



A Study on the Impact of Game Features on Player Behaviour in Mobile Games

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ABSTRACT

This study examines the relationship between game features and player behaviour in mobile games, with player motivation included as a related construct. The study focuses on rewards, challenges, social interaction, customization, and progression systems. Primary data were obtained from a structured questionnaire containing demographic questions and 1–5 numeric response items. The supplied spreadsheet contained 99 responses. Descriptive statistics, Pearson correlations, a chi-square test, one-way ANOVA, and simple linear regression were used to analyse the responses. The mean score for game features was 3.26 (SD = 0.84), the player-motivation score was 3.38 (SD = 0.87), and the behaviour-influence score was 3.40 (SD = 0.81). Game-feature scores positively predicted behaviour scores ($\beta = 0.535$, $R^2 = 0.312$, $p < .001$). The ANOVA indicated differences in mean behaviour scores across game types, $F(4, 94) = 7.98$, $p < .001$. The chi-square test did not reach the 5% significance threshold ($\chi^2(4) = 8.92$, $p = 0.063$). Results are based on self-reported cross-sectional data and should be interpreted as associations rather than causal effects.

Keywords: mobile games, game features, player behaviour, player motivation, engagement, regression, ANOVA, chi-square

1. Introduction

Mobile games have become a common form of digital entertainment, and their design often combines reward systems, challenges, social functions, customization, and progression mechanisms. These features can shape how players interact with a game, how much effort they invest, and whether they intend to continue playing. Understanding the relationships between game design and player behaviour can help developers improve user experience while avoiding design choices that unnecessarily pressure players to spend time or money.

Player behaviour in this study is considered through reported influence on engagement, continued play, and related actions. Motivation is included because players may respond to game features for different reasons, including personal interest, external rewards, achievement, and social connection. The research uses the survey responses supplied by the researcher to explore these relationships.

2. Review of Literature

Prior research suggests that game design elements can affect engagement through psychological mechanisms rather than having a uniform effect in every setting. Deng, Lee, and Tan (2024) analysed player engagement in online mobile games using gameplay data and found that perceived challenge and reward-ad mechanisms were associated with transitions between engagement states. Their work highlights the importance of balancing challenge and rewards.

Pechenkina et al. (2017) studied a gamified mobile learning application and reported improvements in engagement and retention following its introduction, while noting that causal relationships require careful investigation. Although the context was education rather than entertainment gaming, the study illustrates how mobile features can support sustained participation.

Han and Lee (2026) examined MOBA players and proposed pathways linking game mechanics (goal clarity, immediate feedback, and reward systems), perceived competence, flow experience, and continuance intention. Their results underline the role of sequential psychological processes in the relationship between game design and retention, with task complexity moderating the competence–flow link.

Research on player retention and churn provides additional context for understanding how features shape behaviour. Hadiji et al. (2014) developed game-agnostic behavioural features for churn prediction across multiple free-to-play (F2P) games and found that session frequency and inter-session timing were among the strongest predictors. Drachen et al. (2016) demonstrated that rapid retention prediction is feasible from very short observation windows (first session, day, or week), with total playtime and current absence time emerging as key features. Mustac et al. (2022) applied supervised machine

learning to a free-to-play mobile storytelling game and achieved useful early-churn detection using activity-distribution features within as little as one day of play.

Social interaction has also been shown to matter for retention. Oskarsdottir et al. (2022) enriched churn-prediction models in a mobile F2P game with features extracted from friend and similarity networks and found that network information substantially improved predictive performance beyond purely behavioural metrics. Demediuk et al. (2018) applied survival analysis to League of Legends and reported that longer average match durations and longer gaps between matches were associated with reduced likelihood of continuing to play.

Motivation and monetisation pathways further illuminate feature–behaviour links. Watola, Han, and Strzelecki (2025) modelled the antecedents of financial commitment to microtransactions and found that motivation was the strongest direct predictor of spending, mediating the effects of perceived ease of use, attitude, and satisfaction. Abdelqader (2026) used generative AI to analyse large volumes of game reviews and identified platform-specific drivers of enjoyment, noting that spatial presence was central for VR while gameplay and replayability dominated on PC, and that cosmetic-only monetisation was viewed more favourably than aggressive microtransactions.

Bilski, Łabędzki, and Bilski (2024) proposed a Big-Data pipeline for predicting maximum advancement level (a proxy for retention) from detailed in-game event data in mobile F2P games, emphasising the practical value of periodic model updates. Collectively, these studies support examining multiple game features—rewards, challenges, social interaction, customisation, and progression—alongside player motivation and behaviour, while recognising that effects may vary by game type, platform, and player context.

Research gap: the present survey provides a compact, respondent-level analysis of five commonly used game features and self-reported behaviour among mobile game users. It compares game-type groups and explores the association between aggregate feature, motivation, and behaviour scores. Unlike telemetry-driven churn or retention models, it relies on perceptual measures obtained through a structured questionnaire, offering a complementary, accessible perspective for academic and design-oriented inquiry.

3. Research Objectives

- To analyse the influence of different game features on player behaviour in mobile games.
- To analyse the relationship between game features and player motivation among mobile game users.
- To analyse the relationship between player behaviour and player motivation.
- To identify which measured game-feature dimensions show the strongest association with player behaviour.
- To examine whether player-behaviour scores differ across the types of mobile games played.

4. Conceptual Framework

The framework contains three constructs: Game Features (independent construct), Player Behaviour (dependent construct), and Player Motivation (related/mediating construct). Game Features comprise rewards, challenges, social interaction, customization, and progression. Player Behaviour includes engagement, time spent, retention, in-game purchases, and continuance intention as the conceptual dimensions specified in the source document. Player Motivation includes intrinsic, extrinsic, achievement, and social motivation. Age, gender, gaming experience, game type, and device are treated as control variables in the original framework.

Operational note: the questionnaire export does not contain separate direct measures for every conceptual dimension listed in the framework. Therefore, statistical analysis uses the actual question groups available in the spreadsheet. Questions 7–11 are treated as a game-feature perception composite, Questions 12–16 as a motivation-related composite, and Questions 22–26 as a self-reported game-feature influence on behaviour composite. The results should not be interpreted as separate validated measures of every conceptual dimension.

5. Research Hypotheses

- H1: Rewards significantly influence player behaviour in mobile games.
- H2: Challenges significantly influence player behaviour in mobile games.
- H3: Social interaction features significantly influence player behaviour in mobile games.
- H4: Customization features significantly influence player behaviour in mobile games.
- H5: Progression features significantly influence player behaviour in mobile games.
- H6: Game features as a whole significantly influence player behaviour in mobile games.
- H7: Game features significantly influence player motivation among mobile game users.

- H8: Player behaviour significantly influences player motivation among mobile game users.

6. Research Methodology

The study uses a quantitative, cross-sectional survey design. The supplied Excel file contains 99 responses. The questionnaire includes six profile/frequency questions and numeric 1–5 response items. The exported file did not include verbal labels for the numeric scale, so the analysis treats the values as ordered numeric ratings without assigning unprovided labels. No additional responses were created or imputed.

The analysis was conducted using the following procedures: frequency and percentage summaries for respondent characteristics; mean and standard deviation for survey items and composite scores; Cronbach's alpha as an exploratory internal-consistency check for the three item groups; Pearson correlations for each feature item against the behaviour composite; a chi-square test of game type and behaviour category; one-way ANOVA comparing behaviour means across game types; and simple ordinary least-squares regressions.

Composite construction: Game Features = mean of Questions 7–11; Player Motivation = mean of Questions 12–16; Player Behaviour Influence = mean of Questions 22–26. The behaviour category used in the chi-square test was created by splitting the behaviour composite at its sample median. Because the data are cross-sectional and self-reported, statistical relationships do not establish causality.

7. Data Analysis and Results

A total of 99 responses were available in the supplied spreadsheet. The largest age group was 18–24 years (75 respondents, 75.8%). The most frequently reported device was Android smartphone (63, 63.6%).

7.1 Respondent profile

Variable	Category	Frequency	Percent
What is your age group?	18–24 years	75	75.8%
	Below 18 years	9	9.1%
	25–34 years	6	6.1%
	35–44 years	6	6.1%
	45 years and above	3	3.0%
What is your gender?	Female	54	54.5%
	Male	39	39.4%
	Other	3	3.0%
	Prefer not to say	3	3.0%
How long have you been playing mobile games?	Less than 1 year	30	30.3%
	More than 10 years	27	27.3%
	3–5 years	21	21.2%
	1–2 years	18	18.2%
	6–10 years	3	3.0%
What type of mobile game do you play most often?	Battle Royale / Multiplayer Online	27	27.3%
	Sports / Racing	24	24.2%
	Puzzle / Casual	24	24.2%
	Other	12	12.1%
	Action / Adventure	12	12.1%
Which device do you mainly use to play mobile games?	Android smartphone	63	63.6%
	iPhone	24	24.2%

Variable	Category	Frequency	Percent
	Other	9	9.1%
	Tablet	3	3.0%
How often do you play mobile games?	Every day	39	39.4%
	Less than once a week	27	27.3%
	1–2 days a week	21	21.2%
	3–4 days a week	9	9.1%
	5–6 days a week	3	3.0%

7.2 Composite scores and internal consistency

Construct/item group	Mean	SD	Cronbach's alpha
Game features	3.26	0.84	0.867
Player motivation	3.38	0.87	0.866
Player behaviour influence	3.40	0.81	0.860

The three item groups show exploratory internal-consistency estimates above .80. These values suggest that items within each group co-vary in this sample; they do not by themselves establish construct validity. The item groups are researcher-defined composites based on the available questionnaire wording.

7.3 Individual feature relationships with behaviour

Feature dimension	Mean rating	Pearson r	p-value	Decision
Rewards	3.33	0.334	< .001	Supported
Challenges	3.21	0.463	< .001	Supported
Social interaction	3.03	0.548	< .001	Supported
Customization	3.27	0.424	< .001	Supported
Progression	3.45	0.480	< .001	Supported

All five feature items were positively correlated with the behaviour-influence composite at the 5% level. Social interaction had the strongest bivariate association ($r = 0.548$, $p < .001$), followed by progression and challenges. These are correlations between single feature items and the composite, not independent causal effects.

7.4 Chi-square test

A chi-square test of independence was conducted between the type of mobile game most often played and the behaviour category (at/above versus below the sample median).

Game type	At/above median	Below median	Total
Action / Adventure	3	9	12
Battle Royale / Multiplayer Online	18	9	27
Other	6	6	12
Puzzle / Casual	15	9	24
Sports / Racing	9	15	24

The test result was $\chi^2(4, N = 99) = 8.917$, $p = 0.063$. Since p is greater than .05, the null hypothesis of no association was not rejected. The sample does not provide sufficient evidence of an association between game type and the median-split behaviour category. The smallest expected cell count was 5.82; all expected counts were above five, supporting the usual approximation.

7.5 One-way ANOVA

Game type	N	Mean behaviour score	SD
Other	12	3.75	0.87
Battle Royale / Multiplayer Online	27	3.58	0.82
Puzzle / Casual	24	3.57	0.39
Sports / Racing	24	3.38	0.48
Action / Adventure	12	2.35	1.10

One-way ANOVA found a statistically significant difference in mean behaviour-influence scores among game types, $F(4, 94) = 7.979$, $p < .001$. The highest sample mean was for “Other” games ($M = 3.75$), while Action / Adventure had the lowest mean ($M = 2.35$). ANOVA indicates that at least one group mean differs; it does not identify which specific pairs differ. No post-hoc pairwise test was conducted, so pair-specific conclusions should not be made.

7.6 Linear regression

Model	Outcome	Predictor	Intercept	Slope	R ²	F	p-value
1	Player behaviour	Game features	1.655	0.535	0.312	43.892	< .001
2	Player motivation	Game features	0.589	0.855	0.696	222.359	< .001
3	Player motivation	Player behaviour	0.534	0.836	0.612	153.211	< .001

Model 1: Game-feature composite scores positively predicted behaviour-influence scores, $b = 0.535$, $t = 6.625$, $p < .001$. The model explained 31.2% of the observed variance ($R^2 = 0.312$). The fitted equation is Behaviour = $1.655 + 0.535 \times \text{Game Features}$.

Model 2: Game features were positively associated with the motivation composite, $b = 0.855$, $R^2 = 0.696$, $p < .001$. Model 3: The behaviour-influence composite was positively associated with the motivation composite, $b = 0.836$, $R^2 = 0.612$, $p < .001$. Because these are simple regressions on cross-sectional data, they do not establish temporal order or causal influence.

8. Hypothesis Summary

Hypothesis	Effect/correlation	p-value	Decision
H1 Rewards → behaviour	0.334	< .001	Supported
H2 Challenges → behaviour	0.463	< .001	Supported
H3 Social interaction → behaviour	0.548	< .001	Supported
H4 Customization → behaviour	0.424	< .001	Supported
H5 Progression → behaviour	0.480	< .001	Supported
H6 Overall game features → behaviour	0.535	< .001	Supported
H7 Game features → motivation	0.855	< .001	Supported
H8 Behaviour → motivation	0.836	< .001	Supported

Note: H1–H5 are assessed using bivariate Pearson correlations between each feature item and the behaviour composite, which is an operational approximation based on the available questionnaire. H6–H8 are assessed using simple regression. These tests should be understood in light of the questionnaire’s item wording and construct limitations.

9. Discussion

The analysis indicates a positive relationship between perceived game features and self-reported behaviour influence. The overall game-feature composite explained about one-third of the variance in the behaviour composite in the simple regression model. This suggests that game features are relevant to players’ reported behaviour, although other factors not measured here may also be important.

Social interaction showed the strongest individual feature correlation with the behaviour composite. This may indicate that playing with others, communicating, or maintaining social connections is particularly relevant to reported behaviour in this sample. The finding aligns with network-based churn research showing that social and similarity-network features improve retention prediction (Oskarsdottir et al., 2022). Progression and challenge also showed positive relationships, consistent with the idea that goals and appropriately difficult tasks can sustain participation, as emphasised in flow and competence models (Han & Lee, 2026; Deng et al., 2024).

The significant ANOVA result suggests that behaviour-influence scores vary by game type. However, the group means are based on a modest sample and the “Other” category combines potentially different games. Follow-up research should use larger samples, more detailed genre categories, and post-hoc comparisons. The chi-square result was not significant, indicating that the median-split behaviour category was not demonstrably associated with game type in this sample.

The strong associations between game features and motivation, and between behaviour influence and motivation, are consistent with models that place motivation as a central pathway linking evaluations of game systems to continued engagement and spending (Watola et al., 2025). Because the present data are cross-sectional, these relationships remain correlational.

10. Conclusion

Based on the 99 survey responses, the study finds positive associations between rewards, challenges, social interaction, customization, progression, and the behaviour-influence composite. Social interaction had the strongest individual correlation among the five feature items. Game features significantly predicted the behaviour composite and the motivation composite in simple regressions, while the behaviour composite was also positively associated with motivation. Mean behaviour scores differed across reported game types, but the chi-square association between game type and a median-split behaviour category was not statistically significant.

Overall, the findings support the practical importance of considering game features and player motivation together when designing mobile games. The results should not be generalized to all mobile players without further sampling and replication.

11. Recommendations

- Developers should test reward systems that provide clear feedback without making progress feel excessively dependent on spending.
- Social features such as cooperative goals, friend groups, and fair multiplayer interaction deserve attention because social interaction showed the strongest feature-item correlation in this sample.
- Challenges should be balanced to encourage skill development without creating unnecessary frustration.
- Progression and customization should give players meaningful choices and visible progress.
- Game teams should evaluate feature effectiveness separately across genres and player groups rather than assuming one design works for every audience.
- Future research should use validated multi-item scales, larger and more diverse samples, and behavioural usage data such as session length, retention, and actual purchase records.

12. Limitations

- The data are cross-sectional and self-reported; causal relationships cannot be established.
- The sample has a strong concentration in the 18–24 age group, which limits generalization.
- The exported questionnaire did not include verbal labels for the numeric response scale.
- The conceptual framework lists dimensions such as actual in-game purchases and continuance intention, but the supplied survey contains proxy/related statements rather than distinct behavioural records for every dimension.
- The chi-square analysis uses a median split, which simplifies a continuous score and can reduce information.
- ANOVA identifies overall group differences but no post-hoc test was performed to determine which pairs of game types differ.

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Appendix A: Analysis decisions

The supplied spreadsheet was used as the source of respondent-level data. Empty export columns labelled “Column 1” onward were excluded because they contained no values. Composite scores were calculated as arithmetic means of the item groups described in the methodology. P-values are reported to three decimal places except where $p < .001$. The Excel companion file contains the raw responses, composite scores, descriptive statistics, chi-square output, ANOVA output, and regression results.