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Gamified Recommendation Engines and their Role in Fostering Continuous Intention to Use Streaming Media Services

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ABSTRACT

This study investigates how users' ongoing intentions to interact with over-the-top (OTT) streaming media services are improved by gamified recommendation engines. Users of streaming media services who had dealt with gamified recommendation algorithms were given a quantitative survey to complete. A strong direct effect ($R^2 = 0.864$) of Gamification-Recommendation Engine Usage (GREU) on user engagement makes it an effective predictor. Intrinsic Motivation (IM) has a moderately positive effect on Continuance Intention towards Streaming Media (CISM), while Extrinsic Motivation (EM) has a negative effect on (CISM), which shows that excessive external benefits might not be helpful. GREU has significant impacts on both IM and EM, which makes its effect on driving factors stronger. The study lacks a longitudinal technique; therefore, it cannot determine variable relationships or user behaviour progression. The study only examines streaming media platforms and no other digital service sectors that use gamification and recommendation systems. AI-powered gamified recommendation systems and experience-oriented incentives (e.g., exclusive material, milestone achievements) can boost user retention through personalised playlists, narrative features, and interactive tools. This study highlights the special relationship between gamification, motivation, and consistent use of streaming services, adding to the expanding body of research on gamification and digital media engagement.

Keywords: Gamification, Recommendation Engine, Intrinsic Motivation, Extrinsic Motivation
JEL Classifications: M30, M31

1. INTRODUCTION

With the rapid growth of over-the-top (OTT) streaming media services, which provide consumers with a vast array of content options, the entertainment industry has undergone a dramatic change. OTT platforms are increasingly employing gamified recommendation algorithms to address this challenge by personalising user experiences and enticing users to continue using their services. Gamification is capable of positively influencing and changing user behaviour. It is possible to solve societal issues and encourage constructive social change through gamification research. It could encourage environmentally friendly behaviour, civic involvement, and group efforts to address global problems (Bengtsson et al., 2021). Gamification builds upon the encouraging shards of survey data. The gamification concept can be the most effective way to modify people's behaviour if it is applied correctly. Concurrently, research on the application of gamification strategies has surfaced in a variety of domains, such as computer science, education, and medical (Ciuchita et al., 2023). Businesses are gamifying their online platforms and mobile apps more frequently in the marketing industry to improve the digital experiences of their clients. No systematic study has examined gamification's function in co-creating brand value, despite the fact that several have examined its impact on user engagement in various industries (Merhabi et al., 2021). To assist consumers in choosing the best product for their needs from the wide range of possibilities available, recommender systems were first created in the mid-1990s. They were developed on the premise that we often rely on the views of our peers before attempting somewhat new, such as before purchasing a laptop or smartphone, before going to a new restaurant, before going to the movies, or even before seeing a doctor. To date, a large number of recommender systems have been created for diverse domains utilising a variety of recommendation methodologies (Sharma and Singh, 2016). The usage of recommender systems to provide users with recommendations based on their preferences is common. To counter the ever-growing amount of information on the internet, recommender systems have been a useful tool. It is important to stress the use of recommender systems because they can assist with a number of over-choice problems (Vogel, 2025). Recommendation systems come in many different forms, each with unique ideas and techniques. Several industries have adopted recommendation systems, including media, e-commerce, transportation, healthcare, and agriculture (Fayyaz et al., 2020).

The recommender system appeared soon after the World Wide Web was created, and together industry and academics have given associated technologies a great deal of research and use. By suggesting numerous types of material, such as news feeds, videos, e-commerce products, music, movies, books, games, friends, jobs, and more, recommender systems have emerged as one of the most popular online applications today, benefiting billions of users daily. These days, recommendation systems—which automatically comprehend user preferences and offer suggestions—are frequently utilised (Hasan and Wang, 2020). One of the key technologies used to create personalisation services is the recommendation system. Because computer users' behaviours are changing, personalisation trends are growing, and internet access is expanding, recommender systems are effective tools for filtering online material (Roy and Dutta, 2022). A popular area of study is recommender systems (RS), which try to assist customers in finding products online by making recommendations that closely align with their interests (Singh et al., 2021). By giving customers of e-commerce more varied and accurate ideas, a recommendation system plays a crucial role in raising user happiness. Numerous studies have looked into the diversity and accuracy of different recommendation systems. On the other hand, little is understood about the psychological processes by which the recommendation system affects user happiness (He et al., 2024).

These days, video platforms are essential parts of many different applications, including corporate training, e-learning, entertainment, online documentation, and news delivery. In order to guarantee effective content consumption, personalised access features are becoming an essential necessity as the amount and complexity of video material increase (Deldjoo et al., 2024). In order to meet this need, recommender systems have become useful resources that offer individualised access to videos. These systems are quite good at suggesting films that are extremely relevant to each user by using historical user-specific video consumption data and the preferences of users who are similar to them (Lubos et al., 2023). The richness of media was a major issue in the development of real and true parasocial relations. As a result, these conversations significantly impact how people act while making purchases. However, it was shown that authenticity and media naturalness were only necessary but not sufficient requirements for purchasing. Marketing managers will be able to create programs that increase conversion rates if they have a clear understanding of the function that media richness and naturalness play in social media marketing (Chidiac and Bowden, 2023). The way information is consumed has changed dramatically due to the explosive expansion of streaming media services, which has given consumers access to a wide range of possibilities.

By making content discovery more interesting, pleasurable, and rewarding, gamified recommendation algorithms in streaming media aim to boost user engagement (Wang and Zhu, 2024). This study aims to explore how gamified recommendation engines contribute to users' continued intention to utilise streaming media services. The likelihood that users would consistently return to a platform over time is expressed by continuous intention, which is a crucial indicator of its success and user pleasure. In an increasingly competitive streaming industry, this study aims to clarify how innovative, game-based strategies could foster user loyalty and sustained engagement by examining the relationship between gamification and recommendation systems. In order to keep users interested and competitive, streaming platforms are expected to get valuable insights from the results regarding how to integrate gamification into their recommendation systems.

2. LITERATURE REVIEW

2.1. Gamification - Recommendation Engine Usage

A recommendation system's objective is to infer the thought processes of its users and forecast their interests. This system can deliver users with the necessary information built on their needs and their interests. To make better recommendations, an additional complete data analysis is needed. With a variety of approaches, many recommendation systems have been created. Thus far, research into such systems has become more popular as OTT platforms, shopping, travel, and other websites are growing and trying to progress their user suggestions as fast as possible. In the absence of an appropriate recommender system, retrieving necessary data from online apps is quite challenging. Web apps employ recommender systems to give consumers relevant information according to their preferences and interests (Mishra et al., 2021). The bias in the platform's user-specific suggestions when one content supplier has smaller royalties than the other. If consumers are not sensitive enough to bias, the recommendation system enables the platform to legitimately threaten upstream providers to divert consumers from their content, thereby diminishing their market strength (Bourreau and Gaudin, 2022). Millions of people use the Internet for a variety of reasons, including shopping, education, and leisure. Every day, for example, one billion hours of YouTube videos are seen. Recommendation systems based on user history and the content of websites visited are among the main characteristics of these platforms, which include commerce and entertainment platforms. They offer similar content to save search time and improve data availability. When users search more within a category and with general query terms, their behaviour indicates that recommendation and search are complementary. When they obtain fewer product recommendations in the category of interest, consumers raise the number of searches in the relevant category and employ long-tail query words as a substitute among search and suggestion to counteract this decline (Geiger et al., 2021). To reinvent content discovery and encourage curiosity, inquiry, and learning across a wide range of knowledge domains, the new algorithmic recommendation engine for diversified content discovery makes tiny, gradual improvements based on ongoing user feedback. In light of the user's selected educational learning pathway, the suggested e-learning material makes more sense. Customers are finding it increasingly difficult to find reliable and accurate content in their specific regions due to the deluge of information available online. Recommendation algorithms, which provide customised content recommendations based on user preferences, have solved this problem (Magadum et al., 2024).

H_1: Gamification - Recommendation Engine Usage (REU) has a direct positive effect on Continuance Intention towards Streaming Media (CISM).

H_2: Gamification - Recommendation Engine Usage (REU) positively influences Extrinsic Motivation.

H_3: Gamification - Recommendation Engine Usage positively influences Intrinsic Motivation.

2.2. Intrinsic Motivation

According to Shahid and Paul (2021), Our "ideal self" is in line with the inner driving behaviour that can address a variety of behavioural outcomes, such as increased engagement with an activity and a purposeful and consistent attempt to carry it out. The greatest influence on consumers' willingness to participate in circular food consumption (CFC) was seen in intrinsic motivation. The consumer readiness for participating in circular food consumption (CFC) was highly influenced by sociodemographic characteristics, notably age and gender (Raimondo et al., 2024). Customers have an innate desire to purchase organic food, which causes them to purchase a larger percentage of organic products in their shopping baskets and to be more inclined to spend more of their budget on them (Buil and Mata, 2024). Modern consumers look for better luxury experiences to elevate their sense of self through luxury consumption. Considering how much effort has gone into creating a luxury experience, purchases with an intrinsic motivation are crucial in capturing this essence (Shahid and Paul, 2021). When making purchases, consumers are motivated more by internal than by external factors, and they have greater influence when making luxury purchases online (Lama et al., 2024). Using a mobile app that is facilitated by shopping engagement, intrinsic motives (such as shopping gamification, intensive attention, shopping satisfaction, and socialness) indirectly affect the desire to purchase. The most striking finding is that the intention to purchase through a mobile app channel is positively moderated by the online purchasing experience (De Canio et al., 2021). Social networking sites are a great place for intrinsic motivation to work (Sharma and Joshi, 2021). Purchase intents are positively and significantly impacted by perceived quality, which is linked to the product's inherent qualities (Fandos and Flavián, 2006). Extrinsic (or intrinsic) rewards encourage consumers to take accomplishment in order to achieve a benefit that is inside (unlike from) the goal of their purchase orientation and have a favourable effect on loyalty (Meyer-Waarden, Benavent and Castéran, 2013).

H_6: Intrinsic Motivation positively influences Continuance Intention towards Streaming Media (CISM).

2.3. Extrinsic Motivation

Interestingly, the desire for treasure hunting turned out to be stronger than both the ethical and economic motivations combined, explaining attitudes toward second-hand clothing (Halicki et al., 2024). The adoption of organic products is significantly influenced by extrinsic factors, including social and familial influences, worries about the COVID-19 pandemic, and other considerations (Ortiz-Regalado et al., 2024). Green purchasing behaviour is positively influenced by green purchasing intention, which is positively influenced by intrinsic motivation and environmental attitude. Concurrently, customers' environmental attitude and intrinsic motivation are positively impacted by the satisfaction of their three fundamental psychological needs—autonomy, competence, and relatedness—while the conversion of environmental attitude into green purchasing intention is moderated by subjective standards. It has been discovered that prosocial and intrinsic motivations are important indicators of long-term pro-environmental consumption behaviours (PECB). More significantly, in addition to the direct impacts of prosocial and intrinsic incentives, the authors discovered that both prosocial and intrinsic motivation positively interact with extrinsic motivation to promote long-term pro-environmental consumption behaviours (PECB) (Pham et al., 2022). While extrinsic (stimulus) factors including store atmosphere, PA, and stimulation factors had a beneficial effect on customers' impulsive buying tendency (IBT), product attributes had no effect on IBT. Compulsive buying was also impacted by impulsive buying (organism) and a positive mediating link among extrinsic circumstances (stimulus factors) and consumers' compulsive buying (response factor). The adoption of wearable fitness technology (WFT) has been associated with either intrinsic or extrinsic motivation in previous research. However, little is known about how consumers' decisions to adopt WFT are influenced by the identifiable, introjected, and external subcategories of extrinsic incentives (Haider et al., 2024). Scarcity and the COVID-19 epidemic show significant moderation among organism and reaction, while organism factors (panic and impulsive buying inclinations) positively inclined impulsive purchase when compared to stimulus (intrinsic and extrinsic) and response variables (Lavuri and Thaichon, 2023a; Lavuri et al., 2023b).

H_4: Extrinsic Motivation positively influences Intrinsic Motivation.

H_5: Extrinsic Motivation positively influences Continuance Intention towards Streaming Media (CISM).

2.4. Continuance intention towards streaming media

The intention to continue is influenced by social influences, computer self-efficacy, perceived enjoyment, satisfaction, and interactivity (Obeid et al., 2024). Businesses must comprehend the goals of OTT retail consumers to stick with them in light of the fierce competition in the OTT market. Perceived behavioural control, attitude, and habit were the factors that had the greatest effects on continuance intention, whereas perceived behavioural control, perceived enjoyment, and attitude were the ones that performed the best (Soren and Chakraborty, 2024). Positive effects are observed for the excellence of information, services, systems, perceived utility, and validation on e-satisfaction and intention to continue. Perceived risks and perceived concern, though, have an effect on continuing intention rather than e-satisfaction. The effects of perceived threat, e-satisfaction, perceived anxiety, and quality magnitudes on customers' e-satisfaction, continuance intention, and e-loyalty (Al Amin et al., 2024). Accessibility and content quality played a major role in influencing the hedonic value and attitude of OTT viewers, which in turn influenced their happiness and intention to continue using OTT services. Additionally, viewers' intention to continue using OTT services was found to be significantly influenced by their level of happiness. A number of important correlations, whereby perceived value strongly increases continuance intention while social attendance, perceived crowdedness, vulnerability to informational influence, and trust in broadcasters all considerably impact perceived value. Furthermore, the association between perceived worth and continuing intention is moderated by broadcasters' credibility (Chong et al., 2023). Customers' decision to continue using omnichannel channels is positively impacted by their attitude towards perceived values, including utilitarian, hedonistic, and social values (Chang and Geng, 2022).

H_7: Gamification - Recommendation Engine Usage (REU) has an indirect effect on Continuance Intention towards Streaming Media (CISM) through Intrinsic and Extrinsic Motivation.

H_8: Gamification - Recommendation Engine Usage (REU) has an indirect effect on Continuance Intention towards Streaming Media (CISM) through Intrinsic Motivation.

Although recommendation algorithms and gamification have been studied separately, not much is known about their combined effects on OTT streaming media user engagement and retention. Most research fails to investigate gamified recommendation engines' effects on intrinsic motivation (IM) and extrinsic motivation (EM). Gamification and OTT platform retention can be improved by addressing these gaps.

This conceptual framework Figure 1 Conceptual Framework contributes to the understanding of how gamification can impact long-term user engagement with streaming media services and encourage motivation. It takes into account the direct impacts of gamification on continuance intention and supports hypotheses evaluating the mediation roles of intrinsic and extrinsic motivation. The conceptual framework is modified from the original (Liu et al., 2024).

3. RESEARCH METHODOLOGY

3.1. Research Context and Data Collection

The platform uses a gamification-empowered customer experience effort to enhance customer satisfaction and service delivery. The study aims to pinpoint important variables, like gamification components integrated into recommendation engines, and investigate how they affect users' ongoing propensity to utilise streaming services. The survey is divided into several sections, such as demographics, user experiences with streaming services, and whether or not gamified elements have affected user's intentions to stick with the service. Respondent's agreement with statements on gamification and continuous usage intention was measured using a Likert scale (1-5). The study focused on streaming media service customers who engage with gamified recommendation engines and used non-probability sampling. The online population samples were selected with special attention to communities and user bases that are known to use streaming services. The technique of purposive sampling ensures that respondents meet certain requirements. Participants have to make frequent use of streaming media platforms, possess knowledge of and experience with gamified recommendation systems on many platforms, and engage with the recommendation system of the service.

3.2. Measurements

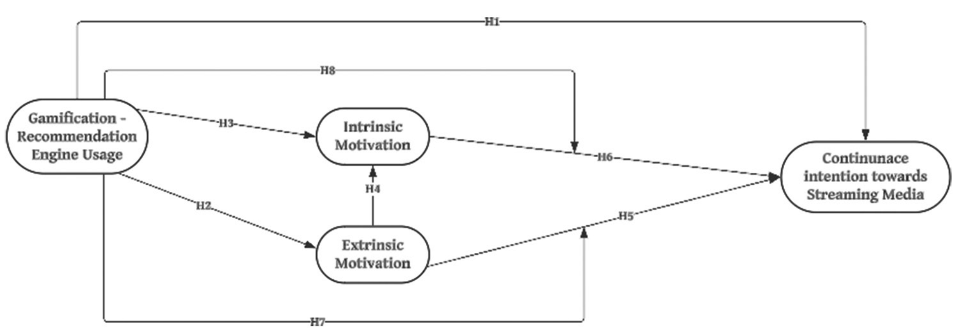
Most of the variables utilised in this study are measured using items developed by consulting the existing literature. The Five-point Likert scale is used to measure the items. The items for Gamified - Recommendation Engine Usage (8 items) were adapted from (Afridi, 2018), items for Intrinsic Motivation (6 items) were adopted from (Yoo and Huang, 2013), (Liu et al., 2024), items for Extrinsic Motivation (6 items) were adopted from (Yoo and Huang, 2013), (Liu et al., 2024), and items for Continuous Intention to Use Streaming Media (6 items) were adopted from (Yang and Jong, 2021; Liu et al., 2024).

4. DATA ANALYSIS

4.1. Reliability

From Table 1 Reliability Statistics, A Cronbach's Alpha of 0.986 indicates that the 26-item scale has excellent reliability and that the items consistently measure the same construct. With this scale,

Figure 1: Conceptual framework



Source: (Liu et al., 2024)

you can proceed with the data analysis with confidence because the dependability is well within acceptable bounds.

4.2. Descriptive Statistics Concerning the Sample

From Table 2 Demographic Profile and Characteristics, the demographic information of 444 respondents is displayed in the table according to their gender, age, level of education, and monthly income. Among the respondents that participated in the survey, the majority of respondents are female, accounting for 55.86% (248 individuals), while the male respondents make up 44.14% (196 individuals). There was not a single respondent who selected the "Prefer not to say" option. Individuals who are in the middle of their lives make up the most significant demographic in the sample, as indicated by the fact that the biggest proportion of respondents (54.95%) fall within the age range of 36-55 years old. There are 19.82% of respondents fall into the age range of 18-35 years old, while there are 25.23% of respondents fall into the age range of 56-65 years old. Post-graduation degrees are held by the majority of respondents (49.10%), followed by Undergraduate degrees (33.11%), and then Doctoral or comparable level degrees (17.79%) on the list of respondents. Among the respondents, none of them reported having an education that was "Up to Schooling." The distribution of monthly income reveals that the biggest proportion of respondents has a monthly income that falls between the range of Rs. 40,001-60,000 (36.71%), followed by Rs. 60,001-80,000 (21.17%). A smaller percentage makes more than 100,000 rupees (12.16%), while just 7.21% earn <20,000 rupees. The dataset offers a balanced distribution across age groups, genders, economic levels, and educational attainment, which may be helpful in examining the ways in which these variables impact the development of habits and behavioural intentions in mobile augmented reality applications.

Table 1: Reliability statistics

Reliability statistics	
Cronbach's Alpha	N of Items
0.986	26

Table 2: Demographic profile and characteristics

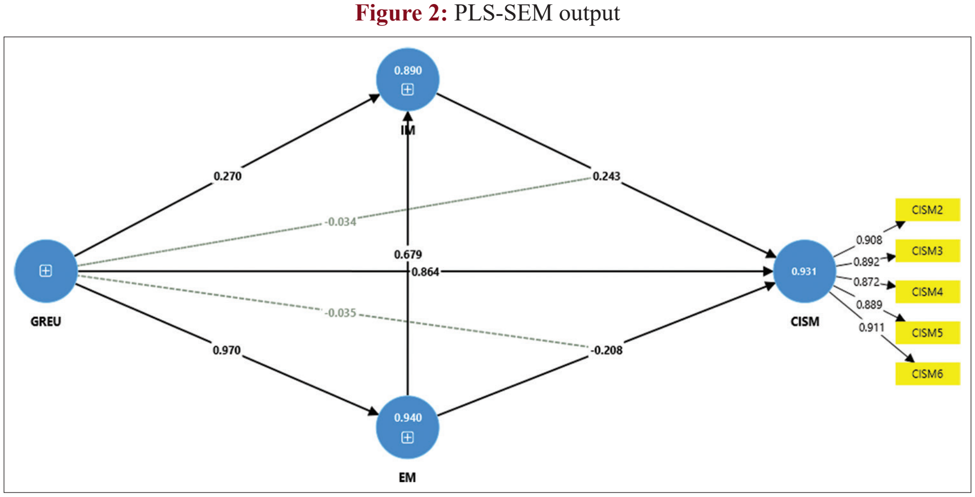
S. No.	Attributes	Options	Frequency	Percentage
1	Gender	Male	196	44.14
		Female	248	55.86
		Prefer not to say	0	0
		Total	444	100
2	Age Group	18-35	88	19.82
		36-55	244	54.95
		56-65	112	25.23
		Total	444	100
3	Education	Up to schooling	0	0
		Under graduation	147	33.11
		Post-graduation	218	49.10
		Doctoral or equivalent level	79	17.79
		Total	444	100
4	Monthly Income	<Rs. 20000	32	7.21
		Rs. 20001-40000	86	19.37
		Rs. 40001-60000	163	36.71
		Rs. 60001-80000	94	21.17
		Rs. 80001-1,00,000	15	3.38
		Above Rs. 1,00,000	54	12.16
		Total	444	100

(Source: Prepared by Authors, 2024)

4.3. PLS – SEM

From Figure 2 PLS-SEM Output, it is inferred that in a gamification context, the diagram appears to depict a structural model that illustrates the relationships between variables and how they impact user behaviour or system satisfaction (perhaps in the context of gamified recommendation engines or ongoing intention to use). According to the coefficient of determination (0.864), Gamification-Recommendation Engine Usage (GREU) has a significant direct impact on Continuance Intention towards Streaming Media (CISM), which indicates that it is a main driver of CISM. Therefore, Intrinsic Motivation (IM) has a moderately positive impact on CISM (0.243), which indicates that it is not a highly powerful influencer but plays a role. It is important to note that Extrinsic Motivation (EM) has a negative effect on CISM (-0.208), which suggests that higher levels of EM may have the potential to reduce the number of CISM outcomes. Indicating that GREU is a strong predictor of both mediators, GREU has a considerable influence on both IM (0.270) and EM (0.970). This indicates that the indirect effects, which are represented by dotted lines, are weak and negative (−0.034 and −0.035), indicating that

Figure 2: PLS-SEM output



(Source: Prepared by Authors, 2024)

there are insignificant suppressor effects. The GREU was found to be the most accurate predictor of CISM, both directly and indirectly through mediators. While EM appears to have a reducing effect, Intrinsic Motivation (IM) makes an important contribution. Taking everything into consideration, the model indicates that the paths from GREU to CISM are highly significant.

4.4. Hypothesis Testing

Table 3 Hypothesis Testing- Direct Effects display each hypothesis's decisions, standard deviations (SD), coefficients, β-values, and P-values as a consequence of the hypothesis testing. A significant and highly positive effect on CISM is caused by GREU, which may be a predictive variable. With this data, it appears that an increase in GREU is associated with a significant increase in CISM. Evidence of the strength of this connection is demonstrated by the strong t-statistic (10.542). The positive impact that GREU has on EM is extremely strong and extremely important. A nearly perfect association is indicated by the t-statistic (162.423), which is very high. It would appear from this that GREU is a significant factor in determining EM. When it comes to IM, GREU has a beneficial effect, although a weaker one.

In addition to the fact that the association is significant, the t-statistic (2.026) and the P-value (0.043) show that it is much less effective than the impact on either EM or CISM. CISM is positively affected by IM in a way that is not only moderate but also significant.

It may be inferred from this that IM plays a role in the development of CISM, but to a smaller level than GERU. It is interesting to consider that EM has an adverse effect on CISM that is actually quite significant. One may conclude from the reality that the coefficient is negative (−0.208) that an increase in EM results in a decrease in CISM. Both the significance (P = 0.006) and the moderate t-statistic (2.752) provide evidence that this impact is significant.

Table 4 represents the Hypothesis Testing – Indirect Effects. The indirect effect of GREU on CISM through IM is positive (β = 0.066), however it is not statistically significant (P = 0.116 has a significance level >0.05). The t-statistic, which is 1.574, does not satisfy the standard criterion for significance, which is normally t >1.96. It indicates from this that IM does not play a significant part in mediating the interaction between GREU and CISM. At the level of statistical significance (P = 0.006 < 0.05), the indirect effect of GREU on CISM through EM is found to be negative (−0.201). In this particular relationship, the presence of a negative β-value indicates that EM acts as a reducer. This implies that when the GREU increases, it strengthens EM, which in turn reduces CISM. EM had a direct negative impact on CISM (β = −0.208). The fact that the t-statistic (2.750) is greater than the acceptable threshold (t > 1.96) demonstrates that there is a significant mediation effect.

Table 5 displays the Hypothesis Testing – Moderating Effects. Based to the statistical evaluation, the relationship impact of GREU and IM on CISM is negative (−0.034), although it is not statistically significant (P = 0.436 > 0.05). The t-statistic, which is 0.779, is less than the standard threshold, which is 1.96, which indicates that there is no significant moderating impact. This indicates that the relationship between GREU and CISM is not significantly moderated by its inclusion in the model. The interaction impact of GREU and EM on CISM is statistically insignificant (P = 0.404 > 0.05) and has a negative value (−0.037). EM does not have a significant moderating influence on the association between GREU and CISM, as indicated by the observation that the t-statistic, which is 0.834, is below the threshold, that is 1.96.

Table 3: Hypothesis testing – direct effects

Hypothesis	β-value	t-statistics	SD	P-value	Decision
GREU→CISM	0.864	10.542	0.082	0.000	Supported
GREU→EM	0.970	162.423	0.006	0.000	Supported
GREU→IM	0.270	2.026	0.133	0.043	Supported
IM→CISM	0.243	4.360	0.056	0.000	Supported
EM→CISM	−0.208	2.752	0.075	0.006	Supported

(Source: Prepared by Authors, 2024)

Table 4: Hypothesis testing – indirect effects

Hypothesis	β-value	t statistics	SD	P-value	Decision
GREU→IM→CISM	0.066	1.574	0.042	0.116	Not Supported
GREU→EM→CISM	−0.201	2.750	0.073	0.006	Supported

5. FINDINGS AND DISCUSSION

This study's findings reveal that the Gamification-Recommendation Engine Usage (GREU) significantly and directly influences Continuance Intention towards Streaming Media (CISM), with a coefficient of determination of 0.864, indicating that GREU is a key determinant of CISM. This highlights the important function of gamified recommendation systems in influencing user engagement and continuous platform usage. The significant t-statistic (10.542) further supports the significance of the association. Intrinsic Motivation (IM) showed a moderate positive effect on CISM (0.243), demonstrating that although IM promotes continuous consumption, its influence is less significant than that of GREU. In contrast, Extrinsic Motivation (EM) demonstrated a negative impact on CISM (−0.208), suggesting that increased extrinsic rewards or external pressures might reduce user retention. This research indicates that an excessive dependence on extrinsic incentives, such as discounts or financial rewards, may undermine the intrinsic allure of streaming media consumption. GREU was also determined to significantly affect both IM (0.270) and EM (0.970), highlighting its vital role in influencing motivational elements. While GREU positively impacted IM, its effect on EM was very high, perhaps increasing the adverse effect of EM on CISM. The indirect effects of GREU via IM (0.066) and EM (−0.201) indicate that EM acts as a suppressor, diminishing the overall favourable impact of GREU on CISM.

Table 5: Hypothesis testing – moderating effects

Hypothesis	β-value	t statistics	SD	P-value	Decision
GREU*IM→CISM	−0.034	0.779	0.043	0.436	Not supported
GREU*EM→CISM	−0.037	0.834	0.043	0.404	Not supported

The moderating effects of IM and EM on the GREU-CISM association were determined to be statistically insignificant. This indicates that neither IM nor EM much modifies the direct impact of GREU on CISM. The findings highlight the importance of improving GREU to improve user engagement while cautiously managing extrinsic motivators to prevent negative impacts on retention. The significant relationships highlight important factors affecting consumer satisfaction and engagement in digital or augmented reality environments. The study's insights can enhance the efficacy of recommendation engines by incorporating gamification features, user emotions, and interactive methods. Organisations can leverage these insights to enhance mobile AR applications, hence increasing user engagement and retention. The study's results regarding the impact of expectancy and motivation on behaviour may assist in the development of more effective influencer marketing and gamification methods. Companies can utilise data-driven insights to refine their online platforms, improve customer experiences, and promote sustained engagement.

6. CONCLUSION

This study demonstrates the crucial impact of Gamification-Recommendation Engine Usage (GREU) on improving Continuance Intention towards Streaming Media (CISM). GREU serves as a significant predictor of user retention, exhibiting a strong direct effect ($R^2 = 0.864$). Intrinsic Motivation (IM) shows a favourable although moderate influence on CISM, whereas Extrinsic Motivation (EM) negatively affects CISM, suggesting the possible drawbacks of excessive external incentives. GREU significantly influences both IM and EM, hence enhancing its impact on motivational elements. The results highlight the necessity to enhance GREU while strategically managing extrinsic motivators to maintain user engagement and retention on streaming media platforms. Streaming platforms must prioritise gamification-driven recommendation engines to improve user engagement and retention. Features such as interactive challenges, reward-based personalised content suggestions, and achievement-based progress tracking can sustain user interest and promote long-term usage.The paper's results imply that streaming platforms should promote entertainment, autonomy, and social engagement to increase Intrinsic Motivation (IM) while minimising dependence on Extrinsic Motivation (EM) such as discounts. Investing in AI-powered gamified recommendation systems and experience-oriented incentives (e.g., exclusive content, milestone achievements) can enhance user retention, assuring continuous participation through personalised playlists, narrative elements, and interactive tools.

All of the data needed for the study is gathered at once using a cross-sectional survey method. The sample may not adequately represent the larger community, constraining the generalisability of the findings across various user demographics and types of digital services. The study's cross-sectional design limits its capacity to explain the shifting connects among gamification, motivation, and the continuous intention to use streaming media over time. Due to the absence of a longitudinal strategy, the study lacks the ability to definitively identify connections between variables or examine the evolution of user behaviours. The emphasis on extrinsic motivation (EM) may neglect the significance of intrinsic motivation (IM) in fostering user engagement.

The study concentrates entirely on streaming media platforms and does not investigate other digital service sectors that utilise gamification and recommendation systems. In the future, studies may adopt a longitudinal approach to examine how users' intentions to continue using streaming services have changed over time. Performing a longitudinal analysis to assess the progressive influence of gamification, motivation, and recommendation systems on sustained usage behaviour. Examining how intrinsic motivation promotes enduring user engagement and affects the ongoing desire to utilise streaming media, as opposed to external incentives. Analysing the impact of tailored gamification components (e.g., social competition, individualised incentives, and adaptive challenges) on user engagement and retention. Investigating the impact of AI-driven gamified recommendation models on user satisfaction, retention rates, and churn mitigation in streaming services. Formulating a comprehensive framework that delineates optimal methods for creating gamification systems to augment user engagement and retention.

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