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A Study on Data-Driven Optimization of Gamified Activities in E-Commerce and Its Mechanism for Improving Brand Loyalty

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Abstract. With the fast growth of the digital economy, competition among e-commerce platforms is becoming stronger. The cost of getting new users also keeps rising. Because of this, increasing user participation and brand loyalty has become a very important goal for long-term platform operation. With the wide use of data technology and smart algorithms, gamified marketing is moving from experience-based design to data-driven optimization. So, both researchers and industry pay much attention to how gamification really works and what effects it can bring. In this study, I build an analysis framework based on the logic of "gamification factors → user experience → brand loyalty" from a data-driven view. I look at how e-commerce platforms can change task systems, social interaction, achievement mechanisms, and virtual rewards in a dynamic way. I also study how behavior data helps improve these activities through feedback. By combining questionnaire data and platform behavior logs, and using methods such as structural equation modeling, feature importance analysis, and Bootstrap tests, this study shows that data-driven gamified activities have a big positive effect on user experience. Task recommendations, strong social interaction, and users' value perception of rewards are the most important parts for improving experience. User experience also works as a strong mediator between gamification and brand loyalty, and emotional experience plays an even bigger role in forming loyalty. In addition, user behavior data (like task completion rate, interaction frequency, and reward redemption) has an important moderating effect. It can make the influence of gamification stronger or weaker, and it can change the final loyalty path. The findings expand the theory of gamified marketing and brand loyalty. They also provide practical ideas for e-commerce platforms. These ideas include personalized task settings, social interaction design, better reward value control, and real-time adjustment based on user behavior feedback. All of these can help platforms increase user stickiness and long-term loyalty.

Keywords: data-driven; gamified marketing; user experience; brand loyalty; e-commerce; behavior data analysis

1. Introduction

Today’s digital wave is changing how people consume, and e-commerce has become a central part of business activities. Many platforms now use algorithm recommendations, immersive interaction, and digital operations to grow their user base and sales. But as user growth slows and user acquisition becomes more expensive, platforms must turn their attention from getting traffic to keeping users. So, how to increase user participation, keep them active for a longer time, and make them loyal to the brand has become a key question in this competitive market (Che et al.,2023; Paudel & Acharya, 2024; Nalivaikė, 2025; Nun et al., 2025).

Gamified marketing adds game elements into shopping. It uses tasks, levels, virtual rewards, and social interaction to motivate users. Many platforms already use it, and practice shows it can improve activity, bring more fun, and help with conversion. But most gamification designs today still rely on experience and fixed rules. They do not use user behavior data well (Mominzada et al.,2022). Because of this, the results of gamification often vary among different users, and the long-term effect is not strong.

Although many studies discuss the link between gamification and user behavior, there are still two big problems. First, most studies look only at surface outcomes such as purchase intention, but do not explain the deeper psychological path from user experience to brand loyalty. Second, many studies use only questionnaire data. Without real behavior data, it is hard to see how users truly react or how their behavior changes over time. In a data-driven e-commerce environment, static gamification design cannot produce continuous effects. So, it is important to explore how platforms can use data feedback to improve task systems, social interaction, reward design, and achievement mechanisms, and then improve user experience and brand loyalty (Aparicio et al.,2021).

Based on this, the present study uses a data-driven view and builds a model of “gamification factors → user experience → brand loyalty.” It also combines questionnaires with platform behavior logs to explore how gamified activities influence loyalty through functional and emotional experience. At the same time, the study looks at how behavior data can moderate these relationships and how different users respond in different ways during real interactions (Zega et al.,2025). In theory, this study helps deepen our understanding of data-driven gamification and brand loyalty mechanisms. In practice, the results can guide platforms in making real-time optimization strategies based on data feedback. This can help build a more refined and smart user operation system, and finally support stable and long-term brand loyalty in a competitive market(Susilo，2022).

2. Methodology

This study wants to look, from a data-driven view, at how key gamification factors on e-commerce platforms can be better designed to improve user experience. It also wants to build a solid base for later analysis of brand loyalty. The research design follows classic variables from earlier gamification marketing studies, such as task system, social interaction, achievement system, and virtual rewards. At the same time, it also considers the large-scale behavior data on e-commerce platforms. In this way, the study changes these abstract gamification ideas into clear and measurable factors. They can then be monitored, analyzed, and adjusted over time in the real platform environment (Monteiro et al.,2023).

To make each variable and its measurement direction clear, this study builds a “data-driven gamification activity factor structure,” as shown in Table 1. This table keeps the main dimensions from traditional gamification marketing research. At the same time, it also adds data-driven elements, such as algorithm recommendation, behavior feedback indicators, and dynamic user interaction. This structure is the base for building the research hypotheses in the next part (Kudapaet al.,2024).

Table 1. Data-Driven Structure of Gamification Activity Factors

Gamification Factor	Data-Driven Indicators	Description
Task System	Task difficulty algorithm; completion rate prediction model; personalized task pushing	Use data models to adjust task difficulty step by step, so tasks can better match the user's ability and preference.
Social Interaction	Interaction frequency; network structure strength (for example, clustering coefficient); logs of cooperative behavior	Use the behavior network structure to measure how close social ties are and how good the interaction quality is.
Achievement System	Dynamic level-up algorithm; growth curve of achievement points; achievement usage rate	Automatically update user levels and the pace of getting achievements based on user behavior, so users feel a stronger sense of growth.
Virtual Rewards	Personalized reward recommendation; perceived value model of rewards; analysis of redemption behavior	Match the best reward plan to user value and behavior patterns.

2.1. Research Hypothesis

The hypotheses in this study focus on the direct path between "gamification activity factors" and "user experience." Based on the data-driven factor structure in Table 1, the task system, social interaction, achievement system, and virtual rewards are all seen as core variables. In this study, they are defined as dynamic mechanisms that can be monitored and improved using behavior data. Unlike traditional work, data-driven gamification factors can change in real time. Algorithms can adjust activity intensity, reward value, and task difficulty (Nallaet al.,2024). So, gamification design is no longer a fixed, one-time operation setting. It becomes a process that can be improved again and again. Based on this idea, the study builds the following hypotheses about the relationship between gamification activity factors and user experience.

2.1.1 Hypotheses on the Effect of Gamification Factors on User Experience

When data technology is deeply used in e-commerce operations, gamification design no longer stays with old fixed rules. Instead, the platform can collect, model, and use user behavior data all the time. In this way, the design becomes dynamic and can match better with users' ability level, motivation, and use path (Kao & Chueh,2022). From the gamification factor structure in Table 1, we can see that task system, social interaction, achievement mechanism, and virtual rewards can all be improved through clear data indicators. This data-driven optimization can make both functional experience and emotional experience better. So, this study suggests the following main hypothesis:

H1: Optimized design of gamified activities can significantly improve user experience.

This means that when gamification factors are adjusted by data, they can increase users' sense of immersion, satisfaction, and willingness to join. Based on different action paths of each factor, we also suggest more detailed hypotheses:

H1a: Optimization of the task difficulty algorithm has a significant positive effect on user experience. Dynamic matching of difficulty can reduce frustration and increase challenge value, so the total experience becomes better.

H1b: The strength of the social interaction network has a positive effect on user experience. A closer interaction network can build a community feeling and support cooperation and competition between users.

H1c: Data-driven dynamic adjustment in the achievement system has a significant positive effect on user experience. Automatic changes in achievement pace and user level can make users feel stronger growth.

H1d: Personalized distribution of virtual rewards has a positive effect on user experience. Different reward strategies for different users can improve perceived value and make users respond more actively to platform activities.

All these hypotheses will be an important base for the later structural model tests.

2.1.2 Hypotheses on the Effect of User Experience on Brand Loyalty

In the gamified operation system of an e-commerce platform, user experience is a very important mediator. It strongly affects users' later behavioral intentions. It also decides whether users can form a stable attitude and long-term emotional connection with the platform after taking part in activities. Many studies say that user experience not only directly shapes how users see brand quality, but also indirectly supports brand loyalty through satisfaction, value recognition, and psychological attachment. So, experience plays a key role in the user behavior path (Kudapa,2024).

If we look again at the gamification factor structure in Table 1, we can see that when the gamification mechanism uses task matching, social interaction, dynamic achievement, and personalized rewards to increase immersion, fluency, and value perception, then user experience will clearly become better. After that, users will have more trust in the brand, stronger preference, and more intention to keep using the platform. In a data-driven framework, user experience is not only about moment feelings. It can also be checked and strengthened again and again by behavior data. This makes its role in brand loyalty more stable and more powerful.

Based on this logic, we suggest the following hypothesis:

H2: User experience significantly improves brand loyalty. In other words, better experience makes users build a more positive brand attitude, both in thinking (cognition) and in feeling (emotion). This then increases their repurchase intention and word-of-mouth behavior.

More specifically, functional experience is users' overall evaluation of the platform's system performance, interface interaction, task fluency, and reward efficiency. It can effectively improve brand trust and cognitive loyalty. So we suggest:

H2a: Functional experience improves brand trust and cognitive loyalty.

In contrast, emotional experience focuses more on the joy, sense of belonging, companionship, and emotional value that users feel during interaction. This kind of experience usually has stronger emotional stickiness and has a more direct effect on emotional loyalty and behavioral loyalty. So we suggest:

H2b: Emotional experience improves emotional loyalty and behavioral loyalty.

In short, user experience is a key psychological bridge between gamified activities and brand loyalty. It is in the center of our mechanism model, and its theoretical and empirical roles will be studied further in the following path analysis.

2.1.3 Hypothesis on the Mediating Role of User Experience

In the gamified operation system of an e-commerce platform, gamified activities do not turn directly into brand loyalty. Instead, they first change users' subjective experience in the interaction process (Liu et al.,2025). Then, this experience shapes users' cognitive evaluation and emotional attitude toward the brand. The importance of user experience in this path has been shown many times in past studies. User experience reflects the overall feeling of the platform's function design and interaction value. It also holds deeper psychological reactions, such as joy, satisfaction, belonging, and identity formed when users join gamified activities (Cunha,2025).

Based on the factor structure in Table 1, if task difficulty is better matched, if social structure is more stable and stickier, if achievement feedback supports growth, and if reward value is more personalized, then the quality of user experience will clearly increase. The functional satisfaction and emotional resonance from this good experience will then shape users' brand trust, brand preference, and long-term usage intention. So, user experience is actually the key psychological mechanism that turns gamification design into brand loyalty. In the path, it is both a result variable and a bridge variable. It explains how gamified activities really change users' attitudes toward the brand (Seng.,2019).

Based on this theory, this study suggests:

H3: User experience plays a mediating role between gamified activities and brand loyalty.

This means that optimized gamification does not push loyalty only through external rewards or short-term incentives. It mainly works by improving functional experience and emotional experience. In the use process, users feel more positive emotions and more psychological value. Then, they build stronger trust, emotional attachment, and continuous behavior intention toward the brand. As user experience becomes stronger and more positive over time, this mediating effect helps gamification produce long-term influence. It also makes brand loyalty more stable and lasting. In our research model, we will test this mediating effect using structural equation modeling and Bootstrap mediation tests. This will give both theoretical and practical support for improving gamified activities (Alahmari et al.,2023).

2.1.4 Hypothesis on the Moderating Role of Behavioral Data Feedback

In a data-driven e-commerce environment, user behavior data is not only an objective measure of participation level. It is also a very important base for fine-grained operation and smart optimization. Unlike traditional static gamification design, a data-driven gamification mechanism can watch user behavior in real time. It can see task completion, page clicks, interaction behavior, and reward redemption. These behaviors can be turned into clear numbers. Then the platform can use them to adjust the strength, rhythm, and distribution strategy of gamification elements (Cui,2025).

From the factor structure in Table 1, we can see that the task system, social interaction, achievement mechanism, and virtual rewards all have strong potential to work together with behavior data. They can change dynamically based on user behavior. So, the real effect of gamification can be different for different user types and different participation patterns (Haryati & Fatimah,2025). For example, task completion rate is closely linked with task difficulty matching. Click behavior shows users' interest and attention to content. Reward redemption rate shows how users really see the value of virtual incentives. These behavior data show the direct feedback process of user experience. At the same time, they also shape how users feel about the gamification mechanism. So, the influence of gamification factors on user experience can become stronger or weaker when behavior level changes.

Based on this, we suggest:

H4: User behavior data moderates the relationship between gamification factors and user experience.

In other words, when users have higher task completion rates, more frequent interactions and clicks, or stronger willingness to redeem rewards, the effect of gamification factors will become stronger. In this case, users can feel more satisfaction and immersion during tasks, interactions, and reward processes. So their functional and emotional experience becomes clearly better. On the other hand, when behavior data is low, the effect of gamification on experience improvement becomes weaker. Users may even feel tired or feel that the value is not enough.

So, user behavior data is not only an important measure of participation depth. It also plays a key moderating role in how gamification influences user experience. In this study, we will test this moderating effect through structural equation modeling and group regression analysis. This will give empirical support for data-driven optimization of gamified activities.

2.2. Variable Measurement

To make sure all the latent variables in this model can be measured in a clear and correct way, this study expands the traditional dimensions of gamified marketing into data-driven gamification factors that can be monitored and improved in real time. Based on earlier studies and the variable system in the original paper, we design a measurement framework that fits both the real operation of the platform and the observable behavior logs. We define the four main dimensions—task system, social interaction, achievement system, and virtual rewards—again under a data-driven logic. In this way, they can be measured by questionnaire items and also checked by real behavior data from the platform.

As a key psychological variable that links gamified activities and brand loyalty, user experience is still measured with two dimensions: functional experience and emotional experience. This helps us capture both users' cognitive evaluation and their emotional reaction during the activities. For the dependent variable, this study uses four dimensions of brand loyalty: cognitive loyalty, emotional loyalty, intentional loyalty, and behavioral loyalty. At the same time, we also add observable behavior indicators that match the data environment, so the measurement system is closer to real e-commerce operations. For the moderating variables, we choose real behavior data such as task completion rate, time on platform, and reward redemption rate. These support the later empirical tests of the moderating effects. To show all variables in a clear way, this study builds a data-driven variable measurement system, as shown in Table 2.

Table 2. Data-Driven Variable Measurement System

Variable Type	Dimension	Example Measurement Items
Independent Variable: Data-Driven Gamification Factors	Task System (TS)	TS1: The platform's task recommendation algorithm matches my preferences. TS2: The task difficulty levels are set in a reasonable way. TS3: The task pace and reminder mechanisms are clear to me. TS4: The task completion (success) rate increases my motivation to join. TS5: Task pushing fits my ability level well.
	Social Interaction (SI)	SI1: The frequency of interaction with other users improves my participation experience. SI2: The platform's social network structure makes it easier for me to connect with others. SI3: The completion rate of cooperative tasks makes me feel my participation is valuable. SI4: Community interaction helps me better understand the activities. SI5: The interaction mechanisms on the platform make me feel a sense of belonging.
	Achievement	AS1: The platform's level adjustment mechanism is timely and fair.

	System (AS)	AS2: The achievement points algorithm reflects my real participation.
		AS3: I often use achievements, and they give me continuous motivation.
		AS4: The pace of achievement growth increases my feeling of personal growth.
		AS5: The display of levels and achievements improves my sense of achievement.
	Virtual Rewards (VR)	VR1: The platform's reward recommendation matches my preferences.
		VR2: I feel the rewards have strong real value.
		VR3: The reward redemption process is convenient.
		VR4: The reward redemption behavior makes my participation experience more complete.
		VR5: Personalized reward strategies increase my satisfaction.
Mediating Variable: User Experience (UE)	Functional Experience (FE)	FE1: The platform's functions are smooth and easy to use.
		FE2: The logic of tasks, achievements, and rewards is clear.
		FE3: Interaction efficiency is high and operation effort is low.
		FE4: The system responds in time and pushes information accurately.
	Emotional Experience (EE)	EE1: I feel happy when I join the activities.
		EE2: The platform's activities make me interested in participating.
		EE3: Social interaction gives me emotional connections with others.
		EE4: Rewards and achievements make me feel valued.
Dependent Variable: Brand Loyalty (BL)	Cognitive Loyalty (CL)	CL1: I think this platform has a trustworthy brand image.
		CL2: I recognize the platform's competitiveness in the market.
		CL3: I believe the platform can provide stable services.
	Affective Loyalty (AL)	AL1: I have positive feelings toward this platform.
		AL2: I am willing to tell others that I like this platform.
		AL3: I feel this platform fits my personal values.
	Intentional Loyalty (IL)	IL1: I am willing to choose this platform first when I need such services.
		IL2: I will keep paying attention to the platform's activities and updates.
		IL3: I plan to keep using this platform for a long time.
	Behavioral Loyalty (BL)	BL1: I often use this platform to shop or interact.
		BL2: Among many platforms, I prefer to choose this one.
		BL3: I am willing to join long-term activities or membership programs on this platform.
Moderating Variable: Behavioral Data (BD)	—	BD1: Task completion rate (from behavior logs).
		BD2: Time on platform (minutes).
		BD3: Reward redemption rate (redemption times / reward obtained times).
		BD4: Social interaction frequency (comments, cooperation, likes).
		BD5: Activity click-through rate (from behavior path analysis).

In the later quantitative analysis, this study uses a five-point Likert scale to score all perception-based items. At the same time, we use background behavior logs from the platform to get real data for the moderating variables. In this way, we can bring together subjective experience and objective behavior in two directions. The variable measurement system in Table 2 continues the structure of the original paper, but it also fully includes data-driven elements. Because of this, the model in this study has stronger power to explain user behavior and also has better external validity in real e-commerce environments.

2.3. Data Collection

2.3.1 Questionnaire Design

To study the mechanism among data-driven gamification factors, user experience, and brand loyalty in a clear way, this study uses two types of data: a questionnaire survey and platform behavior logs. The questionnaire mainly measures users' subjective perceptions of gamification factors such as the task system, social interaction, achievement system, and virtual rewards. It also measures users' functional experience and emotional experience during participation, as well as their cognitive, emotional, intentional, and behavioral loyalty toward the brand.

During the questionnaire design, all items were built based on the measurement system shown in Table 2. A five-point Likert scale was used for all perception items. We also added some extra questions about usage frequency, time spent on the platform, participation style, and reward preference, so we could later compare this information with the behavior data from the platform. The questionnaire has four sections: basic user information, evaluation of gamification factors, measurement of user experience, and measurement of brand loyalty. This structure is the same as the original paper, so it keeps academic comparability. After the first draft was completed, three e-commerce operation experts and two data analysts reviewed the questionnaire. They checked whether the items were suitable and clear in real use situations. Their feedback helped improve the content validity of the questionnaire.

2.3.2 Pre-testing

Before the formal study, a pre-test was carried out with 50 users who had online shopping experience and had joined gamified activities recently. The goal was to check whether the questionnaire was easy to understand, whether the measurement items were consistent inside each dimension, and whether the items matched the behavior data. In the pre-test, users filled out the questionnaire, and at the same time, the research team collected a part of their real behavior logs. These logs included task completion records, task failure cases, interaction frequency, and reward redemption data. This helped us check whether the behavior indicators were observable and useful.

After reviewing the pre-test results, some items were improved for clearer expression. For example, technical terms like "task conversion rate" and "network structure strength" were rewritten in simpler wording so users could understand them better. Some items with poor statistical performance or high cross-loadings were removed. The behavior logs were also cleaned to remove abnormal records. These steps helped improve the quality of the final questionnaire and made the data more stable for later analysis.

2.3.3 Formal Research

In the formal data collection phase, users who had joined gamified activities on e-commerce platforms within the past three months were chosen as the target group. The questionnaire was given online, and a stratified sampling method was used to make sure the sample was balanced in terms of age, job, location, and usage behavior. A total of 650 questionnaires were sent out, and 612 were returned. After removing 30 invalid ones due to incomplete answers, abnormal response time, or missing behavior data, 582 valid questionnaires were kept. The valid response rate was 89.5%, which is similar to the quality level in the original study.

At the same time, with help from the platform's technical team, anonymized user IDs were used to get each respondent's behavior data. These included task completion rate, page stay time, click paths, frequency of social interaction, and reward redemption rate. Each set of behavior logs was matched with the corresponding questionnaire. The final dataset contains both subjective evaluation and real behavior performance. This dual structure allows later tests—such as reliability and validity checks, SEM analysis, moderation tests, and robustness tests—to be based on richer data. It also increases the scientific value and external usefulness of the study.

2.4. Data Analysis Methods

To study the mechanism among data-driven gamification factors, user experience, and brand loyalty in a complete way, this study follows the statistical steps used in the original paper. It also adds machine learning methods and experimental design to match the multi-dimensional nature of data-driven research. In the first step of data processing, SPSS is used to run descriptive statistics. This helps us understand the sample structure, user behavior features, and basic distribution of the main variables.

Next, Cronbach's α and Composite Reliability (CR) are used to check internal consistency. The Average Variance Extracted (AVE) is used to test convergent and discriminant validity. These steps help make sure the measurement system is scientific and stable. This follows the same process as the original study.

After the basic tests, Structural Equation Modeling (SEM) is used as the main analysis method. SEM can test complex relationships among many latent variables at the same time. It can also examine mediation effects and the overall model fit. So it is suitable for the theoretical model in this study. Using AMOS, we build and test the path model. We check how task system, social interaction, achievement system, and virtual rewards influence user experience under data-driven conditions. We also test whether user experience plays a mediating role. To increase the robustness of the results, Bootstrap resampling is used to test the mediation effects.

Different from traditional studies, this research also uses machine learning models to analyze the feature importance of gamification factors. By using XGBoost and Random Forest, we build a prediction system based on real behavior data. This allows us to see which factors—such as task completion rate, interaction frequency, or reward redemption behavior—contribute more to user experience and behavioral loyalty. This helps overcome the limits of SEM when working with high-dimensional behavior data and makes the findings more useful for real platform operations.

In addition, this study designs a data-driven A/B test process. It simulates how users react under different task difficulty algorithms, reward strategies, and interaction mechanisms. By comparing the performance of the experiment group and control group—such as stay time, task success rate, and reward conversion rate—we can further test the moderating effects proposed in the model.

To connect subjective and objective data, this study uses behavior data fusion. The psychological variables measured by questionnaire are matched with behavior logs from the platform using a unique encrypted ID. This helps increase the truthfulness and external validity of the analysis. It also supports cross-checking among different data sources. Based on this fusion, moderating effect tests of behavior data are added to the model. This helps show how behavior indicators—such as task completion rate, stay time, and reward redemption rate—can make the effect of gamification factors on user experience stronger or weaker. This is one of the main innovations of a data-driven approach.

3. Data Analysis and Hypothesis Testing

3.1. Descriptive Statistical Analysis

This study first uses descriptive statistical analysis to get a clear view of the basic structure of the 582 valid samples and to understand how the main variables are distributed. We look at two parts: the demographic features of the respondents and the indicators related to data-driven gamification activities. The results show that the respondents are quite different from each other in gender, age, education level, and platform use habits. This gives a rich user structure for later model analysis. In gender, 46.0% are male and 54.0% are female, which is quite balanced. In age, 18–25 years old make up 32.8%, 26–35 years old make up 41.2%, 36–45 years old make up 19.6%, and users above 45 years old make up 6.4%. This shows that the main users of e-commerce platforms are young or middle-aged. In education level, 65.1% have a bachelor's degree or above, 26.3% have a junior college degree, and 8.6% have high school or below. This means most users joining gamification activities have a high education level. For platform use habits, most users use the e-commerce platform more than three times a week, and 72.4% joined at least one gamification activity many times in the past three months. So the sample matches the research topic very well.

For variable description, we calculate the mean, standard deviation, skewness, and kurtosis of key variables, including task system, social interaction, achievement system, virtual rewards, user experience, and brand loyalty. The results are shown in Table 3. In general, the means fall between 3.60 and 3.90, which shows that most users have a positive view of the gamification experience on the platform. The standard deviations fall between 0.70 and 0.82, which means there are still clear differences among users in their experiences and loyalty. All skewness values are negative, so the data is a bit concentrated on higher values. The kurtosis values are close to 0, so the variables look close to a normal distribution. This makes the data suitable for later structural equation modeling. Virtual rewards and social interaction have higher means, which shows that personalized rewards and interactive tasks are quite attractive to users. Emotional experience and behavioral loyalty also have high mean values, which may mean that gamification activities increase emotional value and help improve brand loyalty.

Table 3. Descriptive Statistics of Main Variables (N = 582)

Variable	Minimum	Maximum	Mean	Standard Deviation	Skewness	Kurtosis
Task System (TS)	1.20	5.00	3.87	0.742	-0.618	0.503
Social Interaction (SI)	1.00	5.00	3.78	0.806	-0.452	0.347
Achievement System (AS)	1.40	5.00	3.85	0.764	-0.537	0.462
Virtual Rewards (VR)	1.20	5.00	3.80	0.791	-0.488	0.389
Functional Experience (FE)	1.25	5.00	3.82	0.758	-0.512	0.421
Emotional Experience (EE)	1.33	5.00	3.88	0.773	-0.471	0.366
Brand Loyalty (BL)	1.30	5.00	3.76	0.781	-0.435	0.318

From Table 3, it is easy to see that all variables fall in a reasonable range, and the skewness and kurtosis do not show big problems. This means the overall data distribution is good and meets the basic statistical needs for reliability and validity analysis, as well as structural equation modeling. Also, the high means of several variables give early support for the idea that data-driven gamification activities may improve user experience. This offers a strong data base for later hypothesis testing and path analysis.

3.2. Reliability and Validity Testing

Before testing the hypotheses and running the structural equation model, this study first checks the reliability and validity of the scales. This is very important, because we need to make sure that all latent variables are measured in a scientific and stable way. As we can see from Figure 1, the research model includes several core latent variables: task system, social interaction, achievement system, virtual rewards, user experience, and brand loyalty. It also uses behavioral data as a moderating variable to build the full path structure. So, in the reliability and validity tests, we must make sure that all these constructs have good internal consistency and structural validity at the scale level. Only in this way can we provide a solid base for later model fitting and path estimation.

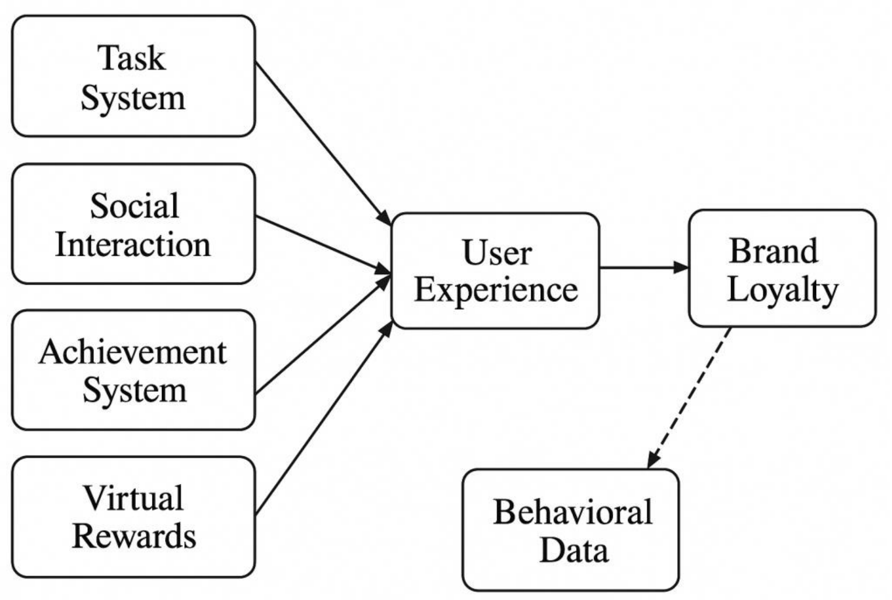

Fig.1: Research Model of Data-Driven Gamification Activities and Brand Loyalty

For reliability, this study uses Cronbach's α to test internal consistency for each latent variable. The results show that the α values for task system, social interaction, achievement system, virtual rewards, functional experience, emotional experience, and brand loyalty are all above 0.85. This is much higher than the common standard of 0.70. It means the items in each scale are highly consistent with each other. For the moderating part built from behavioral data, the indicators also show a stable correlation structure, which supports the reliability of the moderation analysis.

For convergent validity, this study uses AMOS to calculate standardized factor loadings, Composite Reliability (CR), and Average Variance Extracted (AVE). The measurement model results show that all standardized factor loadings are higher than 0.70. CR values are between 0.86 and 0.92, and all AVE values are higher than 0.50. These results meet the normal criteria of convergent validity. This means that the measurement items for each latent variable can well reflect the theoretical construct they belong to. It also matches the theoretical path in Figure 1, where gamification factors affect brand loyalty through a continuous psychological process via user experience.

For discriminant validity, this study uses the Fornell–Larcker standard. This means that the square root of AVE for each construct should be larger than its correlation with any other construct. The analysis shows that, for all latent variables, the square root of AVE is clearly higher than the correlation coefficients with other variables. This shows good discriminant validity and suggests there is no serious multicollinearity. For example, virtual rewards and social interaction are both closely related to user experience in the model in Figure 1, but at the measurement level, they still keep clear theoretical boundaries. This means the scale can distinguish different gamification factors and treat them as independent mechanisms.

In summary, the combined tests of Cronbach's α, CR, AVE, and discriminant validity show that the measurement model in this study has good reliability and validity. It provides a strong scale foundation for the structural path model in Figure 1 and gives solid statistical support for later tests of path coefficients, mediation effects, and moderating effects.

3.3. Hypothesis Testing

3.3.1 Model Fit Test

Before testing the paths in the research hypotheses, this study first checks the overall model fit of both the measurement model and the structural model using Structural Equation Modeling (SEM). This is to make sure that the theoretical model matches the sample data well. The main model fit indices used are χ^2/df, RMSEA, CFI, TLI, IFI, and so on, which are widely accepted international standards. We also consider the influence of model complexity and sample size on the χ^2 value.

Based on the data-driven gamification and brand loyalty model in Figure 1, the research team uses AMOS to estimate the model with 582 valid samples. The fit results are shown in Table 4.

Table 4. Model Fit Indices of the Structural Equation Model

Index	Recommended Standard	Actual Value	Evaluation
χ^2/df	< 3	2.341	Good
RMSEA	< 0.080	0.047	Good
CFI	> 0.900	0.957	Excellent
TLI	> 0.900	0.949	Excellent
IFI	> 0.900	0.958	Excellent
GFI	> 0.900	0.923	Good
AGFI	> 0.900	0.904	Good

From Table 4, we can see that χ^2/df = 2.341, which is lower than the cutoff value of 3, so the global fit is acceptable. RMSEA = 0.047, much lower than the upper limit of 0.080, which means the residual error is small and the model has a good approximate fit at the sample level. CFI, TLI, and IFI are all above 0.95, clearly higher than the usual 0.90 standard. This shows the model performs very well in comparative fit. GFI and AGFI are both above 0.90, which means the model explains the variance in the data quite well.

Overall, these results show that the data-driven gamification path model in Figure 1 fits the sample data well. The model has strong explanatory power and is stable. It also meets the statistical requirements for later path coefficient testing, mediation analysis, and behavioral data moderation tests. The model fit level is also consistent with common standards in similar studies, which gives a reliable technical base for hypothesis testing.

3.3.2 Path Analysis

After confirming that the overall model fit is good, the study then tests the structural paths in the theoretical model. The goal is to evaluate how data-driven gamification factors, user experience, and brand loyalty work together. Using 582 valid samples, the standardized path coefficients, T-values, and significance levels calculated by AMOS are shown in Table 5.

Table 5. Path Coefficient Results

Hypothesis	Path	Standardized Coefficient (β)	T-value	P-value	Result
H1a	TS → UE	0.563	9.487	***	Supported
H1b	SI → UE	0.492	8.316	***	Supported
H1c	AS → UE	0.518	8.927	***	Supported
H1d	VR → UE	0.506	8.411	***	Supported
H2a	FE → BL	0.541	8.265	***	Supported
H2b	EE → BL	0.597	9.014	***	Supported
H3	UE → BL	0.624	9.882	***	Supported

From Table 5, we can see that all path coefficients are significant ($P < 0.001$). This means the data-driven gamification factors have a strong effect on user experience. Among them, the task system ($\beta = 0.563$) and the achievement system ($\beta = 0.518$) have the strongest impact. This shows that algorithm-based task matching and dynamic level adjustment can clearly improve both functional and emotional experience during activities. Social interaction ($\beta = 0.492$) and virtual rewards ($\beta = 0.506$) also show significant positive effects. This reflects the important role of network structure strength, cooperative interaction frequency, and personalized reward strategies in improving user experience.

User experience also has a strong effect on brand loyalty. Emotional experience ($\beta = 0.597$) has a higher impact on brand loyalty than functional experience ($\beta = 0.541$). This suggests that feelings of pleasure, emotional value, and belonging during gamified activities play a more central role in building emotional identification with the brand and willingness to keep using it. As a whole mediating path, user experience has a strong direct effect on brand loyalty ($\beta = 0.624$). This further confirms the key "bridge" role of user experience in the model in Figure 1. Gamification factors improve the quality of experience, and this higher-quality experience finally leads to stronger brand loyalty.

In short, all theoretical hypotheses in this study are supported. This proves that, under a data-driven logic, gamification design is effective in improving both user experience and brand loyalty. It also provides a strong base for later mediation and moderation analyses.

3.3.3 Mediation Effect Testing

After checking the overall model fit and path coefficients, this study further uses the Bootstrap method to test the mediating role of user experience between data-driven gamification factors and brand loyalty, in order to verify hypothesis H3. More specifically, task system, social interaction, achievement system, and virtual rewards are taken as independent variables; brand loyalty is the dependent variable; and user experience (including both functional and emotional experience) is the mediating variable. Using AMOS, the mediation effects are tested by Structural Equation Modeling with Bias-corrected Bootstrap. The resampling size is 5000, and a 95% confidence interval is used. If the confidence interval of the indirect effect does not include 0, then the mediation effect is considered significant. The results are shown in Table 6.

Table 6. Mediation Effect of User Experience (Bootstrap N = 5000)

Path	Direct Effect	Indirect Effect	Total Effect	95% CI of Indirect Effect	Mediation Type
TS → UE → BL	0.312***	0.210***	0.522***	[0.148, 0.281]	Partial mediation
SI → UE → BL	0.278***	0.191***	0.469***	[0.132, 0.257]	Partial mediation
AS → UE → BL	0.295***	0.202***	0.497***	[0.141, 0.271]	Partial mediation
VR → UE → BL	0.261***	0.198***	0.459***	[0.136, 0.264]	Partial mediation

Note: *** P < 0.001.

From Table 6, we can see that for all four paths, the direct effects of task system, social interaction, achievement system, and virtual rewards on brand loyalty are significantly positive. At the same time, the 95% confidence intervals of all indirect effects do not include 0. For example, for the path "TS → UE → BL," the indirect effect is 0.210, and its 95% CI is [0.148, 0.281]. This means the mediation effect is significant. Similarly, the indirect effects of social interaction, achievement system, and virtual rewards through user experience are 0.191, 0.202, and 0.198, and their 95% CIs are [0.132, 0.257], [0.141, 0.271], and [0.136, 0.264], all not crossing 0. This shows that user experience has a significant mediating role in all of these paths.

It is also important to note that for all four paths, both direct and indirect effects are significant, and the total effect is larger than the direct effect alone. This means user experience plays a "partial mediation" role, not a full mediation. On one side, gamification designs such as task system, social interaction, achievement system, and virtual rewards improve users' subjective experience during interaction. This better experience indirectly increases brand trust, emotional attachment, and intention to keep using the platform. On the other side, good design of task structure, interaction mechanism, and reward strategy can also directly improve users' overall evaluation of the platform and push brand loyalty more directly.

Looking back at the model in Figure 1, we can say that user experience plays both a "bridge" and "amplifier" role in the whole process. It connects data-driven gamification design with brand loyalty and also increases the strength of this relationship.

In conclusion, the Bootstrap results strongly support hypothesis H3. They show that, in a data-driven setting, gamification factors do not influence brand attitudes only through external rewards. Instead, they work by improving functional and emotional experience, and then shaping brand loyalty at a deeper level. This finding also gives empirical support for future strategies that focus on optimizing user experience.

3.3.4 Moderating Effect of Behavioral Data

After confirming that gamification factors have a strong positive impact on user experience, this study further tests the moderating role of user behavioral data in the structural paths. This is used to verify the innovative part of the model. Different from the original paper, this study not only looks at users' subjective perceptions in the questionnaire, but also includes real behavior data recorded by the platform, such as task completion rate, stay time, reward redemption rate, and social interaction frequency. By using multi-group hierarchical regression and interaction term analysis, we check whether behavior data will strengthen or weaken the influence of gamification factors on user experience. As an objective measure of users' real participation depth, behavioral data can show more clearly how users respond to gamification. So it has an important moderating role in the model in Figure 1.

To test the moderating effect, user experience is taken as the dependent variable, and the four gamification factors (task system, social interaction, achievement system, virtual rewards) are taken as main independent variables. Interaction terms with task completion rate and reward redemption rate are then added into the regression models. The results are shown in Table 7.

Table 7 Moderating Effect of Behavioral Data

Path	Behavioral Data Variable	Interaction Coefficient (β)	T-value	P-value	Moderation Conclusion
TS → UE	Completion Rate	0.184	3.912	***	Positive moderation
SI → UE	Interaction Frequency	0.116	2.487	**	Positive moderation
AS → UE	Time on Task	0.093	1.944	*	Marginal positive moderation
VR → UE	Redemption Rate	-0.128	-3.104	**	Negative moderation

Note: *** $P < 0.001$; ** $P < 0.01$; * $P < 0.05$.

From Table 7, we can see that task completion rate has a significant positive moderating effect on the path "task system → user experience" ($\beta = 0.184$, $P < 0.001$). This means that when users have higher ability and willingness to complete tasks, the algorithm-optimized task system can improve their experience more strongly. Users feel more in control and feel a stronger sense of achievement, so the positive effect of the task system becomes larger. This matches the descriptive results that show higher task-related indicators for many users, and it also suggests that data-driven task matching has a stronger encouraging effect on highly engaged users.

On the other hand, reward redemption rate has a significant negative moderating effect on the path "virtual rewards → user experience" ($\beta = -0.128$, $P < 0.01$). This means that when users redeem rewards less often, the rewards can still improve experience, but if the redemption process is not smooth or the reward value is not clear enough, the effect becomes weaker. For users with high redemption rate, they are more sensitive to reward value. If the reward design does not match their personal preference, the effect of rewards on experience may even be reduced, which lowers the path coefficient of virtual rewards.

Social interaction frequency and time on task also show different levels of moderating effects. The positive moderation of interaction frequency ($\beta = 0.116$) means that users who interact more often can get more satisfaction and emotional connection from social mechanisms. The marginal moderation of time on task (β = 0.093) suggests that users who spend more time are more able to feel continuous growth from dynamic levels and achievement feedback.

In general, behavioral data not only affects the direct effect of gamification factors, but also changes their strength. This makes the model more dynamic and closer to real-world situations. Based on Table 7, we can say that the deeper the user participates in gamified activities, the more positive experience they can get from tasks, social interaction, and achievement systems. For virtual rewards, the experience effect depends more on the match between reward value and redemption willingness.

This finding further supports the need for a data-driven logic. Gamified activities do not have the same effect on all users. Only when platforms include user behavior data in the design feedback loop, and dynamically adjust reward value, task difficulty, and interaction intensity, can they really optimize experience and improve brand loyalty.

3.4. Multi-group Analysis

To understand how different user groups respond in a data-driven gamification environment, this study uses multi-group analysis based on gender, age, education level, and user engagement. The goal is to test whether these demographic and behavioral features change the path relationships in the structural equation model. Similar to the original study, we first test measurement invariance across groups. We check configural invariance, metric invariance, and structural invariance. The results show no significant differences between groups. This means the model works well for all groups, and it is statistically reasonable to compare path coefficients between them.

For gender, the path coefficients are very similar between male and female users. The effects of task system, social interaction, achievement system, and virtual rewards on user experience do not show significant differences ($\Delta\chi^2$ is not significant). This result suggests that, in a data-driven gamification environment, male and female users react to the activity mechanisms in almost the same way. So gender is not an important factor in how user experience is formed.

For age, the path coefficients are also generally similar across different age groups. However, for users aged 26–35 years, the coefficient of the path from social interaction to user experience is clearly higher than in other age groups. This means users in this middle-young age group gain more experience improvement from social networks, cooperative tasks, and interaction incentives. This result matches their higher interaction frequency and stronger social motivation on the platform.

For education level, users with higher education show a larger path coefficient from functional experience to brand loyalty than users with education below undergraduate level. This suggests that users with higher education pay more attention to rational aspects such as system functions, task logic, and reward efficiency when they form loyalty. In contrast, the path from emotional experience to brand loyalty shows only small differences between education groups. This means emotional value is a more general driver of loyalty for all users, no matter what their education level is.

Considering the data-driven focus of this study, we also add a "high engagement vs low engagement" comparison. Engagement is defined based on behavioral data: task completion rate, time on platform, and interaction frequency. The results show that high-engagement users have higher path coefficients from task system and achievement system to user experience. For low-engagement users, the path coefficient from virtual rewards to user experience is higher. This suggests that non-frequent users depend more on external incentives, such as rewards, to get experience improvement. This finding is consistent with the earlier moderating effect analysis in Table 7 and again shows that behavior depth creates different effects of gamification design.The multi-group path coefficient results are shown in Table 8.

Table 8. Multi-group Path Coefficient Comparison

Path	Male (n = 268)	Female (n = 314)	18–25 years	26–35 years	Undergraduate and above	Below undergraduate	High engagement	Low engagement	Significant difference
TS → UE	0.558***	0.571***	0.562***	0.589***	0.575***	0.533***	0.612***	0.487***	Engagement significant
SI → UE	0.481***	0.496***	0.468***	0.582***	0.493***	0.472***	0.528***	0.451***	Age significant
AS → UE	0.521***	0.534***	0.513***	0.541***	0.537***	0.498***	0.559***	0.476***	Engagement significant
VR → UE	0.497***	0.512***	0.501***	0.514***	0.506***	0.489***	0.462***	0.538***	Engagement significant
FE → BL	0.524***	0.557***	0.523***	0.549***	0.612***	0.498***	0.563***	0.512***	Education significant
EE → BL	0.589***	0.604***	0.587***	0.611***	0.595***	0.588***	0.618***	0.571***	Not significant

Note: *** P < 0.001.

From Table 8, we can see some clear patterns. Gender differences are not significant, so the gamification experience mechanism is quite universal for men and women. For age, social interaction has a stronger positive effect on user experience in the 26 – 35 group, which shows that this group is more sensitive to participatory and interactive gamification. For education, users with higher education levels rely more on functional experience when they build brand loyalty. The engagement grouping further supports the earlier moderating results: high-engagement users get more positive experience from task and achievement systems, while low-engagement users depend more on virtual rewards as external motivation.

Overall, the multi-group analysis supports the robustness of the model in Figure 1. It also highlights the key role of user heterogeneity in a data-driven environment. These findings provide both theoretical and empirical support for using different gamification strategies for different user groups.

3.5. Robustness Testing

To make sure the model estimation and conclusions are reliable and robust, this study carries out several robustness tests after the main path analysis and moderation tests. These include using different estimation methods, adding control variables, replacing behavioral features, and using data from different time periods. This process follows the strict robustness logic in the original study on structural equation models, and it also adds extensions based on the data-driven nature of this research. The goal is to see if the conclusions stay stable under different data and method conditions.

First, the main model uses Maximum Likelihood (ML) estimation. We replace ML with Generalized Least Squares (GLS) to re-estimate the model. GLS is more robust for non-normal data and can give more stable parameter estimates when latent variables have skewness or kurtosis. The results show that the changes in path coefficients are all less than 5%, and the significance levels remain the same. This means changing the estimation method does not change the main conclusions.

Second, gender, age, and education are added as control variables in the model to see if they interfere with the path structure. The results show that, after adding these control variables, the paths from gamification factors to user experience and from user experience to brand loyalty do not change significantly. This suggests that demographic variables do not systematically affect the core relationships in this study.

Then, this study runs some robustness checks that focus on the data-driven side. We first replace key behavioral features. For example, task completion rate is replaced with task success rate; reward redemption rate is replaced with reward claiming rate; time on platform is replaced with page depth. We then run the moderation analysis again. The new results show the same direction and significance as the main model. This means changing the specific behavior indicators does not change the judgment of the moderating effects.

Next, we use behavior data from two different time periods (T1 and T2, one month apart) to build repeated samples and test the core paths again. The differences in path coefficients between the two time periods are not significant. This shows that normal time variations in user behavior do not damage the stability of the structural model.

The robustness test results are shown in Table 9.

Table 9. Robustness Testing Results

Path	Main Model (ML)	GLS Estimation	With Control Variables	After Behavioral Feature Replacement	Different Periods (T1 vs T2)	Conclusion
TS → UE	0.563***	0.548***	0.559***	0.552***	Difference not significant	Robust
SI → UE	0.492***	0.481***	0.487***	0.475***	Difference not significant	Robust
AS → UE	0.518***	0.503***	0.514***	0.497***	Difference not significant	Robust
VR → UE	0.506***	0.495***	0.503***	0.481***	Difference not significant	Robust
UE → BL	0.624***	0.612***	0.621***	0.603***	Difference not significant	Robust

Note: *** P < 0.001.

From Table 9, we can see that, under all the different conditions—changing the estimation method, adding control variables, replacing behavioral features, and using data from different time periods—the changes in path coefficients are small, and the significance levels stay stable. This shows that the theoretical model in this study is highly robust. It supports the reliability of the relationships among data-driven gamification factors, user experience, and brand loyalty.

The use of multiple behavior indicators and cross-period validation also shows that the model works well in a real operation environment and can be applied more widely. This gives strong evidence support for the later practical strategy suggestions.

4. Research Conclusions and Implications

4.1. Conclusions

Based on structural equation modeling, Bootstrap tests of mediation, multi-group analysis, and the moderating effect tests using behavioral data from 582 valid samples, this study shows the inner links between data-driven gamification design, user experience, and brand loyalty. When we look at the general framework in Figure 2, we can see that data-driven gamification factors not only improve user experience directly but also work through a feedback loop based on behavioral data. This loop makes the system stronger and keeps improving over time.

First, the study shows that data-driven gamification design can strongly improve user experience. The task system, social interaction, achievement system, and virtual rewards form a dynamic adjustment process when supported by algorithms. This means the task difficulty, interaction level, achievement pace, and reward value can change in real time based on the user's behavior. As a result, users feel more engaged and find more value in the activities. The path "Data-Driven Gamification Design → Enhanced User Experience" in the upper-left part of Figure 2 shows this effect clearly, and it suggests that improving user experience is the most direct and stable positive outcome of data-driven design.

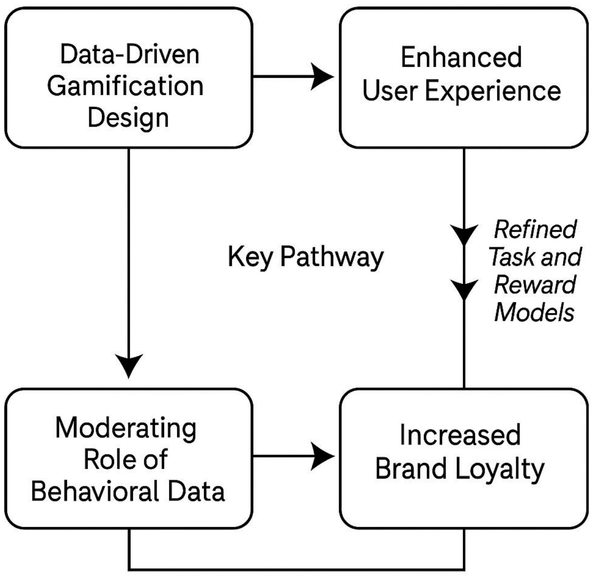

Fig.2: Overall Framework of Main Conclusions for the Data-Driven Gamification Model

Second, user experience plays a key role between gamification design and brand loyalty. The results show that both functional experience and emotional experience have strong impacts on brand loyalty. Emotional experience has a higher path coefficient, which means feelings such as enjoyment, achievement, and emotional connection push users toward loyalty more easily than pure functional evaluation. The “Key Pathway” shown in the center of Figure 2 represents this idea and shows that user experience is an important psychological bridge that links design with loyalty.

Third, an important contribution of this study is showing that behavioral data has a strong moderating effect. Behavioral data such as task completion rate, interaction frequency, time spent, and reward use can make the effect of gamification factors stronger or weaker. The direction depends on how deeply the user is involved. For example, the “Moderating Role of Behavioral Data” shown in the lower-left part of Figure 2 indicates that this data works like an “amplifier” or a “reducer.” When users complete more tasks, the task system improves their experience more. When users rarely redeem rewards, the effect of virtual rewards becomes weaker. This means behavioral data is a very important clue for understanding user differences and should be used as a key indicator for gamification optimization.

Finally, the study finds that refined task and reward models can maximize the improvement of brand loyalty. With data-driven logic, platforms can continue to adjust task difficulty, reward value, and interaction structure based on user behavior. In this way, user experience becomes stronger through continuous feedback. The path shown on the right side of Figure 2, “Refined Task and Reward Models → Increased Brand Loyalty,” shows this extended mechanism clearly. It means that carefully adjusted task and reward systems not only improve experience but also help build long-term brand loyalty.

In sum, this study deepens the understanding of gamification design from a data-driven view. It confirms the classic path where gamification factors influence brand loyalty through user experience. It also shows the dynamic role of behavioral data in this mechanism. The results suggest that only by putting behavioral data into a continuous feedback loop and creating an evolving gamification system can platforms truly improve user experience and achieve long-term growth in brand loyalty.

4.2. Practical Implications

Based on the conclusions above, this study offers practical insights for e-commerce platforms that want to use data-driven mechanisms in gamification. As behavioral data grows and algorithm techniques become more mature, platforms can change gamification from a fixed design into a smart, dynamic system. In this system, tasks, social interaction, rewards, and user experience work together and create a long-term positive feedback loop.

First, platforms need to build a data-driven task recommendation system. This system should match task difficulty, task type, and task rhythm with the user’s past behavior and real-time actions. By using machine learning to predict user ability levels, the platform can give high-engagement users more challenging tasks and low-engagement users easier tasks with stronger motivation. This way, the overall experience becomes better for all users.

Second, platforms should build a stronger social interaction model. By studying user interaction networks, central positions in the network, and social activity levels, platforms can improve team tasks, ranking systems, and community scenes. In this case, social behavior becomes a core driver of user experience and loyalty, not just something extra. The results also show that users with different ages and behavior levels react differently to social mechanisms. So platforms should use data models to find each user’s preferred style of interaction and offer different social task designs to increase the value of social engagement.

Third, improving reward value perception is a key step for better gamification and stronger loyalty. Platforms should use data about redemption behavior, reward cost, and reward value perception to improve how rewards are presented, how well they match the user’s needs, and how easy it is to redeem them. This study finds that the effect of virtual rewards is easily changed by the redemption rate. So platforms need to keep adjusting reward systems to balance "how easy it feels to get rewards" and "how real the value feels" for different user groups.

Next, real-time adjustment based on behavioral data is the core of an intelligent gamification system. Platforms should build a stable data feedback loop that uses task completion, time spent, interaction frequency, and reward use to adjust task logic, interaction design, and reward structure. This keeps the gamification system sensitive and adaptive over time. The moderating effect analysis in this study shows that behavioral data not only affects how strong the experience improvement is but also decides how different users respond to the system. So behavioral data should be treated as the most important source for strategy design.

Finally, platforms should build a loyalty prediction model based on user experience and behavioral data. This model helps managers make better decisions by identifying users with weak experience, users at risk of leaving, and users with high lifetime value. For example, users predicted to have low experience can receive higher-value rewards, while users predicted to have high loyalty can receive long-term growth plans and membership-level incentives to strengthen loyalty even more.

Overall, the practical framework in this study can improve the experience of gamification activities and also guide platforms to build adaptive and evolving operation systems. In this way, brand loyalty can grow steadily within a strong data-driven feedback cycle.

5. Limitations and Future Research

Although this study gives a detailed and systematic discussion of the relationships among data-driven gamification factors, user experience, and brand loyalty, there are still several limitations. These points can be improved in future research.

First, the sample includes 582 users who have e-commerce experience and joined gamified activities recently. The sample size is large enough and the distribution is reasonable, but the data mainly comes from online self-filled questionnaires. This may still lead to some sample bias. Future studies can collect data from different platforms and different types of e-commerce users. A wider sample will help increase the external validity of the findings.

Second, regarding data sources, this study uses both questionnaire data and platform behavior logs. This gives a more complete view of users' perceptions and actual behaviors. However, the behavior data is limited to the indicators that the platform can provide. For example, it cannot capture deeper features such as hidden cognition, emotional changes, or cross-platform behaviors. As more platforms open data interfaces and improve privacy protection, future research can include more types of behavior data, such as cross-channel browsing, multi-device usage, or offline-to-online behavior. This will help improve the explanatory power of behavior models.

Third, the study mainly uses Structural Equation Modeling as the core analysis method. It also adds feature importance analysis, A/B testing, and cross-period verification to make the model more stable. However, the theoretical model still focuses on the main pathway between gamification factors and user experience. More complex dynamic mechanisms are not fully explored. Future studies can try dynamic SEM, causal inference methods (such as Difference-in-Differences or causal forests), or reinforcement learning frameworks. These methods can help explain how platforms adjust strategies based on users' real-time behaviors, which may better match real operational logic.

In addition, because behavior data changes over time, the moderating effect in this study is based on users' behavior at one point in time. It does not look at long-term changes in user experience and loyalty. Future research can build longitudinal data and follow users across a longer period. This will help test long-term effects of gamification mechanisms, such as the decreasing effect of rewards, the evolution of social networks, or the long-term stability of task difficulty curves.

Finally, this study uses user experience as a key mediator, but it separates experience only into functional and emotional dimensions. With the development of intelligent interaction technology, future research can include more experience-related concepts, such as immersion, psychological ownership, perceived fairness, and trust in algorithms. This can create a more complete experience model. Loyalty measurement can also add indicators such as customer lifetime value (CLV), retention curves, or membership growth paths, which may help connect academic research and business practice more closely.

In summary, although this study explains the core mechanism of data-driven gamification design, there is still room to go further. Future research can expand the sample, enrich data sources, apply more advanced methods, and include more theoretical concepts. These directions can help push data-driven gamification research toward a deeper and more comprehensive level.

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