

Predicting participation and expenditure on distinct gambling-like mechanics: financial engagement, selective problem gambling effects and a gaming disorder null

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Abstract

Purpose – Quantitative work on gambling-like mechanics (GLMs) in video games has largely treated them as a uniform category, overlooking differences in reward structure and similarity to traditional gambling. This study examines predictors of expenditure across three disaggregated GLM categories – cosmetic loot boxes (CLB), game-affecting loot boxes (GALB) and other in-game gambling-like content (OGLC).

Design/methodology/approach – Data were collected via an online survey of adult gamers (N = 587). Three model sets used the same gaming engagement and problem behavior indicators as predictors, each comprising a two-part approach: binary logistic regression on the full sample to predict purchase participation, and OLS linear regression among purchasers to predict expenditure amounts.

Findings – Financial engagement – expenditure on non-random free-to-play content and battle passes – emerged as the dominant predictor class; gaming frequency and gaming disorder were null throughout. Problem gambling severity predicted participation selectively – most strongly for OGLC – but predicted expenditure amounts in no category. Predictor patterns dissociated between participation and amount decisions in ways aggregated or uniform analytic approaches would have obscured.

Practical implications – Increased focus should be given to paid game mechanics that closely mimic the visual and esthetic presentation of traditional gambling formats. Engagement systems such as battle passes should be carefully assessed for their association with increased expenditure on GLMs. Attention should be paid to the risks related to purchase entry into GLMs, rather than to expenditure amounts alone.

Originality/value – This study is among the first to apply a disaggregated GLM taxonomy empirically and to model participation and expenditure amount as distinct outcomes.

Keywords Gambling-like mechanics, Loot boxes, Game monetization, Problem behavior, Regression analysis, Survey study

Paper type Research article

1. Introduction

Video games have long generated revenue beyond the point of initial access. Supplementary monetization through expansion packs, subscription tiers, and downloadable content predates the smartphone era (Lizardi, 2012). The distinction between games requiring an upfront purchase to play, the pay-to-play (P2P) model, and those offered free of charge, the free-to-play (F2P) model, has existed since the early commercial internet titles (Johnson and Brock, 2020; King and Delfabbro, 2019). What changed in the 2010s was scale. Frictionless in-app payment systems allowed publishers to deploy supplementary purchases at unprecedented



scale, establishing *microtransactions* (MTX) – small, discrete in-game purchases – as the economic backbone of F2P titles (Kim *et al.*, 2017; Zendle *et al.*, 2020b).

Scientific interest in video game *gambling-like mechanics* (GLM) that MTXs can incorporate has grown substantially over the past decade (Mattinen *et al.*, 2023a). Among GLMs, *loot boxes* – purchasable containers delivering randomized in-game rewards (Macey and Hamari, 2018; Nielsen and Grabarczyk, 2019) – achieved prominence (Xiao *et al.*, 2024). Recent meta-analyses have consistently linked higher loot-box expenditure to elevated indicators of problematic gaming and gambling behavior (Garea *et al.*, 2021; Spicer *et al.*, 2022). Yet the literature on which these syntheses draw has predominantly conflated mechanically distinct categories. Most notable of these are cosmetic loot boxes (CLB), delivering purely esthetic items, and game-affecting loot boxes (GALB), conferring competitive advantages. Recent systematic reviews have explicitly identified unmet needs to draw distinctions between the two in empirical research (Gibson *et al.*, 2022; Montiel *et al.*, 2022; Spicer *et al.*, 2022). GLMs also encompass *other in-game gambling-like content* (OGLC) – including casino-themed minigames, wheel spins, and wagering mechanics – which represent the closest structural approximation to conventional gambling found within video game environments (Macey *et al.*, 2024; Nielsen and Grabarczyk, 2019). These mechanics have received comparatively little empirical attention as a distinct category, with scholars arguing that collapsing them into the loot box construct is analytically unwarranted (Zendle *et al.*, 2022).

The conflation of mechanically distinct GLM categories has substantive consequences, as these mechanics differ in the degree to which they visually resemble traditional gambling and confer gameplay advantages. Pooling GLMs into a single construct risks averaging across heterogeneous predictor-outcome relationships, obscuring category-specific associations in both directions. GALB- or OGLC-related associations may be wrongly attributed, while null or weaker associations for CLBs may be masked. The resulting estimates offer limited guidance for the regulatory and clinical responses that increasingly cite this literature. This gap in empirical measurement and operationalization motivates the two research questions of the present study: (RQ1) *what predicts purchase participation across distinct GLM categories*, and (RQ2) *among those who purchase, what predicts the expenditure amount?* These questions are addressed sequentially in Section 2, with the *a*-hypotheses corresponding to RQ1 and the *b*-hypotheses to RQ2.

1.1 Present study

To answer the research questions and test the stated hypotheses empirically, a two-part regression approach is applied to data from 587 video game players collected in autumn 2023. The first part addresses RQ1 by predicting purchase participation using binary logistic regression on the full sample; the second addresses RQ2 by predicting expenditure amounts using OLS linear regression on purchaser subsamples only. Together, these analyses examine how gaming engagement, in-game purchasing behavior, and behavioral risk indicators differentially predict expenditure across three GLM categories: CLB, GALB, and OGLC. Figure 1 presents the conceptual framework of the study, illustrating the three-model structure of the analysis and the two-part regression approach applied across RQ1 and RQ2.

This study makes three contributions to understanding GLM expenditure in video games. First, it applies a disaggregated taxonomy of GLMs and demonstrates that the distinction produces meaningfully different predictor patterns across categories – an operationalization the literature has called for but rarely applied empirically. Second, it establishes financial engagement within the broader F2P monetization ecosystem, including BP expenditure, as the strongest predictor of GLM expenditure – rather than frequency of play or gaming disorder symptomatology. Third, it advances understanding of behavioral risk in this context, finding that problem gambling severity predicts participation but not expenditure amounts, while gaming disorder symptoms are null throughout.

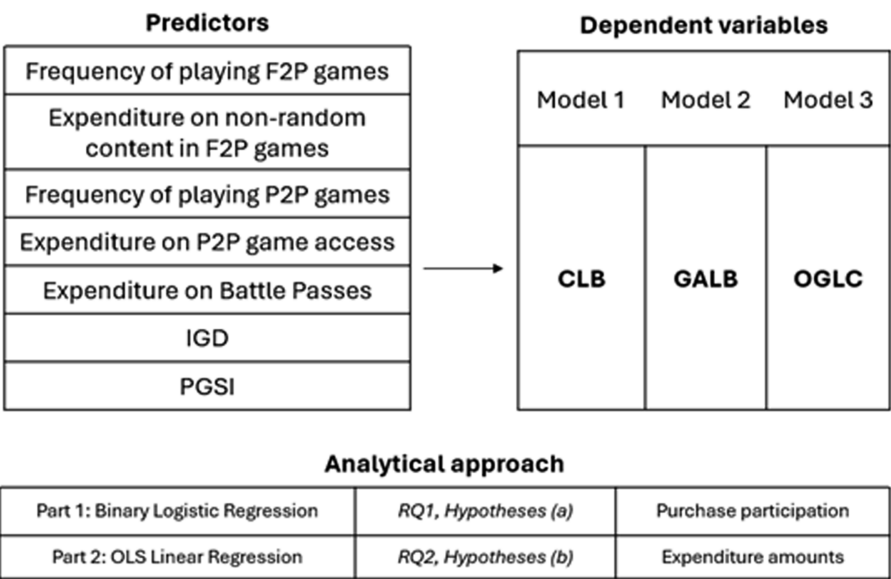


Figure 1. The conceptual framework of the present study. Source: Authors’ own work

2. Theory and hypotheses

This study understands GLM expenditure as arising from the combined interaction of platform-level design incentives and individual-level psychological and behavioral response tendencies. At the platform level, digital environments are broadly structured to sustain engagement and extract financial participation through designs that focus on maximizing monetization opportunities (Joseph, 2021), often with the help of data-driven algorithms (Shin, 2022). At the individual level, the hypotheses below draw on complementary mechanisms related to behavioral economics. These include the role of financial commitment, urgency created by scarce or time-limited rewards, and reward schedules whose fixed or variable structure may differentially affect habitual engagement. Two established indicators of behavioral risk are also examined alongside engagement and expenditure predictors: one capturing compulsive play irrespective of financial behavior, the other capturing harm defined in explicitly financial and loss-related terms. Each hypothesis below develops the specific mechanism and supporting literature relevant to its predictor in turn.

F2P games apply the logic of platform-level architectures through continuous engagement loops, artificial scarcity, probabilistic reward mechanics, and limited-time availability (Montefiore and Formosa, 2026; Neely, 2021; Niknejad et al., 2024). Empirically, play frequency of F2P games has been positively associated with monetary expenditure (Costes and Bonnaire, 2022), consistent with an association between greater exposure and expenditure. Once started, expenditure on deterministic F2P content – character skins, fixed bundles, gameplay enhancements – can normalize and lower the psychological barrier to subsequent microtransactions (Gibson et al., 2023; King and Delfabbro, 2018; Neely, 2021). Sunk cost dynamics, whereby prior investment shapes continued financial commitment (Arkes and Blumer, 1985; Liang et al., 2014), can amplify this effect, as initial non-random purchases create an expenditure context within which GLM expenditure more readily presents as a continuation of prior investment. Together, these mechanisms suggest that both F2P play frequency and financial engagement with non-random F2P content should positively predict expenditure on GLMs across content types. We therefore hypothesize that:

- H1a. F2P play frequency positively predicts purchase participation across each GLM category.
- H1b. F2P play frequency positively predicts expenditure amounts among those who purchase within each GLM category.
- H2a. Expenditure on non-random F2P content positively predicts purchase participation across each GLM category.
- H2b. Expenditure on non-random F2P content positively predicts expenditure amounts among those who purchase within each GLM category.

In contrast to F2P titles, P2P games rely on upfront purchase fees or ongoing subscriptions, reducing the centrality of MTXs. Where GLMs do appear in P2P titles, community backlash has created a meaningful disincentive for their incorporation (Macey and Bujić, 2022). This structural difference suggests that P2P engagement operates differently depending on the level of analysis. At the level of purchase participation, time spent in P2P environments displaces exposure to the F2P contexts where GLMs are concentrated, and financial engagement with P2P content would predominantly signal engagement with non-GLM ecosystems. Though direct empirical evidence for this substitution logic is limited, both mechanisms point toward a negative relationship with GLM purchase entry. We therefore tentatively hypothesize that:

- H3a. P2P play frequency negatively predicts purchase participation across each GLM category.
- H4a. P2P access expenditure negatively predicts purchase participation across each GLM category.

Among those who already participate in GLM purchasing, however, the same predictors are expected to reverse direction. Greater P2P play frequency may reflect engagement with the subset of P2P titles that do incorporate GLMs, and higher P2P access expenditure likely signals a larger overall gaming budget and broader financial commitment to gaming as a consumer activity. We therefore also hypothesize that:

- H3b. P2P play frequency positively predicts expenditure amounts among those who purchase within each GLM category.
- H4b. P2P access expenditure positively predicts expenditure amounts among those who purchase within each GLM category.

Drawing on traditional subscription and season-pass models, publishers began introducing *battle passes* (BP) (Zanescu *et al.*, 2019). Accompanied by both free and premium components, purchasing the BP grants access to a tiered sequence of exclusive, predetermined rewards unlocked through play or additional purchases over a set period (Joseph, 2021; Mattinen *et al.*, 2023b; Zanescu *et al.*, 2021). The design of BP systems often incorporates structural features that generate sunk cost sensitivity and fear of missing out (FOMO), and frame non-completion as forfeiting already-invested resources (Gibson *et al.*, 2023; Kahneman and Tversky, 1979). These systems further apply operant conditioning principles through fixed-ratio reinforcement schedules that may establish habitual expenditure patterns extending beyond the BP itself (Delfabbro *et al.*, 2023). BPs also frequently coexist within the same game economies as GLMs, with some implementations directly awarding chance-based content as progression rewards (Joseph, 2021; Mattinen *et al.*, 2023b; Zanescu *et al.*, 2021), producing routine exposure to GLM expenditure opportunities. We therefore hypothesize that:

- H5a. BP expenditure positively predicts purchase participation across each GLM category.
- H5b. BP expenditure positively predicts expenditure amounts among those who purchase within each GLM category.

Internet Gaming Disorder (IGD) operationalized in this study via the IGDS9-SF (Pontes and Griffiths, 2015) captures symptoms of compulsive play – preoccupation, loss of control, withdrawal, and continued use despite negative consequences. Prior research has linked IGD scores to loot box expenditure across diverse samples, with small to moderate effect sizes (González-Cabrera *et al.*, 2022, 2023; Lemmens, 2022), and expenditure on F2P games more broadly shows positive associations with disordered gaming (Costes and Bonnaire, 2022). No prior studies have examined IGD in relation to the differentiated categories examined here, but the consistency of associations in the broader literature provides sufficient basis to expect effects across content types. We therefore hypothesize that:

H6a. IGD positively predicts purchase participation across each GLM category.

H6b. IGD positively predicts expenditure amounts among those who purchase within each GLM category.

The *Problem Gambling Severity Index* (PGSI), in contrast, was specifically designed to assess gambling-related harm, with five of its nine items directly addressing financial behavior (Orford *et al.*, 2010). The examined GLMs share both structural and psychological features with conventional gambling. Most notable of these are variable-ratio reinforcement schedules (Delfabbro *et al.*, 2023), which produce the most persistent response patterns precisely because outcomes remain unpredictable – providing a direct theoretical link between PGSI and GLM expenditure. Empirically, numerous studies have established a robust association between problem gambling severity and engagement with GLMs, though prior measurement work has often treated loot boxes as a homogeneous category (Brooks and Clark, 2019; Wardle and Zendle, 2021; Zendle *et al.*, 2020a; Zendle and Cairns, 2018). We therefore hypothesize that:

H7a. PGSI positively predicts purchase participation across each GLM category.

H7b. PGSI positively predicts expenditure amounts among those who purchase within each GLM category.

3. Methods

3.1 Participants, procedure, and sample characteristics

This study collected data via an online survey administered in autumn 2023. Recruitment was initially conducted through social media channels (*Facebook*, *Instagram*, and *Reddit*), which yielded limited responses ($n \approx 30$). This prompted a supplemental recruitment via the paid participant recruitment platform *Prolific*. The survey, offered exclusively in English, targeted individuals with digital gaming experience in the previous 12 months and incorporated multiple eligibility filters. From an initial pool of 831 responses, 244 were removed during data cleaning for incomplete responses, outliers, or failing more than one of three embedded attention checks, yielding a final sample of 587 valid responses. The sample was geographically concentrated in Europe (63.4%) and South Africa (33.6%), reflecting the timing of *Prolific* deployment during European daytime hours. The mean age was 29.2 years (range: 18–57). Further demographic characteristics are presented in Table 1, and the most played and highest-expenditure game titles reported by the sample are summarized in Appendix 1.

3.2 Measures

3.2.1 Gaming and gambling-like content consumption measures. For both free-to-play and pay-to-play games, participants were asked how frequently they played each game type, using a 7-point scale ranging from “Never” to “Daily.” Expenditure was assessed through separate items asking about expenditure rates on non-random content in F2P games, access to P2P

Table 1. Demographics of the sample, N = 587

	Category	n (%)
<i>Age</i>	18–21	80 (13.6%)
	22–25	172 (29.3%)
	26–29	120 (20.4%)
	30–33	83 (14.1%)
	34 or over	132 (22.5%)
<i>Gender</i>	Male	273 (46.5%)
	Female	308 (52.5%)
	Non-binary or did not specify	6 (1.0%)
<i>Education</i>	Lower than secondary school	3 (0.5%)
	Secondary or equivalent school	209 (35.6%)
	Bachelor's degree	261 (44.5%)
	Master's degree	107 (18.2%)
	Doctorate degree	7 (1.2%)
<i>Residence</i>	Europe	372 (63.4%)
	South Africa	197 (33.6%)
	Australia & New Zealand	6 (1%)
	Middle East	5 (0.9%)
	Asia	3 (0.5%)
	South America	2 (0.3%)
	Central America	1 (0.2%)
	North America	1 (0.2%)

Source(s): Authors' own work

games, and BPs and similar progression systems, each covering the past 12 months. Finally, participants reported expenditure on each of the three GLM categories: CLB, GALB, and OGLC.

3.2.2 Internet Gaming Disorder scale – short-form (IGDS9-SF). The IGDS9-SF is a widely used psychometric instrument designed to assess the severity of Internet Gaming Disorder based on the nine diagnostic criteria outlined in the DSM-5 (Pontes and Griffiths, 2015). The scale evaluates both online and offline gaming behaviors using a 5-point Likert scale ranging from 1 (*Never*) to 5 (*Very Often*), yielding total scores between 9 and 45, with higher scores indicating greater disorder severity. All nine items were included in the present study, producing a sum score used as a continuous predictor in all models, consistent with the instrument's standard scoring procedure (Pontes and Griffiths, 2015). Internal consistency in the present sample was good (Cronbach's $\alpha = 0.866$).

3.2.3 The Problem Gambling Severity Index (PGSI). The Problem Gambling Severity Index (PGSI) is a nine-item self-report instrument designed to measure gambling problem severity in general populations (Orford et al., 2010). Respondents rate each item on a four-point scale ranging from 0 (*never*) to 3 (*almost always*), yielding total scores between 0 and 27, with higher scores reflecting greater severity. The PGSI is accompanied by four established clinical risk groupings (Currie et al., 2013): no risk (score = 0), low risk (score = 1–2), moderate risk (score = 3–7), and high risk (score ≥ 8). Internal consistency in the present sample was excellent (Cronbach's $\alpha = 0.914$).

3.3 Data analysis

3.3.1 Two-part modeling approach. All three GLM expenditure outcomes were positively skewed, with most participants reporting zero expenditure in each category (CLB: 73.6%, GALB: 76.7%, OGLC: 78.7%). These zeros reflect a qualitatively distinct behavioral state – non-participation – generated by a different process than the amount decision, so log transformation alone cannot adequately address the resulting zero-inflation. Diagnostic

inspection of a single log-transformed OLS model applied to the full sample confirmed unacceptable non-normality attributable to this structural zero-inflation rather than to skew among purchasers.

A two-part approach was therefore adopted, consistent with established practice for zero-inflated expenditure data (Humphreys *et al.*, 2010). Part 1 models the participation decision using binary logistic regression on the full sample ($N = 587$, coded 1 = positive expenditure, 0 = no expenditure). Part 2 models the expenditure amount using OLS linear regression, run separately for each GLM category on the subsample of participants who reported spending in that category, with $\log(x+1)$ -transformed amount as the outcome. Three alternatives – Tobit models, zero-inflated count models, and a Heckman-style selection model – were considered and rejected as incompatible with this zero-generating process or with the study's predictor structure (see Appendix 2 for further details).

3.3.2 Predictor specification. The three models share the same core predictor set in both parts: frequency of F2P play, frequency of P2P play, expenditure on non-random F2P content, expenditure on P2P game access, expenditure on battle passes, the IGD sum score, and PGSI. Frequency of play is entered as a numeric predictor throughout. Treating ordered scales with seven or more response categories as continuous is well-established (Havlicek and Peterson, 1976; Norman, 2010). The three expenditure predictors are $\log(x+1)$ -transformed, consistent with both the outcome-variable treatment above, and previous gaming expenditure literature (Brooks and Clark, 2023). The IGD sum score is entered as continuous in both parts.

PGSI is entered differently across the two parts. In Part 2 it is retained as a continuous sum score, like the IGD. In Part 1 it is entered as three dummy variables representing the established clinical risk groupings (Section 3.2.3), with the no-risk group as reference. This is because PGSI failed the linearity-of-log-odds assumption required for logistic regression as a continuous predictor – a violation that does not apply to OLS, where continuous entry remains appropriate. The full test sequence behind this finding is reported in Appendix 2.

3.3.3 Model adequacy. Sample size was adequate for both parts of the analysis, clearing standard benchmarks for events-per-predictor in Part 1 (Peduzzi *et al.*, 1996) and for minimum N and cases-per-predictor in Part 2 (Green, 1991; Pituch and Stevens, 2016). Model assumptions were also checked and satisfied for both parts – Part 1 via the Box-Tidwell procedure (Hosmer *et al.*, 2013; Tabachnick *et al.*, 2019), Part 2 via standard residual diagnostics – with no violations beyond the PGSI exception already noted in Section 3.3.2. As a further check, the Part 2 models were re-estimated using a Gamma-distributed GLM with a log link on the untransformed expenditure amounts; results were consistent with the primary specification, with one minor divergence for OGLC discussed in Appendix 2. Full derivations, diagnostic results, and sensitivity analysis output are reported in Appendix 2.

4. Results

The following section details the descriptive statistics and results of the analyses and hypotheses for Parts 1 (Section 4.2) and 2 (Section 4.3). All data was analyzed using *IBM SPSS Statistics*.

4.1 Descriptive statistics

The sample was predominantly oriented toward F2P gaming: 57.4% of respondents reported playing F2P games multiple times per week or daily, and only 2.0% reported never playing F2P games. P2P engagement was more heterogeneous: 25.4% had not played P2P titles in the past 12 months, while 27.2% played multiple times per week or daily. The median play frequency was 6 (multiple times per week) for F2P gaming and 4 (monthly) for P2P gaming.

Descriptive statistics for all expenditure variables, including conditional amounts among the purchaser subsamples, are presented in Table 2. Expenditure across all categories was heavily right-skewed and zero-inflated, consistent with the distributional properties that

Table 2. Descriptive statistics of expenditure variables

Variable	M (SD)	Median	Range	Purchaser % (n)
<i>Predictor expenditure (€, past 12 months)</i>				
Non-random F2P content	26.22 (58.43)	0.00	0–480	–
P2P game access	44.31 (75.75)	10.00	0–500	–
BPs	11.44 (29.14)	0.00	0–200	–
<i>Outcome expenditure (€, past 12 months)</i>				
Cosmetic loot boxes (CLB)	9.68 (27.13)	0.00	0–240	26.4% (<i>n</i> = 155)
Game-affecting loot boxes (GALB)	7.98 (26.09)	0.00	0–240	23.3% (<i>n</i> = 137)
Other gambling-like content (OGLC)	10.30 (32.65)	0.00	0–300	21.3% (<i>n</i> = 125)
<i>Purchaser subsamples (€, past 12 months)</i>				
CLB purchasers	36.65 (42.49)	20.00	1–240	–
GALB purchasers	34.18 (45.07)	12.00	1–240	–
OGLC purchasers	48.39 (56.39)	30.00	1–300	–

Note(s): “Purchaser” indicates the proportion of the full sample (*N* = 587) who reported any positive expenditure in that category; these subsamples were used in the Part 2 OLS analyses. — = not applicable

Source(s): Authors’ own work

motivated the two-part approach described in [Section 3.3.1](#). Among those who reported any expenditure, conditional amounts were substantially higher than full-sample means suggest, with OGLC participants showing the highest conditional expenditure despite the lowest participation rate.

Mean IGD scores in the present sample were 17.61 (*SD* = 6.14, median = 17.00, range = 9–38). This positions the sample below the midpoint (range: 9–45). For problem gambling severity, 45.7% of respondents scored zero on the PGSI, indicating no gambling-related risk; 21.6% fell in the low-risk category; 21.6% in the moderate-risk category; and 11.1% in the high-risk category (see [Section 3.2.3](#) for category nominations). Mean PGSI score was 2.68 (*SD* = 4.17, median = 1.00, range = 0–27). The distribution was positively skewed, with most scores concentrated at zero and low values. Notably, 54.3% of the sample exhibited at least some level of problem gambling risk, a proportion substantially higher than general population estimates, though broadly consistent with prior online gamer convenience samples ([Zendle and Cairns, 2019](#)).

4.2 Part 1: predictors of purchase participation

Part 1 addresses RQ1 by predicting purchase participation across the three GLM categories, using binary logistic regression on the full sample (*N* = 587). Box-Tidwell diagnostics confirmed that model assumptions were satisfied, with the treatment of PGSI and the expenditure predictors described in [Section 3.3.3](#).

4.2.1 Model fit and results overview. All three logistic regression models produced significant omnibus tests, confirming that the predictor sets explained meaningful variance in purchase participation beyond the intercept-only baseline. The CLB model showed the strongest overall fit (Nagelkerke R^2 = 0.292), followed by OGLC (R^2 = 0.253) and GALB (R^2 = 0.243). Hosmer-Lemeshow tests were non-significant across all three models, indicating adequate calibration between predicted probabilities and observed outcomes. Full fit diagnostics are reported in [Appendix 2](#).

Overall classification accuracy improved meaningfully over the null model in each case, remaining similar across all three models at around 79%. Participant classification was considerably lower than non-participant classification across all three models, which is expected given that participants represent only 21%–26% of the sample (see [Section 4.1](#)). The CLB model, however, identified participants notably more reliably (40.6%) than the GALB and OGLC models (27.0 and 26.4%, respectively).

Odds ratios and 95% confidence intervals for all predictors across the three Part 1 models are presented in Table 3. The following subsections address game engagement predictors and problem behavior predictors for Part 1 in turn.

4.2.2 *Game engagement predictors.* All three expenditure predictors were positively associated with purchase participation across all three outcomes. BP expenditure was the dominant predictor in the CLB model, while non-random F2P expenditure led in the GALB model. P2P access expenditure was significant in CLB and GALB models but not the OGLC model, though its direction was positive across all three models. Neither frequency variable was significant in any of the three tested models.

As such, H1a, H3a, and H4a were not supported. H2a and H5a were both fully supported.

4.2.3 *Problem behavior predictors.* The PGSI risk tier pattern differed meaningfully across GLM categories. For the CLB model, only the moderate-risk group showed a significant elevation in participation odds. For the GALB model, both the moderate- and high-risk groups were significant in an escalating pattern, while the low-risk group was non-significant. For the OGLC model, all three risk tiers were significant, with odds ratios escalating steeply – the high-risk group produced the largest individual predictor effect across the entire Part 1 analysis (OR = 8.063, $p < 0.001$). IGD was non-significant across all three models, with coefficients close to zero throughout.

As such, H6a was not supported. H7a was partially supported, as at least one PGSI risk group predicted participation across each GLM category, but only in the OGLC model did all three groups predict participation.

4.3 Part 2: predictors of expenditure amounts

Part 2 addresses RQ2, examining expenditure amounts among the purchaser subsamples of each category: CLB ($n = 155$), GALB ($n = 137$), and OGLC ($n = 125$). Residual diagnostics confirmed model assumptions were satisfied; see Section 3.3.3 for full details.

Table 3. Part 1 binary logistic regression: Odds ratios and 95% confidence intervals

Predictor	CLB OR [95% CI]	CLB <i>p</i>	GALB OR [95% CI]	GALB <i>p</i>	OGLC OR [95% CI]	OGLC <i>p</i>
<i>F2P frequency</i>	1.020 [0.890, 1.169]	0.774	0.932 [0.812, 1.070]	0.320	1.080 [0.930, 1.254]	0.315
<i>F2P non-random expenditure</i>	1.149 [1.012, 1.303]	0.031	1.301 [1.146, 1.478]	<0.001	1.187 [1.040, 1.356]	0.011
<i>P2P frequency</i>	0.928 [0.814, 1.058]	0.265	0.894 [0.780, 1.024]	0.107	0.904 [0.786, 1.040]	0.159
<i>P2P access expenditure</i>	1.175 [1.028, 1.343]	0.018	1.186 [1.035, 1.360]	0.014	1.149 [0.997, 1.325]	0.055
<i>BP expenditure</i>	1.467 [1.275, 1.688]	<0.001	1.267 [1.102, 1.457]	<0.001	1.229 [1.062, 1.422]	0.006
<i>IGD score</i>	1.012 [0.974, 1.053]	0.538	1.013 [0.974, 1.054]	0.515	0.991 [0.952, 1.033]	0.680
<i>PGSI low</i>	1.321 [0.737, 2.367]	0.350	1.386 [0.770, 2.494]	0.276	1.919 [1.024, 3.598]	0.042
<i>PGSI moderate</i>	3.813 [2.198, 6.615]	<0.001	2.144 [1.210, 3.798]	0.009	3.532 [1.932, 6.457]	<0.001
<i>PGSI high</i>	1.993 [0.952, 4.172]	0.067	2.594 [1.254, 5.365]	0.010	8.063 [3.812, 17.057]	<0.001

Note(s): Significant predictors ($p \leq 0.05$) in italic. Reference category for PGSI dummies: no risk (PGSI score = 0). All expenditure predictors log(x+1)-transformed prior to analysis. CLB = cosmetic loot boxes; GALB = game-affecting loot boxes; OGLC = other gambling-like content. N = 587

Source(s): Authors' own work

4.3.1 Model fit and results overview. All three OLS models were found to be significant. The CLB and GALB models explained meaningful variance in expenditure amounts among purchasers ($R^2 = 0.257$ and 0.313 , respectively), while the OGLC model's fit was comparatively weak ($R^2 = 0.129$, adjusted $R^2 = 0.077$), indicating that the predictor set accounts for less than 8% of variance in OGLC expenditure amounts among purchasers. Full model fit statistics are reported in [Appendix 2](#).

Standardized coefficients and significance values for all predictors are presented in [Table 4](#). The following subsections address game engagement predictors and problem behavior predictors for Part 2 in turn.

4.3.2 Game engagement predictors. Non-random F2P expenditure was the only predictor significant across all three models and was the leading predictor in both the GALB and OGLC models. BP expenditure was significant in the CLB and GALB models but collapsed to near zero in the OGLC model – notably, despite BP expenditure predicting OGLC participation in the Part 1 model. P2P access expenditure was non-significant in all three models.

Neither F2P frequency nor P2P frequency reached significance in any of the three models. Coefficients were small in absolute terms and directionally inconsistent across the three tested models.

As such, [H1b](#), [H3b](#), and [H4b](#) were not supported. [H2b](#) was fully supported, and [H5b](#) partially supported.

4.3.3 Problem behavior predictors. Both PGSI and IGD were non-significant across all three Part 2 models. PGSI coefficients were close to zero throughout, with the OGLC model coefficient effectively zero – a striking contrast to the strong participation-level prediction observed in the Part 1 model. IGD was similarly null across all three models. As such, both [H6b](#) and [H7b](#) were not supported.

5. Discussion

5.1 Expenditure patterns as the core predictors

5.1.1 Financial engagement, not frequency of play, predicts GLM expenditure. The results suggest that financial engagement within F2P ecosystems may reflect a general disposition toward monetary participation in these environments ([King and Delfabbro, 2018](#)) – one that extends to GLM expenditure rather than remaining confined to non-random or deterministic content. Players exhibiting this disposition appear more likely both to participate in purchasing GLMs and, among those who do, to report greater expenditure on them.

The broader financial engagement profile interpretation extends at least partially to P2P contexts, as P2P expenditure positively predicted participation in CLB and GALB, contrary to

Table 4. Part 2 OLS linear regression: Standardized coefficients

Predictor	CLB β	CLB p	GALB β	GALB p	OGLC β	OGLC p
<i>F2P frequency</i>	−0.096	0.223	0.008	0.927	−0.039	0.675
<i>F2P non-random expenditure</i>	<i>0.199</i>	<i>0.013</i>	<i>0.325</i>	<i><0.001</i>	<i>0.277</i>	<i>0.010</i>
<i>P2P frequency</i>	−0.016	0.865	0.026	0.776	−0.062	0.601
<i>P2P access expenditure</i>	0.152	0.109	0.123	0.207	0.145	0.252
<i>BP expenditure</i>	<i>0.304</i>	<i><0.001</i>	<i>0.237</i>	<i>0.003</i>	−0.040	0.681
<i>IGD score</i>	0.011	0.884	0.062	0.465	0.082	0.392
<i>PGSI score</i>	0.050	0.511	0.077	0.358	−0.004	0.964

Note(s): Significant predictors ($p \leq 0.05$) in italic. All expenditure predictors $\log(x+1)$ -transformed prior to analysis. CLB = cosmetic loot boxes; GALB = game-affecting loot boxes; OGLC = other gambling-like content

Source(s): Authors' own work

H4a. However, P2P access failed to predict actual amounts in any model. This dissociation likely reflects a structural difference between the two gaming contexts. As F2P economies are designed around continuous, layered monetization with no natural expenditure ceiling, they may create the conditions under which accumulated financial engagement functions as a persistent predictor of expenditure amounts. P2P access, by contrast, is a bounded and typically one-time transaction. The fact that it predicts participation, but not amounts, suggests that while it may reflect a general willingness to spend on gaming, it does not reflect the sustained financial engagement (**H2b**, **H5a**, and **H5b**) that predicted GLM expenditure in these models.

Frequency of play proved a consistently poor predictor of GLM expenditure across the three models in both parts – a pattern that is theoretically important rather than merely inconclusive. Many players devote substantial time to F2P games, yet do not engage in MTXs, choosing instead to progress through in-game grinding (**Alha et al., 2018**). Conversely, small subgroups of high-expenditure players tend to generate the majority of F2P revenue despite potentially lower playtime (**Close et al., 2021**; **Dreier et al., 2017**). This offers support for the consistent pattern throughout our sample that financial engagement, not frequency of play, predicts GLM expenditure.

Prior work finding positive associations between F2P time engagement and in-game purchasing has also measured any MTX expenditure across all F2P content (**Costes and Bonnaire, 2022**). The present study examines GLMs specifically, and the divergence may reflect a meaningful distinction. Play frequency plausibly predicts general monetization engagement, but GLM expenditure may reflect a more specific player orientation defined by financial participation rather than time investment. This is consistent with arguments that platform nudge architectures are specifically deployed to condition purchasing behavior (**Shin, 2022**, pp. 60–61). GLMs, defined by variable and uncertain outcomes, can be seen as one format in which this conditioned purchasing orientation becomes realized.

5.1.2 BP expenditure predicts all but OGLC amounts. The association between BP and GLM expenditure is not immediately self-evident: BPs are ostensibly organized around deterministic, progression-based reward tracks, while GLMs, especially loot boxes, involve individually purchased, chance-based draws. However, it becomes more interpretable when considered at the level of the monetization ecosystems in which both systems tend to operate. BPs and GLMs do coexist and are offered in parallel within the same F2P game economies (**Mattinen et al., 2023b**; **Zanescu et al., 2021**), and GLM content frequently features as part of what the BP itself bundles or makes more accessible. Players who purchase BPs have already demonstrated a willingness to engage financially with these ecosystems – and the BP buyer is, in this sense, precisely the player for whom individual GLM expenditure holds appeal. The two can thus be thought of as complementary expenditures converging on the same financially embedded player disposition, not as competing alternatives.

Beyond purchase participation, BP expenditure also predicted expenditure amounts on CLB and GALB. The sunk-cost sensitivity and FOMO dynamics that BP structures have been seen to foster (**Gibson et al., 2023**) provide a plausible mechanism: both have direct structural analogs within GLM spending, where individual content is similarly offered on timed rotations and where expenditure occurs within the same monetization ecosystem. Further, where BPs may condition players through fixed-ratio reinforcement schedules, GLMs apply variable-ratio schedules to chance-based draws – a structurally distinct but overlapping reinforcement context within the same ecosystem.

For OGLC, however, this pattern was not replicated. BP expenditure predicted participation but did not predict expenditure among those who had purchased such content. OGLC amounts were not inherently unpredictable, as F2P non-random expenditure predicted them significantly, but why BP expenditure specifically failed to predict OGLC expenditure amounts remains an open empirical question that cannot be thoroughly explained with the present data.

5.2 PGSI predicts GLM participation but not expenditure amounts

The observed predictive pattern of PGSI across GLM categories warrants further attention. Among them, OGLC was the only model where all three PGSI risk groups significantly predicted purchase participation. A plausible reading is that the PGSI, as an instrument designed to register gambling-related risk, is best positioned to predict engagement with products whose form and mechanics most directly mirror established gambling. OGLC is where that resemblance is most explicit in the present taxonomy. Yet, the cross-sectional design precludes any claim about direction. This study cannot assert whether individuals with elevated gambling risk are drawn to OGLC specifically, or whether the PGSI simply registers existing engagement with gambling-resembling content. Shin (2022, p. 71) has identified this directional ambiguity more broadly in terms of whether platform mechanics generate behavioral predispositions or merely echo them.

For GALB, both the moderate- and high-risk groups significantly predicted participation, and here a different mechanism is plausible: instrumental reward value. Popular game modes like FIFA's/EA FC's *Ultimate Team*, and many collectible card game formats, strongly incentivize players to engage with randomized content to remain competitive (Mattinen *et al.*, 2023b). For individuals already scoring higher on problem gambling measures, this combination of structural pressure and tangible reward value may compound susceptibility in ways that purely cosmetic randomized content does not.

Notably, OGLC partially shares this reward logic. Wheel spins, wagering contests, and casino-themed minigames typically yield fungible outputs – in-game currency, consumables, or progression resources – that carry direct instrumental utility rather than cosmetic differentiation alone. OGLC is therefore where these two factors converge, i.e. visual resemblance to traditional gambling and the tangible reward pressure identified in the GALB case.

The weaker, non-monotonic pattern in the CLB model is consistent with cosmetic content offering neither the structural resemblance to traditional gambling nor the instrumental reward value identified as relevant in the GALB and OGLC cases. It is nonetheless notable that CLB participation was partly predicted by the PGSI. Loot box opening mechanics – near-misses, variable audio-visual feedback, and anticipatory animations – closely mirror those of electronic gaming machines regardless of reward content (Barton *et al.*, 2017; Rockloff *et al.*, 2020), and may retain some capacity to engage problem gambling susceptibility. Furthermore, some CLB ecosystems permit cosmetic items to be traded for real monetary value, as in *Steam*'s secondary marketplace (Mattinen *et al.*, 2025), which may partly account for the significant CLB participation findings – though the present data did not consider reward transferability, so this remains speculative.

Another emergent pattern is also of note: P2P expenditure predicted participation in both loot box categories but not in OGLC, while PGSI showed its strongest effects precisely for OGLC. This suggests that OGLC may occupy a distinct position within the taxonomy – one more specifically embedded in F2P ecosystems and more closely associated with problem gambling severity than either loot box category. Whether this finding reflects a meaningful qualitative boundary or sampling variability warrants further investigation.

That PGSI did not predict expenditure amounts in any model is most strikingly illustrated by the OGLC case, where the strong participation-level association observed in Part 1 disappears entirely at the expenditure amount level. One interpretation is that, while the individual gambling risk profile predicts purchase participation of GLMs, the expenditure magnitude among those already purchasing may reflect the monetization environment more than individual risk characteristics. This would be consistent with the pattern explored in Section 5.1, where significant amount-level predictors were structured around F2P and BP financial engagement. However, the present data cannot distinguish between this and alternative explanations cleanly, and the variance left unexplained at the amount level, particularly in the OGLC model, indicates that other predictors of expenditure magnitude remain unaccounted for.

5.3 IGD does not predict GLM expenditure

The consistent IGD null across the three models in both approaches departs from the body of prior work consistently linking problem gaming indicators to GLM engagement and expenditure (Gibson *et al.*, 2022; Montiel *et al.*, 2022; Spicer *et al.*, 2022). Notably, the null holds across all GLM categories, and across both analytical parts, indicating that the absence of association is not category-specific or limited to the participation decision. This does not, however, place the finding in isolation: comparable null results between disordered gaming and GLM engagement have been published (Chew and Neo, 2024; Etchells *et al.*, 2022), indicating that the association may not emerge consistently across varied research and sample contexts. Notably, some prior studies reporting positive associations were conducted on adolescent samples (González-Cabrera *et al.*, 2023; Hing *et al.*, 2023), and the present study's adult sample may partly account for the divergence.

The most plausible account of this pattern begins with a measurement consideration, as the IGDS9-SF captures symptoms of compulsive play – factors not inherently tied to financial behavior. A player may satisfy IGD criteria through excessive time investment without any expenditure, and conversely, substantial GLM expenditure can occur without any behavioral dysregulation the scale is designed to detect. The instrument also does not distinguish between game types or assess financial consequences, which limits its theoretical relevance when expenditure is the outcome of interest. In contrast, the PGSI, which explicitly indexes financial harm, loss-chasing, and risk-tolerance, predicted participation across all three GLM categories. This dissociation validates the perceived distinction: PGSI may carry greater theoretical alignment with GLM expenditure than the IGD does, even when that expenditure occurs within a game context. A further analytical consideration is also relevant: by including specific financial engagement variables alongside IGD in the same model, any variance that might plausibly carry an IGD effect may be absorbed by the expenditure predictors.

5.4 Implications

That two monetization models as structurally distinct as deterministic BPs and chance-based GLMs show linked expenditure patterns is notable and becomes interpretable within Joseph's (2021) "contingent commodity" logic, wherein interface design and temporal scarcity circulate players through successive monetization opportunities. As discussed in Section 5.1.2, BPs and GLMs can be seen as interlocking nodes in a shared monetization architecture, and this interconnectedness can be lost when either mechanic is analyzed in isolation. The finding that non-random F2P expenditure also predicts GLM expenditure extends this logic outward, locating the relevant predictive variable at the level of financial engagement within F2P economies more broadly rather than within any single product category. P2P expenditure complicates the picture only partially: it positively predicts participation in CLB and GALB but not OGLC, suggesting that a general financial disposition toward paid gaming carries across some contexts – a spillover plausibly attributable to the presence of loot boxes within some P2P titles.

The present findings also offer empirical support for why the kind of disaggregation Macey *et al.* (2024) undertake is analytically necessary. Their framework locates GLMs along dimensions of structural and esthetic proximity to traditional gambling – including event format and representational imagery – and when mechanics are treated as a homogeneous category, these distinctions collapse. OGLC, i.e. casino minigames, wheel spins, and wagering mechanics, sits at the direct-translation end of both dimensions simultaneously, and this study found that PGSI showed its most striking and consistent participation effects with these types of mechanics.

The observed predictive value of PGSI across the three GLM categories raises a question for regulatory attention: whether mechanic-level distinctions within GLMs are associated with meaningfully different risk profiles. The present data suggest they may be, but the pattern does not support specific regulatory prescriptions, i.e. causal direction, confounding, and

generalizability remain untested. What it does suggest is that treating GLMs as a homogeneous category may obscure theoretically meaningful variation: visual similarity to traditional gambling and reward tangibility, considered alongside other established risk factors such as reward transferability, may be productive dimensions for further investigation of differential harm potential. The taxonomy introduced in this study offers one starting point for that analysis.

Both proposed and existing regulatory frameworks have also focused on individual “loot boxes” as a form of illegal gambling and a vector of potential harm (Xiao, 2024), leaving BPs largely outside their scope despite industry responses. Yet, the present findings add empirical weight to the concern that the expenditure pathways between BPs and GLMs, especially loot boxes, are not competing, but supplementing each other. Further, as BP architectures can directly incorporate GLMs (Dzhuhalyk, 2025), and pay-to-skip mechanics can accelerate access to them (Aguerri and De Garayo, 2025; Mattinen *et al.*, 2023b), the boundaries between the two may be more blurred than regulatory frameworks have assumed.

The consistent role of problem gambling severity in predicting participation across all three GLM categories suggests that integrated monetization environments combining BP systems with GLMs may be disproportionately engaging players already at elevated risk. The combination of artificial scarcity, time-limited availability, and escalating commitment with GLMs within the same environment warrants heightened ethical scrutiny – not least because the commercial incentive to implement such configurations is, at least among the present findings, empirically supported.

5.5 Limitations

All measures were self-reported, potentially introducing recall error and social desirability bias in expenditure amounts, playtime, and problem behavior estimates. BP structures add a specific complication: expenditure on them and on randomized content is not always architecturally discrete. The direct integration of randomized rewards within some BP progression tracks, and the availability of paid progression skipping across F2P titles (Aguerri and De Garayo, 2025) may create situations where the reported expenditure amounts between BPs and GLMs become muddled. Further, the cross-sectional design rules out causal inference. Longitudinal or experimental work is needed to establish whether the predictors identified here preceded and subsequently drive GLM expenditure, or whether the relationships run in the opposite direction or reflect shared underlying causes.

Generalizability is constrained along several dimensions. Recruitment via social media and *Prolific* skews the sample toward English-speaking adults with above-average digital literacy. As the survey aimed to capture participants with at least some gaming engagement in the past 12 months, the sample foremost represents video game players rather than any broader population. The geographic distribution is also markedly uneven: 63.4% European, 33.6% South African, and these regions differ substantially in regulatory context (Xiao, 2024; Xiao *et al.*, 2022). Further, Asian markets, where the expenditure norms may differ substantially from Western contexts, are almost entirely absent. Replication in North American, Asian, and more diverse samples is needed before strong generalization is warranted. The present models also omit several variables with potential associations to loot box expenditure, including gender, age, income, and game genre.

Part 2 OLS models were estimated on purchaser-only subsamples of 125–155 cases, which satisfy established power and cross-validation thresholds for medium effects (Green, 1991; Pituch and Stevens, 2016). However, the OGLC subsample (~125 cases) approaches the boundary of cross-validation reliability if the true population R^2 falls below 0.50, plausible given restriction of range in purchaser subsamples, and thus the OGLC Part 2 results warrant caution. Null findings in Part 2 may also reflect the absence of detectable medium or large effects, and as such, small associations cannot be ruled out.

6. Conclusions

Across both research questions, financial engagement remains the most consistent predictor of GLM expenditure, while gaming disorder symptoms are null throughout and PGSI's role is confined to purchase participation (Sections 5.1–5.3). Critically, predictors operative at the participation level do not uniformly carry through to the amount level. PGSI predicts purchase participation across all GLM categories, with effects most pronounced for OGLC, yet carries no predictive weight at the expenditure amount level. For the expenditure predictors, P2P access and BP predict participation, but while BP expenditure predicts amounts for all but OGLC, P2P access prediction fails entirely at amount levels. The findings thus reveal a structured dissociation between participation and amount predictors that becomes apparent only when mechanic categories and the expenditure decision itself are treated as distinct.

These findings open several productive avenues. The role of PGSI as a predictor of GLM purchase entry warrants direct investigation through multi-group designs stratified by problem gambling risk. The associations between F2P and BP expenditure and GLM engagement invite longitudinal work on causal sequencing and potential mediating mechanisms such as loss aversion and sunk cost sensitivity. Partnering with publishers to access behavioral telemetry could replace self-reports with objective engagement data – though access barriers, data ownership, and commercial sensitivity present non-trivial obstacles to such collaborations.

The present three-category taxonomy produced differential predictor patterns that a uniform treatment would not have registered, while simultaneously exposing its own limits. Finer monetization taxonomies would further sharpen what the present broad categories cannot fully resolve. Pity systems – whereby guaranteed rewards trigger after a set number of draws – represent one such distinction. Others include whether the GLMs are earned through play or purchased directly, and whether rewards are transferable outside the game economy. All carry plausible behavioral consequences that remain untested here.

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Supplementary material

The supplementary material for this article can be found online.

References

- Aguerri, J.C. and De Garayo, A.T.G. (2025), “Where do we fall, guys?”, *International Journal of Cyber Behavior, Psychology and Learning*, Vol. 15 No. 1, pp. 1-18, doi: [10.4018/IJCBPL.373711](https://doi.org/10.4018/IJCBPL.373711).
- Alha, K., Kinnunen, J., Koskinen, E. and Paavilainen, J. (2018), “Free-to-play games: paying players’ perspective”, *Mindtrek '18: Proceedings of the 22nd International Academic Mindtrek Conference*, Tampere, Finland, 10-11 October 2018, ACM, New York, NY, pp. 49-58, doi: [10.1145/3275116.3275133](https://doi.org/10.1145/3275116.3275133).
- Arkes, H.R. and Blumer, C. (1985), “The psychology of sunk cost”, *Organizational Behavior and Human Decision Processes*, Vol. 35 No. 1, pp. 124-140, doi: [10.1016/0749-5978\(85\)90049-4](https://doi.org/10.1016/0749-5978(85)90049-4).
- Barton, K.R., Yazdani, Y., Ayer, N., Kalvapalle, S., Brown, S., Stapleton, J., Brown, D.G. and Harrigan, K.A. (2017), “The effect of losses disguised as wins and near misses in electronic gaming machines: a systematic review”, *Journal of Gambling Studies*, Vol. 33 No. 4, pp. 1241-1260, doi: [10.1007/s10899-017-9688-0](https://doi.org/10.1007/s10899-017-9688-0).

- Brooks, G.A. and Clark, L. (2019), "Associations between loot box use, problematic gaming and gambling, and gambling-related cognitions", *Addictive Behaviors*, Vol. 96, pp. 26-34, doi: [10.1016/j.addbeh.2019.04.009](https://doi.org/10.1016/j.addbeh.2019.04.009).
- Brooks, G.A. and Clark, L. (2023), "The gamblers of the future? Migration from loot boxes to gambling in a longitudinal study of young adults", *Computers in Human Behavior*, Vol. 141, 107605, doi: [10.1016/j.chb.2022.107605](https://doi.org/10.1016/j.chb.2022.107605).
- Chew, P.K.H. and Neo, G. (2024), "Internet gaming disorder and problem gambling severity do not predict money and time spent on games with loot boxes", *Trends in Psychology*. doi: [10.1007/s43076-024-00425-9](https://doi.org/10.1007/s43076-024-00425-9).
- Close, J., Spicer, S.G., Nicklin, L.L., Uther, M., Lloyd, J. and Lloyd, H. (2021), "Secondary analysis of loot box data: are high-spending 'whales' wealthy gamers or problem gamblers?", *Addictive Behaviors*, Vol. 117, 106851, doi: [10.1016/j.addbeh.2021.106851](https://doi.org/10.1016/j.addbeh.2021.106851).
- Costes, J.-M. and Bonnaire, C. (2022), "Spending money in free-to-play games: sociodemographic characteristics, motives, impulsivity and internet gaming disorder specificities", *International Journal of Environmental Research and Public Health*, Vol. 19 No. 23, 15709, doi: [10.3390/ijerph192315709](https://doi.org/10.3390/ijerph192315709).
- Currie, S.R., Hodgins, D.C. and Casey, D.M. (2013), "Validity of the problem gambling severity index interpretive categories", *Journal of Gambling Studies*, Vol. 29 No. 2, pp. 311-327, doi: [10.1007/s10899-012-9300-6](https://doi.org/10.1007/s10899-012-9300-6).
- Delfabbro, P., King, D. and Parke, J. (2023), "The complex nature of human operant gambling behaviour involving slot games: structural characteristics, verbal rules and motivation", *Addictive Behaviors*, Vol. 137, 107540, doi: [10.1016/j.addbeh.2022.107540](https://doi.org/10.1016/j.addbeh.2022.107540).
- Dreier, M., Wöfling, K., Duven, E., Giral, S., Beutel, M.E. and Müller, K.W. (2017), "Free-to-play: about addicted whales, at risk dolphins and healthy minnows. Monetization design and internet gaming disorder", *Addictive Behaviors*, Vol. 64, pp. 328-333, doi: [10.1016/j.addbeh.2016.03.008](https://doi.org/10.1016/j.addbeh.2016.03.008).
- Dzhuhalyk, D. (2025), "Overwatch 2 will reintroduce loot boxes two years after their removal", *Mezha*, 13 February, available at: <https://mezha.ua/en/2025/02/13/overwatch-2-will-reintroduce-loot-boxes-two-years-after-their-removal/> (accessed 18 February 2026).
- Etchells, P.J., Morgan, A.L. and Quintana, D.S. (2022), "Loot box spending is associated with problem gambling but not mental wellbeing", *Royal Society Open Science*, Vol. 9 No. 8, 220111, doi: [10.1098/rsos.220111](https://doi.org/10.1098/rsos.220111).
- Garea, S.S., Drummond, A., Sauer, J.D., Hall, L.C. and Williams, M.N. (2021), "Meta-analysis of the relationship between problem gambling, excessive gaming and loot box spending", *International Gambling Studies*, Vol. 21 No. 3, pp. 460-479, doi: [10.1080/14459795.2021.1914705](https://doi.org/10.1080/14459795.2021.1914705).
- Gibson, E., Griffiths, M.D., Calado, F. and Harris, A. (2022), "The relationship between videogame micro-transactions and problem gaming and gambling: a systematic review", *Computers in Human Behavior*, Vol. 131, 107219, doi: [10.1016/j.chb.2022.107219](https://doi.org/10.1016/j.chb.2022.107219).
- Gibson, E., Griffiths, M.D., Calado, F. and Harris, A. (2023), "Videogame player experiences with micro-transactions: an interpretative phenomenological analysis", *Computers in Human Behavior*, Vol. 145, 107766, doi: [10.1016/j.chb.2023.107766](https://doi.org/10.1016/j.chb.2023.107766).
- González-Cabrera, J., Basterra-González, A., Montiel, I., Calvete, E., Pontes, H.M. and Machimbarrena, J.M. (2022), "Loot boxes in Spanish adolescents and young adults: relationship with internet gaming disorder and online gambling disorder", *Computers in Human Behavior*, Vol. 126, 107012, doi: [10.1016/j.chb.2021.107012](https://doi.org/10.1016/j.chb.2021.107012).
- González-Cabrera, J., Basterra-González, A., Ortega-Barón, J., Caba-Machado, V., Díaz-López, A., Pontes, H.M. and Machimbarrena, J.M. (2023), "Loot box purchases and their relationship with internet gaming disorder and online gambling disorder in adolescents: a prospective study", *Computers in Human Behavior*, Vol. 143, 107685, doi: [10.1016/j.chb.2023.107685](https://doi.org/10.1016/j.chb.2023.107685).
- Green, S.B. (1991), "How many subjects does it take to do a regression analysis", *Multivariate Behavioral Research*, Vol. 26 No. 3, pp. 499-510, doi: [10.1207/s15327906mbr2603_7](https://doi.org/10.1207/s15327906mbr2603_7).
- Havlicek, L.L. and Peterson, N.L. (1976), "Robustness of the pearson correlation against violations of assumptions", *Perceptual and Motor Skills*, Vol. 43 No. 3_suppl, pp. 1319-1334, doi: [10.2466/pms.1976.43.3f.1319](https://doi.org/10.2466/pms.1976.43.3f.1319).

- Hing, N., Russell, A.M.T., King, D.L., Rockloff, M., Browne, M., Newall, P. and Greer, N. (2023), "Not all games are created equal: adolescents who play and spend money on simulated gambling games show greater risk for gaming disorder", *Addictive Behaviors*, Vol. 137, 107525, doi: [10.1016/j.addbeh.2022.107525](https://doi.org/10.1016/j.addbeh.2022.107525).
- Hosmer, D.W., Lemeshow, S. and Sturdivant, R.X. (2013), *Applied Logistic Regression*, 3rd ed., Wiley, Hoboken, NJ, doi: [10.1002/9781118548387](https://doi.org/10.1002/9781118548387).
- Humphreys, B.R., Lee, Y.S. and Soebbing, B.P. (2010), "Consumer behaviour in lottery: the double hurdle approach and zeros in gambling survey data", *International Gambling Studies*, Vol. 10 No. 2, pp. 165-176, doi: [10.1080/14459795.2010.502180](https://doi.org/10.1080/14459795.2010.502180).
- Johnson, M.R. and Brock, T. (2020), "The 'gambling turn' in digital game monetization", *Journal of Gaming and Virtual Worlds*, Vol. 12 No. 2, pp. 145-163, doi: [10.1386/jgvw_00011_1](https://doi.org/10.1386/jgvw_00011_1).
- Joseph, D. (2021), "Battle pass capitalism", *Journal of Consumer Culture*, Vol. 21 No. 1, pp. 68-83, doi: [10.1177/1469540521993930](https://doi.org/10.1177/1469540521993930).
- Kahneman, D. and Tversky, A. (1979), "Prospect theory: an analysis of decision under risk", *Econometrica*, Vol. 47 No. 2, p. 263, doi: [10.2307/1914185](https://doi.org/10.2307/1914185).
- Kim, H.S., Hollingshead, S. and Wohl, M.J.A. (2017), "Who spends money to play for free? Identifying who makes micro-transactions on social casino games (and why)", *Journal of Gambling Studies*, Vol. 33 No. 2, pp. 525-538, doi: [10.1007/s10899-016-9626-6](https://doi.org/10.1007/s10899-016-9626-6).
- King, D.L. and Delfabbro, P.H. (2018), "Predatory monetization schemes in video games (e.g. 'loot boxes') and internet gaming disorder", *Addiction*, Vol. 113 No. 11, pp. 1967-1969, doi: [10.1111/add.14286](https://doi.org/10.1111/add.14286).
- King, D.L. and Delfabbro, P.H. (2019), "Video game monetization (e.g. 'loot boxes'): a blueprint for practical social responsibility measures", *International Journal of Mental Health and Addiction*, Vol. 17 No. 1, pp. 166-179, doi: [10.1007/s11469-018-0009-3](https://doi.org/10.1007/s11469-018-0009-3).
- Lemmens, J.S. (2022), "Play or pay to win: loot boxes and gaming disorder in FIFA ultimate team", *Telematics and Informatics Reports*, Vol. 8, 100023, doi: [10.1016/j.teler.2022.100023](https://doi.org/10.1016/j.teler.2022.100023).
- Liang, A.R.-D., Lee, C.-L. and Tung, W. (2014), "The role of sunk costs in online consumer decision-making", *Electronic Commerce Research and Applications*, Vol. 13 No. 1, pp. 56-68, doi: [10.1016/j.elerap.2013.10.001](https://doi.org/10.1016/j.elerap.2013.10.001).
- Lizardi, R. (2012), "DLC: perpetual commodification of the video game", *Democratic Communiqué*, Vol. 25 No. 1, doi: [10.7275/democratic-communicue.278](https://doi.org/10.7275/democratic-communicue.278).
- Macey, J. and Bujić, M. (2022), "The talk of the town: community perspectives on loot boxes", in Ruotsalainen, M., Törhönen, M. and Karhulahti, V.-M. (Eds), *Modes of Esports Engagement in Overwatch*, Springer International Publishing, Cham, pp. 199-223, doi: [10.1007/978-3-030-82767-0_11](https://doi.org/10.1007/978-3-030-82767-0_11).
- Macey, J. and Hamari, J. (2018), "Investigating relationships between video gaming, spectating esports, and gambling", *Computers in Human Behavior*, Vol. 80, pp. 344-353, doi: [10.1016/j.chb.2017.11.027](https://doi.org/10.1016/j.chb.2017.11.027).
- Macey, J., Hamari, J. and Adam, M. (2024), "A conceptual framework for understanding and identifying gamblified experiences", *Computers in Human Behavior*, Vol. 152, 108087, doi: [10.1016/j.chb.2023.108087](https://doi.org/10.1016/j.chb.2023.108087).
- Mattinen, T., Macey, J. and Hamari, J. (2023a), "Gambling in digital games and esports: a scoping review", *Proceedings of the 56th Hawaii International Conference on System Sciences*, pp. 3921-3930, doi: [10.24251/HICSS.2023.479](https://doi.org/10.24251/HICSS.2023.479).
- Mattinen, T., Macey, J. and Hamari, J. (2023b), "A ruse by any other name: comparing loot boxes and collectible card games using magic arena", *Proceedings of the ACM on Human-Computer Interaction*, Vol. 7 CHI PLAY, pp. 721-747, doi: [10.1145/3611047](https://doi.org/10.1145/3611047).
- Mattinen, T., Macey, J. and Hamari, J. (2025), "Play, pay, profit: exploring when gaming becomes gambling", *Proceedings of DiGRA 2025: Games at the Crossroads*, doi: [10.26503/dl.v2025i2.2436](https://doi.org/10.26503/dl.v2025i2.2436).

- Montefiore, T. and Formosa, P. (2026), "Dark patterns meet the Gamer's dilemma: contrasting morally objectionable content with systems in video games", *Games and Culture*, Vol. 21 No. 6, pp. 1255-1274, doi: [10.1177/15554120251319173](https://doi.org/10.1177/15554120251319173).
- Montiel, I., Basterra-González, A., Machimbarrena, J.M., Ortega-Barón, J. and González-Cabrera, J. (2022), "Loot box engagement: a scoping review of primary studies on prevalence and association with problematic gaming and gambling", *PLoS One*, Vol. 17 No. 1, e0263177, doi: [10.1371/journal.pone.0263177](https://doi.org/10.1371/journal.pone.0263177).
- Neely, E.L. (2021), "Come for the game, stay for the cash grab: the ethics of loot boxes, microtransactions, and freemium games", *Games and Culture*, Vol. 16 No. 2, pp. 228-247, doi: [10.1177/155541201988765](https://doi.org/10.1177/155541201988765).
- Nielsen, R.K.L. and Grabarczyk, P. (2019), "Are loot boxes gambling?: random reward mechanisms in video games", *Transactions of the Digital Games Research Association*, Vol. 4 No. 3, pp. 171-207, doi: [10.26503/todigra.v4i3.104](https://doi.org/10.26503/todigra.v4i3.104).
- Niknejad, S., Mildner, T., Zargham, N., Putze, S. and Malaka, R. (2024), "Level up or game over: exploring how dark patterns shape mobile games", in Matvienko, A., Niess, J. and Kosch, T. (Eds), *MUM '24: Proceedings of the 23rd International Conference on Mobile and Ubiquitous Multimedia*, Stockholm, Sweden, 1-4 December 2024, ACM, New York, NY, pp. 148-156, doi: [10.1145/3701571.3701604](https://doi.org/10.1145/3701571.3701604).
- Norman, G. (2010), "Likert scales, levels of measurement and the 'laws' of statistics", *Advances in Health Sciences Education*, Vol. 15 No. 5, pp. 625-632, doi: [10.1007/s10459-010-9222-y](https://doi.org/10.1007/s10459-010-9222-y).
- Orford, J., Wardle, H., Griffiths, M., Sproston, K. and Erens, B. (2010), "PGSI and DSM-IV in the 2007 British gambling prevalence survey: reliability, item response, factor structure and inter-scale agreement", *International Gambling Studies*, Vol. 10 No. 1, pp. 31-44, doi: [10.1080/14459790903567132](https://doi.org/10.1080/14459790903567132).
- Peduzzi, P., Concato, J., Kemper, E., Holford, T.R. and Feinstein, A.R. (1996), "A simulation study of the number of events per variable in logistic regression analysis", *Journal of Clinical Epidemiology*, Vol. 49 No. 12, pp. 1373-1379, doi: [10.1016/S0895-4356\(96\)00236-3](https://doi.org/10.1016/S0895-4356(96)00236-3).
- Pituch, K.A. and Stevens, J.P. (2016), *Applied Multivariate Statistics for the Social Sciences: Analyses with SAS and IBM's SPSS*, 6th ed., Routledge, New York, NY.
- Pontes, H.M. and Griffiths, M.D. (2015), "Measuring DSM-5 internet gaming disorder: development and validation of a short psychometric scale", *Computers in Human Behavior*, Vol. 45, pp. 137-143, doi: [10.1016/j.chb.2014.12.006](https://doi.org/10.1016/j.chb.2014.12.006).
- Rockloff, M., Browne, M., Greer, N., Armstrong, T. and Thorne, H. (2020), "Mobile EGM games: evidence that simulated games encourage real-money gambling", *Journal of Gambling Studies*, Vol. 36 No. 4, pp. 1253-1265, doi: [10.1007/s10899-019-09869-6](https://doi.org/10.1007/s10899-019-09869-6).
- Shin, D.D. (2022), *Algorithms, Humans, and Interactions*, Routledge, New York, NY.
- Spicer, S.G., Nicklin, L.L., Uther, M., Lloyd, J., Lloyd, H. and Close, J. (2022), "Loot boxes, problem gambling and problem video gaming: a systematic review and meta-synthesis", *New Media and Society*, Vol. 24 No. 4, pp. 1001-1022, doi: [10.1177/14614448211027175](https://doi.org/10.1177/14614448211027175).
- Tabachnick, B.G., Fidell, L.S. and Ullman, J.B. (2019), *Using Multivariate Statistics*, 7th ed., Pearson, Boston, MA.
- Wardle, H. and Zentle, D. (2021), "Loot boxes, gambling, and problem gambling among young people: results from a cross-sectional online survey", *Cyberpsychology, Behavior, and Social Networking*, Vol. 24 No. 4, pp. 267-274, doi: [10.1089/cyber.2020.0299](https://doi.org/10.1089/cyber.2020.0299).
- Xiao, L.Y. (2024), "Loot box state of play 2024: another trip around the world of regulation", *GamesIndustry.biz*, 17 December, available at: <https://www.gamesindustry.biz/loot-box-state-of-play-2024-another-trip-around-the-world-of-regulation> (accessed 13 June 2025).
- Xiao, L.Y., Henderson, L.L., Nielsen, R.K.L. and Newall, P.W.S. (2022), "Regulating gambling-like video game loot boxes: a public health framework comparing industry self-regulation, existing national legal approaches, and other potential approaches", *Current Addiction Reports*, Vol. 9 No. 3, pp. 163-178, doi: [10.1007/s40429-022-00424-9](https://doi.org/10.1007/s40429-022-00424-9).

- Xiao, L.Y., Henderson, L.L., Nielsen, R.K.L., Grabarczyk, P. and Newall, P.W.S. (2024), "Loot boxes: gambling-like mechanics in video games", in Lee, N. (Ed.), *Encyclopedia of Computer Graphics and Games*, Springer International Publishing, Cham, pp. 1075-1081, doi: [10.1007/978-3-319-08234-9_459-1](https://doi.org/10.1007/978-3-319-08234-9_459-1).
- Zanescu, A., Lajeunesse, M. and French, M. (2019), "Gaming DOTA players: iterative platform design and capture", *DiGRA 2019 Conference: Game, Play and the Emerging Ludo-Mix*, doi: [10.26503/dl.v2019i1.1859](https://doi.org/10.26503/dl.v2019i1.1859).
- Zanescu, A., French, M. and Lajeunesse, M. (2021), "Betting on DOTA 2's battle pass: gamblification and productivity in play", *New Media and Society*, Vol. 23 No. 10, pp. 2882-2901, doi: [10.1177/1461444820941381](https://doi.org/10.1177/1461444820941381).
- Zendle, D. and Cairns, P. (2018), "Video game loot boxes are linked to problem gambling: results of a large-scale survey", *PLoS One*, Vol. 13 No. 11, e0206767, doi: [10.1371/journal.pone.0206767](https://doi.org/10.1371/journal.pone.0206767).
- Zendle, D. and Cairns, P. (2019), "Loot boxes are again linked to problem gambling: results of a replication study", *PLoS One*, Vol. 14 No. 3, e0213194, doi: [10.1371/journal.pone.0213194](https://doi.org/10.1371/journal.pone.0213194).
- Zendle, D., Cairns, P., Barnett, H. and McCall, C. (2020a), "Paying for loot boxes is linked to problem gambling, regardless of specific features like cash-out and pay-to-win", *Computers in Human Behavior*, Vol. 102, pp. 181-191, doi: [10.1016/j.chb.2019.07.003](https://doi.org/10.1016/j.chb.2019.07.003).
- Zendle, D., Meyer, R. and Ballou, N. (2020b), "The changing face of desktop video game monetisation: an exploration of exposure to loot boxes, pay to win, and cosmetic microtransactions in the most-played steam games of 2010-2019", *PLoS One*, Vol. 15 No. 5, e0232780, doi: [10.1371/journal.pone.0232780](https://doi.org/10.1371/journal.pone.0232780).
- Zendle, D., Cairns, P., Meyer, R., Waters, S. and Ballou, N. (2022), "Response to Xiao *et al.*: if everything is a loot box, nothing is", *Addiction*, Vol. 117 No. 9, pp. 2555-2556, doi: [10.1111/add.15976](https://doi.org/10.1111/add.15976).

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