human participants. Ethical approval was obtained from the Research Ethics Committee of Universitas Kuningan, Indonesia, under approval number No. 726.28/UNIKU-KNG/PP/2025.

6.5. Informed Consent Statement

All participants involved in this study provided their informed consent prior to participation. The participants were clearly informed about the purpose of the study, the voluntary nature of their participation, and the confidentiality of their responses.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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