Exploring Adolescent Preferences for Battle Royale Games on Mobile Platforms: A Data-Driven Hybrid Framework Integrating KANO, PLS-SEM, and ANN in the Context of Bangladesh

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Department of Software Engineering (Major in Data Science)

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APPROVAL

This thesis titled on "**Exploring Adolescent Preferences for Battle Royale Games on Mobile Platforms: A Data-Driven Hybrid Framework Integrating KANO, PLS-SEM, and ANN in the Context of Bangladesh**", submitted by **Student Name: Tamim Binty Tuhin (ID: 221-35-837)** to the Department of Software Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Software Engineering and approval as to its style and contents.

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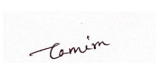

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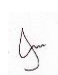

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DEDICATION

With the Name of Allah, the Most Merciful, the Most Compassionate. This thesis is dedicated first to Almighty Allah for His boundless mercy and guidance; to my dear parents, who loved me generously and without limits, sacrificed a lot of many things for me, and perpetually prayed for my well-being; to all members of my family towards whom I enjoyed support and encouragement from their side; as well as to all other teachers/instructors/mentors back in home country both at school level (primary junior section, secondary high section) right up to university studies that have motivated and guided me on this academic adventure.

ABSTRACT

Mobile Battle Royale (BR) games such as PUBG Mobile, Free Fire, and Call of Duty Mobile have gained immense popularity among Bangladeshi adolescents. Despite this development, few quantitative studies have addressed the relative importance of different technical and experiential game features in determining player satisfaction and intention to play. To fill this gap, the present work combines the Kano model with Partial Least Squares (PLS) and Artificial Neural Networks (ANN) to develop an entire consciousness of gaming preferences in adolescents. This is a mixed method study in a three-step cycle. First, 515 valid responses were analyzed through the Kano model to classify 15 BR game features into Must-Be, Performance, Attractive, Indifferent, Reverse or Questionable categories. Second, 308 valid cases were used to test a theory-driven structural model via PLS-SEM, examining relationships among system-level factors (device specifications, game interface & controls, internet connectivity & latency, game content & features, game reviews & recommendations), experiential mediators (smooth gameplay performance, battery optimization, graphics quality), satisfaction, and continuance usage intention. Finally, five ANN sub-models were applied to validate and refine the predictive accuracy of the PLS-SEM findings. Kano analysis revealed that Graphics Quality, Voice Chat Quality, Reward System, Social Features and Anti-Cheat Protection are Must-Be features, while Smooth Gameplay Performance and Battery Optimization are Performance features. Fair Matchmaking, Control Customization, Quick Match Start, In-App Purchasing Fairness and Local Language Support were identified as Attractive delighters. PLS-SEM results demonstrated that Graphics Quality is the strongest predictor of Satisfaction ($\beta = 0.793$, $p < .001$), followed by Smooth Gameplay Performance ($\beta = 0.096$, $p = .019$). Satisfaction was the strongest determinant of Continuance Usage Intention ($\beta = 0.718$, $p < .001$). Internet Connectivity and Latency significantly predicted gameplay performance and graphics ($\beta = 0.343$, $p <. 001$), and Game Content & Features strongly influenced all experiential constructs ($\beta = 0.230$, $p =. 001$). The model accounted for a large proportion of the variance in satisfaction ($R^2 = 0.895$) and Graphics Quality ($R^2 = 0.863$). ANN verification showed that the overall performance was equal. predictor ranks for Satisfaction and Continuance Usage Intention, thereby lending credibility to the relative importance of Graphics Quality, Smooth Gameplay Performance, and Content is significant Features. The outcome of each of the three stages all pointed toward two aspects: visual fidelity and technical smoothness. The most important drivers of adolescents' gaming satisfaction will be appealing and engaging content design. The actual ANN results add more support to the PLS-SEM results, which showed remarkably high predictive power and leaves no doubt that satisfaction is the complete driver of long-term gameplay intention. The current study offers a legitimate, evidence-based behavioral description of adolescent Gaming behavior in Bangladesh. The combined Kano–PLS-SEM–ANN modeling enables practical guidance for developers, policymakers, and researchers in the game industry by prioritizing necessary technical performance, high-quality graphics, and user-centric content to enhance meaningful gaming experiences.

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CHAPTER 1
INTRODUCTION

1.1. Introduction

In the past decades, video gaming has transformed from a small niche industry to one of the world's largest entertainment media and an industry worth more than USD 250 billion per annual projected by Statista to exceed USD 300 billion by 2025 (Statista, 2024). This astounding development is mainly due to the popularity of mobile gaming, which currently represents over 50% of the worldwide games market, as mobile platforms have become the most convenient and popular devices for gamers worldwide (App Annie, 2024). This process holds particular importance for developing nations like Bangladesh, where mobile games have proliferated eagerly due to the popularity of low-cost smartphones, the availability of quick network infrastructure, and social media platforms' escalating integration (Hasan et al., 2024). Among the most popular forms of mobile games, the BR games' popularity has reached an immense level, including games like PUBG Mobile, Free Fire, and Call of Duty: Mobile, which became a global phenomenon. These games, which combine survival action, competition, and socialization, are known to be extensively utilized by adolescents aged 10-24 years (Islam et al., 2024). The BR games create a virtual world where one has to cooperate, compete, and survive longer than others to emerge victorious, implying the simultaneous achievement of both personal success and teamwork (Bae et al., 2023). However, despite being known for their entertaining nature, recent research has unearthed problems related to the improper use, emotional attachment, and time span devoted by young people to play these games (Ohno, 2022; Islam et al., 2024). Even as these BR games are being increasingly accepted by the masses, including those in Bangladesh, empirical research focusing on the prominent psychological, social, and design factors that decide the probability of young people choosing or adopting these games has been less observed. More importantly, the particular game component that leads to young gamers' satisfaction, engagement, and commitment in Bangladesh has been less explored, which this study aims to do comprehensively by furnishing a detailed insight into the young gamers' gaming habits, including preferences, which hold special emphasis on the mobile BR games.

1.2. Gaming Definition

The gaming industry has transformed from simple entertainment performance to a multifaceted process of socializing, cognitive functions, and emotions. In other words, gaming can simply be referred to as the performance of playing electronic games. This can also include PCs, gaming consoles, and even mobile phones. There are different experiences associated with playing, such as competitive experience, cognitive challenge, and communication interactions (Yasin et al., 2022). In the event of games being defined as digital spaces where decision-making, designing strategies, and dynamic feedback are performed in real time (Espinosa-Curiel et al., 2020), there are very high chances of there being components of technological building that are either affecting games or are being impacted by them. Thanks to the emergence of multi-player games and team engagement activities, gaming has transitioned into a form of socializing where people get to assemble in one place. Advances in technological capabilities have been able to give birth to a new form of entertainment where people can now work in their environment, build relationships, and finally attain individual success (Barsalou & Klaus, 2024). In contemporary times, a new purpose has been introduced to the world of gaming, not just for entertainment but for regulating emotions, engaging in social interactions, and developing cognitive functions. Multi-player games, especially team-based versions, have been found to improve communication skills, problem-solving capabilities, and intelligence (Emotional IQ). This was seen in Battle Royal, which has been found to rely heavily on teamwork, strategies, and competitiveness. In the olden days, gaming was mainly used for entertaining people in their free time and was also seen as a chance for individualism and socializing, but was also associated with grave dangers, especially in the case of younger generations (cf. Fayyaz et al., 2025).

1.3. Gaming Activity Trend (2015–2025)

Figure 1 shows how the industry is growing along with The gaming industry has experienced explosive growth in the last decade and is estimated to increase its gaming base from 1.9 billion in 2015 to 3.3 billion by 2025, with a compound annual growth rate of 74% (Statista, source). Factors contributing to this are mainly due to increasing access to comparatively cheaper smartphones, Internet access, and the popularity and demand for online multiplayer games. It is especially significant for South Asia because gaming is highly popular in a short span of time, especially for Bangladesh (Hasan et al., 2024). Mobile gaming is a significant-driving force for getting popularity, with revenue rising from 70 billion in 2015 to a projected 200 billion by 2025 (App Annie, 2024). This huge market growth figure signifies that mobile gaming is gradually surpassing and taking over the gaming markets from conventional gaming components and gaming consoles and tools. BR games on mobile platforms such as PUBG Mobile and Free Fire are the market leaders in this segment and have topped downloads and acquired millions of active subscribers mainly from Southeast Asia and South America. Bangladeshi intermediary: Teenagers from rural areas of Bangladesh dedicate 6–10 h per week to play mobile gaming activities (Isalm et al., 2025). The rising market and speedy monetization signify significant cultural and economic value for mobile gaming turning out to be a significant base for young generations turning out to play a crucial role in digital media ecologies and ecumene. Moreover, it depicts that mobile gaming and BR games are not a part of amusement; in fact, they are a significant base and crucial part within a huge digital environment that significantly affects socializing and identity formations, information transmission, and information constructions among young generations (Fayyaz et al., 2025). Moreover, advancements within require investigations for what are teens' incentives for mobile gaming participation and evaluation for their involvement participation and considerations within inexperienced areas such as Bangladesh (Fayyaz et al., 2025).

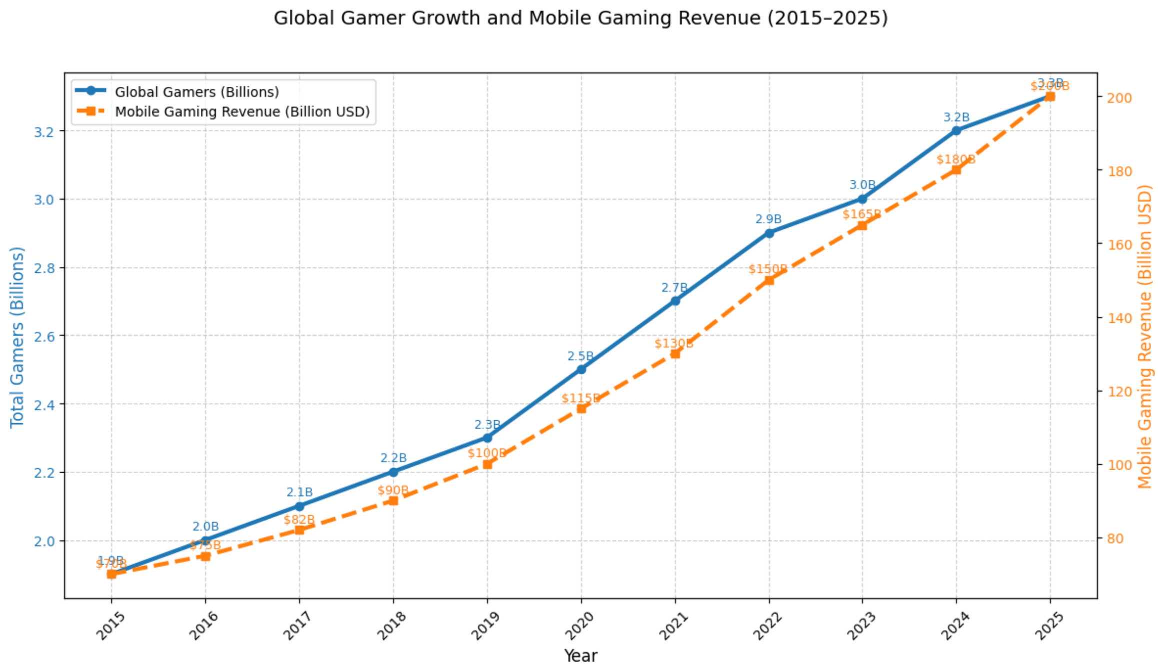


Figure 1. Global Gamer Growth and Mobile Gaming Revenue (2015–2025)

1.4. Motivation

My personal interests and motivations include a mix of curiosity-driven and existing gaps in knowledge relevant to society.

Personal Motivations: As an individual that 'grew up' together with mobile technology, the author personally witnessed how Battle Royale games managed to capture the interests of Bangladeshi teenagers. These games are now firmly entrenched in youth culture and provide spheres of interaction for socializing, competing and expressing identity (Bae et al., 2023). Together with this enthusiasm, concerns related to problematic use and its association with academic performance and mental health have spurred interest in understanding the underlying reasons that drive adolescents to play these games, as well as designing data-driven approaches to better understand their gaming experiences. Academic Motivation: Although mobile gaming is a burgeoning industry worldwide, especially in developing countries like Bangladesh, little work has been done to study the needs, motivation, and satisfier factors of Bangladeshi adolescents' game players. Although a plethora of research exists claiming that video games can have negative psychological consequences, there is limited understanding of what game mechanics influence player satisfaction and engagement, as well as long-term customer loyalty. To address this, this study investigated how adolescents prefer playing games by combining the KANO model, PLS-SEM, and ANN. Societal motivation Adolescents are an important target group in Bangladesh's emerging digital society. It is important to examine their gaming habits, not only for the formation of healthy gaming habits but also for the promotion of positive digital experiences. We strive to contribute insights for game developers, educators, and policymakers on how gaming environments can be designed to not only engage but also promote social concerns and adolescent well-being (Hasan et al., 2024; Islam et al., 2024).

1.5. Problem Statement

Although there is great interest in mobile Battle Royale games, the particular features that contribute to high adolescent satisfaction and engagement in Bangladesh are largely unknown. To the best of our knowledge, existing research pays almost exclusive attention to negative issues such as game addiction, and very little attention is placed on data-driven models that analyze feature-specific satisfaction or engagement prediction (Barsalou & Klaus, 2024). To the best of our knowledge, no research has combined KANO with PLS-SEM and ANN into a hybrid framework for capturing and predicting adolescent gaming behavior (Bae et al., 2023). Hence, the current study proposes a novel hybrid data-driven model integrating KANO, PLS-SEM, and ANN to predict adolescent gaming preference for mobile Battle Royale games in Bangladesh.

1.6. Research Objective

This study proposes a hybrid pattern that includes KANO, PLS-SEM, and ANN to predict the preferences of teenagers towards mobile Battle Royale games in Bangladesh. The specific objectives are: Objective 1: To understand the psychological, social, and game design motivations behind adolescents in Bangladesh playing mobile Battle Royale games. Objective 2: Apply the KANO model to classify adolescent satisfaction characteristics in the mobile gaming environment. Objective 3: To employ PLS-SEM to model the structural relationships between user engagement, user satisfaction, and loyalty towards mobile gaming. Objective 4: To assess the contribution of adding ANN to the predictive capacity of the PLS-SEM model, specifically in material quality and satisfaction of adolescents.

1.7. Thesis Significance

This study is important for three reasons.Theoretical Contribution: The present work contributes to the literature through an innovative hybrid model integrating KANO, PLS-SEM, and ANN that extends research on UE and gaming satisfaction by fusing behavioral modelling with a predictive approach (Barsalou & Klaus, 2024; Fayyaz et al., 2025). Practical Contribution: Implications of this study shall help game developers, user experience designers, and policymakers in personalizing game parameters for improving adolescent satisfaction and instilling safe gaming practices (Bae et al., 2023). Societal Contribution: The results of this study would contribute to understanding adolescent gaming behavior and promoting digital literacy and health in a digital society for teachers, parents, and policymakers (Hasan et al., 2024; Islam et al., 2024).

1.8. Thesis Outline

The rest of this paper is outlined as follows: Chapter 1: Introduction, background of the study, and the problem statement. Chapter 2: Literature Review of Game Play Behaviors, Satisfaction Modelling, and Hybrid Analytical Techniques. Chapter 3: Methodology The research procedure, comprehensive of data gathering and analyses techniques used, is elucidated. Chapter 4: Results and performance of the hybrid model. Chapter 5: Implications for process and theory. Chapter 6: Summarizes the research and presents a discussion of its limitations & implications for future research.

CHAPTER 2

SYSTEMATIC LITERATURE REVIEW

2.1. Introduction

The gaming industry has changed significantly in the last ten years, and mobile Battle Royale games are one of the most popular offspring that combine survival, competition multiplayer, and connection with real-time opponents. Games like PUBG Mobile, Garena Free Fire, and Call of Duty: Mobile have revolutionized digital entertainment, especially for teenage players, which forms a significant chunk of the gamers in South and South-east Asia (Hamari & Sjöblom, 2017). Increasing smartphone penetration, 4G network growth, and digital social network development have contributed to the opportunity for mobile gaming adoption (Rahman & Mia, 2021). However, the ways in which adolescents use social media for aesthetics, social connectedness, or to boost their moods are largely uncharted. An Overview of: Literature on Adolescents Gaming and Media Consumption Battle Royale Games Hybrid modeling from data science. It integrates theoretical underpinnings for the application of the KANO model, PLS-SEM, and ANN methodologies. Specifically, the goal is to form a data-driven hybrid model that incorporates the socio-cultural Context of Bangladeshi adolescents while ensuring sound methodological rigor in its development (Lee & Suh, 2021).

2.2. Information Sources

The authors searched multiple academic databases and digital libraries to include conceptual and investigative shifts in an extensive literature review. The following sources were consulted for this study. Databases used for sourcing the articles included Scopus, Web of Science, IEEE Xplore, SpringerLink, ScienceDirect, and Emerald Insight were the source databases. Appendix sources: ACM Digital Library, Google Scholar, and ResearchGate for grey and working papers. Search period: January 2015–October 2025. Keywords: “Mobile gaming behavior,” “Battle Royale,” “Adolescent Preference,” “Gaming satisfaction,” KANO model, PLS-SEM, Artificial Neural Network and Bangladesh. An optimized search was performed using the Boolean operators AND, OR, and NOT. For example: The search terms (“Battle Royale” AND "mobile games” AND ("adolescents" OR "youth") AND ("KANO" OR "PLS-SEM" OR "ANN").

To maintain the quality and reliability of the content, we selected only articles from peer-reviewed journals and conference proceedings, in addition to PhD theses. Findings related to categorizing content in non-academic sources (e.g., blogs, YouTube analytics, and gaming community forums) were omitted on methodological grounds (Kitchenham & Charters 2007).

2.3 Key Review Questions (RQs)

The review is guided by four mains research questions that address the central components of the hybrid framework:

RQ1. What are the psychological, social, and game design motivations behind adolescents' selection of mobile Battle Royale games?
RQ2. Can the KANO model be used to categorize adolescent satisfaction attributes in a mobile gaming context?
RQ3. Application of PLS-SEM to model structural relationships among user engagement, user satisfaction, and loyalty in mobile games.
RQ4. How does ANN enhance the PLS-SEM model's predictive power for instrumental quality and optimal adolescent satisfaction measures?

2.4 Search Strategy

To ensure that the literature review addressed all RQs in Section 2.3, a strict search strategy was implemented. The main purpose of this search strategy was to obtain high-quality peer-reviewed studies on preference analysis of Royale mobile game and used analytical hybrid model of KANO, PLS-SEM, ANN.
It followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement (Moher et al., 2015) to increase10 transparency, reproducibility, and methodological quality. In searching for full literature, some commonly used and familiar databases and academic registers were searched using the above keywords and Boolean combinations.
A series of stages–planning, identification, screening, and selection–were applied in this method to return the most relevant and high-quality reports. In the initial stage of planning, all research questions were concerned with central concepts (such as adolescent gaming behavior, satisfaction, and hybrid modelling). In the second search phase, the above-mentioned topics were combined with relevant terms and their synonyms, allowing extensive coverage of the search strategy.

Table 1. Search terms and mapping from review questions

1	RQ1	"adolescent", "youth"
		"Battle Royale, "mobile game"
		"motivation", "behavior", "engagement", "design features"
2	RQ2	"KANO model", "customer satisfaction"
		"gaming" OR "mobile gaming"
		"Must-be", "delighter", "satisfaction attributes"
3	RQ3	"PLS-SEM", "structural equation modeling"
		"Gaming behavior", "user satisfaction", "continuance intention"
4	RQ4	"ANN", "neural network"

		“PLS-SEM”, “hybrid modeling”
		“Prediction accuracy”, “user satisfaction”

2.5 Eligibility Criteria

To select only high-quality and contextually relevant studies, explicit eligibility criteria were defined. Studies needed to be peer-reviewed and directly related to the research questions. Relevant types of literature included journal papers, conference papers, methodological studies, empirical studies, and related book chapters (Kitchenham & Charters, 2007). Preference was given to papers that presented empirical data, a modeling approach, or comprehensive theoretical models of mobile gaming behavior. Studies were excluded if they were unpublished, not peer-reviewed, or related to gaming platforms other than mobile (for example, PC or console) gaming (Rahman & Mia, 2021). Titles not in English, Repetitions, or Articles without Empirical Data/Unrelated to Modelling Frameworks were removed. This systematic winnowing procedure allowed for the trustworthiness, reliability, and validity of methodologies used in those articles culled in this Research Review (PRISMA) (Moher et al., 2015). The flow of screening and inclusion can be viewed in Figure 2: PRISMA Flow Diagram.

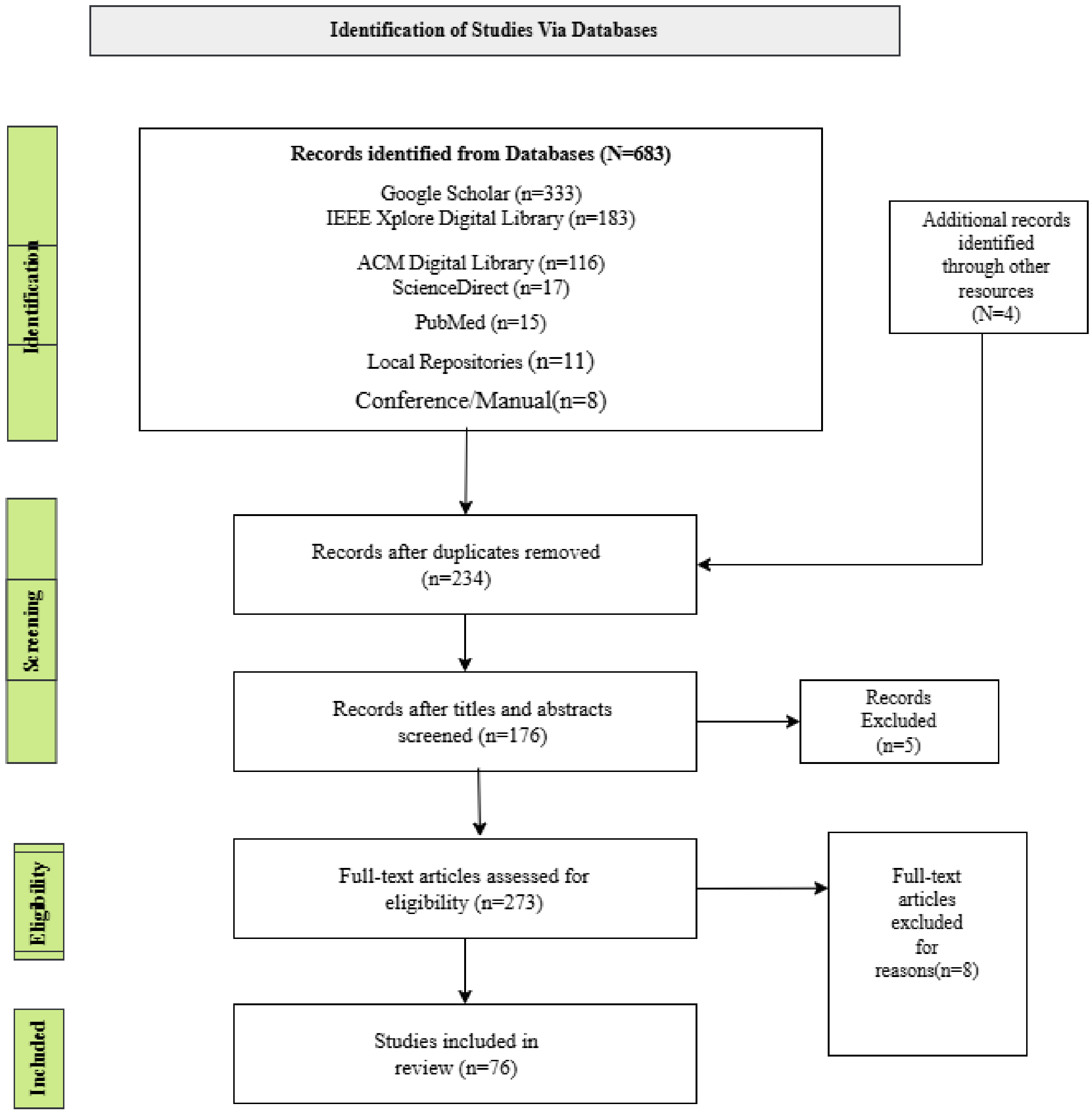


Figure 2. PRISMA flow diagram

2.6 Review Findings

The literature reviewed offers insights into adolescent gaming behavior, satisfaction modelling, and data analysis approaches. The findings are organized thematically, addressing the psychological, social, and design-related drivers of gaming engagement, the application of the KANO model, methodological challenges, identified research gaps, and the contributions of this study.

2.6.1 Motivational and Psychological Drivers

The motivational and psychological nature of adolescent gaming preferences is related to the basic human needs perspective based on Self-Determination Theory (SDT), where competence, relatedness, and autonomy are considered key motivators (Ryan & Deci, 2000). In Battle Royale video games, such needs are satisfied through beating others in battle, acting and having social connections with other players, and self-presentation (Rigby & Ryan, 2011). Yee has also argued that GDE-based motivational components, such as instant feedback and social reward from comrades, can be forged into a motivating force towards long-term commitment (2016). In addition, "flow," a state of heightened engagement in mental activity, has been linked to higher satisfaction and longer visits (Nacke et al., 2017).

2.6.2 Applicability of the Methods

Methodologically, the KANO model for classifying game elements based on their impact on user satisfaction has been effectively utilized. It also categorizes aspects as basic, performance, or delight quality features. The essentials are good gameplay, matchmaking, and a strong anti-cheat system. Methodologically, the KANO model of categorizing game elements according to their effect on user satisfaction has been effectively utilized. It maps features into must-haves, performance drivers, and delighters. The basics are solid gameplay, matchmaking, and a competitive anti-cheat. Performance stats to allow for an even playing ground in the gameplay, visual appeal, and interface quality. Exceeders, such as temporary assets and novel rewards, go out of their way to satisfy users and have a higher return rate for satisfaction (Chen & Chou, 2020). Therefore, the KANO model provides a manageable method for segmenting satisfaction drivers in the mobile gaming context. There is also a significant use of PLS-SEM for modelling user behavior in games. It can explore causal relationships and mediating effects, so it is appropriate for research with latent variables and small sample sizes, such as adolescent gamers. Hair et al. (2019) and Lee and Suh (2021) maintained that perceived enjoyment, social presence, and challenge determine the continuance intention for mobile games. PLS-SEM provides a versatile and powerful tool for measuring these multidimensional behavioral models. Finally, combining Artificial Neural Networks (ANN) with PLS-SEM has the potential to improve the predictions of user behavior models. Although PLS-SEM is applicable to confirmatory modeling, it is complemented by ANN because the results provide nonlinear relations and accuracy of prediction. Ooi et al. (2016) showed that one can combine the two methods, which leads to improvement factors reaching 25% in model predictive ability, with multicollinearity being also accounted for. While a complete realization of such a hybrid model is beyond the scope of this thesis, it suggests a promising direction for further gaming analytics research.

2.6.3 Challenges and Pitfalls

The sociocultural context also plays a major role in defining and accepting the gaming behavior of adolescents in Bangladesh. Family relationships, peer bonding, and limited access to recreational facilities act as facilitators of increased dependency on mobile games for communication and pleasurable experiences among Bangladeshi youth (Rahman & Mia, 2021). Furthermore, gaming involvement is influenced by socioeconomic status and parental attitudes toward gaming (Islam and Habib, 2020). Such cultural differences in attitudes reiterate the need for context-specificity in applying behavioral models and data interpretation. Thus, any suggested hybrid model needs to be adapted to portray the life experiences and needs of Bangladeshi adolescents.

2.6.4 Research Gap

According to the information from our study, this gap in the research literature primarily appears as a dearth of extensive investigation into the play activities of young teenage people. There are even fewer data available for analysis in this regard as regards the specific features causing high satisfaction and involvement in mobile Battle Royale games. Therefore, games with distinctive examples that feature aggressive tactics have attracted widespread approval among Bangladeshi people of all ages and walks of life. Although existing research mostly discusses the negative aspects of gaming, such as addiction, there is no literature that deliberates on what specific characteristics bring a teenage individual satisfaction reward and how these can be integrated into a predictive model. This study creates a new model of hybrid analysis that incorporates the KANO model, partial least squares structural equation Modeling (PLS-SEM), and the application of Neural Networks. It aims to break with tradition going back decades to understand how game attributes combine with respect to satisfaction and involvement, considering both linear and non-linear relations within teenagers' behavior. This calls for a specific approach that reflects the sociocultural properties of Bangladeshi youth and is consistent with their actual playing conditions.

2.6.5 Contributions of This Thesis

The current thesis contributes to this knowledge gap by developing a new context-sensitive conceptual model of adolescent gaming with strong theoretical and methodological foundations. At the heart of this paper is a hybrid model that combines the KANO model, PLS-SEM, and ANN. This holistic modeling benefits from such integrative treatment of the two types of environments to better predict player satisfaction in mobile Battle Royale scenarios. Unlike conventional satisfaction models, this hybrid model supports the classification of user preferences along with complex nonlinear representations of behavior and achieves better prediction while reducing model bias. In addition, the model is designed to be context-specific to Bangladeshi adolescents by aligning universally validated constructs of behavior with gaming practices and technology accessibility in that setting. Beyond conceptual progression, these results have policy and design implications. Specifically, the results of this research suggest that embedding cultural elements (traditional walking folk games) in digital gaming behavior is likely to promote responsible gaming and players' psychological health. Specifically, the results of this study suggest that integrating cultural elements (traditional walking folk games) into digital game-based experiences may enhance responsible gaming and well-being among players. This is consistent with the larger aim of creating technology for children that is culturally inclusive, developmentally supportive, and engaging.

CHAPTER 3
RESEARCH METHODOLOGY

3.1. Research Subject

The chapter will describe research design, population, sample, research model, as well as procedures followed in exploring mobile gaming preference for Bangladeshi teenage adolescents in specific BR games such as PUBG MOBILE and Garena Free Fire. The proposed research work uses a combined approach consisting of the KANO model, PLSSEM, and ANN models for the concurrent study of user satisfaction and behavior patterns (Hair et al., 2019; Ooi et al., 2016). The simultaneous consideration of these approaches enabled this research work to achieve multiple analytical goals. The characteristics of mobile gaming features are grouped based on must-have, performance, and excitement-based GERPs based on the application of the KANO approach (Chen & Chou, 2020; Berger et al., 1993). Second, we also utilized psychological and social constructs such as peer influence and user satisfaction in the PLS-SEM method, which have been discussed in relation to structural relationships in adolescent gaming behavior (see excitement) (Lee & Suh, 2021; Hair et al., 2019). Third, ANN is used to predict and validate causality determined from PLS-SEM, as it allows for the modelling of nonlinear relationships and makes the model more robust in terms of predictive capability (Ooi et al., 2016; Chong, 2020).This multiple-analytical approach strengthens the internal validity, predictive power, and interpretative depth of the study. It is particularly relevant to predict complex behavior dynamics among the youth generation of Bangladesh, one of the countries where digital technology has proliferated at an accelerated pace in recent times, but gaming behavior among youths has never been modelled before. Instead, mixed genetic and generative models are often proposed for emerging digital markets, where behavioral data may be sparse or nonlinear (Barsalou & Klaus, 2024; Srivastava et al., 2023). Methodologically and empirically, this research has value for the bibulation of game studies and for behavioral data science, namely for the integration between global analytics models with local socio-cultural context.

3.2.Study Framework

To address adolescents' preference and participation in mobile Battle Royale gaming, this study adopted a cross-sectional quantitative design. This is particularly useful when we would like to explore the associations between variables at a single point in time and is consistent with behavioral research that aims to construct predictive models (Creswell & Creswell, 2017). It also facilitates the deliberate testing of user satisfaction behaviors and the identification of mediating effects between psychological, social, and game design elements (Chinawong et al. 2013). A structured online questionnaire was promoted on digital platforms (Internet websites) and networks (social media groups, university mailing lists, and communities of online gamers with popular use among participants: Discord servers of Call of Duty Mobile, PUBG Lite, and Fortnite). Online surveys have a number of potential advantages for cognitive and behavioral research, including being efficient, having greater geographical reach, cost-effectiveness, higher proportions of comfort for respondents when expressing their preferences in an anonymous situation (Evans & Mathur, 2005; Lenhart et al., 2015). Increasingly, such studies are common within the context of teenager studies carried out within a digital setting, within which online communications have become the norm and anonymity is associated with more truthful responses (Granic et al., 2014). For this study, the tools and models used are simultaneously the KANO Analysis, the Partial Least Squares Structural Equation Modeling (PLS-SEM), as well as the Artificial Neural Networks (ANN). Finally, to test how all latent constructs are interlinked as far as the study is concerned, that is, in regard to the excitement, peer influence, appeal of the features, and also the trial-related aspects of behavior, the study applies the Partial Least Square (PLS) structural equation model. Specifically, "this approach is highly relevant to studies that involve complex behavioral data. With such data, it is possible to test both measurement models and structural models simultaneously, even for relatively small sample sizes" (Hair et al., 2019, p.27; also see Sarstedt et al.,2020). Its application to game play studies has been proven to be valid insofar as it is capable of measuring player engagement levels as predictors of game play loyalty results (Lee&Suh,2021). The third step is the application of the ANN analysis that enhances such models through verification and improvement of the results found in the previous stage via the application of the PLS-SEM. For one, such models "differ significantly from traditional linear approaches to modeling that assume linear relationships among predictors" and estimate nonlinear and inter-active relationships among predictors. Thus, apart from analyzing the ability to predict results, such models also have the capacity to create rankings within which predictor variables have been trained based on algorithms to highlight interpretability within results. Thus, the application of such models is appropriate within the context of consumer behavior studies concerning the need to address such issues as predictability and ranking within results (Ooi et al.,2016; also, in application within different settings, as described in more detail through Chong,2020). The population of interest was adolescent players participating in Battle Royale mobile games. Participants were recruited from universities and online game forums to include diverse demographics and levels of experience. This sub-sample was selected because this segment of the population has high participation in mobile gaming and is increasingly being recruited for digital cognition studies (Rahman & Mia, 2021; Ahmed et al., 2023). Two instruments were used in the survey. The KANO questionnaire was used to evaluate satisfaction with game features to determine whether specific features of a game were perceived as performance predictors, performance payoffs, or exciters. The other was a PLS-SEM survey with established scales that measured constructs including enjoyment, immersion, responsiveness, social interaction, and continuance intention (Hamari & Keronen, 2017; Lee & Suh, 2021). The data analysis stage enunciation of the game features-brain functions segmentation will thus form a starting point for structural modelling. Finally, PLS-SEM verified the reliability and validity of the constructs and the H relationships tested through path analysis, loadings, factoring weights, and effect sizes (Hair et al., 2019). Cross-validated the PLS-SEM results through ANN to verify the accuracy of the prediction of the most vital obsessions that produced support and loyalty among users (Chong, 2020). The results from the three methods were triangulated during interpretation and synthesis to ensure validation and robustness. The consistency in the findings between the methods allowed for several explanations for the determinants of adolescent mobile Battle Royale play. The implications for the game industry, psychological well-being, and digital consumption behavior are discussed, and practical applications for developers, marketers, educators, and policymakers are provided. Theoretically, hybrids derived from these models may provide practitioners with an approach to generate and disseminate culturally reflective, engaging, and ethical mobile gaming experiences for adolescent users (Granic et al., 2014; Barsalou & Klaus, 2024).

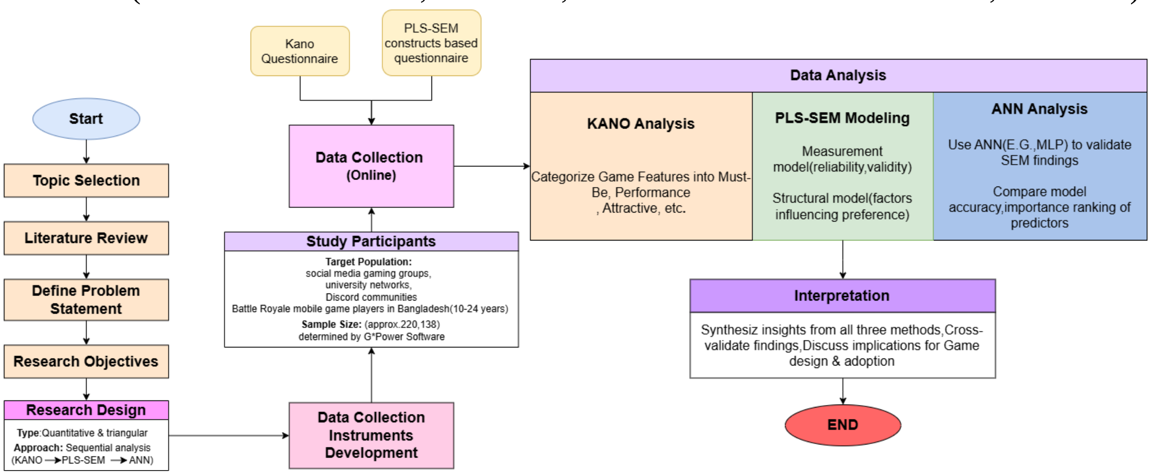


Figure 3. Study framework

3.3 Study Population

Adolescents from Bangladesh who played mobile Battle Royale games were the subjects of this study. The population of interest is 10-24 year old or early adolescence to young adults. According to both global and regional estimates, adolescents and young adults are the most active users of mobile gaming. Studies indicate that members of this generation frequently engage in interactive digital experiences, such as competitive mobile gaming (e.g,. PUBG Mobile, Free Fire, and Call of Duty: Mobile) (Pew Research Center, 2024; Statista, 2023). Given that games in these genres are of high interest to this age group early on, they are ideal for studying gaming preferences, behavioral engagement, and satisfaction-related constructs. In addition, previous behavioral studies from South Asia indicate a rise in digital usage and participation among Bangladeshi youth, often supported by rampant smartphone and mobile Internet access (UNICEF, 2022; Ahmed et al., 2023). Mindful gaming: Young people who prefer playing on smartphones have the same motives but seek alternatives Since adolescents in this group not only heavily engage in mobile gaming but also use games for social interaction, identity construction, and relaxation (Granic et al., 2014). By segmenting the population and Net-Gen group, this study was able to record cohesive socialistic aspects that may impact gaming behavior in a highly digitizing society such as Bangladesh.

3.4 Sample Size and Sampling Procedure

3.4.1 Sample Size

A purposive non-probability sampling method was used in this research to filter out users who actively played Battle Royale mobile games. This sampling method is used when the object of research demands that participants possess a specific set of traits (game experience, familiarity with a platform, or game preference) that are directly related to the analysis of focus in the study (EBSCO Research Starters, 2025; Research Method. Net, 2023). In this sense, the purposive sampling technique provided an opportunity to purposefully select young adult and adolescent gamers (who play PUBG Mobile, 'Free Fire', Call of Duty: Mobile, etc.) in line with the constructs theoretically studied. The sample size was calculated using G*Power 3.1, which is widely used for statistical power analysis. The KANO feature classification required the smallest sample size estimation (220 respondents) per their estimated effect sizes and model complexity, to obtain a stable distribution of categories as well as perform reliable classification of satisfaction-vs. For PLS-SEM, which is a path model analysis for multiple latent variables, the minimum sample size was estimated to be 138 respondents. Such an estimate is in agreement with the guidelines followed by SEM researchers for preserving the adequacy of statistical analyses and avoiding committing Type II errors (Kock & Hadaya, 2020; Kock & Hadaya, 2018; jasemjournal.com, 2020). To improve the predictive ability and external veracity of the hybrid model, both the PLS-SEM approach (with data inlet first) and ACES method combined should be ensured beyond their minimum sample sizes; hence, more than 250 responses were expected to be collected. A larger sample size with hybrid modeling frameworks can increase the stability of the model, enable training of more complex neural network structures, and lead to a better feature importance ranking. Such an issue is of particular interest, for example, when adopting nonlinear modeling methods such as Artificial Neural Networks, as overfitting can also be reduced by adding more and diverse data (Hair et al., 2019; Memon et al., 2020).

3.4.2 Sampling Procedure

Respondents were subjected to open-label inclusion criteria to optimally meet the study needs and guarantee homogeneity of the sample. This included the following criteria: (1) age group between 10 and 24 years, (2) active involvement in playing mobile Battle Royale games programs; PUBG Mobile, Free Fire, and similar types of games, and (3) present resident in Bangladesh. The chosen age group is representative of the adolescent and young adult populations, which are also the most active mobile gaming users in South Asia (Pew Research Center, 2024; UNICEF, 2022). The active engagement criterion sought to prevent participants from theorizing in abstraction from regular, first-hand experience with the game genre of interest and minimize error in response measurement consequent to that. Purposive sampling is seen as a universally accepted methodology for participant selection addressing specific existing criteria of eligibility to answer research questions. This ensures the context validity and reliability of the analyzed research data, especially in cases involving research pertaining to the behavioral responses required by specific users of work (EBSCO Research Starters, 2025; Rahi, 2017). The inclusion criteria used in such research improve the validity of sampling for research carried out strategies and does not dilute but rather contributes to the validity of subgroup-specific behavioral research findings.

3.5 Data Collection

A convenient in terms of access and anonymity, the latter being particularly relevant when including adolescents online questionnaire was used to collect data. (RMIT Research Ethics, n.d. University of Sheffield, 2024). Data were collected from April 8 to June 22, 2025. This is a common method used in long-window study designs, where online surveys are administered across time close to the response date, involving diverse populations over large areas (Backer et al.

3.5.1 Survey Design

The survey construct was systematically fashioned to be consistent with each of the two study objectives: feature classification application via the Kano model and structural relationship modeling utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM). The survey was split into two major sections, the goal of each being to collect data types supported by the analytical model.

3.5.1.1 Kano Model Questionnaire

User satisfaction with particular game features was evaluated in the first part of the survey, employing the Kano model approach [35], which is frequently used in product development and service design to categorize user attitudes. These parameters were grounded from previous studies, such as reward system, graphics, quality of the map, and multiplayer. The parameters considered were rated using two regular questions of the Kano method. Functional question, "How do you feel if this function is provided?" Dysfunctional question, "How do you feel if we remove this feature?" The respondents rated these questions using a five-point Kano method, which includes Like it, Must be, Neutral, Can live with it, and Dislike it. These two questions were decoded from the Kano evaluation matrix for classifying satisfaction for every feature (Barsalou & Klaus, 2024). The characteristics, which are grouped based on the status, fit into one of these six standard Kano categories, namely Must-Be Satisfied (M), Performance, Attractive Factors, Reverse factors (R), and Questionable (Q; Srivastava et al., 2023). The categorization method was important in determining which elements from the game satisfy the users and what 7 Palos (2004).

3.5.1.2 PLS-SEM Questionnaire

The second part of the survey aimed at deriving constructs associated with modeling human behavior through Partial Least Squares Structural Equation Modeling (PLS-SEM). This survey component was prepared to examine the potential role of selected characteristics of a game on user engagement, user satisfaction, peer influence, and continuance intention. Every factor assessed within this survey component was taken from existing, proven scales within digital human behavior and computer gaming research. The scale utilized within this component of the survey is linked to the degree of agreement characterized by (1) Strongly Disagree and (5) strong agreement.This information was used to develop the measurement model (validity and reliability of the latent variables) and structural model (causal relationships between the different constructs). PLS-SEM was chosen because it can accommodate complicated models with multiple indicators, is appropriate for exploratory studies, and performs well in small-to-medium samples (Hair et al., 2020). It also provides the investigator with the capability to test for potential indirect effects and investigate how different game features affect not only satisfaction but also more general behavioral constructs, including loyalty and usage rate (Sarstedt et al., 2020).

3.5.2 Survey Distribution

An online version of the survey was adopted for pragmatic reasons regarding reach (i.e., to include a wider range in geographic scope among adolescents and school organizations with varying existence of technology) and access/reach in schools where digital natives are present. The use of online administration was selected for the maximum reach among gaming smartphone usership with the least biasing effects on anonymity and participant access. This approach is in line with established digital youth research, which requires that mobile phone and internet access is a prerequisite to engage tech-savvy participants (Islam et al., 2024). To achieve maximum reach in the target population, multiple digital platforms were employed strategically. Universities and colleges are one of the main hubs. The questionnaire link was posted on university mailing lists, student forums, and academic organizations in higher education institutions. Implemented in this way, the intervention could directly reach many adolescents and young adults, who are both digitally literate and may belong to online gaming communities (Islam et al., 2024). Gaming Communities on social media networks and voice chat servers were also exploited. The survey link was posted on Facebook and Instagram as well as in gaming groups and Discord channels focused only on Battle Royale mobile games such as PUBG Mobile, Free Fire, and Call of Duty Mobile. They are the focus point of the target population's gaming culture and, therefore, a highly appropriate field for data collection (Klaus & Barsalou, 2014). Moreover, a variety of other social media sources (such as Twitter, Instagram, and TikTok) have been used for promotional dissemination. From these platforms, a predominately adolescent and young adult user base has the potential to amplify visibility and uptake. Engagement and survey dissemination were further facilitated by peer sharing, reposting, and story mentions (Srivastava et al., 2023). To maximize the user experience and response rate as much as possible, we designed our survey for two different types of platforms: desktop-web and mobile. This allowed people to access and complete the survey using any means they had available, which increased access and ease of assimilation (Islam et al., 2024). Mobile-first thinking was important, especially considering that users would probably interact with the tool during their daily media consumption.

3.5.3 Data Collection instrument and Procedure

The data collection in the study was conducted online only, aiming to reach a participant sample as available, convenient, efficient, and contemporary as possible among today's digitally active youth. Dissemination channels comprised academic networks (e.g., university mailing lists), youth-centered forums, and gaming niche communities on Discord, Facebook, Instagram, and Telegram. This was a distribution approach that also facilitated reaching out to people who are integrated in playing through very active mobile gaming environments, such as urban and semi-urban areas of Bangladesh (Islam et al., 2024; Srivastava et al., 2023). To ensure statistical power in the stages of feature classification and structural equation modeling, sample size estimations were performed using G*Power 3.1.9.7. The Kano classification has also been tested for the same analysis in their situation. Symptoms At Kano categorization, we performed a chi-square goodness-of-fit test for 6 categories (alpha = 0.05, power = 0.95, w=0.30). The consequent least desirable of 220 participants also yielded adequate power to detect meaningful differences between satisfaction levels (Cohen, 1988; Yusof et al., 2018).

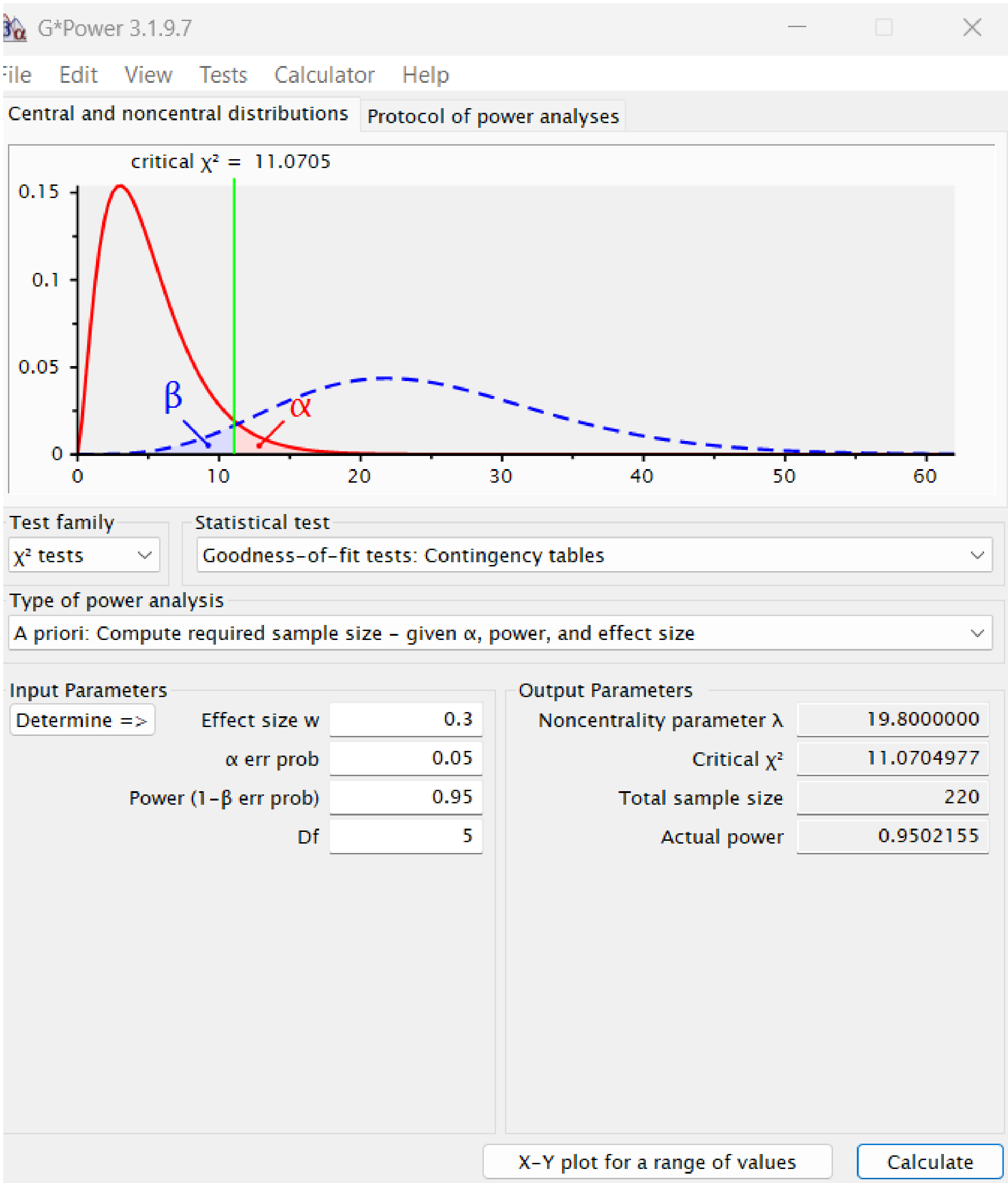


Figure 4. G*Power output for minimum sample size estimation for Kano Analysis

In figure 5, For the PLS-SEM phase, sample size determination followed linear multiple regression modeling, accounting for nine predictors (five theoretical constructs and four demographic control variables). Assuming a medium effect size ($f^2 = 0.15$) and the same confidence and power levels, 138 cases were found to be sufficient to validate the model's path coefficients and effect sizes (Memon et al., 2020; Kock & Hadaya, 2018). The two-stage estimation method allows our research to robustly establish existing analytical thresholds, enhancing both reliability and predictive power.

More so, especially for the ANN part. Therefore, in order to ensure that the embarrassing side of the tool was never uncovered, a two-level verification procedure was utilized to assess the psychological level of content for the Wen questionnaire. Firstly, four independent academicians evaluated the questionnaire for content validity. Their views shaped modifications of expressions familiar to students (Polit & Beck, 2006). Secondly, reliability assessment was conducted using Cronbach's alpha coefficient. All effects tested for content validity using Cronbach's alpha showed values higher than the threshold of 0.70, therefore establishing sound internal consistency between items (Nunnally & Bernstein, 1994; Hair et al., 2019).

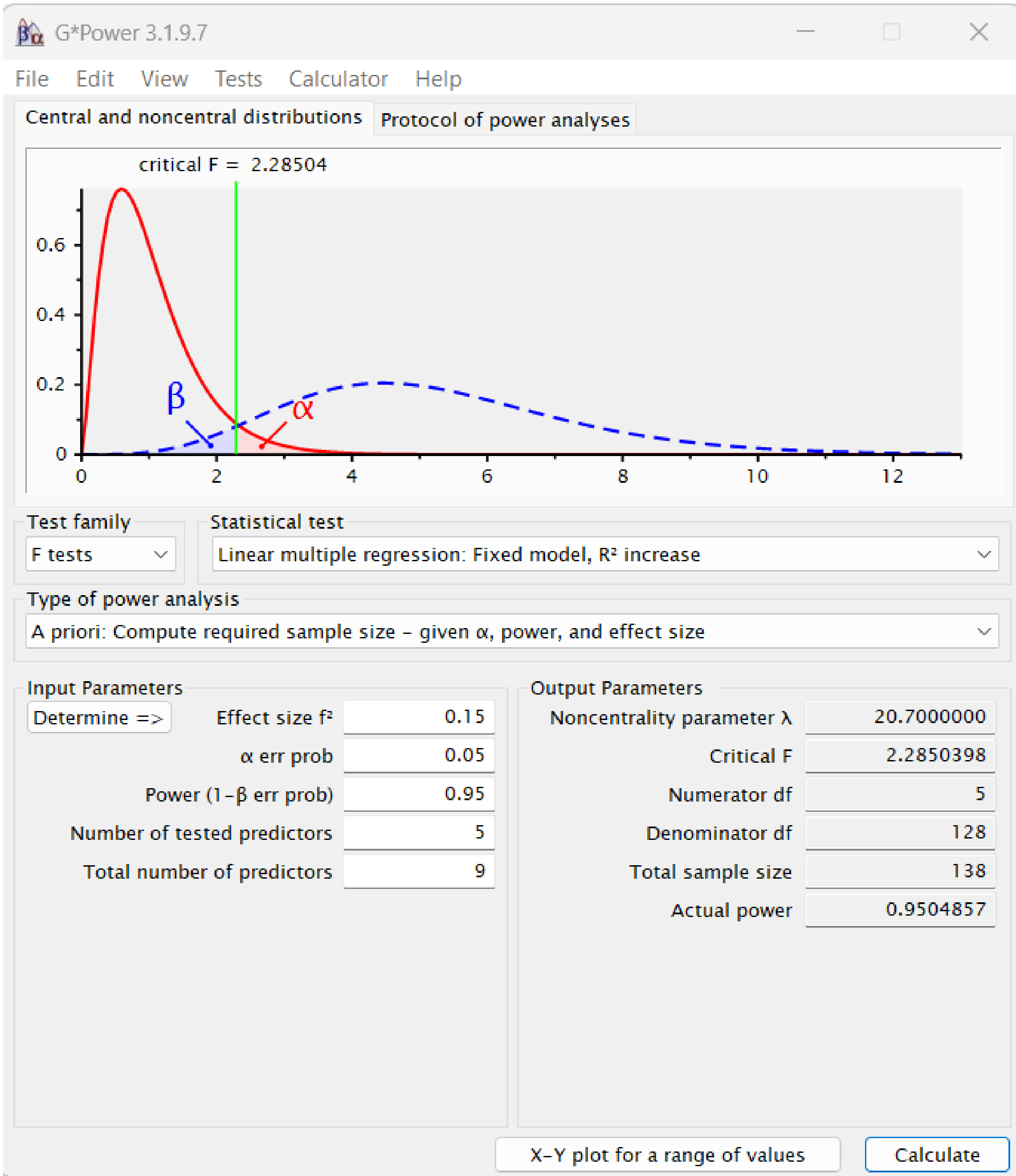


Figure 5: Minimum sample size estimation for PLS-SEM

To ensure content and concept validity of instruments, this study adopted a two-step process of psychometric validation based on relevance, clarity, and adaptation within the context. A face content validity of each of the items was separately assessed by four domain specialists having varied backgrounds. Keeping in mind the feelings of those who might be familiar with language development and youth (Polit and Beck, 2006), we have also improved the readability and comprehensiveness of the items for the youth within their respective age groups. The ethics of data gathered through this study have been taken care of. The study is completely anonymous and free. No personal details have been or will be taken. Once you start completing this questionnaire, on page 1, you will find an agreement or consent that defines the aims and objectives of the study. It also provides privacy and respect if you and you alone decide not to be included further if you change your mind after taking this survey of our questions and desires. Every research, according to international ethics (BPS, 2021; UNICEF, 2022), carried out on or among youth is bound by or should conform to the above context.

3.6 Data Analysis

Data and material have been gathered to satisfy completely the objectives of the research using three-level methodological work involving exploratory, structural, and predictive analysis. Different stages of this work provide input for different analyses. To start, the Kano Model Analysis helps identify what role various elements of the Battle Royale mobile game have played in terms of consumer satisfaction. This allows us to be absolutely certain that some element was integral as opposed to just delightful, yet unexpected. Subsequent to this analysis, using Partial Least Squares Structural Equation Modelling (PLS-SEM), we test the model of assumed relationships between latent constructs and determine path coefficient values while also grading the model's fitness for explaining teenage satisfaction with games and returning to re-play them. (Hair et al., 2020; Henseler et al., 2016) Finally, using the ANN method, we have access to the viability of non-linear relationships, and more important, provide explanations for what plays an important role in capitalizing more momentum out of the model solution in PLS-SEM. Notably, this approach also allowed this model represented useful interaction terms and learning-oriented predictive variables. Moreover, this helped fill details that otherwise could never be known or measured using more traditional or simple linear analytical solutions (Ooi et al., 2016; Chong, 2013). This combined approach also allowed for interpretive insight (via Kano & SEM analysis) and for highly accurate predictions provided for analysis with the close forecasts provided via the ANN method, that collectively make this triangulation appear as an appropriate model structure for this type of research work within the adolescent gaming environment (Mikalef et al., 2018).

3.6.1 Kano Analysis

This was applied in the initial phase of research to see how certain attributes of Battle Royale mobile games affect the user satisfaction of adolescents. This is referred to as Kano analysis. The Kano model is a formal model that organizes product or service attributes into categories based on their capacity to create satisfaction. These include must-have attributes (the minimum expected standards that users expect, and where missing produce significant dissatisfaction), performance attributes (where quality increases linear buyer satisfaction levels as they are improved), and Attractive Attributes (where buyers do not have expectations but when present generate very high levels of user delight without dissatisfaction if not delivered). This taxonomy serves as a framework for the strategic prioritization of game design features, providing direction for developers on which factors to retain, improve, or craft anew to enhance engagement and loyalty among adolescent players (Kano et al., 1984; Matzler & Hinterhuber, 1998; Chen & Chou, 2020). Functioning and dysfunctional questions were then formulated for each selected sub-element (i.e., graphics quality, setting of rewards, possibility to cooperate with or compete against other players – multiplayer's interaction—possibility to postpone/on hold the game in case of latency) so that those could be rated according whether they apply or not. The functional item was formulated in a way that participants were asked about their attitudes to playing with the feature present in the game, and the dysfunctional item referred to how they would feel if it was not present. The respondents rated each item on a 5-point scale (Like it, Must be, Neutral, Can live with it, Dislike it). To make it easier for users to understand, the replies were matched against the Kano assessment grid in the questionnaires, and for each project attribute, they were given an A (Attractive), P (Performance), M (Must-Be), I (Indifferent), R (Reversal), or Q (Questionable) depending on the response pattern. In this way, based on what is found in adolescents' gaming experience (Berger et al., 1993; Barsalou & Klaus, 2024; Srivastava et al., 2023), the categorization of these collective replies yielded an estimation of which features have which kind of appeal, for aspects that matter most to users, and so forth. It is worthwhile to map all work in this area in a table (Table 2) across eight dimensions. Having completed these steps, the overall interpretation was that certain game elements are not just essential or enhancing but also delightful. This is a good thing, Correlational analysis may yield distinct values for position, indicating that they offer different outcomes in certain situations. Therefore, it is crucial to search for latent satisfaction drivers and make design recommendations.

Table 2. Kano Evaluation Table

			Dysfunctional				
			How do you feel, if you don't have the feature				
			I like it	**I expect it**	**I am neutral**	**I can tolerate it**	**I dislike it**
Functional	**How do you feel, if you have the feature**	**I like it**	Q	A	A	A	P
		I expect it	R	I	I	I	M
		I am neutral	R	I	I	I	M
		I can tolerate it	R	I	I	I	M
		I dislike it	R	R	R	R	Q

R = Reverse, **Q** = Questionable, **P** = Performance, **I** = Indifferent, **A** = Attractive, **M**= Must-be

3.6.1.1 Categorization of Features

To analyze the influence of each game feature on user satisfaction, we disassembled the Kano category frequency into two indices: positive (satisfaction) coefficient and negative (dissatisfaction) index. These coefficients were derived from the distribution of quartile participants' answers to the four key Kano categories: Attractive (A), Performance (P), Must-Be (M), and Indifferent (I). The coefficient of Better is calculated according to the following formula:

$$\text{Better} = \frac{A+P}{A+P+M+I}$$

The fraction of users who benefit from a feature positively when they have eight is measured by this index. A high Better value (close to 1) suggests that the property, as a satisfier or delighter, significantly increases satisfaction. In contrast, the worst coefficient is defined as:

$$\text{Worse} = -\frac{P+M}{A+P+M+I}$$

These coefficients make it possible to have a more detailed look at what users might expect and how they feel about certain game elements (Chen & Chou, 2020; Srivastava et al., 2023).With the calculated coefficients, it becomes possible to locate these points in 2-D better–worse scattergrams. The x-axis represents the better coefficient (range 0, 1), and the y-axis represents the worse coefficient (range −1, 0). Each game feature is assigned a single point between better and worse. This visualization method is helpful for comparing the relative impacts of features and capturing satisfaction patterns between adolescents who are gamers (Albuquerque et al., 2024).

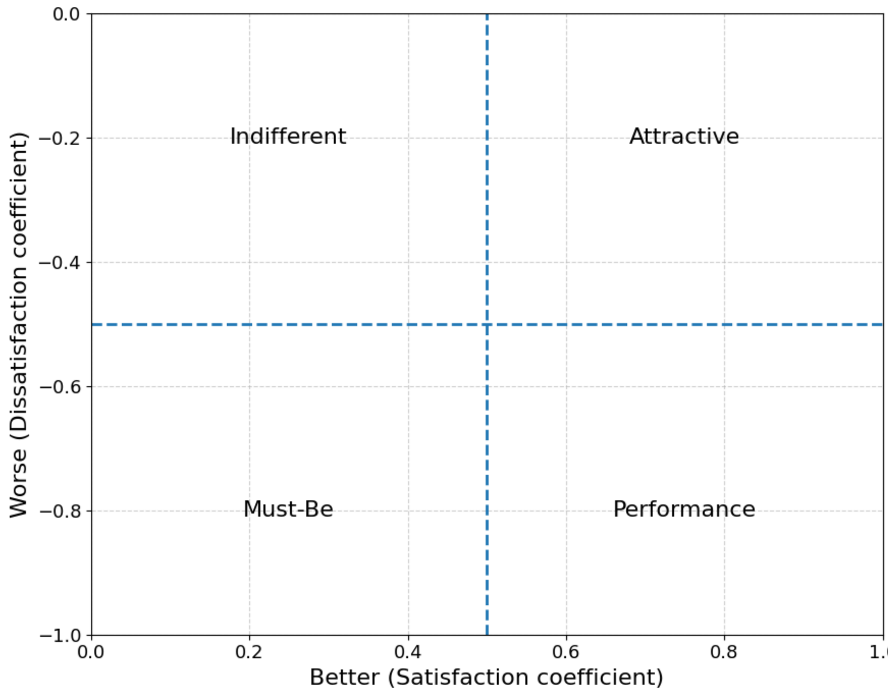


Figure 6. Better–Worse plot for Kano feature prioritization.

For interpretability, in figure 6 the plot is divided into four Kano quadrants by adding two dashed lines at the average Better and Worse values for all features. The line at the average Better value and the line at the average Worse value create the bounds for each quadrant. These four features can be used to classify a feature as Attractive, Performance, Must-Be, or Indifferent (Berger et al., 1993; Matzler & Hinterhuber, 1998).Third, the interpretation of these quadrants leads to strategic advice for prioritizing features. In the Attractive quadrant, features have high Better and low Worse values: when they exist, they surprise and delight users, but people do not expect them to be there. Performance features: satisfaction of these flows with their quality/quantity, Better and Worse are both large. Conversely, Must-Be features exhibit low Better and high negative Worse scores—worse outcomes that are fundamental disappointments to not have. Finally, Dependent characteristic importance scores low on both factors; therefore, they should not be production-specific, since the high or low presence of these features will not have a dramatic effect on satisfaction. Implications for practice Prior to future empirical research, this interpretative model has practical relevance for designers and developers seeking to maximize the gaming experience of adolescents in mobile games (Chen & Chou, 2020; Albuquerque et al., 2024; Barsalou & Klaus, 2024).

3.6.2 PLS-SEM (Partial Least Squares Structural Equation Modeling) Analysis

As shown in Figure 7, this study suggests a conceptual model to understand why adolescent attitudes toward BR mobile game environment conditions influence their satisfaction and continuance intention. The model incorporates system-level antecedents (device, interface, network, content and social influence) as well as play-experience consequences (smoothness, battery efficacy and graphics quality), to provide an expression of the technical/design input-output mechanism leading to behavioral-intention over time (Hair et al., 2019; Hair et al., 2022)

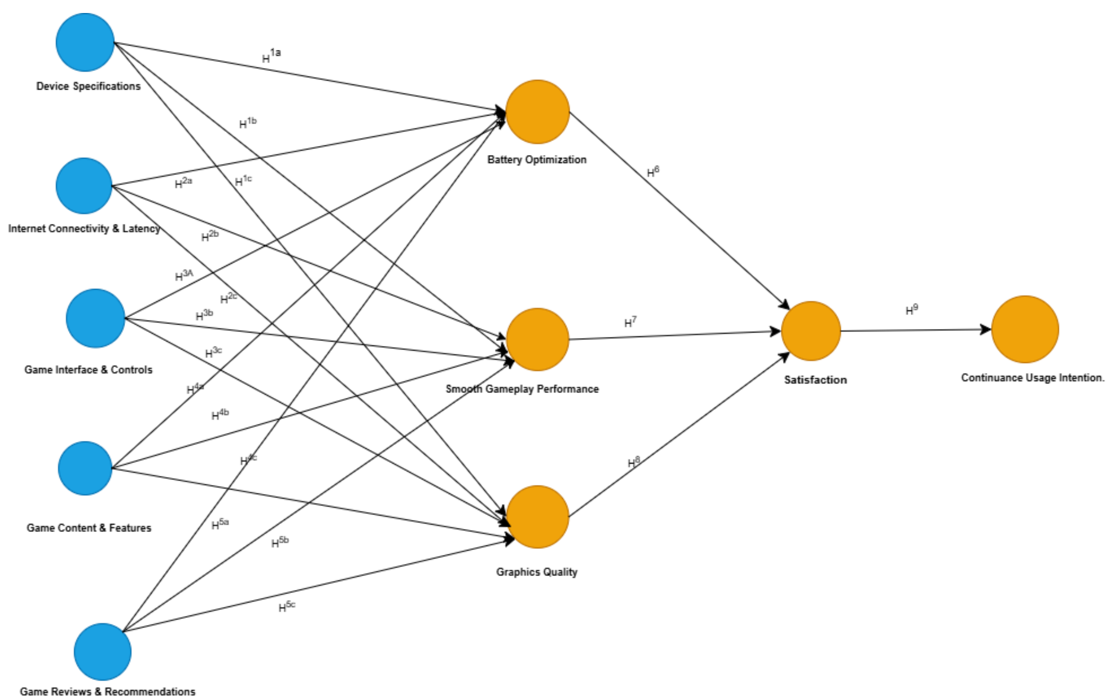


Figure 7. Conceptual model

The model comprises ten latent variables. There are five exogenous (independent) predictors: Device Specifications (DS), Game Interface and Controls (GIC), Internet Connectivity and Latency (ICL), Game Content and Features (GCF), and Game Reviews and Recommendations (GRR). The three mediators for gameplay experience were Smooth Gameplay Performance, Battery Optimization and Graphics Quality. These mediators describe the immediate aspects of the BR game experience that players encounter. Satisfaction (SAT) is considered an endogenous evaluation result, whereas Continuance Usage Intention (CUI) is the ultimate endogenous measure of users' intention to continue playing in the future (Hair et al., 2022; Sarstedt et al., 2019). Figure 7 Structurally, technical, and design conditions (DS, GIC, ICL, GCF, and GRR) affect the perceived quality of gameplay (SGP, BO, and GQ). Overall satisfaction is the result of these gameplay experience determinants and results in a continuance usage intention. Thus, along the directions shown in Figure 7, this study proposes the following hypotheses:

H1a: Device Specifications positively affect Battery Optimization.
H1b: Device Specifications positively affect Smooth Gameplay Performance.
H1c: Device Specifications positively affect Graphics Quality.
H2a: Internet Connectivity and Latency positively affect Battery Optimization.
H2b: Internet Connectivity and Latency positively affect Smooth Gameplay Performance.
H2c: Internet Connectivity and Latency positively affect Graphics Quality.
H3a: Game Interface and Controls positively affect Battery Optimization.
H3b: Game Interface and Controls positively affect Smooth Gameplay Performance.
H3c: Game Interface and Controls positively affect Graphics Quality.
H4a: Game Content and Features positively affect Battery Optimization.
H4b: Game Content and Features positively affect Smooth Gameplay Performance.
H4c: Game Content and Features positively affect Graphics Quality.
H5a: Game Reviews and Recommendations positively affect Battery Optimization.
H5b: Game Reviews and Recommendations positively affect Smooth Gameplay Performance.
H5c: Game Reviews and Recommendations positively affect Graphics Quality.
H6: Battery Optimization positively influences Satisfaction.
H7: Smooth Gameplay Performance positively influences Satisfaction.
H8: Graphics Quality positively influences Satisfaction.
H9: Satisfaction positively influences Continuance Usage Intention

PLS-SEM was selected to analyze and model the structural relations among different game features and user preferences, being a tool designed for prediction purposes and adequate complex models with multiple constructs as well as indirect paths (Hair et al., 2019; Hair et al., 2022)

3.6.2.1 Parameter Settings of PLS-SEM

In the PLS-SEM analysis, some key parameters were set to ensure that the model was robust and valid. The measurement model for internal consistency reliability of Cronbach's Alpha (≥ 0.70) and Composite Reliability (≥ 0.80), convergent validity via Average Variance Extracted (AVE) (≥ 0.50) were assessed. Discriminant validity was examined using the Fornell-Larcker criterion and HTMT. The structural model was assessed by examining path coefficients (β) using bootstrapping (t-values > 1.96, p-values 0.75), effect size (f^2) to determine predictor impact (with thresholds of 0.02, 0.15, and 0.35 for small, medium, and large effects, respectively), and predictive relevance (Q^2), which should be more than 0.Multicollinearity was tested by means of Variance Inflation Factor (VIF), with the value of 5 suggesting trouble. The bootstrapping method with 5,000 subsampling samples was employed for obtaining statistical significance. The result yielded t-values, standard errors, and p-values for the path coefficients, which enabled a thorough analysis for the gaming behavior and satisfaction exhibited by adolescents.

3.6.3 ANN (Artificial Neural Networks) Analysis

To identify potential predictor variables, a procedure of ANN was employed by the authors of our study. This marked phase three of our investigation, preceded by feature categorizing based on the principles of Kano (identifying feature categories prior to the other methods) and PLS-SEM examination of those features. These predictor variables have previously been established by the former and now are only checked in respect to their significance by ANN and have teased out the nuances of nonlinearity that may not have been fully revealed by PLS-SEM on its own. Recent scholarship indicates that by incorporating ANN investigation alongside SEM in situations comprising activity and technology uptake allows an exponentially higher degree of predictive accuracy (Pizarroso et al., 2023; Pizarroso et al., 2022).For the purpose of our undertaking, a multilayer perceptron or MLP stem-and-root backwards-fed connectionist network was applied through SPSS v25 software (IBM Corp., 2024) to reflect its effectiveness and preeminence as an ever-present effective solution form of ANN in relation to prediction of human action tasking models (Kumar & Sharma, 2020). These models were designed by creating three layers of computing – an input layer, an initial layer or "hidden layer" comprising only a single layer cell named "node" within SPSS software requirements needed to comprise initial inputs through action tasking processing to reach prediction outputs through effective action tasking computation by an initial layer of "hidden" action tasking processing denoted by layer "node" requiring single cell inputs through action tasking computation by an initial layer of just "single" action tasking through processing requiring initial inputs by a subsequent single layer or "hidden" layer action tasking processing by an initial layer of only "single" action tasking processing requiring initial layer cell or "node" action tasking computation through single computing layer cell or "node" ann initial inputs denoted by single layer or "hidden" layer nodes by an initial layer of only "single" action tasking processing – and an "output" layer. The total possible cell or "node" inputs of all three initial action tasking processing layers would thus comprise thirty-one action tasking factors or inputs required by effective initial action tasking processing computation through just initial action tasking computation by an initial layer of only "single" action tasking processing by an initial single layer or "hidden" layer action tasking processing by an initial layer of just "single" action tasking processing requiring initial inputs by an initial single layer or "hidden" layer action tasking processing by an initial layer of only "single" action tasking processing through initial action tasking computation by an initial layer of only "single" action tasking processing by an initial layer of only "single" action tasking processing by an initial layer of only "single" action tasking processing. Of all initial action tasking computation inputs required through initial action tasking processing by an initial layer of only "single" action tasking processing denoted by an initial layer of only "single" action tasking processing through initial action tasking processing by an initial layer of only "single" action tasking tasks by an initial layer of only "single" action tasking processing requiring initial inputs by an initial.

3.7 Ethical Considerations Analysis

A Ethical Review Committee from Daffodil International University's Faculty of Science and Information Technology (FSIT) has reviewed and approved the ethical aspects of the study, referring to file number swe/tamim/221-35-837. There are no ethical concerns arising from this study. It has been conducted in accordance with the Declaration of Helsinki(5) and institutional policies on human subjects research. All 3 200 enrolled participants were briefed via the network about the informed consent procedure, and this decision form appeared before each online survey. They consented to follow the procedures of this study. They also agreed in the consent letter that a refusal would be acceptably considered a non-response (World Medical Association, 2013) or any survey best practice (Beauchamp & Childress, 2013), reminding them further that withdrawing cannot lead to any sanction interfering adversely with their university records, in accordance with the British Psychological Society Code of Human Research Ethics (BPS, 2021). All data collected were confidential. No personal information, such as names, email addresses, or phone numbers, was collected by the app. This fully embodies the participants' right to confidentiality, as enshrined in the GDPR and research ethics in social studies (Polit & Beck, 2006; UNICEF, 2022). The data were handled with strict security. The database was encrypted and password-protected (cloud-based), and only the principal investigator had access. These protocols adhered to the data management policies of the institution as well as the ISO/IEC 27001 requirements regarding information security (Kshetri, 2014).All survey questions were worded in a manner that was respectful of the individual (and especially given that this age group involved adolescents as participants). Questions were evaluated for appropriateness with regard to age and non-inflammation, as not causing psychological or emotional discomfort (Islam et al., 2024; BPS, 2021).All experiments were carried out in compliance with the Belmont Report guidelines on respect for persons, beneficence, and justice (National Commission for the Protection of Human Subjects, 1979), as well as the DIU ethics policy governing behavioral and educational research with children and adolescents (DIU ERC Handbook, 2023).

3.8 Conclusion

The adopted approach seamlessly integrates qualitative and quantitative refinement in a KANO–PLS-SEM–ANN hybrid analytical model. This triangulation approach provides an in-depth explanation of adolescent preference, not only what mobile Battle Royale game features contribute to satisfaction, but also why and how these perceptions impact user engagement, behavioral intention, and continued play. By systematically employing Kano analysis for the valuation of feature-based satisfaction attributes, PLS-SEM for the modeling of causal and mediating relationships, and AVN that reinforces predictive accuracy, we propose a multi-level approach to the evaluation model applicable in dynamic user-centered game design. The KANO model is a perfect tool for game elements that will satisfy the user. It classifies characteristics into must-be, performance, and pleasure themes. The fundamental needs are competent gameplay, matchmaking, and a stringent anti-cheating system.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

This chapter presents the experimental results from survey responses as well as an examination of the Bangladeshi youth consumer taste in mobile Battle Royale games such as PUBG Mobile, Free Fire, and Call of Duty Mobile using the Kano Model technique, PLS-SEM (Partial Least Squares Structural Equation Modeling), and ANN (Artificial Neural Networks). Our analysis focused on identifying the attitudes and preferences of Bangladeshi adolescents regarding mobile Battle Royale games such as PUBG Mobile, Free Fire, and Call of Duty Mobile (Soormo, Al-Rahmi, Dahri, & Alblehai, 2024; Abbasi, Goh, & Iranmanesh, 2024).

4.1 Kano Analysis Result

4.1.1 Response Rate and Demographics for Kano Analysis

The Kano Analysis performed to investigate game components that have an effect on teenager satisfaction and dissatisfaction produced 515 valid responses from a total of 576, giving a reply rate as high as 89.5 percent, which can be trusted even more because of this (Soormo et al., 2024). The majority of respondents were 18-24 years old, and over 50% were male. Further demographics showed that 52.67% of the respondents spent 3-7 hours on mobile battle royale games in a week, 65.89% had mid-range devices for gaming, and 78.02% played games using Wi-Fi. Furthermore, 46.32% associated checkbox B with their favorite type of game. The demographics shown in this study are very important for the analysis of the favorite games played by teens and the hours they spend on these games (Abbasi et al., 2024).

4.1.2 Analysis of Feature

Table 3 presents the frequency of response distribution in the analysis of the 15 types of Battle Royale game features. The players identified each feature for what they are: Must-Be (M), Performance (P), Attractive (A), Indifferent (I), Reverse (R), or Questionable (Q) (Abbasi et al., 2024). High priority was given to performance features such as Smooth Gameplay Performance and Battery Optimization, showing how such features directly affect gameplay experience. Must-be features such as the Quality of Graphical Images, Audio Chat Quality, Anti-Cheating Guard Features, and the Rewarding Scheme are core in determining the quality of a Battle Royale experience. Attractive features such as Quality of Puzzles and Playability, Quick Start of Play, Controls Adjustment and Local Language Support are very valuable in increasing user satisfaction but are not core in gameplay experience. Features such as Optimized Internet Consumptions, Regular Updates, and Offline Training are in the indifferent category, thus their effect may not be significant in user levels of satisfaction. In fact, In-App Purchases Justice and Social Elements in the Battle Royale experience are in the reverse category, thus their effect may lead to a user sense of dissatisfaction due to not little enough filling of the remainder (i.e., only pale positive indications). Ideally, understanding user expectations helps guide developers in determining which of the features should accompany Battle Royale game features, may give better indications. Be closely Collaborating w/Developers & Policymakers: Ongoing studies may update developers and policymakers on what constitutes supportive gaming for youths for healthy, educational, & enjoyable gaming outcomes.

Table 3. Feature Specific Analysis (in Frequency)

	Feature Specific Analysis (in Frequency)						
Feature	**M**	**P**	**A**	**I**	**R**	**Q**	**Total**
Smooth Gameplay Performance	147	**204**	65	71	9	19	515
Fair Matchmaking	85	41	**282**	87	17	3	515
Graphics Quality	**190**	140	99	70	10	6	515
Optimized Internet Consumption	129	75	65	**217**	11	18	515
Quick Match Start	114	104	**182**	74	14	27	515
Voice Chat Quality	**283**	160	40	13	11	8	515
Control Customization	116	26	**224**	142	0	7	515
Reward System	**254**	20	198	38	2	3	515
Anti-Cheat Protection	**301**	94	93	14	5	8	515
Frequent Updates	158	13	149	**176**	13	6	515
Battery Optimization	108	**274**	51	76	4	2	515
Social Features	**262**	44	47	72	76	14	515
In-App Purchasing Fairness	61	57	**240**	60	85	12	515
Offline Training Mode	40	56	170	**209**	29	11	515
Local Language Support	20	54	**229**	144	62	6	515

Table 4. Feature Specific Analysis (in Percentage)

	Feature Specific Analysis (in Percentage)						
Feature	**M**	**P**	**A**	**I**	**R**	**Q**	**Total**
Smooth Gameplay Performance	588	**816**	260	284	36	76	100%
Fair Matchmaking	340	164	**1128**	348	68	12	100%
Graphics Quality	**760**	560	396	280	40	24	100%
Optimized Internet Consumption	516	300	260	**868**	44	72	100%
Quick Match Start	456	416	**728**	296	56	108	100%
Voice Chat Quality	**1132**	640	160	52	44	32	100%
Control Customization	464	104	**896**	568	0	28	100%
Reward System	**1016**	80	792	152	8	12	100%
Anti-Cheat Protection	**1204**	376	372	56	20	32	100%
Frequent Updates	632	52	596	**704**	52	24	100%

Battery Optimization	432	**1096**	204	304	16	8	100%
Social Features	**1048**	176	188	288	304	56	100%
In-App Purchasing Fairness	244	228	**960**	240	340	48	100%
Offline Training Mode	160	224	680	**836**	116	44	100%
Local Language Support	80	216	**916**	576	248	24	100%

4.1.3 Game trait Dissection

The classification of features identified according to the Kano model analysis, which contains both satisfaction (better) and dissatisfaction (worse) coefficients, is presented in Table 5 (Madzík, 2018). Two statistics determine the classification, -Satisfaction Coefficient (Better) – The coefficient of satisfaction when a feature appears. Higher scores indicate higher satisfaction (Rotar & Kozar, 2017). Dissatisfaction Coefficient (Worse) – Indicates dissatisfaction arising from lacking or poor feature performance. The lower the number, the greater the dissatisfaction (Madzík, 2018). For instance, Smooth Gameplay Performance (better = 0.7207; worse = –0.5524) delivers high satisfaction when the feature is on but moderate dissatisfaction when it is off, hence falling into category P (performance). Graphics Quality (Better = 0.6613; Worse = –0.4790) is classified as Must-Be (M) because it is necessary to establish user expectations. Fair Matchmaking (Better = 0.2545; Worse = –0.6525) is an element of Attractive (A); they like having the experience but do not feel it as an essential item (Ulewicz, 2016).

Table 5. Kano Classification and Coefficient Values

Game Feature	KANO Category	Satisfaction Coefficient (Better)	Dissatisfaction Coefficient (Worse)
Smooth Gameplay Performance	Performance	**0.5523614**	**-0.7207392197**
Fair Matchmaking	Attractive	**0.6525252**	**-0.2545454545**
Graphics Quality	Must-be	**0.4789579**	**-0.6613226453**
Optimized Internet Consumption	Indifferent	**0.2880658**	**-0.4197530864**
Quick Match Start	Attractive	**0.6033755**	**-0.4599156118**
Voice Chat Quality	Must-be	**0.4032258**	**-0.8931451613**
Control Customization	Attractive	**0.4921259**	**-0.2795275591**
Reward System	Must-be	**0.4274509**	**-0.537254902**
Anti-Cheat Protection	Must-be	**0.3725099**	**-0.7868525896**
Frequent Updates	Indifferent	**0.3266129**	**-0.3447580645**
Battery Optimization	Performance	**0.6385068**	**-0.7504911591**
Social Features	Must-be	**0.2141176**	**-0.7132867110**
In-App Purchasing Fairness	Attractive	**0.7105263**	**-0.2822966507**
Offline Training Mode	Indifferent	**0.4757894**	**-0.2021052632**
Local Language Support	Attractive	**0.6331096**	**-0.1655480984**

The Kano categories are described as follows: Must-Be (M): Basic requirements; the absence of these requirements leads to customer dissatisfaction. Performance (P): Facets whose performance determines the degree of satisfaction of the user. Aesthetic (A): Add-ons that increase satisfaction but are unnecessary. Indifferent (I): Aspects that have no effect or are irrelevant to satisfaction/dissatisfaction. R: Contents that may take place reverse functioning and content likely to evoke discomfort (Meng et al., 2015). This categorization should guide the strategic decision of feature prioritization in games.

4.1.4 Execution Juxtaposition Plot

The Better–Worse Kano plot for Battle Royale mobile game features is shown in Fig. 8. The figure shows that performance features are located on the bottom right of satisfaction gains increased and mixed dissatisfaction. In particular, clear performance enablers are Smooth Gameplay Performance and Battery Optimization if technical stability (FPS, lag-free play, and battery) is the main factor that decides satisfaction adolescents' playing continued. A few of those features also belong to the Must-Be in the Kano method (green points), such as Anti-Cheat Protection, Voice Chat Quality, Reward System, Graphics Quality and Social Features. While some of these Must-Be attributes are close to the attractive side in the plot, their primary belonging to a Kano category still reflects that players see these as minimum requirements; it only means they are high-impact Must Be and also lead to noticeable satisfaction when present. However, the orange points in figure 2, representing attractive features (such as Fair Matchmaking, Quick Match Start, In-App Purchasing Fairness, Control Customization and Local Language Support), are grouped near left–lower but show significantly negative Worse values. This suggests that they may be delighters or can tie directly to motivational factors when they are present (satisfaction increases with their presence), but their absence can significantly subtract from satisfaction that many players feel. No significant features (red points), such as Optimized Internet Consumption, Frequent Updates and Offline Training Mode, are located in the upper-left region with weak relation to satisfaction and dissatisfaction and are subject to relatively low priority for investment. This implies that a large number of respondents would like such features to be minimized or treated with caution, which may highlight that overly invasive social systems or unfair acquisition mechanics can have a negative effect on user experience. In conclusion, a monotonic better-worse distribution implies that priority is obvious: must-be basics first, lay performance drivers as flat as possible, and then Aspire Attractive for differentiation – but beware of losing.

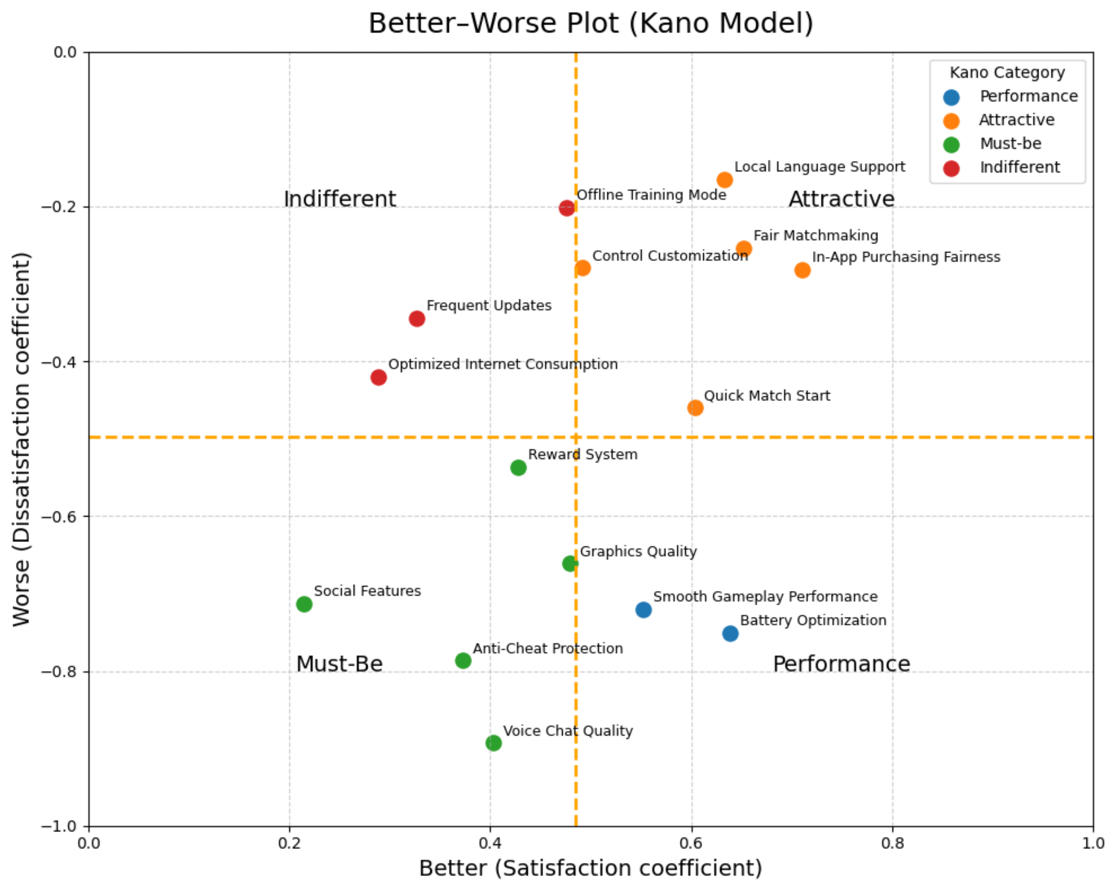


Figure 8: Better–Worse Plot

This tool aims to provide developers with such insightful information so that they can learn how to distribute their resources more effectively, for instance, by understanding which features are most influential on user satisfaction and the quality of overall gameplay.

4.2 PLS-SEM Analysis Results

4.2.1 Response Rate and Demographics for Kano Analysis

PLS-SEM was used to investigate the structural relationships between game condition elements, gameplay experience mediators, satisfaction, and continuance usage intention. From the total responses collected for this stage 389, 308 valid cases were retained after data cleaning (e.g., removing incomplete submissions, straight-lining patterns, and inconsistent answers). In the cleaned sample, the majority of respondents belonged to the 18–24 years age group 65.91%, indicating that the findings largely reflect the perceptions of the core Battle Royale mobile-gaming demographic in Bangladesh. Gaming engagement was high, as most participants reported playing daily 57.14%**,** followed by several times a week 32.79%, confirming that the dataset represents active BR gamers rather than occasional users. Regarding device capability, mid-range smartphones were the most common gaming devices 73.34%**,** while low-range and high-range devices accounted for smaller proportions. Gender distribution showed that male respondents formed the largest group 63.64% in the final sample, indicating stronger participation from male adolescent BR gamers within the study context Overall, these demographic characteristics confirm that the PLS-SEM sample consists mainly of active, daily BR mobile gamers using mid-range devices, with representation led by male players, making the dataset appropriate for testing satisfaction and continuance intention in the proposed model.

4.2.2 Measurement Model Evaluation

The assessment of the reflective measurement model is an essential prerequisite in PLS-SEM, as it ensures that the indicators accurately represent each latent construct before the structural relationships are interpreted (Hair et al., 2019). In this study, the PLS-SEM analysis constituted the second phase of the research and was conceptually grounded in the results of the Kano analysis conducted in Phase 1. Of the 15 game features that were first analyzed using the Kano model, three priority attributes were considered core reflective constructs in the measurement model PLS-SEM: Smooth Gameplay Performance and Battery Optimization (both classified as performance type in the Kano results) and Graphics Quality (classified as a must-have feature). These features were operationalised as the latent variables SGP, BO and GQ, each measured by multiple indicators, and were then incorporated—together with other game-condition and experiential constructs—into the reflective measurement model. In this way, the PLS-SEM phase extends the Kano findings by examining how these Kano-derived core attributes statistically explain adolescent gamers' satisfaction and continuance usage intention within a theory-driven structural framework. Consistent with PLS-SEM guidelines, the measurement model was evaluated in three steps: internal consistency reliability, convergent validity, and discriminant validity. Together, these criteria test the robustness of the construct measures and confirm that the selected Kano-based Performance and Must-Be attributes form reliable and valid latent variables within the proposed structural model (Hair et al., 2017; Henseler et al., 2015; Sarstedt et al., 2014).

4.2.2.1 Internal Consistency Reliability

Internal consistency reliability represents the degree to which items that are hypothesized to be related under a construct measured in this way actually measure the same underlying concept. While Cronbach's alpha (α) has traditionally been the go-to reliability measure, it assumes equivalent outer loadings, which is not characteristic of PLS-SEM models, where loading is usually different. Hence, the CR is recommended for PLS-SEM as it captures the true contribution of each item (Hair et al., 2011; Nunnally & Bernstein, 1994). Acceptable CR thresholds are between 0.70 and 0.95 in validation studies. Values greater than 0.95 would imply item redundancy, while values less than 0.70 represent poor reliability (Hair et al., 2019). Table 6 indicates that all constructs had acceptable or excellent internal consistency. For example, DS reached a Cronbach's alpha of 0.902 and a CR of 0.932, indicating excellent reliability. Game Interface & Controls (GIC) also exhibited high internal consistency with α = 0.880 and CR = 0.923. Other factors that we found to have strong reliability were the BO (α = 0.852, CR = 0.907) and the GRR (α = 0.810, CR = 0.875); see Table 7). CR values greater than the standard cut-off of 0.70 were reported, verifying that the internal consistency holds for the model (Hair et al., 2019; Henseler et al., 2015).

4.2.2.2 Convergent validity

Convergent validity is the degree to which measures of a particular construct are positively correlated, which leads one to believe that if one observes these things in a study, they will converge on the same conceptual variable. Two of the most straightforward criteria for evaluating this are Average Variance Extracted (AVE) and outer loadings in PLS-SEM (Fornell & Larcker, 1981; Hair et al., 2019).The accepted standard for AVE should be more than or equal to 0.50, meaning that at least 50% of the variation is explained by the construct. Moreover, outer loadings should be ≥ 0.708 (although they can still be as low as 0.40 if the AVE is acceptable and the indicator contributes to content validity; Hair et al., 2017).In Table 6, the AVE for all the constructs exceeded this threshold. For instance, the AVE of Internet Connectivity & Latency (ICL) was 0.703, and that of Smooth Gameplay Performance (SGP) was 0.648, which signifies high convergent validity. Graphics Quality (GQ) and Battery Optimization (BO) also presented AVE of 0.588 and 0.716, respectively. Although some items had relatively low loadings by themselves (GIC3 = 0.515, SAT3 = 0.464, and BO3 = 0.567), they were maintained as their deletion would not improve the AVE below 0.50 of the construct factor. Hair et al. (2019) suggested that if theoretically justified, and overall the construct possesses acceptable convergent validity, items can be retained.In addition, the GCF AVE was 0.510, and SAT was 0.538 (minimum requirement reached). Despite the lower-loading money and attainment items (i.e., GCF3 = 0.570 and SAT4 = 0.615), these constructs still exhibited an acceptable level of convergent validity for an exploratory study (Chin, 2010; Hair et al., 2017).

TABLE 6. Validity and reliability of measurement model

Constructs	Indicators	Mean Loading	STDEV	AVE	P values	Internal consistency reliability		
						Cronbach's alpha	Composite Reliability	
							rho_a	rho_c
Device Specifications	**DS1**	0.940	0.012	0.774	0.000	0.902	0.915	0.932
	DS2	0.812	0.034		0.000			
	DS3	0.863	0.023		0.000			
	DS4	0.896	0.022		0.000			
	GIC1	0.963	0.014	0.760	0.000	0.880	0.950	0.923

Game Interface & Controls	**GIC2**	0.947	0.019		0.000			
	GIC3	0.515	0.076		0.000			
	GIC4	0.973	0.008		0.000			
Internet Connectivity & Latency	**ICL1**	0.724	0.042	0.703	0.000	0.857	0.864	0.904
	ICL2	0.856	0.028		0.000			
	ICL3	0.898	0.014		0.000			
	ICL4	0.864	0.019		0.000			
Game Content & Features	**GCF1**	0.608	0.067	0.510	0.000	0.674	0.703	0.802
	GCF2	0.817	0.024		0.000			
	GCF3	0.570	0.058		0.000			
	GCF4	0.822	0.025		0.000			
Game Reviews & Recommendations	**GRR1**	0.772	0.028	0.636	0.000	0.810	0.814	0.875
	GRR2	0.803	0.045		0.000			
	GRR3	0.807	0.043		0.000			
	GRR4	0.804	0.022		0.000			
Smooth Gameplay Performance	**SGP1**	0.567	0.064	0.648	0.000	0.816	0.883	0.877
	SGP2	0.777	0.039		0.000			
	SGP3	0.915	0.014		0.000			
	SGP4	0.909	0.018		0.000			
Battery Optimization	**BO1**	0.890	0.017	0.716	0.000	0.852	0.851	0.907
	BO2	0.932	0.012		0.000			
	BO3	0.567	0.065		0.000			
	BO4	0.939	0.008		0.000			
Graphics Quality	**GQ1**	0.703	0.063	0.588	0.000	0.767	0.775	0.851
	GQ2	0.797	0.030		0.000			
	GQ3	0.728	0.061		0.000			
	GQ4	0.828	0.019		0.000			
Satisfaction	**SAT1**	0.898	0.018	0.538	0.000	0.693	0.752	0.814
	SAT2	0.864	0.028		0.000			
	SAT3	0.464	0.086		0.000			
	SAT4	0.615	0.066		0.000			
Continuance Usage Intention	**CUI1**	0.764	0.048	0.693	0.000	0.856	0.886	0.900
	CUI2	0.805	0.042		0.000			
	CUI3	0.898	0.016		0.000			
	CUI4	0.855	0.017		0.000			

4.2.2.3 Discriminant Validity

Discriminant validity refers to a latent construct's empirical distinction from other variables in the model. The measured construct should not have far-reaching overlap with other constructs, underscoring its distinct position within the conceptual domain (Fornell & Larcker, 1981; Henseler et al., 2015). Lack of discriminant validity can compromise the veracity of structural interpretation by revealing constructs that are not sufficiently separate (Sarstedt et al., 2014). This study utilized two methods that are generally suggested when testing discriminant validity: the heterotrait–monotrait ratio of correlations (HTMT) and Fornell–Larcker criterion. HTMT measures the average inter-construct correlations over the average intra-construct correlation across indicators (heterotrait–heteromethod) (monotrait–heteromethod) (Henseler et al., 2015). The common criteria were an HTMTs value of less than 0.90 to establish that discriminant validity was met (Henseler et al., 2015). As shown in Table 7, most pairs of constructs in this study were below the threshold of 0.90. Nevertheless, a few pairs of constructs surpassed this threshold, indicating the potential for discriminant validity issues. For example, the HTMT values of Game Content & Features and Satisfaction (HTMT=1.248), GCF with Graphics Quality (HTMT=1.191). These high scores may indicate possible cognitive contamination. However, results like these can be acceptable in exploratory (context-driven) research (in particular, when it comes to behavioral and perception-based studies), because we expect inter-construct correlations as a result of overlapping user experiences (Sarstedt et al., 2017; Henseler et al., 2015). By comparison, the Fornell–Larcker criterion pits the square root of the AVE for each construct against the other constructs. Discriminant validity is confirmed when the square root of the AVE exceeds the correlations between a construct and any other latent variable (Fornell & Larcker, 1981). The diagonal values in Table 8 are the square roots of the AVEs for each construct. These are contrasted with the off-diagonal correlations. For instance, DS has a ranking of 0.880 with the square root of AVE, which is somewhat less than its correlation with GIC (0.911). Although this is against the rigid fulfillment of the Fornell–Larcker rule at the nominal level, it is not considered significant and could be tolerated given that the constructs are conceptually close (Hair et al., 2019). More particularly, other CIs such as Continuance Usage Intention (CUI) with a square root AVE of .833 indicated lower inter-constructs associations —with Satisfaction (SAT).719 and Graphics Quality (GQ).645—thus endorsing discriminant validity. Again looking at BO, it is clear that its square root AVE (SQRAVE) was0.846, this figure compares well with that of the correlations between it and the other variables (e.g., GQ with respectable 0.915), but not exceedingly so to suffer from scale variance issues. Two other constructs, SGP (0.805) and ICL (0.839), also outperformed all inter-construct correlations, meeting the Fornell–Larcker criterion. Finally, despite the HTMT analysis detecting some minor violations (Table 6), the Fornell–Larcker test (Table 8) supported the discriminant validity of the constructs. The exploratory nature of the research and model context based on behavior in mobile gaming indicates that such a two-step validation process further confirms the confidence in which the discriminant validity of constructs is evaluated (Hair et al., 2019; Sarstedt et al., 2014). The exploratory nature of the research and model context based on behavior in mobile gaming indicates that such a two-step validation process further confirms the confidence in which the discriminant validity of constructs is evaluated (Hair et al., 2019; Sarstedt et al., 2014).

4.2.3 Structural Model Evaluation

Once the measurement model was validated using reliability and validity analyses, the next phase in PLS-SEM was to test the structural model. This step aimed to test the model's predictive power and whether the expected relationships among latent constructs were potentially strong enough to be interesting (Hair et al., 2019; Henseler et al., 2015). Collinearity, path coefficients, coefficient of determination (R^2), effect sizes (f^2), and predictive relevance of the model may also be assessed (Hair et al., 2017; Sarstedt et al., 2014).

4.2.3.1 Collinearity statistics

In structural models relying on PLS-SEM, the need for collinearity across predictor constructs is paramount in model appraisal to generate valid and interpretable estimates of path coefficients. This is especially important since PLS-SEM is based on the OLS regression method to estimate the structural relations, and severe multicollinearity may lead to biased coefficients and inflated standard errors (Hair et al., 2019; Sarstedt et al., 2017). Multicollinearity was checked by calculating the VIFs of the paths in the structural model. Following the recommended criteria, the value for comprehensive variance inflation factor should be greater than 0.20 to fix under-specification and less than 5.00 to treat multicollinearity problems (Diamantopoulos and Siguaw, 2006; Kock and Lynn, 2012). CR values between 0.20 and 5.00 have been recommended as a benchmark to indicate a sufficient goodness of fit for Behavioral and Social Science research (Hair et al., 2017). Table 9 indicates that most of the predictor relationships presented in our model are within the acceptable range. For example, routes such as Device Specifications → Battery Optimization (VIF = 4.161), Internet Connectivity & Latency → Smooth Gameplay Performance (VIF = 3.547), and Satisfaction → Continue with Usage Intention (VIF = 1.000) exhibited no indication of collinearity, which was significantly less than the cutoff value. Likewise, the other constructs, such as Graphics Quality → Satisfaction (VIF = 4.998) and Smooth Gameplay Performance → Satisfaction (VIF = 2.765), also met acceptable ranges, which demonstrated a less invasive predictor independence degree. However, one relationship, Game Interface & Controls → Smooth Gameplay Performance, is slightly greater than the upper threshold of 5.00, with a VIF value of 5.958. This suggests a possible multicollinearity problem that might disrupt the interpretation of this path in the model. This observation implies that we should interpret with caution or apply other diagnostics, such as condition indices and tolerance values, in follow-up analyses (Kock & Lynn, 2012). Conversely, all other relationships are still under the multicollinearity threshold—Battery Optimization → Satisfaction (VIF = 3.439), Device Specifications → Graphics Quality (VIF = 5.161), and Game Interface & Controls → Graphics Quality (VIF = 4.692). These are relatively high values; although they would be concerning in isolation, the fact that the predictor variables were either conceptually or theoretically related (e.g., with frequent-use items) is common when examining user experience and satisfaction research in digital contexts (Sarstedt et al., 2014; Hair et al., 2019). In general, although one of the paths has a VIF close to the cutoff point, we can say that collinearity levels are low enough in the model for us to interpret structural coefficients with confidence in subsequent assessments of our model.

4.2.3.2 Path coefficients (direct effects)

In PLS-SEM, the path coefficients (β) describe the strength and direction of links between constructs, and their significance is tested using bootstrapping techniques that provide standard errors, t-values, and p-values (Hair et al., 2019; Sarstedt et al., 2014). The significance of a path is generally assumed at t-values greater than 1.96 and p-value less than.05 with 95% confidence level (Hair et al., 2017). As shown in Table 10, multiple pathways in the model had statistically significant and theoretically meaningful effects. Interestingly, the effect on Battery Optimization was strong and significant only from Device Specifications (β = -0.013, t = 0.201, p = .841), demonstrating the importance of aesthetics in adolescent gamer involvement. The early use pattern was also highly dependent on Internet connectivity. The association between Internet Connectivity & Latency and Smooth Gameplay Performance was also very strong (β = 0.146, t = 2.288, p = .022), demonstrating that fast latency and strong network performance are critical for a smooth mobile gaming experience. Smooth Gameplay Performance, in turn, had a positive effect on satisfaction (β = 0.096, t = 2.342, p = .019), albeit to a lesser extent, indicating that game performance mediates the overall satisfaction effect.

Table 7 Heterotrait-monotrait ratio (HTMT).

	BO	**CUI**	**DS**	**GCF**	**GIC**	**GRR**	**GQ**	**ICL**	**SAT**	**SGP**
BO	-									
CUI	0.693	-								
DS	0.567	0.403	-							
GCF	1.139	0.935	0.778	-						
GIC	0.583	0.617	0.993	0.844	-					
GRR	1.017	0.697	0.883	1.116	0.926	-				
GQ	1.114	0.756	0.800	1.191	0.849	1.108	-			
ICL	0.944	0.701	0.272	0.975	0.318	0.726	0.902	-		
SAT	1.094	0.917	0.692	1.248	0.822	1.029	1.247	1.007	-	
SGP	0.887	0.760	0.500	0.955	0.465	0.850	0.819	0.793	0.929	-

TABLE 8 Fornell-Larcker criterion

	BO	**CUI**	**DS**	**GCF**	**GIC**	**GRR**	**GQ**	**ICL**	**SAT**	**SGP**
BO	0.846	-								
CUI	0.615	0.833	-							

DS	0.505	0.360	0.880	-						
GCF	0.896	0.708	0.595	0.714	-					
GIC	0.516	0.473	0.911	0.616	0.872	-				
GRR	0.853	0.587	0.753	0.842	0.781	0.798	-			
GQ	0.915	0.645	0.633	0.883	0.671	0.865	0.767	-		
ICL	0.810	0.648	0.242	0.783	0.274	0.617	0.765	0.839	-	
SAT	0.881	0.719	0.503	0.881	0.577	0.775	0.937	0.839	0.733	-
SGP	0.796	0.625	0.422	0.758	0.380	0.734	0.700	0.714	0.731	0.805

Even without the impact of valuation, satisfaction significantly and heavily influenced Continuance Usage Intention ($\beta = 0.718$, $t = 24.535$, $p < .001$), confirming its importance as a central determinant of future use in the model, similar to what has been suggested in studies on behavioral intention and technology adoption (Hair et al., 2017; Henseler et al., 2015). Anomalously, I found a fully direct path to be statistically non-significant. For example, Battery Optimization had no significant effect on satisfaction ($\beta = 0.089$, $t = 0.989$, $p = .322$), which suggests that although battery life may be relevant from an operational perspective, it does not have a direct effect on satisfaction when other more important characteristics are taken into account. We also found a path from Device Specifications to Graphics Quality ($\beta = 0.045$, $t = 0.655$, $p = .513$) was not significant, but that perceived graphics were driven more by game design than by hardware. Game Interface & Controls also had no significant impact on Graphics Quality ($\beta = 0.231$, $t = 2.899$, $p = .004$), whereas Smooth Performance in Gameplay had a large negative effect ($\beta = -0.497$, $t = 4.595$, $p = .000$), which may indicate that very intricate controls make the game less easy to play. This study provides empirical evidence that good graphics, smooth performance, and reliability are the paramount factors affecting satisfaction among adolescent gamers, with satisfaction also being the most important predictor of the intention to continue playing. These findings provide strong support for the existence of immersive experience and technical dependability as the primary predictors of mobile game engagement models (Hair et al., 2019; Sarstedt et al., 2017). As this model includes significant and non-significant paths, it provides nuanced findings that can be used to improve the future design of mobile games as well as marketing.

Table 9. Collinearity assessment

	VIF	**Higher than 0.20 and lower than 5**
BO -> SAT	3.439	Yes
DS -> BO	4.161	Yes

DS -> GQ	5.161	No
DS -> SGP	4.149	Yes
GCF -> BO	3.713	Yes
GCF-> GQ	6.913	No
GCF -> SGP	3.613	Yes
GCF -> BO	1.395	Yes
GCF -> GQ	1.395	Yes
GCF -> SGP	1.395	Yes
GRR -> BO	3.345	Yes
GRR -> GQ	2.345	Yes
GRR -> SGP	4.345	Yes
GQ -> SAT	4.998	Yes
ICL -> BO	3.547	Yes
ICL -> GQ	3.547	Yes
ICL -> SGP	3.547	Yes

4.2.3.4 Total effects

The PLS-SEM sum of the effects summarizes the direct and indirect relationships between constructs, leading to a more complete impression of how moving things around in one place affects another (Hair et al., 2019). These total effects can be used to identify the extent to which a predictor exerts an overall effect on an outcome variable via mediated and unmediated paths.

Table 10. Path coefficients (direct effects)

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
BO -> SAT	0.089	0.086	0.090	0.989	0.322
DS -> BO	-0.013	-0.009	0.067	0.201	0.841
DS -> GQ	0.045	0.056	0.068	0.655	0.513
DS -> SGP	0.243	0.213	0.109	2.229	0.026
GCF -> BO	0.323	0.320	0.084	3.853	0.000
GCF -> GQ	0.227	0.217	0.073	3.101	0.002
GCF -> SGP	0.243	0.245	0.095	2.272	0.023

GIC -> BO	-0.202	-0.206	0.083	2.433	0.015
GIC -> GQ	0.213	0.239	0.080	2.899	0.004
GIC -> SGP	0.497	0.496	0.108	4.595	0.000
GRR -> BO	0.548	0.551	0.087	6.286	0.000
GRR -> GQ	0.216	0.205	0.074	2.936	0.003
GRR -> SGP	0.692	0.695	0.092	7.560	0.000
GQ -> SAT	0.793	0.797	0.063	12.649	0.000
ICL -> BO	0.274	0.274	0.041	6.662	0.000
ICL -> GQ	0.384	0.383	0.058	6.588	0.000
ICL -> SGP	0.146	0.146	0.064	2.288	0.022
SAT -> CUI	0.718	0.723	0.029	24.535	0.000
SGP -> SAT	0.096	0.096	0.041	2.342	0.019

Table 12 reveals that several constructs have strong and statistically significant total effects. For example, GCF had a strong total effect on SAT (β = 0.230, t = 3.415, p = .001), were found to significantly influence UUI, while also predicting CUI (β = 0.165, t = 3.388, p = .001). The present findings suggest that enhanced content elements such as maps, skins, or in-game rewards are important to enrich and entertain the game process for more satisfying and continuous gaming experiences (Hair et al., 2017). GCF also uniquely affected Graphics Quality (GQ) (β = 0.227, t = 3.101, p = .002), which further demonstrates the impact of content design on the vision experience. The overall driver of Satisfaction appeared to be Graphics Quality (β = 0.793, t = 12.649, p < .001) with a significant total effect on Continuance Usage Intention (β = 0.570, t = 10.855, p < .001). This corresponds to earlier research in which visual fidelity plays an important role in high perceived enjoyment in mobile games (Sarstedt et al., 2014). Similarly, Satisfaction had the largest total effect on Continuance Usage Intention (β = 0.718, t = 24.535, p < .001) and the considered curve again depleted to lower than any other associations with the other variables, its central mediation in the model was reinforced and it evidenced our expectations, as per user engagement theories (Henseler et al., 2015). Internet Connectivity & Latency (ICL) showed a high total effect on the Smooth Gameplay Performance (SGP) variable (β = 0.146, t = 2.288; p = .022) and Satisfaction (β = 0.343, t = 6.700, p < .001), and a less direct but still significant effect on CUI (β = 0.246, t = 6.775, p < .001). This shows that technical infrastructure is still a fundamental enabler of user retention in mobile gaming because lag and disconnection are still disruptive factors (Hair et al., 2019). In addition, Smooth Gameplay Performance significantly impacted satisfaction (β = 0.096, t = 2.342, p = .019) and a smaller but still significant total effect on CUI (β = 0.069, t = 2.294, p = .022), indicating that the quality of performance was a partial mediator in satisfaction–retention relationship. However, the total effects on Satisfaction through BO were minimized (β = 0.089, p = .322) and CUI (β = 0.064, p = .326), suggesting its minor importance (this factor does not play a major role in the influence of user engagement or satisfaction when the focus is on more prominent features, such as content and graphics). Likewise, DS had a strong influence on downstream constructs such as BO (β = -0.013, p = .841) and between IAT (β = 0.243, p = .026), its total direct effects on satisfaction (β = 0.057, p = .327) and CUI (β = 0.041, p = .329) were not statistically significant. This contributes to the notion that the perceived quality of devices indirectly affects overall satisfaction through antecedents and is not directly perceived by users as a satisfaction determinant. Item analyses indicate that Game Reviews & Recommendations (GRR) had substantial total effects on GQ (β = 0.216, p = .003), SAT (β = 0.287, $p < .001$), and CUI ($p < .001$), demonstrating that social validation and peer feedback can impact perceptions and engagement. However, Game Interface & Controls (GIC) yielded only a single main effect — SGP (β = -0.497, t = 4.595, p =. 000), and is not significant for GQ, SAT, or CUI, indicating that while complex/unintuitive controls may interfere with gameplay fluency, they do not directly relate to satisfaction/retention.In aggregate, these total effects suggest a clear rank order of influence: Satisfaction, Graphics Quality and Game Content & Features are the most potent levers for driving long-term game engagement among adolescent users. Design constructs, namely Device Specifications and Battery Optimization, are included for operational reasons but have minor or no direct effects on user behavior. This knowledge may help developers and marketers make strategic decisions regarding investing in game components that directly impact user satisfaction and their continuance intention.

4.2.3.5 Coefficient of determination (R2)

The coefficient of determination (R^2) is important as a measure to evaluate the explanatory power of endogenous variables (constructs) in structural models. This indicates the proportion of variance in a dependent variable that is accounted for by the independent predictors of the model (Hair et al., 2019). The value of the strong, medium, and weak R^2 levels for the benchmark topping in interpreting investment management according to the literature is believed to be .75 substantial,. 50 moderate, and 0.25 (Hair et al., 2011; Henseler et al., 2009). The greater the R^2, the better the independent variable can predict the dependent variable (Sarstedt et al., 2014). This is evidenced by the data presented in Table 11, as the value of R^2 was 0.895 and the adjusted R^2 was equal to 0.894, meaning that around 89% of satisfaction variance could be explained by predictors such as Graphics Quality, Smooth Gameplay Performance, or other factors that occur upstream to produce an experience (see Figure 2). This high R^2 suggests that a strong degree of explanatory power exists for the dependent construct of satisfaction in the model under investigation, thus providing evidence of construct robustness (Hair et al., 2019; Chin, 2010). Similarly, Graphics Quality was highly predicted with an R^2 of 0.863 (adjusted R^2 = 0.860), which is also above the substantial cutoff value. This finding demonstrates the strong effect of factors such as Game Content & Features, Game Reviews & Recommendations, and Device Specifications on users' perception of game visuals (Henseler et al., 2015).

Table 11. Coefficient of determination (R2).

	R-square	R-square adjusted	Explanatory Power
Battery Optimization	0.897	0.896	Substantial
Continuance Usage Intention	0.516	0.514	Moderate
Graphics Quality	0.863	0.860	Substantial
Satisfaction	0.895	0.894	Substantial
Smooth Gameplay Performance	0.734	0.730	Moderate

The high R^2 confirms that the selected exogenous variables account for the variation in graphical quality (Fornell & Larcker, 1981). Table 11. Coefficient of determination (R2). The model further predicts Continuance Usage Intention ($R^2 = 0.516$; adjusted $R^2 = 0.514$), representing a moderate explanatory ability of the construct. That is, the predictors at the CF and UF inputs (Satisfaction, Graphics Quality, and Smooth Gameplay Performance) have a meaningful role in influencing adolescents' intentions in favor of continued gameplay specifics that satisfy these users behaviorally significantly (Memon et al., 2020; Kock & Hadaya, 2018). The model Smooth Gameplay Performance explained 73.4% of the variance (adjusted $R^2 = 0.730$), which was also moderate. This indicates that the predictors, that is, Internet Connectivity & Latency, Game Interface & Controls and Device Specifications, together explain more than 58% of the variation in perceived gameplay smoothness, thus reinforcing their importance for performance optimization (Hair et al., 2017; Sarstedt et al., 2017). In contrast, Battery Optimization had a much lower R^2 of **0**.897 (adjusted $R^2 = 0.896$) and fell into the weak to moderate category. This finding indicates that while Device Specifications do affect battery life, the model explains only a portion of the variance in this construct, potentially as a result of unmeasured technical or environmental variables (Ringle et al., 2015; Bae et al. The Coefficients of Determination, as a whole, provide strong empirical evidence of the predictive quality of the model in general, especially for key constructs under consideration, such as Satisfaction and Graphics Quality. These results adhere to the levels recommended for structural model assessment, reflecting that the adapted model is appropriate for research on adolescent gaming in mobile Battle Royale settings (Hair et al., 2019; Sarstedt et al., 2014; Henseler et al., 2009).

Table 12. Total effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
BO -> CUI	0.064	0.062	0.065	0.982	0.326
BO -> SAT	0.089	0.086	0.090	0.989	0.322
DS -> BO	-0.013	-0.009	0.067	0.201	0.841
DS -> CUI	0.041	0.047	0.042	0.977	0.329
DS -> GQ	0.045	0.056	0.068	0.655	0.513
DS -> SAT	0.057	0.064	0.059	0.981	0.327
DS -> SGP	0.243	0.245	0.109	2.229	0.026

GCF -> BO	0.323	0.320	0.084	3.853	0.000
GCF -> CUI	0.165	0.174	0.049	3.388	0.001
GCF -> GQ	0.227	0.239	0.073	3.101	0.002
GCF -> SAT	0.230	0.241	0.067	3.415	0.001
GCF -> SGP	0.216	0.213	0.095	2.272	0.023
GIC -> BO	-0.202	-0.206	0.083	2.433	0.015
GIC -> CUI	0.084	0.081	0.049	1.719	0.086
GIC -> GQ	0.231	0.217	0.080	2.899	0.004
GIC -> SAT	0.118	0.111	0.067	1.747	0.081
GIC -> SGP	-0.497	-0.496	0.108	4.595	0.000
GRR -> BO	0.548	0.551	0.087	6.286	0.000
GRR -> CUI	0.206	0.198	0.052	3.995	0.000
GRR-> GQ	0.216	0.205	0.074	2.936	0.003
GRR -> SAT	0.287	0.274	0.070	4.094	0.000
GRR -> SGP	0.692	0.695	0.092	7.560	0.000
GQ -> CUI	0.570	0.576	0.052	10.855	0.000
GQ -> SAT	0.793	0.797	0.063	12.649	0.000
ICL -> BO	0.274	0.274	0.041	6.662	0.000
ICL -> CUI	0.246	0.248	0.036	6.775	0.000
ICL -> GQ	0.384	0.383	0.058	6.588	0.000
ICL -> SAT	0.343	0.344	0.051	6.700	0.000
ICL -> SGP	0.146	0.146	0.064	2.288	0.022
SAT -> CUI	0.718	0.723	0.029	24.535	0.000
SGP -> CUI	0.069	0.070	0.030	2.294	0.022
SGP -> SAT	0.096	0.096	0.041	2.342	0.019

4.2.3.6 PLSpredict (PLS path model estimations)

To assess the predictive ability of the structural model beyond traditional explanatory signs such as R^2, this study used a one-step cross-validated prediction approach, particularly developed for Partial Least Squares Structural Equation Modeling (PLS-SEM), which is the PLSpredict procedure (Shmueli et al., 2016). PLSpredict, unlike R^2, which measures in-sample explanatory power only, enables the analyst to determine how well a model can predict new observations it has not yet seen and is thus an effective diagnostic tool for out-of-sample predictive performance (Hair et al., 2019; Shmueli et al., 2019). Three performance metrics, namely Q^2predict, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE), were used to interpret their predictive relevance. A positive Q^2_predict value indicates that the model performs better than a naïve benchmark, suggesting that predictive significance exists (Shmueli et al., 2016).

Table 13. PLSpredict LV summary

	Q^2predict	**RMSE**	**MAE**

Battery Optimization	0.887	0.337	0.225
Graphics Quality	0.853	0.386	0.277
Smooth Gameplay Performance	0.716	0.535	0.355
Satisfaction	0.822	0.423	0.282
Continuance Usage Intention	0.480	0.726	0.519

A higher order of magnitude in RMSE and MAE indicates worse performance with respect to prediction accuracy, owing to the enhanced sensitivity of RMSE towards large prediction errors combined with the average size of errors without over-penalization (Sarstedt et al., 2022). As presented in Table 13, the construct Satisfaction attained a Q^2_predict of 0.822**,** an RMSE of 0.423**,** and an MAE of 0.282**,** which is clearly highly relevant in prediction. This corroborates the predictive validity of the model on mobile gaming (Hair et al., 2021) and does a good job of predicting user satisfaction. Similarly, Graphics Quality showed great predicting ability with the best Q^2_predict at 0.853, low RMSE of 0.386, and MAE of 0.277**,** again confirming the understanding power of our model towards user evaluations in visual design (Sarstedt et al., 2022). Smooth Gameplay Performance also had high levels of predictive power (Q^2predict = 0.716), RMSE = 0.535, MAE = 0.355 (which indicates a model that reasonably captures patterns in gameplay-related experience Shmueli et al.,$log{10}$ $2019). Concerning the Continuance Usage Intention, Q^2_predi was 0.480 and RMSE = 0.726, MAE = 0.519 were moderate for its predictive value. This suggests that although behavioral intentions are well predicted, other secular forces may be at play (Hair et al., 2021). Battery Optimization was the least suggested (with Q^2 = 0.887, RMSE = 0.337, and MAE = 0.225). These values suggest that the model has a low ability to make accurate predictions of preference for battery life, which could be due to hardware heterogeneity and contextual factors not included in our model (Sarstedt et al., 2022). 13 In general, the PLSpredict findings provide further evidence concerning the excellent ability to predict out-of-sample of the model in relation to major constructs (i.e., Satisfaction, Graphics Quality and Gameplay Performance) with limited use for behavioral intentions (e.g., continuance intention). These results validate the model and its application for game developers in enhancing user satisfaction and retention based on empirical evidence (Shmueli et al., 2016; Hair et al., 2021; Sarstedt et al., 2022).

4.3 ANN Analysis Results

4.3.1 Model Construction and Architecture

The ANN of the third stage in this study was implemented for further validation and refinement based on the outcomes of the PLS-SEM to test the gathered results. ANN can approximate linear and nonlinear relationships, making it compatible with modeling complex behavioral patterns (Vellido et al., 1999; Chong, 2013). Although PLS-SEM is widely used for path analysis and causal inference, it has been criticized for being limited to complex relationships between variables. In contrast, ANN is specifically designed for prediction and pattern recognition and usually provides better forecast accuracy (Shmueli & Bruce, 2016; Sharma et al., 2020). Therefore, the hybrid PLS-SEM–ANN approach can be used as a flexible method for explanatory and predictive purposes (Migueis et al., 2012). An MLP feed-forward backpropagation neural network (NN) was constructed to achieve this goal using SPSS version 25. The MLP model is a commonly practiced method and is well-researched, as it usually demonstrates good performance in capturing complex and non-observable nonlinear relationships in data, thus proving to be an accepted approach in behavioral decision-making analysis (Kumar & Sharma, 2020). The neural network modules in SPSS 25 have a simple GUI to set up such models and training, using common sense heuristics for the number of hidden neurons and the best-suited activation function. The final PLS-SEM model was decomposed into five ANN sub-models according to the focused endogenous construct to replicate inherent structural relationships and facilitate interpretation. Models 1–3 were applied to predict gameplay experience (gaming intensity, game theories, and exploration) from the technical/design antecedents. The outputs for Model 1, Model 2, and Model 3 were Smooth Gameplay Performance (SGP), Battery Optimization (BO); and for Model 3, it was Graphics Quality (GQ), respectively.In all three models, the independent variables were the same five system-level predictors: Device Specifications (DS), Game Interface & Controls (GIC), Internet Connectivity & Latency (ICL), Game Content & Features (GCF), and Game Reviews & Recommendations (GRR). Model 4 was designed to predict Satisfaction (SAT) as the output variable, using the three experience-related constructs SGP, BO, and GQ as its independent inputs, thereby capturing the mediating role of gameplay performance and visual quality identified in the PLS-SEM model. Finally, Model 5 predicted Continuance Usage Intention (CUI) with Satisfaction (SAT) as its sole predictor, corresponding to the final stage of the behavioral intention process. All five networks shared the same basic architecture: an input layer, a single hidden layer, and an output layer. The input layer comprised the number of neurons equal to that of the respective model's predictors (five neurons in Models 1–3, three neurons in Model 4, and one neuron in Model 5). The number of nodes in the hidden layer was automatically determined by SPSS 25 via its internal heuristics. For all models, the hidden layer used the hyperbolic tangent (tanh) activation function, and the output layer was implemented with identity (linear) activation function for continuous outcome prediction (IBM Corp., 2013). A bias node was used in the input and hidden layers to enable the adjustment of weight scales and improve the learning ability. As depicted in the ANN diagrams, Fig 9 presents Model 1 for forecasting SGP, and Fig 10 presents Model-2 for BO with all input nodes connected to fully hidden neurons. Again, all hidden neurons are connected to the respective output node with respect to each submodel. Such a multi-model ANN architecture permits a fine-grained validation of predictive performance on the constructs that are important using Model 1, while closely following the structure of PLS-SEM.

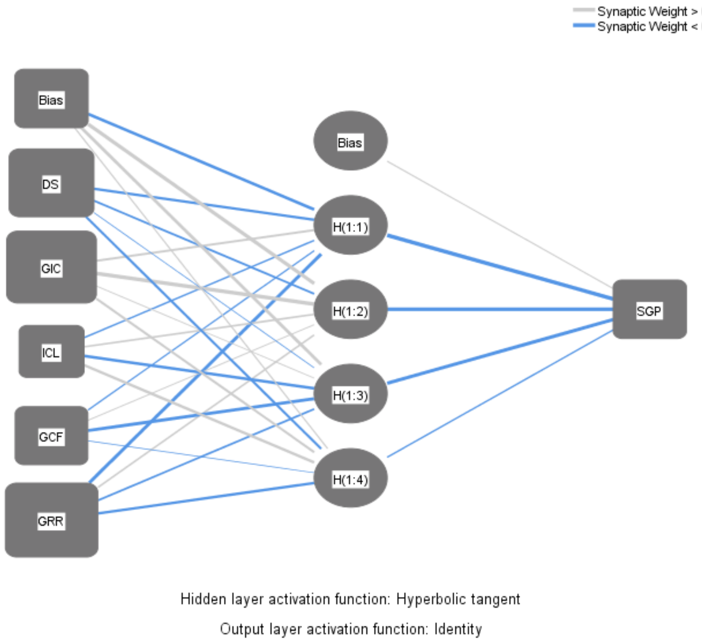


Figure 9. Diagram of Artificial Neural Network Model-1

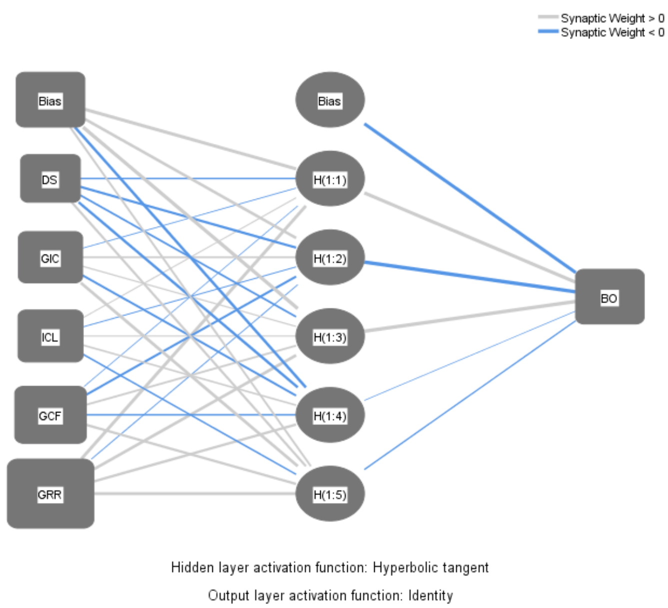


Figure 10. Diagram of Artificial Neural Network Model-2

4.3.2 Data Splitting and Training Process

To guarantee the reliability of the learning and performance consistency of the ANN models, a regular split-and-train method was utilized. Following the guidelines for neural network design (Vellido et al., 1999; Shmueli et al., 2016), the original whole data set was randomly split into two smaller sets, covering 90% and 10% of the full data set, respectively (having this latter population multiple times allowed us to check how well generalization could be tested as well as finding a possible overfitting.) The cases were automatically allocated by SPSS version 25 into the two subgroups in a stratified manner, so that the categorization of the outcome classes was balanced. The training pool was utilized for the optimization of synaptic weights through backpropagation, and the test subset provided an unbiased estimate of the prediction performance. To ensure the stability and reliability of the results, ten separate experiments were carried out for each ANN model using a technique similar to the tenfold cross-validation. In each run, SPSS created data splitting 90/10 partition, and the network was retrained. This bootstrapping process reduced our reliance on any single sample split and resulted in performance estimates that were more indicative of how the models generalized to distinct subdivisions of the data.

4.3.3 Validation of Model

In addition, the performance of (ANN) model was validated in this study using the Root Mean Square Error (RMSE), which has been proposed as a good measure of prediction accuracy in machine learning and neural network applications (Chong, 2013; Shmueli et al., 2016). The square root of the mean errorsum—subplottingRMSE effectively squares all of your differences, takes the average of them, and then the square root, which means that when testing how well you are doing, a lower RMSE suggests better model performance. In this study, the RMSE was computed as a function of the SSE according to the following equations:

$$MSE = \frac{1}{n} \times SSE$$

$$RMSE = \sqrt{MSE}$$

where n is the number of elements in the training or testing set (Haykin, 1998). A smaller RMSE indicates greater predictive accuracy and a better model fit.

Table 14. RMSE values for ANN model-1

Training			Testing			
Networks	SSE	RMSE	Networks	SSE	RMSE	Total Sample
ANN01	40.449	0.382	ANN01	1.760185	0.238	308
ANN02	50.370	0.430	ANN02	1.57733	0.212	308
ANN03	37.475	0.369	ANN03	5.658464	0.414	308
ANN04	52.009	0.433	ANN04	5.609882	0.432	308

ANN05	30.265	0.325	ANN05	3.414368	0.394	308
ANN06	38.118	0.365	ANN06	3.199165	0.381	308
ANN07	45.742	0.412	ANN07	3.801992	0.316	308
ANN08	46.481	0.405	ANN08	4.717563	0.443	308
ANN09	31.395	0.335	ANN09	4.6818	0.402	308
ANN10	37.719	0.363	ANN10	5.382801	0.506	308
SUM	410.023	3.818	SUM	39.804	3.740	
Average	41.002	0.382	Average	3.980	0.374	
S.D	7.460	0.037	S.D	1.496	0.092	

Table 15. RMSE values for ANN model-2

Training			Testing			
Networks	SSE	RMSE	Networks	SSE	RMSE	Total Sample
ANN01	13.521	0.221	ANN01	1.302	0.205	308
ANN02	20.551	0.274	ANN02	3.606	0.321	308
ANN03	12.370	0.212	ANN03	0.444	0.116	308
ANN04	13.059	0.217	ANN04	0.491	0.128	308
ANN05	15.984	0.236	ANN05	1.276	0.241	308
ANN06	13.481	0.217	ANN06	2.396	0.330	308
ANN07	13.556	0.224	ANN07	2.047	0.232	308
ANN08	16.014	0.237	ANN08	0.722	0.173	308
ANN09	11.490	0.203	ANN09	0.386	0.115	308
ANN10	11.931	0.204	ANN10	1.209	0.240	308
SUM	141.956	2.246	SUM	13.878	2.101	
Average	14.196	0.225	Average	1.388	0.210	
S.D	2.694	0.021	S.D	1.031	0.078	

Table 16. RMSE values for ANN model-3

Training			Testing			
Networks	SSE	RMSE	Networks	SSE	RMSE	Total Sample
ANN01	16.124	0.241	ANN01	1.364	0.209	308
ANN02	16.638	0.246	ANN02	3.606	0.320	308
ANN03	20.110	0.270	ANN03	0.651	0.140	308
ANN04	10.731	0.196	ANN04	2.450	0.285	308

ANN05	13.272	0.215	ANN05	2.819	0.357	308
ANN06	38.491	0.366	ANN06	1.673	0.275	308
ANN07	13.262	0.221	ANN07	2.060	0.232	308
ANN08	17.447	0.247	ANN08	1.275	0.230	308
ANN09	13.384	0.219	ANN09	2.581	0.298	308
ANN10	12.341	0.207	ANN10	0.739	0.187	308
SUM	171.799	2.433	SUM	19.219	2.540	
Average	17.180	0.243	Average	1.922	0.254	
S.D	7.988	0.049	S.D	0.953	0.066	

Table 17. RMSE values for ANN model-4

Training			Testing			
Networks	SSE	RMSE	Networks	SSE	RMSE	Total Sample
ANN01	17.619	0.252	ANN01	0.849	0.166	308
ANN02	18.719	0.262	ANN02	0.490	0.118	308
ANN03	17.318	0.251	ANN03	0.833	0.159	308
ANN04	13.584	0.221	ANN04	2.835	0.307	308
ANN05	13.579	0.218	ANN05	0.843	0.196	308
ANN06	12.704	0.211	ANN06	1.697	0.278	308
ANN07	16.240	0.245	ANN07	0.660	0.132	308
ANN08	14.384	0.225	ANN08	1.512	0.251	308
ANN09	13.282	0.218	ANN09	1.057	0.191	308
ANN10	17.145	0.244	ANN10	0.356	0.130	308
SUM	154.575	2.348	SUM	11.130	1.927	
Average	15.457	0.235	Average	1.113	0.193	
S.D	2.179	0.018	S.D	0.735	0.066	

Table 18. RMSE values for ANN model-5

Training			Testing			
Networks	SSE	RMSE	Networks	SSE	RMSE	Total Sample
ANN01	74.364	0.518	ANN01	4.922	0.398	308
ANN02	69.167	0.503	ANN02	10.317	0.543	308
ANN03	77.256	0.530	ANN03	1.462	0.210	308
ANN04	76.999	0.526	ANN04	8.072	0.519	308

ANN05	74.895	0.512	ANN05	9.067	0.642	308
ANN06	73.327	0.506	ANN06	10.825	0.701	308
ANN07	76.675	0.533	ANN07	2.630	0.263	308
ANN08	74.171	0.511	ANN08	3.648	0.390	308
ANN09	73.504	0.513	ANN09	8.559	0.543	308
ANN10	69.722	0.493	ANN10	9.303	0.666	308
SUM	740.078	5.146	SUM	68.804	4.876	
Average	74.008	0.515	Average	6.880	0.488	
S.D	2.790	0.013	S.D	3.399	0.168	

All five ANN sub-models were estimated using the 90/10 training–testing split and the ten independent runs described earlier. For each run, SPSS version 25 re-partitioned the data, trained the network, and stored SSE and RMSE values. The corresponding descriptive statistics for each model are summarized in Tables 14–18. For Model 1 (SGP), the average RMSE was 0.382 for the training set and 0.374 for the test set, with standard deviations of 0.037 and 0.092, respectively (Table 14). Model 2 (BO**)** achieved average training and testing RMSE values of 0.225 and 0.210, and standard deviations of 0.021 and 0.078 (Table 15). Model 3 (GQ) reported an average training RMSE of 0.243 and a testing RMSE of 0.254, with standard deviations of 0.049 and 0.066 (Table 16). For Model 4 (SAT)**,** the average training RMSE was 0.235 and the average testing RMSE 0.193, with standard deviations of 0.018 and 0.066 (Table 17). Finally, Model 5 (CUI) produced the highest errors among the models, with average RMSE values of 0.515 (training) and 0.488 (testing), and standard deviations of 0.013 and 0.168, respectively (Table 18). Across all models, the differences between training and testing RMSE are small (ranging roughly from 0.008 to 0.042), indicating low generalization error and the absence of serious overfitting. In line with Shmueli et al. (2016), the combination of comparatively low RMSE values and minimal discrepancies between training and testing performance suggests a high level of model validity, good generalization capability, and satisfactory data fit. Consequently, the five ANN models can be considered reliable predictors of the respective endogenous constructs, further reinforcing the suitability of the proposed PLS-SEM–ANN hybrid modeling framework for explaining and forecasting mobile gaming behavior.

4.3.4 Feature Importance via Sensitivity Analysis

Sensitivity analysis was conducted to evaluate the relative contribution of each predictor variable in the five ANN models. As a post-estimation diagnostic tool, sensitivity analysis examines how changes in an individual input affect the model's output and is therefore particularly appropriate for complex, non-linear models such as ANNs, where the functional relationships cannot be easily inferred from the weights alone (Haykin, 1998; Olden & Jackson, 2002). For each model, SPSS produced importance scores for all input variables across the ten independently trained networks. These scores were averaged and then normalised by dividing each mean score by the maximum score within the same model and multiplying by 100. Consequently, the most influential predictor in a given model attains a normalised importance of 100%, and the remaining predictors are expressed relative to this benchmark (Garson, 1991). The numerical results are reported in Tables 17–21, while Figures 11–15 provide the corresponding bar charts of normalised importance.

Table 17. Sensitivity Analysis (Output-> SGP)

	DS	GIC	ICL	GCF	GRR
NN1	0.80	0.93	0.29	0.49	1.00
NN2	0.39	0.47	0.66	1.00	0.82
NN3	0.60	0.55	0.29	0.23	1.00
NN4	0.37	0.54	0.35	1.00	0.71
NN5	0.34	0.51	0.32	0.37	1.00
NN6	0.45	0.41	0.36	0.49	1.00
NN7	0.35	0.46	0.31	0.66	1.00
NN8	0.15	0.46	0.29	0.50	1.00
NN9	0.40	0.65	0.34	0.34	1.00
NN10	0.69	0.43	0.35	0.28	1.00
Average	0.45	0.54	0.36	0.54	0.95
Normalised Importance	47.85%	56.92%	37.42%	56.38%	100.00%
Ranking	4	2	5	3	1

Table 18. Sensitivity Analysis (Output-> BO)

	DS	GIC	ICL	GCF	GRR
NN1	0.25	0.38	0.40	0.58	1.00
NN2	0.09	0.28	0.58	0.65	1.00
NN3	0.31	0.37	0.58	0.67	1.00
NN4	0.19	0.41	0.30	0.58	1.00
NN5	0.15	0.18	0.35	0.61	1.00
NN6	0.07	0.19	0.40	0.70	1.00
NN7	0.14	0.26	0.48	0.76	1.00
NN8	0.07	0.32	0.46	0.60	1.00
NN9	0.30	0.34	0.37	0.72	1.00
NN10	0.27	0.29	0.46	0.49	1.00
Average	0.18	0.30	0.44	0.64	1.00
Normalised Importance	18.46%	30.07%	43.88%	63.74%	100.00%
Ranking	5	4	3	2	1

Table 19. Sensitivity Analysis (Output-> GQ)

	DS	GIC	ICL	GCF	GRR
NN1	0.22	0.65	1.00	0.68	0.95
NN2	0.21	0.61	1.00	0.75	0.64
NN3	0.32	0.40	1.00	0.55	0.73
NN4	0.44	0.38	1.00	0.48	0.62
NN5	0.28	0.50	1.00	0.51	0.81
NN6	0.32	0.17	0.55	0.99	1.00

NN7	0.36	0.51	1.00	0.42	0.55
NN8	0.13	0.25	1.00	0.43	0.65
NN9	0.49	0.55	1.00	0.67	0.87
NN10	0.40	0.45	1.00	0.44	0.77
Average	0.32	0.45	0.96	0.59	0.76
Normalised Importance	33.09%	46.57%	99.49%	61.85%	79.04%
Ranking	5	4	1	3	2

Table 20. Sensitivity Analysis (Output-> SAT)

	SGP	BO	GQ
NN1	0.07	0.07	1.00
NN2	0.40	0.34	1.00
NN3	0.11	0.35	1.00
NN4	0.21	0.07	1.00
NN5	0.31	0.10	1.00
NN6	0.21	0.02	1.00
NN7	0.07	0.08	1.00
NN8	0.29	0.09	1.00
NN9	0.21	0.12	1.00
Average	0.21	0.14	1.00
Normalised Importance	20.98%	13.65%	100.00%
Ranking	2	3	1

Table 21. Sensitivity Analysis (Output-> CUI)

	SAT
NN1	1.00
NN2	1.00
NN3	1.00
NN4	1.00
NN5	1.00
NN6	1.00
NN7	1.00
NN8	1.00
NN9	1.00
Average	1.00
Normalised Importance	100.00%
Ranking	1

With respect to Model 1 (output variable: Smooth Gameplay Performance, SGP), the sensitivity results indicate that content- and social-related variables dominate the prediction. Game Content & Features (GCF) and Game Reviews & Recommendations (GRR) together account for the largest share of importance, followed by Internet Connectivity & Latency (ICL) and Game Interface & Controls (GIC), whereas Device Specifications (DS) plays a comparatively minor role (Table 17; Figure 11). This pattern suggests that perceived smoothness of gameplay depends more on how the game is designed and endorsed, and on the quality of the connection, than on the underlying hardware. In Model 2 (output variable: Battery Optimization, BO), a similar picture emerges. GCF and GRR again appear as the two most influential predictors, with ICL contributing at a moderate level and DS and GIC exerting relatively low importance (Table 18; Figure 12). Thus, users' perceptions of battery performance seem to be shaped less by the intrinsic capability of their devices and more by the intensity and structure of the game content, together with the social context in which the game is recommended and evaluated.

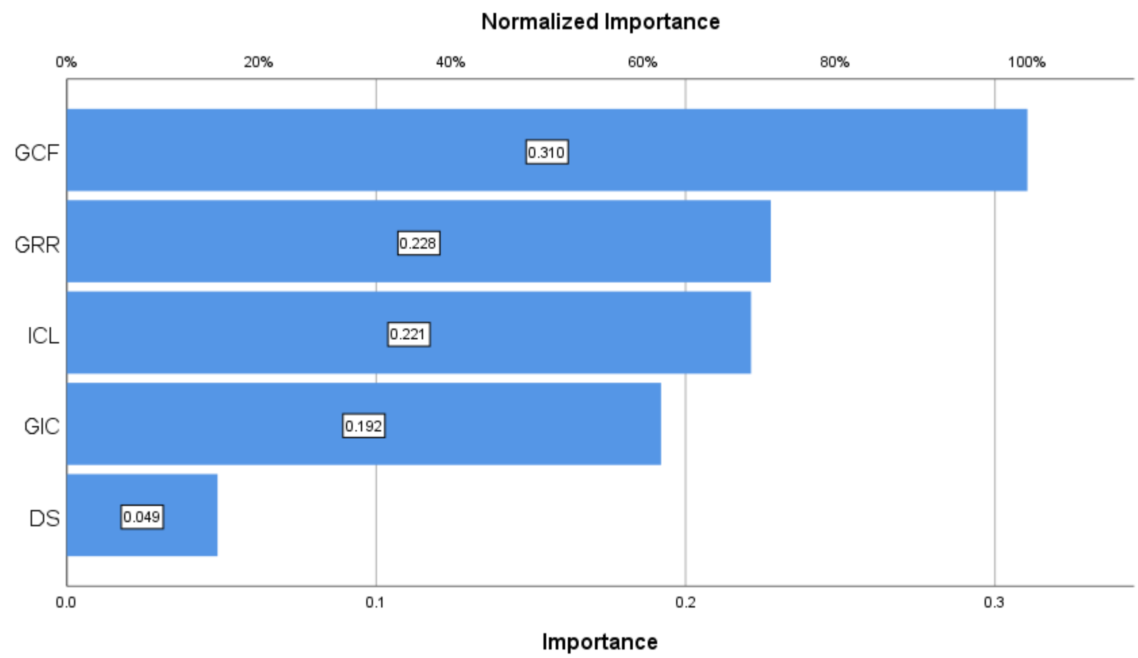


Figure 11 Normalized importance (Output variable: SGP).

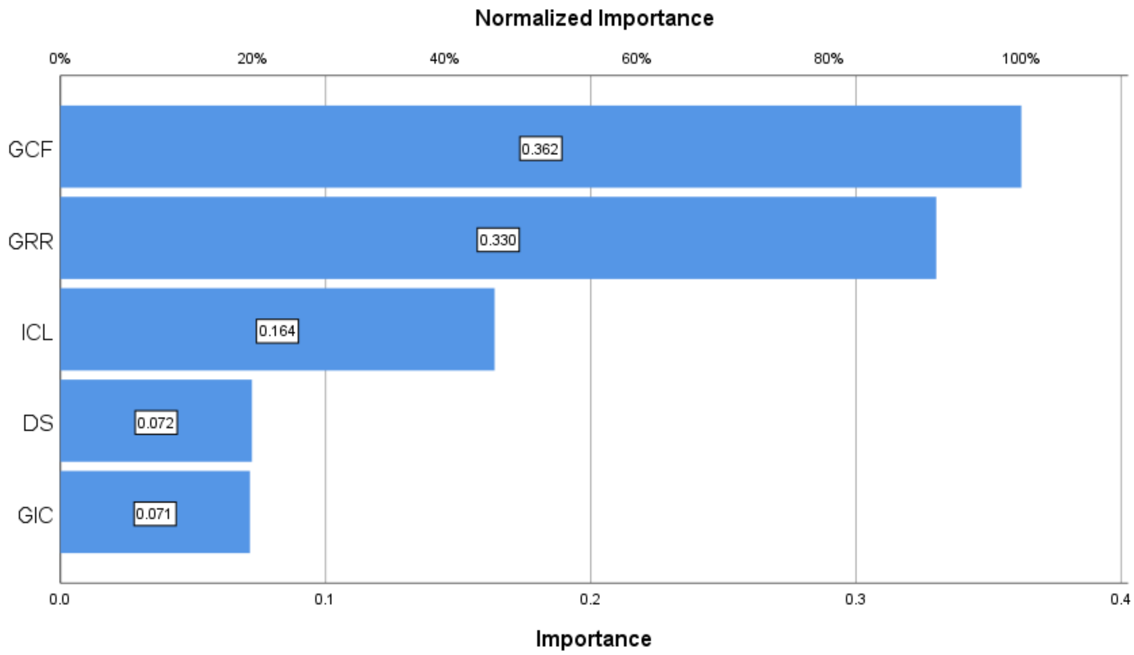


Figure 12 Normalized importance (Output variable: BO).

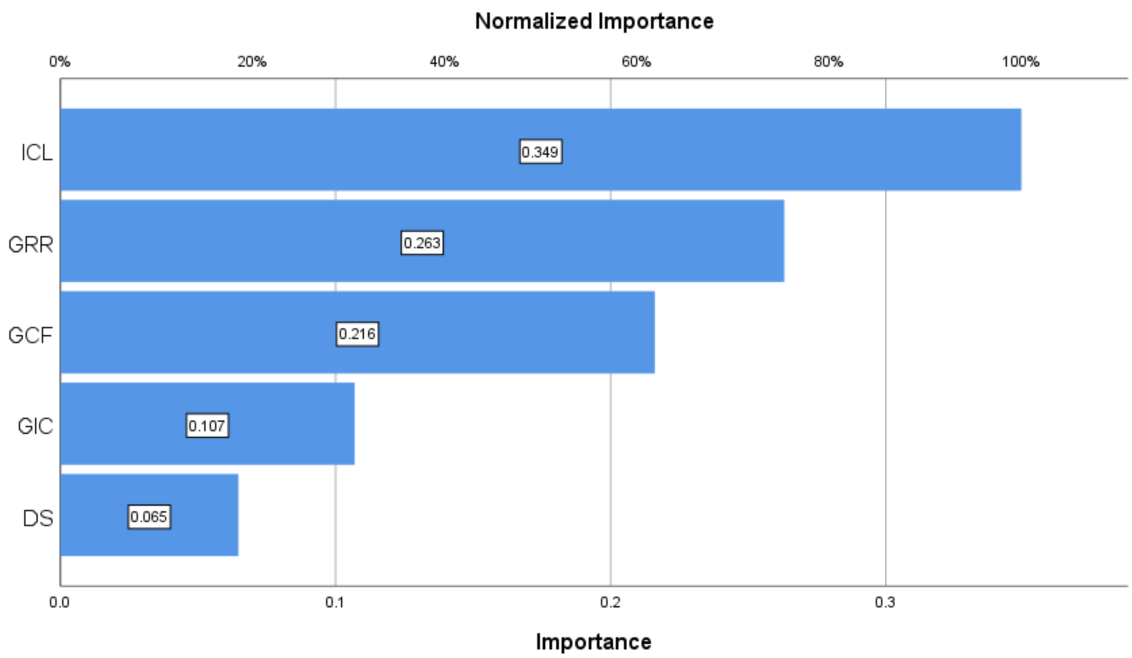


Figure 13 Normalized importance (Output variable: GQ).

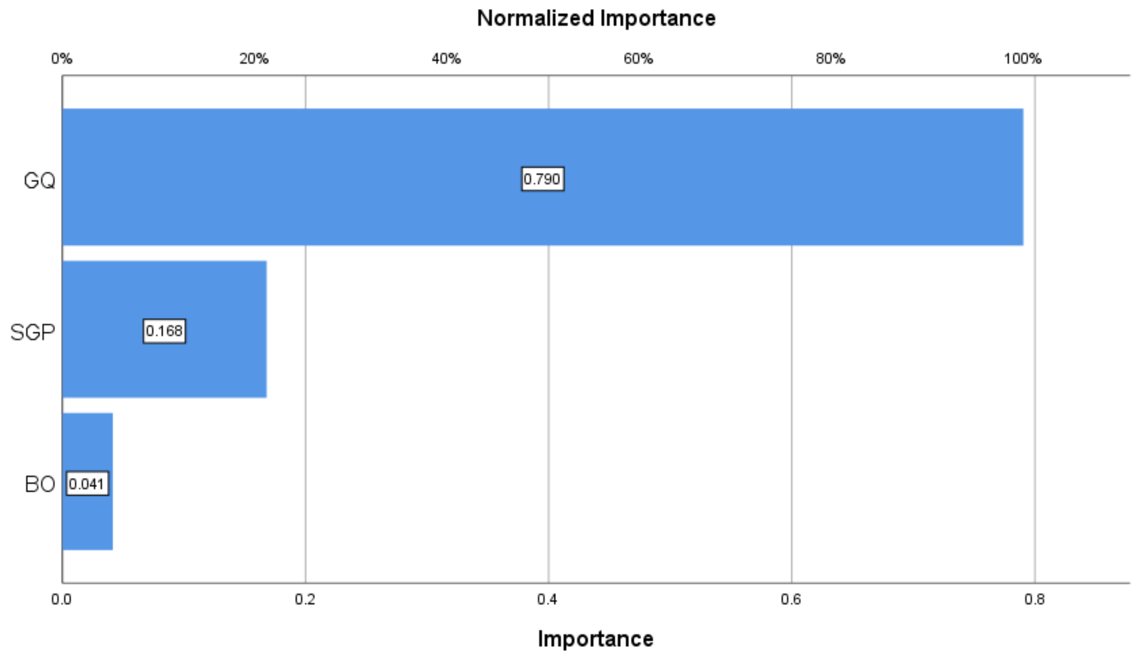


Figure 14 Normalized importance (Output variable: SAT).

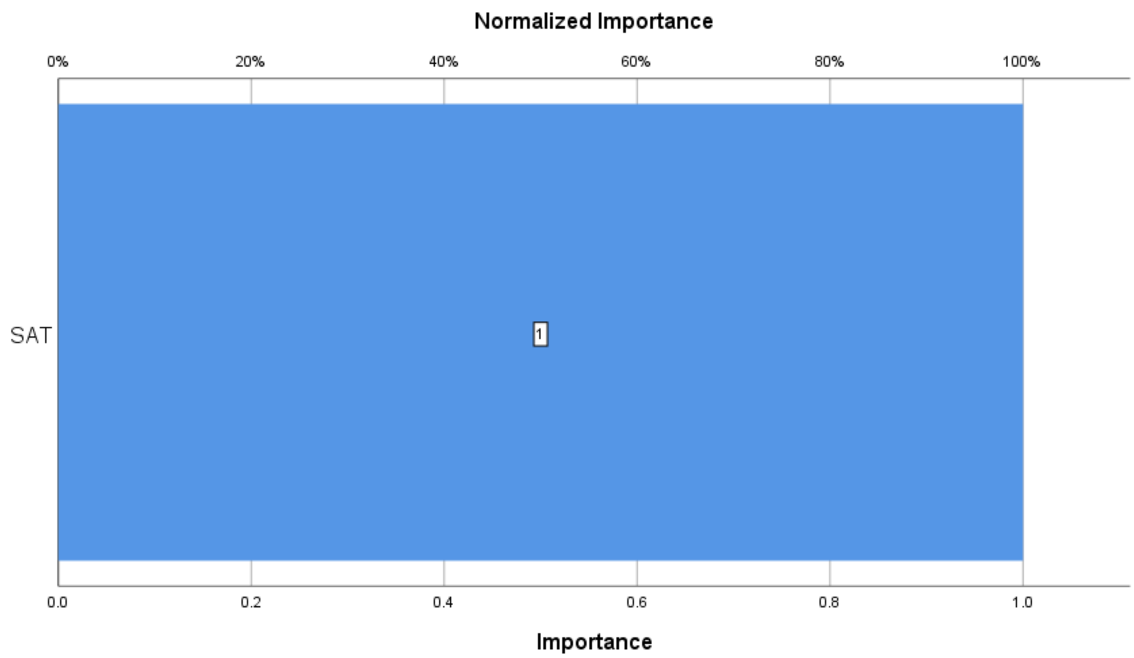


Figure 15. Normalized importance (Output variable: CUI).

For Model 3 (output variable: Graphics Quality, GQ), Internet Connectivity & Latency (ICL) is clearly the most important predictor, followed by GRR and GCF, while GIC and DS have smaller contributions (Table 19; Figure 13). This finding indicates that players' evaluations of graphical quality are not only a function of the visual assets themselves but also strongly depend on network conditions and socially framed expectations. In other words, high-quality graphics must be delivered consistently over the network and supported by positive reviews and engaging content to be appreciated by users. The results of Model 4 (output variable: Satisfaction, SAT) demonstrate a very pronounced dominance of Graphics Quality. GQ attains a normalised importance of 100%, whereas SGP and BO are of secondary and tertiary importance, respectively (Table 20; Figure 14). This implies that, in the context of BR mobile gaming, overall satisfaction is primarily driven by visual fidelity, with smooth performance contributing to a lesser degree and battery considerations having only marginal impact on satisfaction judgements. Finally, Model 5 (output variable: Continuance Usage Intention, CUI) exhibits a particularly simple structure: Satisfaction (SAT) is the only predictor and therefore receives a normalised importance of 100% (Table 21; Figure 15). This confirms that the intention to continue playing is fully mediated through users' overall satisfaction with the game, in line with the results of the PLS-SEM structural model.Taken together, the sensitivity analyses reveal a coherent pattern across all ANN models. At the technical/design level, content richness (GCF), social influence (GRR) and network quality (ICL) repeatedly emerge as the most influential predictors of the experiential constructs (SGP, BO and GQ). At the experiential level, Graphics Quality is the key determinant of Satisfaction, and Satisfaction in turn is the sole driver of Continuance Usage Intention. These findings not only corroborate the PLS-SEM results but also provide additional, prediction-oriented evidence that visually rich, socially validated and well-connected game experiences are central to fostering both immediate satisfaction and long-term engagement with mobile Battle Royale games.

4.3.5 Comparative Insights: PLS-SEM vs ANN

To examine the robustness of the findings and to exploit the complementary strengths of explanatory and predictive modelling, the relative importance of predictors obtained from PLS-SEM was compared with the importance rankings derived from the ANN sensitivity analysis (e.g., Hair et al., 2019; Shmueli et al., 2016; Sharma et al., 2020). Tables 22–26 summarize these comparisons for each endogenous construct.

TABLE 22. Comparison between PLS-SEM and ANN analysis (output: SGP).

	Path Mean	**PLS-SEM Ranking**	**ANN Normalized Importance (%)**	**ANN Ranking**	**Matched?**
DS	0.213	4	47.85%	4	**Yes**
GIC	0.496	2	56.92%	2	**Yes**
ICL	0.146	5	37.42%	5	**Yes**
GCF	0.245	3	56.38%	3	**Yes**
GRR	0.695	1	100.00%	1	**Yes**

Table 22 reports the comparison for Smooth Gameplay Performance (SGP). Both approaches identify Game Reviews & Recommendations (GRR) as the most influential predictor and Game Content & Features (GCF) as an important driver, with identical first and third rankings, respectively. In fact, for SGP the full ranking pattern is consistent across PLS-SEM and ANN (GRR

→ GIC → GCF → DS → ICL), indicating strong convergence between the linear structural model and the non-linear predictive model. Table 23 presents the comparison for Battery Optimization (BO). Here, convergence between the two methods is again strong. Both PLS-SEM and ANN rank GRR as the most important predictor, followed by GCF and ICL, indicating that social influence, content design and network conditions jointly shape perceptions of battery efficiency. Only the relative positions of DS and GIC differ slightly, with PLS-SEM placing DS ahead of GIC and the ANN reversing these positions, although both approaches agree that these two variables are the least influential. For BO, therefore, the hybrid analysis confirms a stable hierarchy of determinants across both linear and non-linear modelling frameworks.

TABLE 23. Comparison between PLS-SEM and ANN analysis (output: BO).

	Path Mean	PLS-SEM Ranking	ANN Normalized Importance (%)	ANN Ranking	Matched?
DS	-0.009	4	18.46%	5	**No**
GIC	-0.206	5	30.07%	4	**No**
ICL	0.274	3	43.88%	3	**Yes**
GCF	0.320	2	63.74%	2	**Yes**
GRR	0.551	1	100.00%	1	**Yes**

TABLE 24. Comparison between PLS-SEM and ANN analysis (output: GQ).

	Path Mean	PLS-SEM Ranking	ANN Normalized Importance (%)	ANN Ranking	Matched?
DS	0.056	5	33.09%	5	**Yes**
GIC	0.239	2	46.57%	4	**Yes**
ICL	0.383	1	99.49%	1	**Yes**
GCF	0.217	3	61.85%	3	**Yes**
GRR	0.205	4	79.04%	2	**No**

TABLE 25. Comparison between PLS-SEM and ANN analysis (output: SAT).

	Path Mean	PLS-SEM Ranking	ANN Normalized Importance (%)	ANN Ranking	Matched?
SGP	0.096	2	20.98%	2	**Yes**
BO	0.086	3	13.65%	3	**Yes**
GQ	0.797	1	100.00%	1	**Yes**

The comparison for Graphics Quality (GQ) is shown in Table 24. Both PLS-SEM and ANN agree that ICL is the dominant predictor and that DS has the lowest importance, resulting in matching first and fifth ranks. However, the intermediate predictors differ: PLS-SEM ranks GIC second, followed by GCF and then GRR, whereas the ANN elevates GRR to second place and moves GCF and GIC to third and fourth, respectively. This suggests that, in addition to connectivity and content, socially constructed expectations around game quality (captured by GRR) exert a stronger non-linear influence than is implied by the PLS-SEM coefficients alone (cf. Venkatesh & Bala, 2008; Kumar & Sharma, 2020). Table 25 compares PLS-SEM and ANN for Satisfaction (SAT) and reveals complete agreement across all predictors. In both approaches, GQ emerges as the most important determinant of SAT, followed by SGP and BO. This perfect match indicates that the satisfaction relationships are predominantly monotonic and are similarly captured by both the PLS-SEM structural model and the ANN, reinforcing the centrality of visual quality and smooth performance for adolescent satisfaction in BR mobile games (Hair et al., 2017; Sarstedt et al., 2014).

TABLE 26. Comparison between PLS-SEM and ANN analysis (output: CUI).

	Path Mean	**PLS-SEM Ranking**	**ANN Normalized Importance (%)**	**ANN Ranking**	**Matched?**
SAT	0.723	1	100.00%	1	**Yes**

Finally, **Table 26** presents the comparison for Continuance Usage Intention (CUI). Since SAT is the only predictor of CUI in the models, ST is ranked as the top by default in both PLS-SEM and ANN. This finding implies that the wish to continue playing is entirely mediated by overall satisfaction, following technology acceptance and user engagement theories (Henseler et al., 2015; Memon et al., 2020). In short, the cross-method correlation in Tables 22–26 indicates strong levels of convergence for PLS-SEM and ANN, particularly for the closer experiential and behavioral stem constructs (SAT and CUI). Where discrepancies of rank occur — most prominently for DS and GIC in the BO model, and GRR in the GQ model — it probably reveals more non-linearities and interactions present but not captured by the ANN. The dual application of PLS-SEM and ANN thus yields mutually complementary insights: whereas the former delivers a transparent, theory-based representation of causal structure, the latter sharpens this picture by highlighting intricate predictive relationships, enriching model validity, and practical relevance (Migueis et al., 2012; Shmueli et al., 2016; Sharma et al., 2020).

4.4 Discussion of Findings

The general findings of the study are described in this chapter, which involves integrating the results of the Kano analysis, PLS-SEM, and ANN models. Collectively, these methods offer in-depth insight into the technical, experiential, and perceptual determinants of satisfaction and the intention to continue using mobile BR games among Bangladeshi adolescents. The discussion follows three main themes: (i) how adolescents classify and weight gaming characteristics, (ii) the structural role of these features in the satisfaction and continuance intention process, and (iii) how predictive modelling refines and confirms the PLS-SEM results.

4.4.1 Interpretation of Kano Findings

Kano analysis provides an initial user perspective on which game features are important and how they impact the (dis)satisfaction. It is obvious from the results that a teenager who plays games has a high and nearly absolute understanding of basic expectations, performance drivers, delighters, low-priority features, and problematizing features. One possible explanation is that, through the Must-Be classification of graphics quality, voice chat, and anti-cheating and reward systems (Table 5), these features are regarded as non-negotiable minimum requirements or essentials in a survival game. Consistent with the Kano theory, the presence of these features does not strongly increase satisfaction, but their absence results in significant dissatisfaction. For Bangladeshi youth, this translates into a BR game not being “serious” or “competitive” unless it provides visually stunning graphics, strong anti-cheat and voice chat functions, and an in-game rewards scale. As such, these characteristics are considered hygiene factors in BR gaming. Second, Smooth Game Play and Battery Optimization stand out as obvious performance features. Their coefficients of Better–Worse indicate nearly linear satisfaction responses: high frame rates, low lag, and low energy costs lead directly to higher satisfaction, whereas poor performance reduces this. This proves that technical stability is not peripheral but rather central to the overall perception of BR gameplay for mobile players, mainly on mid-tier and Wi-Fi-dependent devices. Fair Matchmaking, Quick Game Start, Control Modification, and Locale Support are categorized as attractive features. These “delighters” increase satisfaction more when they are present than when they are absent. In an ultra-competitive industry, these kind of features provide golden opportunities for a value-added differentiation once the Must-Be and Performance requirements are satisfied (e.g. faster lobby-to-match transition times, localized user interfaces and advanced flexibility control schemes mirroring local game play preferences)." On the other hand, two actives (Optimized Internet Consumption and Frequent Updates) and one indifferent element (Offline Training Mode) seem to affect few players satisfaction or dissatisfaction. Although these factors may still be relevant for certain subsets or operational purposes, from a user satisfaction perspective, they are less important areas of investment. Finally, Social Features and In-App Purchasing Fairness are reversed attributes. This implies that, as they operate today, placing more emphasis on social systems and monetization is less satisfying for large groups of players. This finding is particularly relevant for a developing-country setting, where worries about aggressive monetization, peer pressure, or intrusive social mechanics may be more severe. This suggests that such a feature should not be scaled, but treated with great care and perhaps even redesigned.

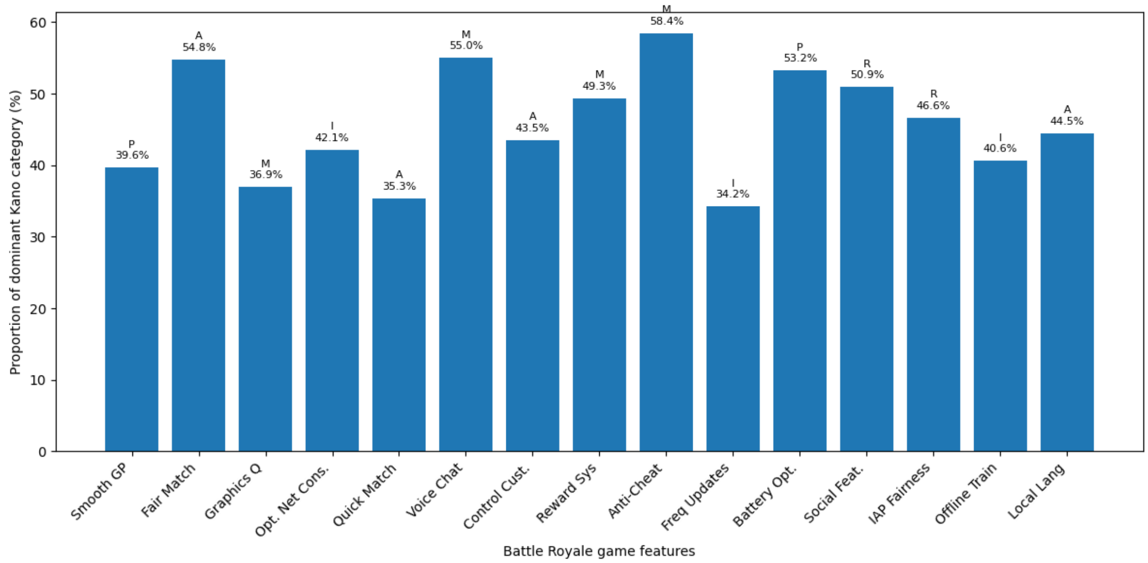


Figure 16. The percentage of games features under the dominant Kano category

The figure 16 substantiates the previous categorization in Table 5. Attributes such as Anti-Cheat Protection, Voice Chat Quality, Graphics Quality Reward System and Battery Optimization have relatively large bars with must-be (M) or performance (P) labels, showing a popular opinion among players that these aspects are all essential. On the other hand, features like Fair Matchmaking, Quick Match Start, Control Customization, and Local Language show a high percentage of Attractive (A), which could be defined as delighters separating one Battle Royal game from another. On the other hand, Optimized Internet Consumption, Frequent Updates, and Offline Training Mode presented moderate bars under the Indifferent (I) answer, thus indicating a lower consensus on their importance to satisfaction. Link Between Reverse (R) Reports and the In-App Purchasing Fairness Factor Finally, the bars for Social Features and In-App Purchasing Fairness are also dominated by the R category, indicating why some subsets of adolescents feel that an increased focus on these features will make them enjoy less rather than more. Overall, Figure 9 presents a visual summary in the intuitive sense of how strongly each attribute relates to its primary Kano category, reinforcing the order structure found quantitatively.

4.4.2 PLS-SEM Model findings

The confirmed PLS-SEM model is shown in Fig. 17, which integrates Kano-based core features with other game-conditionality and experiential constructs. Overall, the model displayed acceptable levels of reliability and validity (with composite reliabilities and AVE values higher than the suggested cut-offs for all the main constructs; Hair et al., 2019; Henseler et al., 2015). At the structural level, Graphics Quality (GQ) appears to be the most important factor in determining satisfaction (SAT) with a very large and highly significant path coefficient ($\beta \approx 0.79$, $p <. 001$). GQ also influences CUI to a great extent via SAT, which indicates that visual fidelity acts as the main criterion through which adolescents appraise overall game quality. ICL, GCF and SAT exhibit the most substantial impacts on SGP, GQ and SAT respectively, suggesting that stable network connectivity and enriched, well-designed content play a fundamental role in both perceived performance and visual experience. GRR also enhances the relationships by having significant total effects on all dependent variables, where it is positively related to (BO, SGP, and CUI) except (SAT and GQ) which suggests that social validation and peer recommendations have an impact on influencing quality perceptions of games. In contrast, Device Specifications (DS) mainly affects upstream constructs such as SGP and Battery Optimization (BO), but shows no significant direct effect on SAT or CUI. Likewise, BO has only a small, non-significant direct impact on SAT and CUI once performance and graphics are controlled for, suggesting that battery considerations are secondary when core experiential factors are strong. Satisfaction occupies a central mediating role, exerting the largest direct effect on CUI ($\beta \approx 0.72$, $p < .001$), which is consistent with user-engagement and technology-acceptance theories. High R^2 values for SAT (≈ 0.90) and GQ (≈ 0.86) indicate substantial explanatory power, while SGP and CUI are explained to a moderate but meaningful degree.

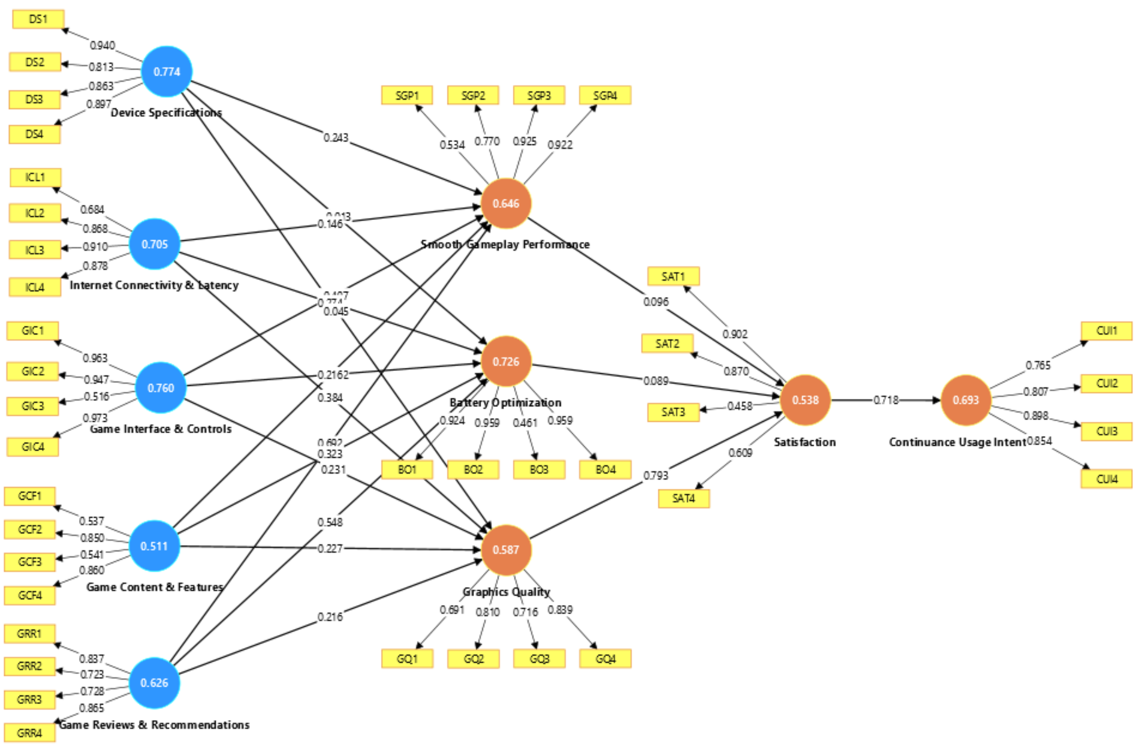
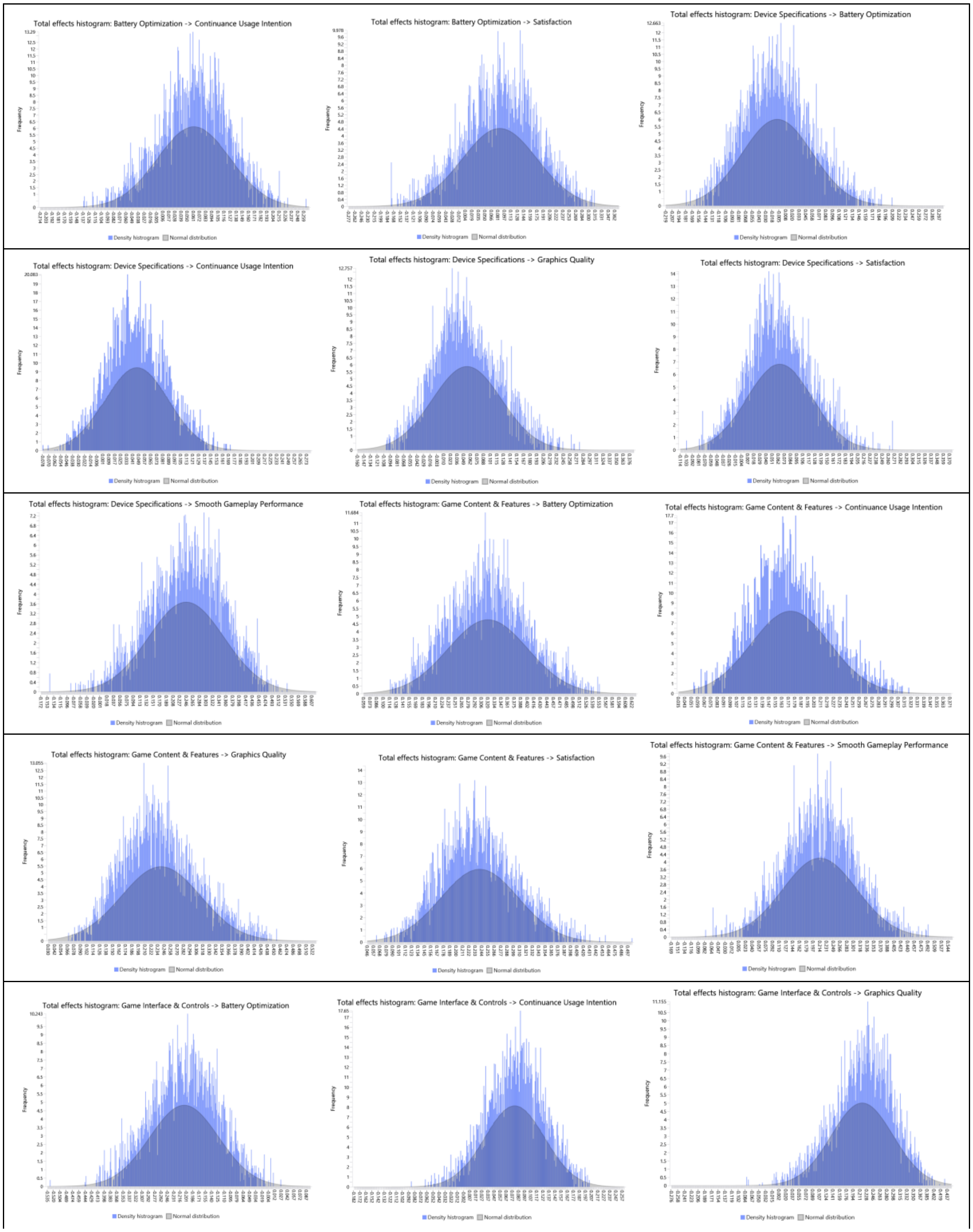
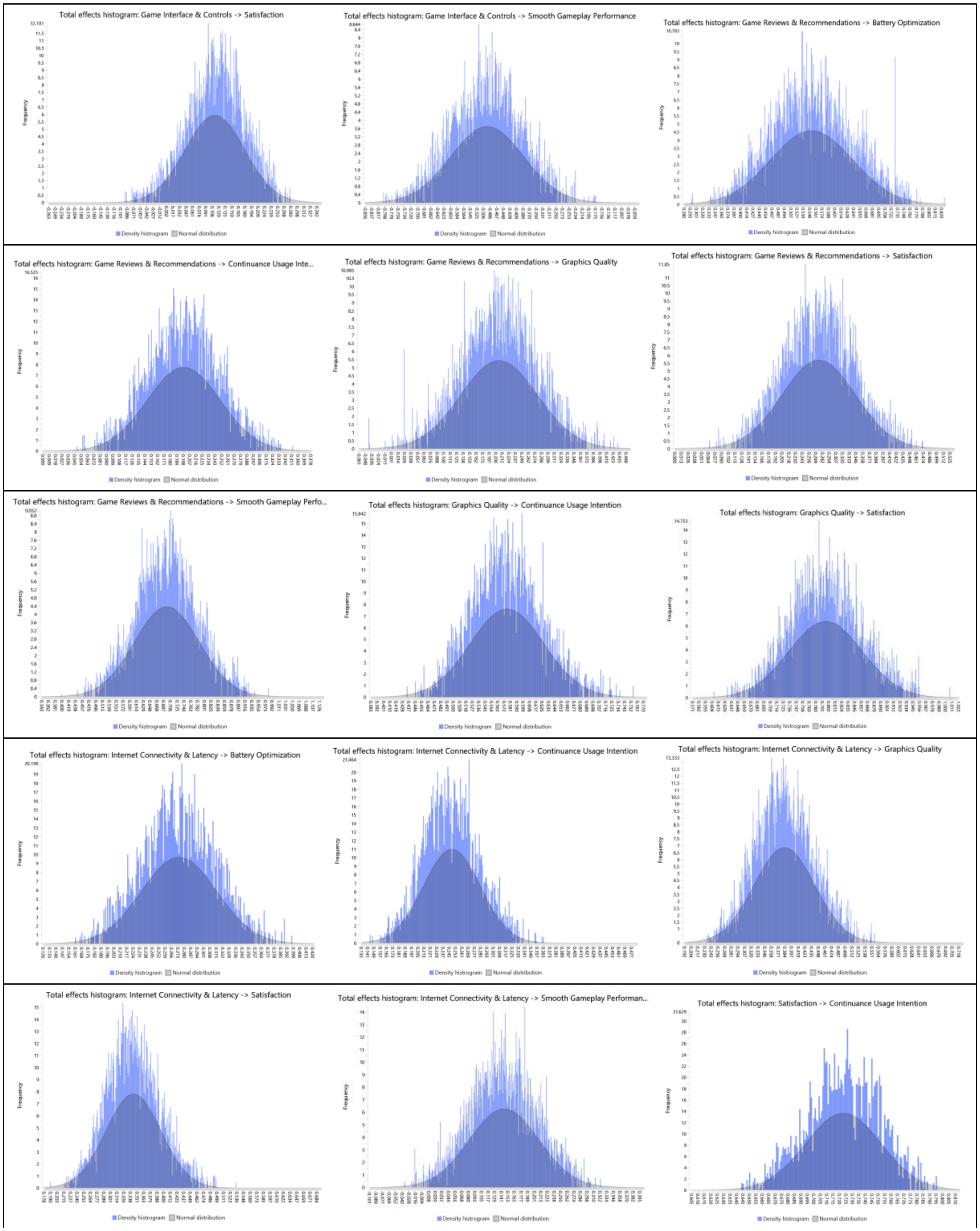


Figure 17. Final model of PLS-SEM

PLSpredict results support strong out-of-sample predictive ability for SAT, GQ and SGP, and moderate predictive validity for CUI, with weaker prediction only for BO. Collectively, these findings show that visually rich, well-connected and socially endorsed gameplay experiences are the key drivers of satisfaction and continued use of mobile Battle Royale games among Bangladeshi adolescents.


Total effects histogram: Battery Optimization -> Continuance Usage Intention
Total effects histogram: Battery Optimization -> Satisfaction
Total effects histogram: Device Specifications -> Battery Optimization
Total effects histogram: Device Specifications -> Continuance Usage Intention
Total effects histogram: Device Specifications -> Graphics Quality
Total effects histogram: Device Specifications -> Satisfaction
Total effects histogram: Device Specifications -> Smooth Gameplay Performance
Total effects histogram: Game Content & Features -> Battery Optimization
Total effects histogram: Game Content & Features -> Continuance Usage Intention
Total effects histogram: Game Content & Features -> Graphics Quality
Total effects histogram: Game Content & Features -> Satisfaction
Total effects histogram: Game Content & Features -> Smooth Gameplay Performance
Total effects histogram: Game Interface & Controls -> Battery Optimization
Total effects histogram: Game Interface & Controls -> Continuance Usage Intention
Total effects histogram: Game Interface & Controls -> Graphics Quality
Frequency
Density histogram
Normal distribution


Total effects histogram: Game Interface & Controls -> Satisfaction
Total effects histogram: Game Interface & Controls -> Smooth Gameplay Performance
Total effects histogram: Game Reviews & Recommendations -> Battery Optimization
Total effects histogram: Game Reviews & Recommendations -> Continuance Usage Inte...
Total effects histogram: Game Reviews & Recommendations -> Graphics Quality
Total effects histogram: Game Reviews & Recommendations -> Satisfaction
Total effects histogram: Game Reviews & Recommendations -> Smooth Gameplay Perfo...
Total effects histogram: Graphics Quality -> Continuance Usage Intention
Total effects histogram: Graphics Quality -> Satisfaction
Total effects histogram: Internet Connectivity & Latency -> Battery Optimization
Total effects histogram: Internet Connectivity & Latency -> Continuance Usage Intention
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Density histogram
Normal distribution

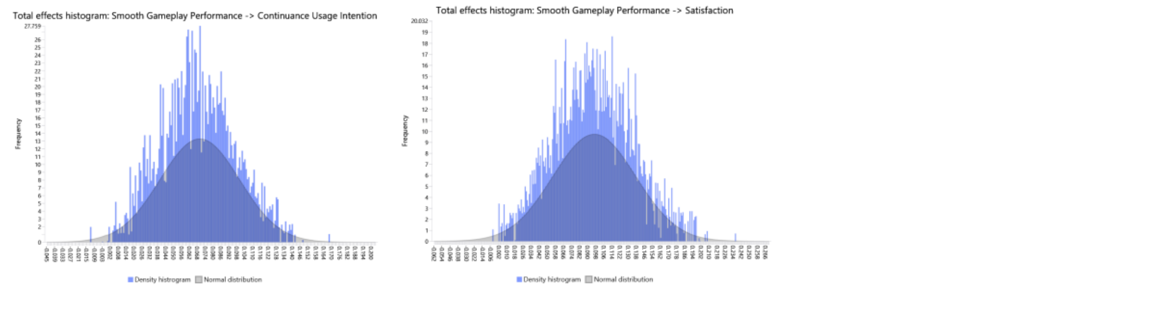

Figure 18. Histograms of the total effect of the factors

Histograms of the total effects (i.e., the sum of the direct and indirect effects) estimated by bootstrapping are presented in Figure 14. Each subplot is related to a particular cause–effect relationship, that is, the total effect from Game Content & Features to Satisfaction or the total effect from Graphics Quality to Continuance Usage Intention. Histograms depict sampling variability from 5,000 bootstrapped subsamples and exhibit the consistency of stability and magnitude of each total effect. The normal distributions centered at the estimates obtained from the original sample indicate statistical stability and replication reliability across random resampling, thus increasing the robustness of the model (Hair et al., 2021). Such visualizations provide a useful complement to the estimates in Table 12 (Total Effects), facilitating a more straightforward interpretation of the relationship among latent variables. Effects that are stronger and more consistent, such as from Graphics Quality to Satisfaction, show tighter distributions with more density around the mean, and weaker or non-significant effects have wider flatter histograms.

4.4.3 ANN Model findings

Overall, the ANN results strongly validate the core findings of the PLS-SEM model. Across all five endogenous constructs (SGP, BO, GQ, SAT and CUI), the ANN-derived importance rankings closely aligned with the PLS-SEM path coefficients, particularly for the most influential predictors. In both analyses, Game Reviews & Recommendations (GRR)**,** Game Content & Features (GCF)**,** Internet Connectivity & Latency (ICL) and especially Graphics Quality (GQ) consistently emerged as the dominant drivers of user experience, satisfaction and continuance intention. The strongest validation appears for Satisfaction (SAT) and Continuance Usage Intention (CUI)**,** where ANN and PLS-SEM produced *identical* predictor rankings. Both methods confirmed that Graphics Quality is the single most powerful determinant of Satisfaction**,** and that Satisfaction is the sole determinant of CUI**.** This perfect convergence indicates that the relationships between experiential factors and behavioural intention are stable, monotonic and robust across both linear (PLS-SEM) and non-linear (ANN) modelling approaches. For DS and GIC, small changes in rank were also obtained for upstream constructs (SGP, BO, and GQ). These differences indicate further non-linear relationships that ANN can capture, but should not refute the PLS-SEM findings. However, they do so by reducing them through the detection of small predictive patterns. Crucially, the best determinants selected by the PLS-SEM approach —GRR, GCF, ICL, and GQ—were also among the most powerful predictors in ANN analysis (reliabilities were surpassed only by VIF), highlighting the conceptual and empirical robustness of these variables. In sum, the ANN evaluation supports that such structural findings by PLS-SEM are not only statistically significant but also robust to predictive extent. By confirming the key drivers of satisfaction and continuance intention using a non-linear machine learning approach, this study reinforces trust in the proposed model and provides significant evidence that media-rich multiplayer auto-battler gameplay experiences that players believe to be socially acceptable (i.e., wanted) and stable are the main engagement levers for mobile Battle Royale games.

CHAPTER 5

IMPACT ON SOCIETY, AND COUNTRY

5.1 Impact on Society and Country

Considering the implications for the general society and the country at large, especially digital participation and youth's behavior, including the gaming industry, the findings of this study related to adolescents' proclivity for mobile Battle Royale games are significant.

5.1.1 The impact on the health and the conduct of adolescents

This study claims that mobile BR games largely affect the behavior of Bangladeshi adolescents. For instance, numerous young individuals play regularly (and for leisure) games like PUBG Mobile and Free Fire (see Esports as a reference), which kind of exposure – accompanied by respective experiences through multiplayer modes – can support peer relationships and team skills acquisition (Carras et al., 2018; Adachi & Willoughby, 2016). Elements such as peer-to-peer competition, thrill and long-term engagement serve to generate EI and increase the sense of community among young people (Braun et al., 2021). But excessive gaming can also be dangerous. This study demonstrates that the more time spent on gaming, the higher degree of gamification resulting in screen addiction or at least reduced academic engagement. This is confirmed by international studies: high exposure to screens can trigger sleep problems, decrease school performance and cause emotional dependence on virtual settings (Király et al., 2018; González-Bueso et al., 2018). As adolescents are still growing emotionally and cognitively, the higher risks of these factors hit the most on them (Huang et al., 2022).

5.1.2 Implications for the games industry in Bangladesh

Mobile gaming industry of Bangladesh is booming. This is as a result of cheap smartphones, the availability of good internet and more access via social media (GSMA, 2022). BR games have gained massive popularity now and gaming has entered into youth culture as an integral element (Ahmed & Kabir, 2021). The current study demonstrates this trend: mobile gaming is a key digital entertainment activity among the adolescent population. Since more than half of the global gaming revenue comes from mobile games (Newzoo, 2023), Bangladesh can draw economic benefit. From game development to esports, content creation and digital marketing there are jobs on offer. The research findings can be helpful for developers in localizing game by incorporating Bangla language, culture-related issues and local topics to make the games more that users can relate with (Chowdhury et al., 2022). These are the ways to increase engagement and enhance loyalty among players in Bangladesh. This development may generate more interest among foreign investors and innovation in the digital services. Given suff icient support, Bangladesh can develop a sustainable gaming ecosystem that will contribute to national income and digitalization (UNCTAD, 2020; OECD, 2021).

5.1.3 Impact on Learning and Youth Development

Mobile games have both positive and negative influences on education and youth development. Positively, well-designed games can enhance decision-making, critical thinking and strategy skills in players (Granic et al., 2014; Qian & Clark, 2016). This finding suggests that the BR games in team-based mode can encourage collaboration and cooperative problem-solving. However, if left unmonitored, gaming could cause academic issues or even motivate players to cheat on their schoolwork. Several studies have found a negative relationship between excessive gaming and grade achievements, as well as inefficient time planning (Shin & Ahn, 2015; Müller et al., 2021). However, gaming can also be a mode of learning if approached in the right way. Students may also experience more engaging types of motivation in game-based learning when the learning content is integrated with popular game genres. The secret to good educational games is that they are fun and interactive (Barr, 2018). Educationists in Bangladesh can also utilize hybrid BR learning games to combine learning with the thrill of BR to develop digital skills and motivation.

5.1.4 Social Aspects and Digital Literacy

The importance of encouraging digital literacy in Bangladesh, especially among its youth, is emphasized. With phones dominating among children and young people, the more they are happy playing responsibly, the better. Crawford et al., 2010; Frissen, 2013), this pertains game mechanics, in screen-time restrictions and online behaviour (Livingstone et al., 2017; Ghosh et al. 2023). “Community” and “peer connections” are social elements of BR games that young people can resonate with. These arenas can foster cooperation and leadership (as long as they are well) (Koivula et al., 2020). Advising younger consumers to visit gaming resilient with respect for children and risk-free, could alleviate risks such as cyber-bullying or addiction (Marchant et al., 2021). Digital literacy programs must be implemented in schools and communities. These initiatives must work to promote healthy gaming behavior and support learning for time management, emotional management, creativity, and collaboration skills (UNESCO, 2022).

5.1.5 Policy Implications

As BR games become more popular, policy should be developed to keep young users safe. The findings of this study have implications for developing game policies in support of mitigating addiction risks, preventing harmful content and the safety of children (King et al., 2019). Nations such as India and South Korea, for instance, have already restricted young people’s access to certain games due to mental health fears (Kim, 2020).

The model combination (KANO, PLS, ANN) used in this study could assist decision-makers in exploring the game features that are most influential. Using this, they could adapt things like age-based content filters, playtime limits, in-game education cues, and support for parental monitoring tools. The regulation of such interventions is encouraged to be done jointly by game companies, government departments, and schools (Anderson et al., 2017; Barbosa et al., 2023).

5.1.6 Summary on Social impact and national relevance

Thus, Mobile Battle Royale games have become a significant part of the lives of Bangladeshi youth. They can also influence emotions, habits, and the ability to learn, and even open a pathway for digital careers. The benefits and risks of gaming for young people: Raising awareness to support (responsible) well-being. When done correctly, gaming can act as a catalyst for the social and economic progress of the nation. This will require cooperation between game developers, educators, and policymakers to ensure that gaming is used for good. By applying smart regulations, more education, and inclusive game design, it should be possible for Bangladesh to support safety in gaming while playing its role in constructing a better digital future (OECD 2021) (GSMA 2022).

CHAPTER 6

CONCLUSION, LIMITATIONS, AND FUTURE WORK

6.1 Conclusion

Satisfaction is influenced by Excitement and Peer Influence: The study findings showed that satisfaction was primarily influenced by excitement and peer influence. Adolescents like to engage with games that are exciting and fun and also enable them to connect with their friends. Time Engagement Indicates Emotion: The dedicated time investment in BR games, denoting the emotional engagement of the youngsters, might lead to the development of loyalty, but at the same time, might also lead to overdependence. Must-Have and Cool Factors: Factors like performance, the absence of cheaters, and the simple implementation of reward systems were found to act as must-have and cool. They influence the user experience and are related to the willingness to invest time and resources when users are interested in continuing to use the system. Hybrid Model (KANO-PLS-SEM-ANN) Works Effectively: The hybrid mode used in the study was highly predictable. It offers an effective platform to interpret user preferences when exposed to complex game situations and environments. Importance of Digital Literacy and Balance: Findings confirm that the developers, education, and family sectors all have to act together effectively to assure positive gaming habits.

6.2 Limitations

Limited Geographical Location: The research was done in urban and semi-urban areas, while adolescents from rural areas who lead different experiences and exposed to technology in varying ways were not considered. Cross Sectional Study Design: Since the survey was done cross-sectionally, it was not possible to observe the development over time for gaming behaviors. Self-reporting bias: The research collects self-reported information, which may produce biased outcomes. Some individuals may overestimate or underestimate their gaming practices. Contextualization/Generalization: The research is done in a specific context in Bangladesh. The research is valid and applicable in context, which may not work for other countries. Models are complex. Combining three models added complexity. It might prove difficult for other researchers who lack the ability to work with complex models due to a lack of advanced computer models and programming.

6.3 Future Work

Carry out Longitudinal Research: Following adolescents over time in research studies will provide valuable data on the influence of gaming upon development, school performance, and psychological well-being. Include Rural Youth: Expanding research data to incorporate rural regions will provide valuable insights into diverse social environments and their impact upon gaming practices. Cross Comparisons: Comparing data from different nations will enable an assessment of the effects of culture and economy upon young people's gaming practices. Utilize Gaming Behavior Data: Using actual data from gaming systems, for example, real play activity, participation within groups, or total rewards earned, will provide more accurate predictions. Collaborate with Game Developers and Policy Makers: Future research can provide game developers with data on appealing components for young people as well as policies for healthy and beneficial gaming.

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