# The Many Faces of Monetisation: Understanding the Diversity and Extremity of Player Spending in Mobile Games via Massive-scale Transactional Analysis

DAVID ZENDLE, University of York, United Kingdom
CATHERINE FLICK, De Montfort University, United Kingdom
SEBASTIAN DETERDING, Dyson School of Design Engineering, Imperial College London, United Kingdom
JOE CUTTING and ELENA GORDON-PETROVSKAYA, University of York, United Kingdom
ANDERS DRACHEN, SDU Metaverse Lab, University of Southern Denmark, Denmark

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With the rise of microtransactions, particularly in the mobile games industry, there has been ongoing concern that games reliant on these obtain substantial revenue from a small proportion of heavily involved individuals, to an extent that may be financially burdensome to these individuals. Yet despite substantive grey literature and speculation on this topic, there is little robust data available. We explore the revenue distribution in microtransaction-based mobile games using a transactional dataset of $4.7B in in-game spending drawn from 69,144,363 players of 2,873 mobile games over the course of 624 days. We find diverse revenue distributions in mobile games, ranging from a "uniform" cluster, in which all spenders invest approximately similar amounts, to "hyper-Pareto" games, in which a large proportion of revenue (approximately 38%) stems from 1% of spenders alone. Specific kinds of games are typified by higher spending: The more a game relies on its top 1% for revenue generation, the more these individuals tend to spend, with simulated gambling products ("social casinos") at the top. We find a small subset of games across all genres, clusters, and age ratings in which the top 1% of gamers are highly financially involved—spending an average of $66,285 each in the 624 days under evaluation in the most extreme case. We discuss implications for future studies on links between gaming and wellbeing.

CCS Concepts: • **Software and its engineering → Interactive games;**

Additional Key Words and Phrases: In-app spending, monetisation, video games, mobile games, mobile gaming

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Authors' addresses: D. Zendle, J. Cutting, and E. Gordon-Petrovskaya, University of York, United Kingdom; emails: david.zendle@york.ac.uk, joe.cutting@york.ac.uk, ep1167@york.ac.uk; C. Flick, De Montfort University, United Kingdom; email: cflick@dmu.ac.uk; S. Deterding, Dyson School of Design Engineering, Imperial College London, United Kingdom; A. Drachen, SDU Metaverse Lab, University of Southern Denmark, Denmark; email: adrac@mmmi.sdu.dk.

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# 1 INTRODUCTION

Throughout the 1980s to early 2000s, the video game industry was dominated by the sale of video games as fixed end products: When one wanted to play *Super Mario World*, or *Pokémon Red*, or *Grand Theft Auto: San Andreas*, one handed over a set amount of money once and was given a physical or (increasingly) a digital copy of the "full" game. This model proved popular: each of these games are reported to have sold tens of millions of copies [2, 4, 7]. However, beginning in the 2000s, subsets of the industry shifted to business, production, and monetisation models where content access and payment were extended, be it through add-ons, (online) subscription fees, or DLC (downloadable content). This shift echoes the "Golden Age" of arcade video games (1977–1993), in which initial commercialisation involved adding coin operation to products such as *Pong* [26]. These games worked on a pay-per-play basis: A player could play for as long as they had coins to put into the machine. Over time, monetisation strategies further evolved from the sale of finite extended sets of discrete in-game products to microtransactions, and with these came further controversy.

## 1.1 Microtransactions

The term microtransaction is typically used to refer to typically uncapped, potentially continuous in-game payments. In recent years, the microtransactions used by the games industry have become diverse, and range from, e.g., progression boosters, in-game currencies, or randomised rewards (loot boxes) to cosmetic items that affect how a player looks [75]. It is worth mentioning that the term microtransaction is broadly used for any kind of monetary transaction in a game: there is no commonly accepted definition of microtransaction versus transaction.

The prevalence of such microtransactions has increased substantially in recent years. Although high-quality, public data are not available for understanding the absolute prevalence or profitability of microtransactions within the global market, some examples can be mentioned. For example, in 2010 only approximately 8.3% of gamers on the desktop platform Steam played a game that featured cosmetic microtransactions; by April 2019 this was estimated to have risen to approximately 85.8% [81]. The freemium and associated free-to-play strategies (see below for definitions) have also proved particularly popular in mobile games. Indeed, it is claimed by some sources that the primary way mobile games currently generate revenue is via the repeated sales of in-game products and services (**"In-App Purchases" (IAPs)** or **"in-game purchases" (IGPs)**) [17].

The development of the iPhone in 2007 has been claimed by some authors as being important to a transition from premium to freemium mobile game monetization, which in turn have been considered to affect desktop and console gaming in turn [8]. Apple's App Store and the Play Store allowed for easy distribution of both games and associated microtransactions.

## 1.2 The Freemium Model of Monetization

Associated with the transitions mentioned above was the rising popularity of a new approach toward monetization in games that was based on the idea of making all or parts of the content of the game freely available, and charging money (a premium) for specific additional content, via IAPs. This approach to revenue generation became popularised under the moniker of "freemium," itself a portmanteau of "free" and "premium," and is thought to be particularly common for mobile game titles.

There are a variety of different strategies adopted by mobile games that feature in-app purchases, and it is generally challenging to create meaningful categories and nomenclature due to the variation in strategies employed, the rate of innovation in game monetization, and the lack of standardised terminology and definitions. However, across all of these strategies, players have the ability to make purchases during play. Adopting definitions from industry handbooks, we can define the following types of strategies [29, 34, 64].

- `Freemium`: Freemium games come in different versions, at least two: one is free, but does not offer all features. These features are locked and players must pay if they want to use them. There can be multiple such purchases possible.
- `Free to Play`: **Free-to-play (F2P)** games provide all content up front, but players can make purchases to help them in the game, e.g., to speed up progression or provide a customised experience (e.g., purchasing more energy, special power boosts, reduce the remaining time on a timer, etc.). Alternatively, players must watch ads to continue playing.
- `Pay to Play`: **Pay-to-play (P2P)** games (also referred to as Premium Games) have an upfront cost that needs to be paid to access the game content. This includes subscription-based games. P2P games can also include DLC and microtransactions in the form of IAPs, e.g., *Mass Effect 2*.
- `Payt to Win`: **Pay-to-win (P2W)** games form a specific subtype of any of the above, where progression or success is gated by the need to make in-game purchases, specifically which provides competitive advantage or progression over other players; increases that would not be possible to achieve without paying.

Freemium and Free to Play games are often considered the same model, and will be treated as such in this article using the term "Freemium."

### 1.3 Spend Distribution in Mobile Gaming

However, this uptake of business models in which mobile games act as a service rather than end products has led to changes in the distribution of spending across their player bases. In a scenario in which a game is sold exactly once to each consumer as an end-product, an approximately uniform spend distribution emerges: Everyone pays roughly the same amount to access game content. However, freemium games may facilitate the creation of an uneven spend distribution, where the game generates its revenue almost exclusively from top percentiles [16]. Such highly engaged spenders are known in the gambling and games industry as "whales" [13]. This has raised concerns about player coercion, exploitation, and overspending, as the nature of gaming as a sales platform means there is a shift in design incentives within games to drive player spend [73]. In fact, in 2021, 88% of the top-grossing mobile games on the Google Play store were seen by players as containing problematic monetisation features [55].

Many markets tend to naturally evolve in such a manner that spending is distributed unequally across consumers. The well-known Pareto principle (or "80/20 rule") suggests that in many systems, approximately 80% of outcomes are generated by 20% of sources [59]. This result replicates in the consumer spending domain [44, 50]. Thus, the ability of a subset of gamers to generate differentially larger levels of revenue for a game are not necessarily a cause for concern: It is plausibly normative to anticipate the top 20% of spenders generating 80% of revenue. Moreover, data-driven design, such as tailoring a game to players who are the top spenders in this game, and using data analytics to learn more about their preferences allows smaller developers to participate in the market and gain enough revenue from their games.

However, substantial grey literature (e.g., Reference [64]) contains reports that some games do rely heavily on their top percentiles to drive the majority of revenue in a way that vastly exceeds this Pareto principle; and that these individuals engage in spending thousands of dollars in-game throughout their lifetime. For example, a report from the market research company Swrve suggests that 0.15% of gamers account for 50% of revenue from in-game purchases [3]; filings from a legal case involving Apple revealed that over 60% of revenue in the Apple app store may be generated by just 1% of consumers, with these highly involved individuals spending thousands of dollars on an annual basis [5].

What would it mean if the distribution of revenue in mobile gaming really were so top-heavy? Within the field of gambling research, such “Hyper-Pareto” distributions are theorised to emerge from a system that depends on disordered spending. In Reference [33], researchers suggest that this highly concentrated distribution is a product of excessive and disordered spending on gambling products amongst individuals suffering from gambling problems. Indeed, research has suggested that disordered gamblers tend to generate the majority of gambling profits [53].

### 1.4 Concerns Regarding Monetisation

There is concern in the academic literature that high-spending individuals in video games may come from vulnerable groups such as children and individuals with gaming disorder or impulse control disorders [16, 69, 82]. Reliance on extracting large amounts of money from these groups may lead to overspending, and hence a spreading pattern of harm similar to that found in the gambling domain. Indeed, multiple stories in news media have recently dealt with individuals spending money in-game that they cannot afford, leading to serious consequences [8, 11, 20]. Thus, it is important to determine whether similarly unbalanced and unusual distributions of spending do occur in some video games, and if these distributions are coupled with financially meaningful levels of spending.

Unsurprisingly, the ethicality of novel approaches to game development has been a topic of considerable interest in the literature. Some theorists argue that live service models can thus be considered player-centric, as they are based on updates, revenues, and player retention. They thus suggest that developers who work on such games may have interpersonal relationship building as a core part of their role, and may even “take pride in looking after players” [32]. Associated arguments suggest that there is no reason to criticise rational self-interest in game development unless a game engages in manipulation techniques [37]; and that if a microtransaction is designed with positive intent in mind, it may be inappropriate to characterise it as unethical or predatory [54].

However, others have taken a different point of view regarding the critique of self-interest within monetisation design, arguing that if engagement with specific forms of monetisation prove harmful to players, this is worthy of concern regardless of a developer’s intention to manipulate or deceive [77, 78]. Indeed, empirical sources in the literature have adopted such a player-centric focus. These sources have investigated predation from the player’s point of view, categorising predatory strategies as those that players deem to have coerced or exploited them, regardless of developer intent [56].

At the same time as broad concerns regarding overspending are being raised, so too are specific concerns regarding subgroups of games and subgroups of monetisation schemes. Most prominent amongst these concerns is the convergence of video games and gambling [77].

A specific genre of video game, known as “social casino” because of its origin on social media platforms such as Facebook, involves individuals engaging in simulated gambling activities [24]. Whilst players of these games may pay real money to engage in these activities (e.g., roulette wheel use, poker, slot machine play), players can never cash out their winnings. Social casino games are not commonly legally regulated as a form of gambling and are instead typically classed as a form of video game. Indeed, the Apple App Store contains a special “casino” game subsection to house this genre of video game [10] The reason for this is alluded to above: players of social casino games may not exchange in-game winnings for real-world money, which in many territories is necessary for a product to be classed as a form of gambling [19, 60]. Because social casino games are not regulated as gambling, they are commonly available for download and installation by young people. However, despite this lack of regulation, some researchers have proposed that the gambling-like nature of social casino play may lead to problematic financial consequences in a similar manner to gambling activities [35, 48].

However, little is known about the diversity of spending distributions present within the video game market. Thus, the role that specific mechanisms or genres play in determining potentially important levels of spending is currently unclear.

### 1.5 The Present Research

Overall, we identify two open research questions that the studies within this manuscript address.

First, there is a lack of clarity in both grey and academic literature regarding how revenue tends to be distributed within mobile games. This leads to RQ1. Second, there are concerns that some games systemically encourage high levels of spending amongst their top percentiles. This leads to RQ2.

- `RQ1`: What distributions of IAP revenue characterise the mobile gaming market?
- `RQ2`: How much money do the top 1% of spenders in mobile games spend, and how does this differ between revenue distributions and genres?

The code available for all major analyses are available from an OSF repository associated with this project, located at: https://osf.io/du4kr/?view_only=a2ecbe65d17c49ada6990c11e5a8a445.

## 2 DATA AND PRE-PROCESSING

### 2.1 Data Acquisition

The data used for the present study were provided by *Unity Technologies*, governed by a legal agreement between Unity Technologies and the involved academic institutions. Due to the commercially sensitive nature of the data, they are not publicly available.

The data access occurs strictly within the infrastructure (data warehouse) of *Unity Technologies* due to the sensitivity of the data. The authors do not have access to any personally identifiable information about Unity's users or the players of the games in the sample of data. They are unable to share such data with others, or facilitate the access of others to Unity's data. They will not deidentify any specific game in this dataset. All data accessed were pre-anonymized by *Unity Technologies*.

*Unity Technologies* did not make design decisions when it came to this study. No funds were disbursed to the research team for the work incorporated into this manuscript. This includes data processing fees for the cloud service the data are hosted at, which were paid by the lead author out of a research stipend from his host institution. Significant technical, organisational, and legal support for the study was put in place by *Unity Technologies*. *Unity Technologies* remain active in collaborations with the global academic community, as documented at https://unity.com/academia-research. This includes a strand of research into virtual economies, which this article contributes toward.

### 2.2 Data Description

*Unity Technologies* are the makers of the Unity game engine, a development environment for games [9]. Games made in this engine commonly implement the *Unity Analytics Toolkit*, which provides a broad range of opportunities for developers to integrate behavioural telemetry tracking in their games, which is a standard practice across the Creative Industries. Included in this package is Unity's IAP engine, a service that allows developers to rapidly implement the ability for players to spend real money on in-game goods and services. All games in the sample have integrated this IAP engine, without which no data would be collected.

Unity IAP provides an easy to implement interface with the *iOS App store* and *Google Play* (the two main stores for accessing mobile games) as well as a wide range of other third party app stores such as the *Samsung Galaxy Store*, which may be important in Asian markets. Unity IAP has no ongoing cost to the developer although they are still subject to fees imposed by the app store in question. Some apps developed in Unity may use alternative telemetry systems instead of Unity IAP, and therefore add bias to the data used here. However, in our investigation of developer forums, we found no good reason for developers to do this, nor evidence that it would be widespread.

In contemporary mobile games (and games on other platforms), telemetry data originates with the game client and is collected via servers. Telemetry data is collected from the client and transmitted to cloud data storage solutions. In the collection layers, data are masked and filtered for compliance with national data protection frameworks, before being analysed for ethics and data collection [62]. From storage, data is extracted and analysed either in the cloud or locally, and in this case made available to the research team.

Pre-anonymised Unity Analytics transaction logs from iOS games implementing the IAP engine constituted the source of data for this study. Access was provided to this data within a Google Cloud Platform BigQuery (an SQL variant) table. Data were aggregated and processed using *BigQuery* before being exported to *R* for analysis and visualisation.The sample under study thus consists of all iOS mobile games that implement Unity's IAP engine that had at least 1,000 individual spenders in the period under test. This cutoff was implemented in order for each game to have a plausible number of datapoints to approximate a distribution of spending. Additional information given regarding the ability of this sample to represent top-grossing games on mobile is given below ("The Unity Data"). Games for other platforms (Unity supports over 20) as well as non-gaming software were not used. This sample consisted of 2,873 games, and 69,144,363 spenders with at least one IAP each. The total spend in the dataset was U.S. $4.7B. The subset of the data used in this article dates August 1, 2020, to April 16, 2022.

Not all transactions in our dataset originally took place in the $USD in which they are presented in this manuscript. An algorithm was used to convert them from their native currency to USD using the relevant exchange rate for the date on which a transaction took place.

In the dataset, users were identified using an anonymous, unique identifier. Additional data features included a record of each IAP transaction made by the user within the confines of a specific game, including an identifier for the game that was played. Users were uniquely identified within games, but not across games. It is therefore possible for players to engage with multiple mobile games at the same time and be counted multiple times. Thus, "player" in the following refers to a game-unique user ID.

It is important to note that the dataset presented does not represent total revenue for the games included. Games can also make revenue from the sales of copies and in-game advertisements.

### 2.3 The Unity Data and the Lack of Other Data Sources on IAPs in Video Games

The use of video game telemetry data, which characterises player behaviour in games stretches back to the early 2000s and even earlier to online games like *Meridian 59* and *EverQuest*, documented across peer-reviewed and grey literature (e.g., References [25, 27, 38, 49, 71]).

The use of such data collectively falls under the domain of *Game Analytics* [62]. Game Analytics—broadly—utilises telemetry data along with other data sources, for example data from social media, financial transactions, user research, game testing and more, to inform decision-making across all aspects of game design and development, including economics and financial decisions, as well as research across a variety of domains [28, 63]. However, despite the maturity of game analytics as a field, the state-of-the-art is challenging to establish, with the majority of research happening in the industry [63]. Similarly, the access to telemetry data from the games industry remains highly uneven. In some areas, notably esports and various online competitive titles, there exists a well-established data sharing relationship between game companies and the communities that engage with their games [14, 45]. Such data-sharing includes in-game behavioural telemetry, but not transactional data. In other areas of the games industry, data sharing is more sporadic, with the exception of **Massively Multiplayer Online Games (MMOGs)** and some multiplayer online games, which either provide company-built data tools or community-built data tools (and potentially even professional services similar to the esports environment) that take advantage of APIs or similar access points. Some game platforms, i.e., services that provide access to multiple games, notably Steam, provide access to some relatively shallow data from the games on the platform, e.g., total playtime [21, 72]. However, there is no known platform for sharing transactional data from games, which is considered commercially sensitive [28, 63].

By and large, this data ecosystem means that prior game analytics research in video games has relied on either highly detailed, behavioural data from one or perhaps a few games, with the most advanced work, utilising deep learning models, being found in esports (e.g., References [22, 43]) with other examples from multi-player online or open-world games (e.g., Reference [67]). Alternatively, analysis can adopt data covering many games, but of a relatively shallow and aggregate nature, e.g., total playtime estimates [21, 66, 72, 81]. Thus, data-driven game monetization has been largely unexplored by peer-reviewed research.

A small subset of studies in the literature do incorporate datasets that deal with video game revenue to investigate monetisation. For example, in Reference [52], researchers used a dataset provided by a private analytics company (*Super Data*) to investigate the ability of Canadian app developers to generate revenue within the Canadian iOS app store. Focusing only on the top-100 yearly highest-grossing games, the authors reported that, in this specific store, these were dominated by US-produced applications. However, the kinds of data used here, obtained from a private analytics company (e.g., *Statista, Newzoo*) or similar source, and cited in numerous other studies, have historically been characterised by specific limitations. For example, in the study referenced above, Super Data generated the dataset via collaboration with credit card companies and payment intermediaries, which covered an unspecified part of the total direct revenue generation, and then employed *"statistical modeling to increase their accuracy to a level that is acceptable to its clients"* [52] thus producing an aggregated dataset of unclear provenance.

In general, when such cross-industry analyses occur, transactional data from large numbers of games are never available to researchers in their raw form (as is the case here). Instead, such analyses typically take place over ranked, aggregated, indirect, or estimated datasets. The use of proprietary and often opaque algorithms in data generation and aggregation means that data accuracy is inherently hard to quantify. Furthermore, the aggregated nature of such data typically leads to a situation in which specific kinds of research questions are difficult to investigate. The data employed in Reference [52], for example, cannot be used to fruitfully investigate financial involvement in video games by individual spenders.

The lack of monetization analyses in Game Analytics research is contrasted by writings outside of academia. As monetization in games is an essential aspect of the global games industry, the topic of how to design game monetization has received widespread interest, as has speculation about player spending in games (e.g., References [29, 34, 39, 64]).

Adding to this industry-based knowledge, game monetization has also historically been the subject of significant attention in games research more broadly, outside of the data-driven domain of game analytics (e.g., References [15, 47, 51]). However, much of the more recent work on game monetization—and freemium mobile game monetization specifically, shows a dearth of empirical data. While the ethical concerns raised by some experts are warranted to study, these lines of inquiry are held back by a lack of data to contextualise these concerns against—for example, analysis on spending patterns and their commonality.

Currently, the primary way to access information about IAP spending in games, as well as other sources of revenue generation, e.g., in-game advertisements, is via private analytics companies and bureaus. Some for-profit analytics companies in the games/creative industries space—such as *Newzoo, SuperData*, and *Statista*—may provide estimates for the number of games on some platforms, their players, playtime, IAPs and other information. However, the methods used to collect the data are not fully available for public scrutiny or evaluation, and the results provided therefore impossible to reliably evaluate.

Jointly, the state-of-the-art in Game Analytics and the lack of prior peer-reviewed work analysing actual IAP transactional data, presents problems when it comes to properly contextualising the data observed here. For example, one may rely on an industry report that mobile games currently account for 53% of all game market revenue to describe the scope of the holistic mobile domain, and thus the importance of our data [74]. Similarly, one may use an industry report that iOS currently has 58% of mobile gaming revenue with the rest going to Android to motivate the scale of the revenue obtained here—for instance, by suggesting that iOS may capture the majority of mobile gaming revenue [40]. However, such motivation would largely be based on a lack of data transparency, and may prove inaccurate. Until we have more work directly based on industry IAP data as is presented here (and data from other monetization channels), and a more accurate and transparent understanding of the global games market, it is difficult to make conclusions about the relative scale of the work presented here, or draw conclusions about how games monetize across the iOS platform (which this article focuses on) versus the Android platform. However, to be as informative as possible, we compared the games in our sample with a list of the top 100 highest-grossing games in the USA on iOS published by business intelligence company *Data.ai*—noting the caveats such publicly available data come with, and as outlined above—for December 8th 2022 (the date on which our manuscript was revised). Ten of these 100 games were represented in our dataset, suggesting that our data may be able to represent the full spread of revenue-generating products across the mobile market. On a final note, according to Unity, over 70% of mobile games are built using the Unity game engine including those by bigger studios such as *Tencent* and *Gameloft* [68].

### 2.4 Ethics of Data Collection

*Unity Technologies* collects a significant amount of data from players using the *Unity Analytics toolkit* and the associated *IAP Engine*, both extensions that need to be enabled by developers using the Unity Engine to operate. The former enables telemetry data to be captured from applications made using the Unity Engine, the latter enables IAP infrastructure (the Analytics toolkit is a requirement for the IAP Engine). Not all games made using the Unity Engine need to have the Unity Analytics toolkit installed, but it is the easiest way to capture user telemetry data, which have become essential in the industry, and therefore the vast majority of games made with Unity include this functionality [28, 62, 63]. Games made using the Unity Engine that has the Unity Analytics toolkit installed prompt a consent agreement when users install the game in question, which explains the collection and use of this data to the player. Unity Technologies has made public a documentation that explains the requirements for collection, storage, and use of analytics data to developers, available on the company's website. Included in the list of uses of the collected data, explained in the collection agreement is for research purposes, which is the purpose under which this data has been shared with the current research team.

The data used in the current study does not include **personally identifiable information (PII)** and the research team does not have access to PII from Unity Analytics. The data used in the current study is aggregated data, which stem from a collection that is pseudonymised by way of a token unique to each player of each individual game—no players are traceable across games, only within any specific game. Collectively, we consider this use of data within reasonable ethical use

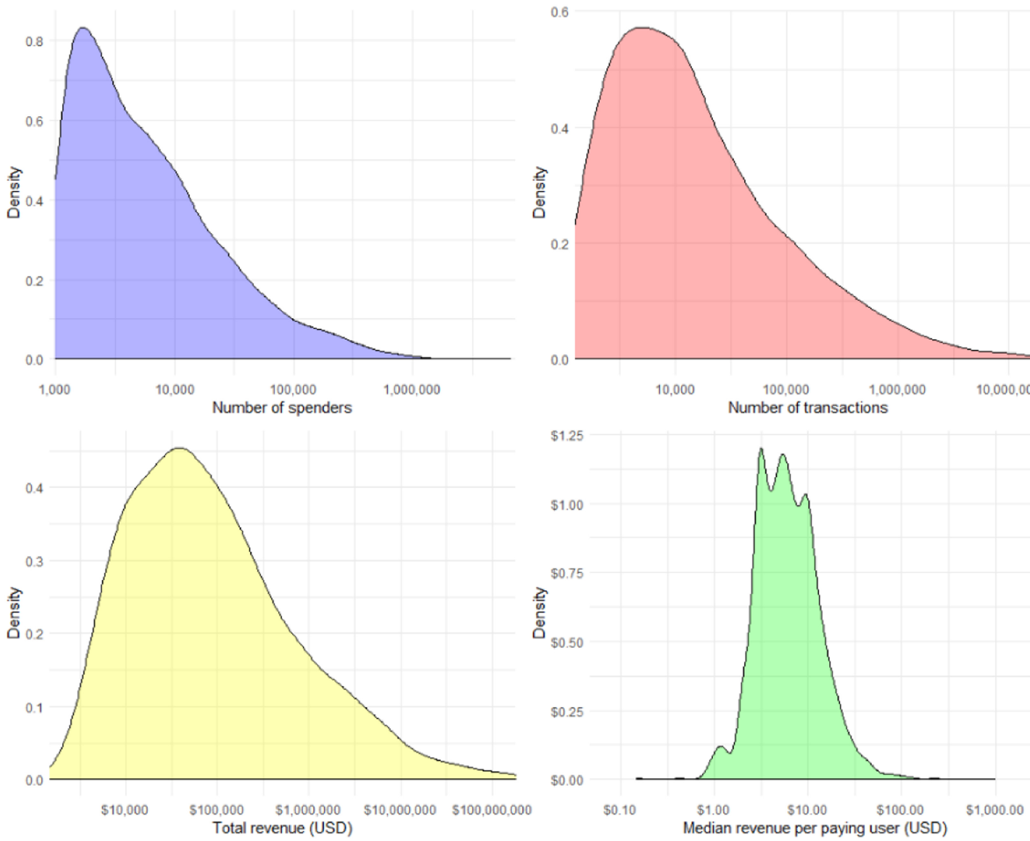


Fig. 1. Density functions describing the games in the dataset. From top to bottom, left to right, graphs describe: the number of spenders for each game; the number of transactions in each game; the total revenue associated with each game; and the median revenue associated with each paying user in each game in the dataset. All x-axes are log-transformed to allow the visualisation of the full range of the distribution.

under research ethics norms and expectations. The research has also received clearance from the University of York Physical Sciences Ethical Review Committee.

### 2.5 Descriptive Statistics

The pre-processed data for this study were anonymized transaction histories for all spenders within 2,873 Apple iOS games ($n$ = 69,144,363) with Unity Analytics enabled. In total, the dataset contained U.S. $4.7B in IAP revenue, across 461,996,143 individual transactions. The dataset covers 624 days, from August 1, 2020 to April 16, 2022.

The games in the dataset have highly varied profiles across IAP spend and number of spenders. We use medians rather than means to take into account the high degree of skew in the dataset, which inflates mean values: the median number of paying users per game is 4,342 (IQR: 1,895–12,857, Range: $1,000–$6,621,993). The median spend per paying user is $6.96 (IQR: $2.99–$21.12, Range: $<0.01–$2,233,935). This indicates diversity not only in the number of paying users that mobile games attract but also how much these users spend. Note that during the 624-day observation window, the number of spending users per game will vary as new paying players enter a game, or leave it, i.e., the underlying population of spending players per game will vary. Figure 1 (below) summarises the distribution of key statistics across all games in our dataset.

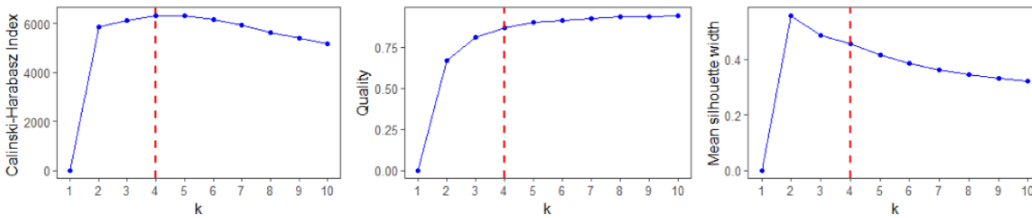


Fig. 2. Calinski-Harabasz index, cluster quality (proportion of sum of squared deviance explained by the model) and mean silhouette width for distributional clustering of revenue. Values are plotted for $k \leq 10$. The dotted vertical line shows the selection of $k = 4$. $k = 4$ maximises the Calinski-Harabasz index whilst also forming a plausible elbow in the cluster quality plot.

Table 1. Calinski-Harabasz Indices, Quality, and Silhouette Scores for Distributional Clustering, $2 \leq k \leq 10$

| $k$ | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|
| C-H | 5,840 | 6,131 | 6,317 | 6,313 | 6,166 | 5,924 | 5,636 | 5,385 | 5,155 |
| Qual. | 0.67 | 0.81 | 0.87 | 0.90 | 0.91 | 0.93 | 0.93 | 0.94 | 0.94 |
| Sil. | 0.56 | 0.49 | 0.46 | 0.42 | 0.39 | 0.36 | 0.34 | 0.33 | 0.32 |

## 3 STUDY 1: THE DISTRIBUTION OF IN-GAME REVENUE

In Study 1, we investigate the distribution of IAP-driven revenue within mobile games, thereby addressing RQ1 *("What distributions of IAP revenue characterise the mobile gaming market?")*.

### 3.1 Method: Modelling Approach

To determine how to segment the mobile games market in terms of differing distributions of spending, we employed a distributional clustering approach, as described in Reference [41]. Under this approach, each game is treated as a probability distribution, defined in this case by the proportion of revenue associated with each percentile of spenders. Wasserstein distances—a distance metric calculated between probability distributions—are then employed to measure the distance between each pair of games. Informally, one may understand this approach in relation to an imaginary earth-mover: The histogram of each game's spend distribution is treated as set of discrete piles of earth; the Wasserstein distance between two games may be conceptualised as the minimum amount of earth needed to be moved in one game's histogram to transform it into the other game's histogram. Once calculated, these Wasserstein distances form a distance matrix over which partitional clustering algorithms such as $k$-means may be run, with cluster centroids represented by Wasserstein barycenters—the gravitational centre or average of the set of distributions forming a cluster. In this case, to render analysis computationally tractable and conceptually interpretable, all distributions were simplified to the percentile level prior to clustering.

### 3.2 Results

Plots representing Calinski-Harabasz indices, within cluster SSE, and mean silhouette indices, respectively, are presented below as Figure 2; the data underpinning these plots are presented as Table 1. Inspection of these plots suggested a solution at $k = 4$, a value that maximises the Calinski-Harabasz index and also forms a plausible "elbow" in terms of the plot of decreasing SSE.

We named the resulting clusters after the well-known Pareto principle, stating that in many economic systems, 80% of outcomes are generated by 20% of individuals [59]. One of our clusters approximates this principle (see Table 2) and hence has been named Quasi-Pareto; another has

Table 2. Summary of the Spenders, Revenue, and Median Revenue per Paying User Associated with Each Cluster

| Category | Metric | Uniform | Sub-Pareto | Quasi-Pareto | Hyper-Pareto |
|---|---|---|---|---|---|
| Volume of revenue | Total | $108,879,855 (2.3%) | $342,505,419 (7.2%) | $2,305,605,691 (48.7%) | $1,977,206,394 (41.8%) |
| | Median per game | $16,451 | $52,377 | $219,826 | $763,848 |
| | IQR per game | $7,305–$44,291 | $20,515–$179,321 | $72,465–$982,238 | $159,949–$2,745,965 |
| | Range per game | $1,355–$37,068,742 | $2,431–$47,399,828 | $5,826–$150,167,002 | $8,328–$199,399,516 |
| Median revenue per paying user | Median per game | $3.58 | $6.40 | $8.96 | $8.26 |
| | IQR per game | $2.99–$5.54 | $3.99–$9.99 | $5.31–$13.64 | $4.99–$14.98 |
| | Range per game | $0.39–$118.16 | $0.46–$137.56 | $0.99–$998 | $0.15–$100.87 |
| Number of games | Total | 989 (34.4%) | 799 (27.8%) | 747 (26.0%) | 338 (11.8%) |

When totals are given, the main figure represents the sum within each cluster; proportions of the data falling within each cluster are given in braces. Median, IQR, and range per-game values are also given for revenue, spenders, and median revenue per paying user for each cluster to describe within and between-cluster variation. For example, the median Uniform cluster game generated $16,451 in revenue during the period under analysis, whilst the median Hyper-Pareto game generated $763,848.

Table 3. Percent of Revenue Cumulatively Associated with Successive Deciles of Spenders, Split between Clusters

| Percent of Spenders | Uniform | Sub-Pareto | Quasi-Pareto | Hyper-Pareto |
|---|---|---|---|---|
| 10% | 5.70% (94.30%) | 1.49% (98.51%) | 0.58% (99.42%) | 0.30% (99.70%) |
| 20% | 12.14% (87.86%) | 3.55% (96.45%) | 1.40% (98.60%) | 0.73% (99.27%) |
| 30% | 19.15% (80.85%) | 6.19% (93.81%) | 2.52% (97.48%) | 1.29% (98.71%) |
| 40% | 26.67% (73.33%) | 9.55% (90.45%) | 4.04% (95.96%) | 2.06% (97.94%) |
| 50% | 34.76% (65.24%) | 13.91% (86.09%) | 6.14% (93.86%) | 3.17% (96.83%) |
| 60% | 43.49% (56.21%) | 19.55% (80.45%) | 9.11% (90.89%) | 4.81% (95.19%) |
| 70% | 53.13% (46.87%) | 27.00% (73.00%) | 13.53% (86.47%) | 7.45% (92.55%) |
| 80% | 64.05% (35.95%) | 37.37% (62.63%) | 20.73% (79.27%) | 12.10% (87.90%) |
| 90% | 77.14% (22.86%) | 53.65% (46.35%) | 34.56% (65.44%) | 22.09% (77.91%) |
| 99% | 94.96% (5.04%) | 86.46% (13.54%) | 75.25% (24.75%) | 61.14% (38.81%) |

Figures in braces show the residual revenue associated with values at or above that percentile. To show the differential impact of the top 1% of spenders on each cluster, the 99th percentile is also presented. For example, in the Quasi-Pareto cluster, 20.73% of spending is cumulatively associated with the lowest 80% of spenders (and 79.27% of spending is associated with the top 20%); in the Hyper-Pareto cluster, 61.14% of spending is drawn from the lowest 99% of spenders (and 38.81% of spending is drawn from the top 1% alone).

spending distributed in a less unequal way than the Pareto principle suggests and is hence termed Sub-Pareto; a third cluster of games tend to generate the majority of their revenue from a smaller subset of players than suggested by the Pareto principle, so these games are termed Hyper-Pareto. In our final cluster, spending is distributed approximately uniformly across spenders, with each percentile contributing approximately equally toward a game's overall revenue. Thus, we term this cluster Uniform.

The shape of each cluster is depicted below in Figure 3; Table 2 summarises key details regarding each cluster; Table 3 summarises the cumulative distribution of revenue within each cluster.

### 3.3 Cluster Descriptions

**Uniform Cluster:** In the Uniform cluster, spending is distributed approximately equally across players—there is a broadly linear relationship between the cumulative percentiles of spenders and spending (see Figure 2). These games are not reliant on highly engaged, heavy-spending gamers for a substantial proportion of their revenue: The top 1% of spenders in Sub-Pareto games, for example, generate only 5.04% of revenue. This cluster includes 34.4% of the games in our sample ($n$ = 989), the largest cluster by cardinality of games. However, the IAP revenue associated with these games is low: median revenue for a Uniform game is $16,451 per game ($3.58 per paying user), with the IQR indicating that 75% of games within this cluster generated less than $44,291 in revenue during the period under analysis. Whilst this cluster spans more than a quarter of spenders in our sample (approximately 17M, 25.7%), it is responsible for only 2.3% ($108,879,855) of the overall revenue observed here (Figure 2, Tables 2 and 3).

**Sub-Pareto Cluster:** In the games in the Sub-Pareto cluster, spending is distributed more unequally across players than in the Uniform cluster. However, revenue is still less concentrated in upper percentiles than predicted by the Pareto principle: For example, the top 20% of spenders in these games are typically only associated with 62% of revenue. It spans roughly 13m spenders (19.3% of the sample), making it the smallest cluster in terms of the number of paying users. Games within the Sub-Pareto cluster tend to be more profitable than those in the Uniform cluster: median revenue is $52,377 during the period in question per game, $6.40 per paying user. Just over a quarter of games in the sample (799, 27.8%) are members of the Sub-Pareto cluster; as with

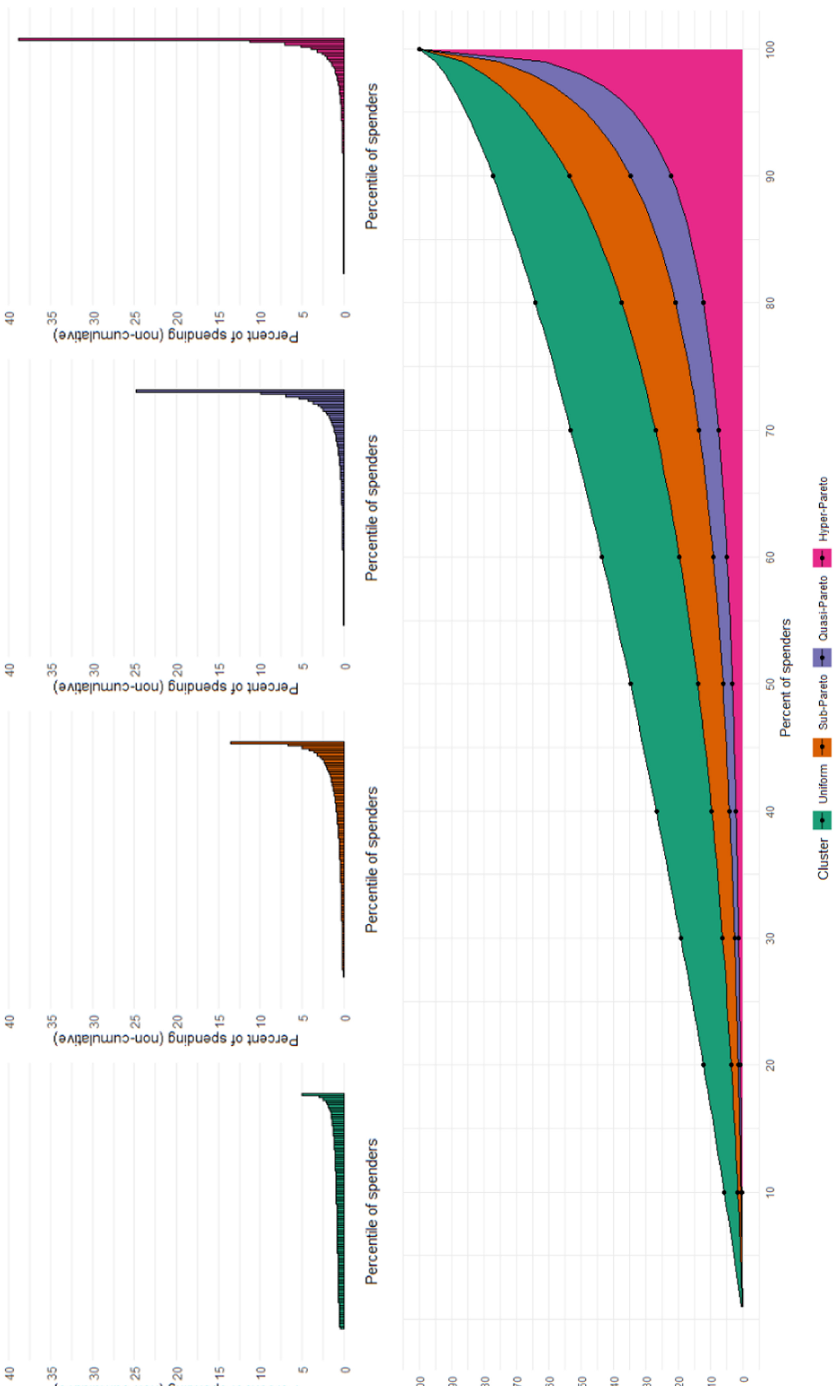


Fig. 3. Percent of spending associated with each percentile of spenders for each cluster, presented in both non-cumulative (top) and cumulative (bottom) forms.

the Uniform cluster, these games are responsible for generating only a fraction of the sample revenue (7.23%, $342,505,419) (Figure 2, Tables 2 and 3).

**Quasi-Pareto Cluster:** This cluster contains 747 games (26.0%) and roughly 24M paying users, making it the most populous cluster in terms of spender base: 35.5% of spenders in our sample were drawn from quasi-Pareto games. It is also the cluster that draws in the most total revenue at around $2.3B (48.7% of the total spending in the data), with a median revenue per user during the 624-day time window of $8.96. This gives a median revenue per game of $219,826. Quasi-Pareto games fit existing grey literature statements about how mobile games are monetised: all percentiles of spenders contribute to overall revenue generation, but higher percentiles are substantially more monetised. They also fit the Pareto principle neatly: 20% of spenders in these games generate an average of 79.27% of spending (Figure 2, Tables 2 and 3).

**Hyper-Pareto Cluster:** In Hyper-Pareto games, the majority of revenue is generated by a small proportion of high-spending gamers. Notably, the top 1% of players in Hyper-Pareto games generate in excess of 38% of revenue. This cluster contains only 338 games (11.8% of the overall sample) and approximately 13.5M paying users (19.6% of the total sample). However, these games generate an outsized proportion of the revenue observed, 41.8%. Hyper-Pareto games also tend to individually be the most profitable: Half of the games generated in excess of $750,000 during the period under analysis; approximately a quarter of them generated more than $2.75M. Furthermore, the revenue range associated with Hyper-Pareto games exceeds that associated with other clusters. The top-grossing game in our dataset, responsible for almost $200M in revenue in and of itself, belongs to the Hyper-Pareto cluster (Figure 2, Tables 2 and 3).

### 3.4 Discussion

Our analysis confirms and quantifies prior speculation in both industry and academic sources [1, 30, 70] that a discrete subset of mobile games do rely almost exclusively on a small proportion of their users to generate the majority of their revenue. In Hyper-Pareto games, the top 10% of spenders are responsible for 78% of overall IAP revenue; the top 1% are responsible for 38% alone. These games have significant reach, with 19.6% of players in our sample ($n$ = 13,525,308) having played Hyper-Pareto games. The concentration of revenue within top percentiles of spenders seen here exceeds that which typifies consumer storefronts, and—whilst not as extreme as the revenue split observed amongst some internet gamblers—is comparable to “hyper-Pareto” patterns seen in gambling [23].

Taken together, this result may seem to support previous theory regarding financial harms amongst heavily involved gamers (e.g., Reference [56]). However, it must be caveated in one crucial way: this analysis gives no direct evidence of the scope of individual financial involvement amongst heavily involved gamers. 1% of spenders may generate the majority of revenue in Hyper-Pareto games, but if each of this top 1% tend to only spend $50–$100, the ability of these games to meaningfully impact financial wellbeing may be limited. This limitation will be addressed in Study 2.

The second contribution of this analysis is to establish the relative size of the aforementioned Hyper-Pareto cluster. Only 11.8% of games in our sample fell into this category: the remaining 88.2% of games were either members of Quasi-Pareto, Sub-Pareto, or Uniform groupings. Thus, assertions that a focus on extracting revenue solely from top percentiles are normative in mobile gaming may be misplaced. Indeed, the most populous group of games found in this analysis were Quasi-Pareto ($n$ = 24M). These games both (a) fall in line with prior theory regarding the natural distribution of spending within storefronts (e.g., Reference [50]), and (b) generate the highest proportion of revenue within the mobile gaming market: 35.5% of spenders and 48.7% of revenue are drawn from Quasi-Pareto games.

Table 4. Overview of Post-hoc Dunn's Tests for Differences in the Distribution of Spending Amongst the Top 1% of Gamers between Clusters

| Cluster | Uniform | Sub-Pareto | Quasi-Pareto | Hyper-Pareto |
|---|---|---|---|---|
| Hyper-Pareto | | | | |
| Quasi-Pareto | 5.67*** | | | |
| Sub-Pareto | 19.33*** | 17.34*** | | |
| Uniform | 37.26*** | 40.75*** | 22.9*** | |

Cells represent the $z$-value associated with the Dunn's test. A positive $z$-value indicates superiority of column over row; a negative value indicates superiority of row over column. Holm's correction for multiple comparisons is used. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Finally, our analysis highlights the existence of further clusters of games in which spending is distributed approximately equally between players: the Uniform and Sub-Pareto clusters. Such a grouping has not been covered previously in the academic literature on mobile game monetisation. However, exposure to these games is high: almost half of the spenders in our sample came from the Sub-Pareto and Uniform clusters. Similarly, approximately a third of games in our sample came from the Uniform cluster alone ($n$ = 989, 34.4%). However, it is important to note that the overall revenue share associated with this engagement is low: Only 9.5% of spending within our sample occurred within Sub-Pareto or Uniform games.

## 4 STUDY 2: INVESTIGATING THE TOP 1%

In Study 1, we investigated the relative distribution of revenue within mobile games. In Study 2, we investigate the absolute distribution of revenue between these games. Again, we take individual games as our basic unit of analysis. To focus on the most heavily involved segment of gamers, we focus our analyses entirely on the top 1% of spenders within each game in our dataset: The top percentile was used here (rather than, e.g., the top 2% or the top 5%) for its conceptual neatness; and for its alignment with previous work from the gambling domain (e.g., Reference [23]). We calculate the amount spent by this group for each game in our dataset, and then investigate how cluster membership, age rating, and genre impact the amount spent by this top percentile.

### 4.1 Method

The core data used in this study are the same as those used in Study 1. To measure the amount that is typically spent by the top 1% in a game, we measured the median value spent by this group for each game in our dataset. To measure the genre of a game, we took the first of its Apple app store genre tags: If no tag was given in the Apple app store, then the game was listed as "Uncategorised" ($n$ = 51).

### 4.2 Results

A Kruskal-Wallis test established that there is a significant difference between revenue distributions (Uniform, Sub-Pareto, Quasi-Pareto, Hyper-Pareto) when it comes to the amount spent by the top 1% of individuals within a game ($p < 0.001$, $\tilde{\chi}^2 = 2295.7$, df = 3). A matrix of post-hoc Dunn's tests associated with this test are reported below as Table 4.

A Kruskal-Wallis test established that there is a significant difference between app-store age ratings when it comes to the amount spent by the top 1% of individuals within a game ($p < 0.001$, $\tilde{\chi}^2 = 207.16$, df = 3). A matrix of post-hoc Dunn's tests associated with this test are reported below as Table 5.

A Kruskal-Wallis test established that there is a significant difference between app-store genres when it comes to the amount spent by the top 1% of individuals within a game ($p < 0.001$, $\tilde{\chi}^2 =$

Table 5. Overview of Post-hoc Dunn's Tests for Differences in the Distribution of Spending Amongst the Top 1% of Gamers between Age Categories

| Age Category | 4+ | 9+ | 12+ | 17+ |
|---|---|---|---|---|
| 4+ | | | | |
| 9+ | $-3.61^{***}$ | | | |
| 12+ | 1.13 | $2.42^{*}$ | | |
| 17+ | $14.15^{***}$ | $9.11^{***}$ | $-12.30^{***}$ | |

Cells represent the $z$-value associated with the Dunn's test. A positive $z$-value indicates superiority of column over row; a negative value indicates superiority of row over column. Holm's correction for multiple comparisons is used. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

355.36, df = 16). A matrix of post-hoc Dunn's tests associated with this test are reported below as Table 7. Table 6 (below) summarises key statistics for each of the subgroups analysed above. Figure 4 presents a graphical overview of differences in distribution between each subgroup under analysis.

### 4.3 Discussion

There are substantial differences in the distribution of spending within all of the factors analysed here. To begin with, this study suggests that the more a game relies on a small fraction of its player-base for the generation of overall revenue, the more each of these individuals tend to end up spending: The top 1% of spenders in a typical Uniform game spend, on average, \$19 throughout their lifetimes. In Sub-Pareto, this rises to \$138; in Quasi-Pareto, \$660; and in Hyper-Pareto, a typical game will have its top 1% spend, on average, over \$1,700 (all $p$ values < 0.001).

The observation that games that encourage their top percentiles to spend the largest amounts of money also tend to make the highest proportion of their revenue from those percentiles is logical: After all, if a game can convince 1 in 100 individuals to hand over a four- or five-figure sum each, then it is plausible that this may constitute a major source of income. However, the reason for how these patterns of spending come about is unclear. It may be the case that Sub-Pareto and Uniform games offer a smaller range of in-app products for purchase; do not allow the purchase of duplicate goods; or in some other way restrict the statistical maximum that even their most extreme spenders may invest in-game. A game that offers nine skins priced at \$5 each can never make more than \$45 per customer, regardless of whether they are at the 99th percentile or not. Conversely, Hyper-Pareto games may implement sophisticated duplicate handling mechanisms, limited time offers, and product decay mechanisms—all of which may theoretically increase investment amongst top-spending individuals. The results of this study are incapable of determining which of these situations is the case—substantial future qualitative research, and granular case studies of individual games, are required to unpick this relationship.

However, one potential mechanism that may lead to this disparity is suggested by the differences in spending that occur across genres. A typical casino game obtains significantly more money from its top 1% than a typical game of almost any other genre: \$2,381 (all $p$'s < 0.001 except for the comparison with Card games; see Table 7). Academics have long discussed the idea that the gambling-like nature of monetised randomised rewards such as loot boxes may lead to heavy levels of spending on these products in-game (e.g., References [76, 77, 79, 82]): it is possible that such an effect may explain both the distribution of revenue in casino games and in Hyper-Pareto games.

Leading on from this point, this study shows significant differences between levels of spending amongst the top 1% across different genres of game. In line with prior literature, the top 1% of

Table 6. Descriptive Overview of Differences in Distribution between Groups, Calculated over the Top 1% of Spenders within Each Game

| Subgroup | Median | IQR | Range | n (games) |
|---|---|---|---|---|
| All | $143 | $30–$590 | $1–$66,285 | 2873 |
| | | | | |
| Uniform | $19 | $11–$32 | $1–$526 | 989 |
| Sub-Pareto | $138 | $81–$240 | $13–$7,534 | 799 |
| Quasi-Pareto | $660 | $346–$1292 | $52–$66,285 | 747 |
| Hyper-Pareto | $1,711 | $773–$3,586 | $130–$45,308 | 338 |
| | | | | |
| 4+ | $107 | $24–$471 | $1–$66,187 | 1503 |
| 9+ | $167 | $46–$490 | $4–$38,158 | 386 |
| 2+ | $116 | $24–$475 | $2–$66,285 | 704 |
| 17+ | $798 | $207–$2,558 | $4–$16,679 | 280 |
| | | | | |
| Action | $132 | $36–$385 | $3–$44,560 | 263 |
| Adventure | $126 | $28–$492 | $4–$10,540 | 211 |
| Board | $225 | $38–$827 | $5–$10,237 | 123 |
| Card | $946 | $221–$2920 | $2–$12,236 | 109 |
| Casino | $2,381 | $954–$4,358 | $49–$16,679 | 60 |
| Casual | $86 | $22–$342 | $2–$3,967 | 349 |
| Family | $31 | $13–$116 | $2–$5,147 | 203 |
| Music | $87 | $47–$305 | $8–$6,566 | 30 |
| Puzzle | $102 | $15–$854 | $2–$66,187 | 319 |
| Racing | $107 | $35–$234 | $1–$1,827 | 103 |
| Role-Playing | $298 | $75–$1,128 | $4–$40,981 | 191 |
| Simulation | $149 | $43–$404 | $1–$66,285 | 441 |
| Sports | $106 | $21–$376 | $4 –$12,361 | 139 |
| Strategy | $275 | $119–$1,038 | $3–$45,308 | 179 |
| Trivia | $67 | $31–$296 | $4–$2,074 | 43 |
| Uncategorised | $21 | $16–$99 | $4–$6,088 | 51 |
| Word | $442 | $130–$734 | $6–$3,812 | 59 |

Median, IQR, and range are presented for the dataset, split by both cluster, age category (i.e., Apple store age rating), and the genre that a game is listed as within the Apple app store. IQR (inter-quartile range) represents the range of values in which 50% of data lie. For legibility, values are rounded to the nearest whole dollar. These statistics are reported on a game-by-game basis and should be interpreted as such: For example, the median value for the "Casino" cluster indicates that a typical casino game within our dataset will charge each of its top 1% a median of $2,381.13; the IQR for this indicates that 25% of Casino games charge their top 1% $4,358.38 or more; the range indicates that one casino game in our dataset charges its top 1% an average of $16,678.80 each.

spenders in typical casino and card games tend to spend more than in most other genres ($2,381 and $946, respectively). However, strategy and role-playing genres also are typified by high levels of spending amongst a top 1: Indeed, at least one game in each of these genres has its top 1% spend in excess of $40,000 each. The reasons for this, again, are unclear: However, both genres may archetypally be associated with the development of resources or levels over time—it may be the case that the opportunity for protracted "levelling" that such genres naturally afford also leads to differentiation in spending patterns. Similarly, games from these genres (e.g., *Genshin Impact*,

Table 7. Overview of Post-hoc Dunn's Tests for Differences between App-store Genres in the Distribution of Spending amongst the Top 1% of Gamers

| | Act. | Adv. | Boa. | Car. | Casi. | Casu. | Fam. | Mus. | Puz. | Rac. | Rol. | Sim. | Spo. | Str. | Triv. | Unc. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Adv. | 0.36 | | | | | | | | | | | | | | | |
| Boa. | −1.57 | −1.8 | | | | | | | | | | | | | | |
| Car. | −7.23*** | −7.26*** | −4.96*** | | | | | | | | | | | | | |
| Casi. | −9.16*** | −9.18*** | −7.23*** | −3.03 | | | | | | | | | | | | |
| Casu. | 2.18 | 1.66 | 3.32* | 9.13*** | 10.65*** | | | | | | | | | | | |
| Fam. | 5.69*** | 5.07*** | 6.15*** | 11.41*** | 12.54*** | 4.00** | | | | | | | | | | |
| Mus. | 0.51 | 0.34 | 1.32 | 4.47 | 6.30*** | −0.42 | −2.22 | | | | | | | | | |
| Puz. | 0.85 | 0.42 | 2.28 | 8.06*** | 9.82*** | −1.38 | −5.13*** | −0.14 | | | | | | | | |
| Rac. | 1.73 | 1.39 | 2.79 | 7.46*** | 9.31*** | 0.21 | −2.73 | 0.49 | 1.15 | | | | | | | |
| Rol. | −4.01** | −4.14** | −1.82 | 3.69** | 6.28*** | −6.21*** | −9.06*** | −2.44 | −4.93*** | −4.76*** | | | | | | |
| Sim. | −0.54 | −0.89 | 1.26 | 7.30*** | 9.22*** | −3.07 | −6.77*** | −0.75 | −1.53 | 2.22 | 3.91*** | | | | | |
| Spo. | 0.66 | 0.34 | 1.94 | 6.98*** | 8.94*** | −1.08 | −4.19** | −0.14 | −0.01 | −1.01 | 4.04** | 1.15 | | | | |
| Str. | −4.82*** | −4.92*** | −2.53 | 2.93 | 5.65*** | −7.02*** | −9.74*** | −2.87 | −5.76*** | −5.40*** | −0.83 | −4.79*** | −4.74*** | | | |
| Triv. | 1.52 | 1.3 | 2.38 | 5.96*** | 7.81*** | 0.44 | −1.68 | 0.64 | 1.1 | 0.26 | 3.73** | 1.82 | 1.03 | 4.22** | | |
| Unc. | 4.17** | 3.88 | 4.86 | 8.62*** | 10.23*** | 3.07 | 0.68 | 2.35 | 3.76** | 2.55 | 6.46*** | 4.60*** | 3.47* | 6.96*** | 1.88 | |
| Wor. | −3.25* | −3.40* | −1.88 | 2.2 | 4.59*** | −4.59*** | −6.76*** | −2.53 | −3.81** | −4.10** | −0.58 | −3.07 | −3.46* | −0.01 | −3.58* | −5.79*** |

Cells represent the $z$-value associated with the Dunn's test. Holm's correction for multiple comparisons is used. A positive $z$-value indicates superiority of column over row; a negative value indicates superiority of row over column. ACT. = Action, ADV. = Adventure, BOA. = Board, CAR. = Card, CASI. = Casino, CASU. = Casual, FAM. = Family, MUS. = Music, PUZ. = Puzzle, RAC. = Racing, ROL. = Role-Playing, SIM. = Simulation, SPO. = Sports, STR. = Strategy, TRIV. = Trivia, UNC. = Uncategorised. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

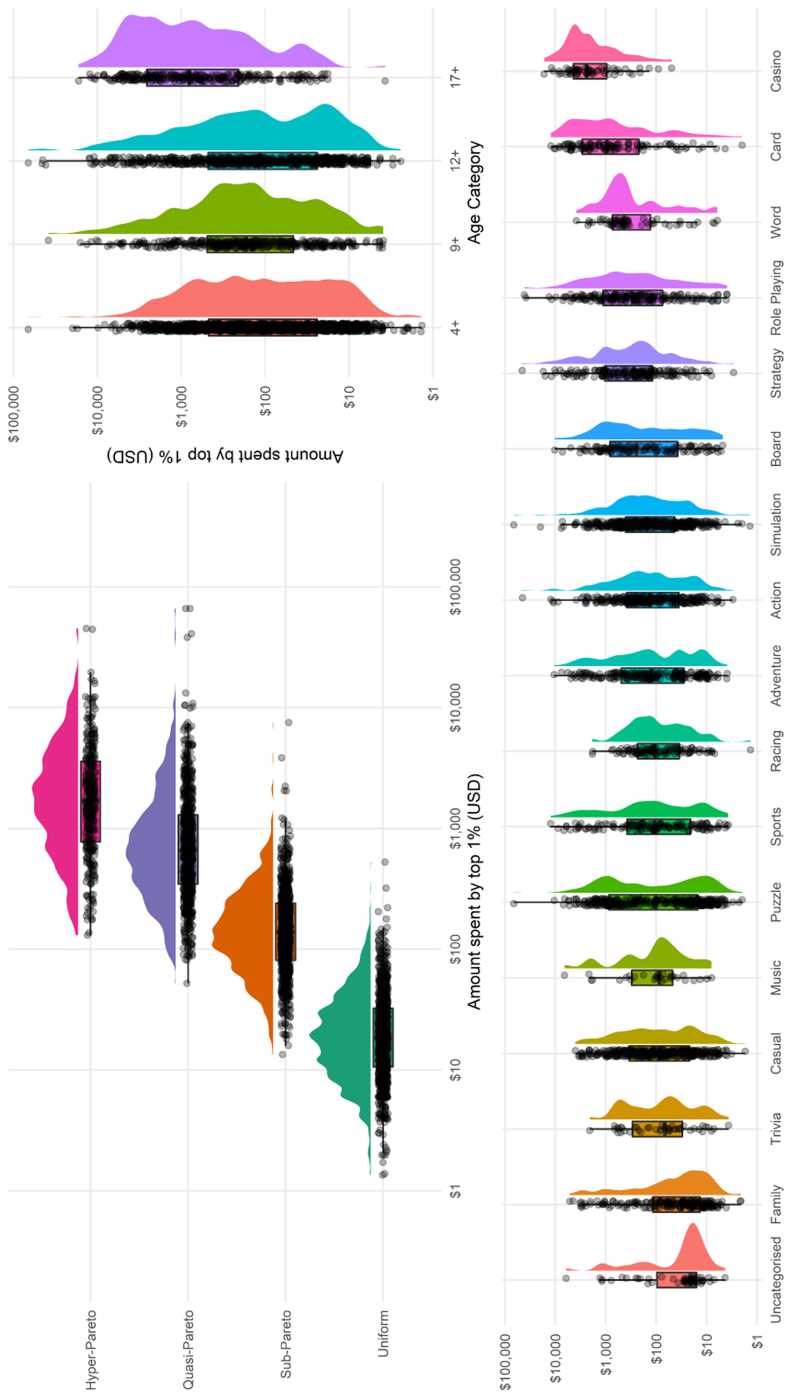


Fig. 4. Raincloud plots showing the distribution of spending amongst the top 1% of spenders within all 2,873 games, split by cluster, age category, and genre. A logarithmic transformation is applied to the $y$-axis to allow the visualisation of the complete distribution of spending. Each datapoint represents a single game.

*Guns of Glory*) are known to feature randomised gacha mechanics and loot boxes: It may be the case that differentiation in monetisation strategy is responsible for these divergences. Conversely, it may be the case that these genres attract a different demographic of spender: both strategy and role-playing gaming has been associated with comparatively heavy levels of in-game engagement, and this difference in audience may explain differences in financial involvement [57].

Our results also highlight a lack of clear connection between the age rating of a game and the amount of money spent by that game's top 1%. Indeed, games rated as suitable for those aged 9+ actually tend to have higher spending amongst their top 1% ($167) than those rated suitable for individuals aged 12+ ($116). It is important to note that games rated suitable for those aged 17+ may provide an exception to this: The top 1% in a typical 17+ game spend $798. However, this may be an indirect effect of Apple's policy that games featuring simulated gambling are rated as suitable for those aged 17+.

A final outcome of this study is to do with the distribution of spending within all groups in our study. Within-group variability in terms of spending amongst the top 1% is high. Within the puzzle genre, for example, games range from those in which the top 1% spend $1.98 to a game in which 1 in 100 spenders expend, on average, in excess of $66,000 throughout their lifetimes. Indeed, games in which the top 1% of spenders invest large amounts of money can be found in all genres, clusters, and age rating categories. These range from an unusually monetised family game in which 1% of spenders tend to invest more than $5,000 each, to a Sub-Pareto game in which the top 1% spend over $7,000 throughout their lifetimes: more than 50 times the median for this group. The sole exception to this is the Uniform cluster, in which even the most extreme game in our dataset has its top 1% spend only $526. All distributions analysed in this study appear fundamentally non-normal and highly skewed (see Figure 4). The reasons for this skewness and within-group diversity are unclear: unpicking why should be a priority for future research.

## 5 LIMITATIONS

There are three major limitations to the research conducted in these studies: The first is noted above, and concerns the data that we were able to analyse regarding each of the individuals in this study. *Unity Technologies* pre-anonymises their data at the point of collection. This means that the collection of demographic, diagnostic, psychometric or economic data about each of the 69 million spenders in our sample is infeasible. Thus, whilst we are able to observe significant volumes of spending (~$4.7B in total), we are unable to directly estimate the impact of all this spending on the people whose data we are analysing. Future work must overcome this limitation—for example, by engaging in processes of data fusion in which large-scale transaction histories are merged with self-report or other data about the wellbeing of the player whose spending is under analysis. Such work is beyond the scope of the research presented here, but forms a flagship area for future work into games and wellbeing.

A second limitation of the work conducted here is its inability to model how specific in-game mechanisms, user groups, and game design decisions determine specific spending outcomes; it is unable to take into account cultural nor development contexts of the game production. As noted during the discussion of Study 2, a great degree of within-group heterogeneity was observed when studying the amount spent by the top 1% of gamers within various clusters and genres. What is established here, for the first time, is the *how*—how much players spend in mobile games. This provides vital information guiding future work addressing the why. Investigating specifically why the top 1% spend tens of thousands of dollars in one strategy game but only $119 in another is beyond the scope of this article, but a vital follow-up question for understanding why people spend money in games and what the consequences of this spending is for them. An approach that investigates deeper the aforementioned contexts of the production of various games is also needed:

freemium games are entrenched in the cultures, platforms, politics, and contexts in which they are produced, and this may affect how and why they generate revenue.

The final limitation of this work concerns its generalisability. The sample used for this research is extraordinarily diverse: Previous research using game telemetry has been limited to the utilisation of data from a few specific games at most, or shallow telemetry from one platform (e.g., Reference [65]). Here, we analyse over 2,800 products and 69 million spenders simultaneously. This represents a step change in the volume and diversity of data analysed in a study of how individuals spend money in games.

However, it is still unable to represent the entire market: To begin with, the games analysed here are all made using the Unity engine and implement Unity's IAP engine. While *Unity Technologies* estimate that their engine is the most commonly used for mobile games [61] it is unclear whether this accurately represents a random subsection of the entire global mobile games market. Perhaps more importantly, the games analysed here are drawn entirely from iOS, and as such do not include data from the Android platform. One may take the view that Apple and Android stores share the vast majority of their games and have similar levels of revenue. However, this is an assumption: As outlined in Section 2.1 above, similarities and differences in revenue generation between iOS and Android stores are not well-understood, nor are they evidenced by transparent data sources and analyses. Furthermore, the data under test here were all collected during a specific time period: 2020–2022. Industry reports have suggested that spending in games has seen significant upturns during this period [12]. Indeed, academic research has shown that the implementation of specific containment and closure policies during this period had potentially meaningful consequences for the number of people playing video games [80]. The ability of the results obtained here to fully generalise beyond these years is thus somewhat unclear, and must be the subject of further research. Finally, we believe it is infeasible to uncritically assume that the patterns observed here generalise beyond the mobile domain to either desktop or console platforms. Ideally, if possible, future work should integrate data on the volume and distribution of spending across different engines and distribution platforms.

## 6 GENERAL DISCUSSION AND CONCLUSIONS

In recent years, a variety of sources have documented situations in which gamers have spent hundreds, thousands, or tens of thousands of dollars in-game [6, 36, 39, 58]. However, it has been unclear until now how common this kind of monetary investment in video games is: Is it an unintended, unwanted, and unexpected side-effect of the transformation of games into more persistent sales platforms through microtransactions and other strategies, or a core aspect of the way that some games make their revenue?

### 6.1 There Are Systemic Patterns in Monetization Across Mobile Games

The studies contained within this manuscript suggest that high levels of financial involvement have become a key source of revenue for a subset of mobile games, across multiple genres but also that there is substantial variance in the IAP spend profiles across mobile games. Some games make the vast majority of their revenue from the top 1% of their spenders, who tend to invest large amounts in-game throughout their lifetimes. High-spending individuals are not outliers—they are systemically involved in the generation of revenue crucial to specific stakeholders within the mobile gaming industry.

The existence of Hyper-Pareto games provides the first evidence for this. A well-known economic principle—known as the Pareto principle—suggests that in many economic systems, 20% of individuals generate 80% of outcomes [59]. Distributional clustering in Study 1 suggests that the majority of mobile games operate according to this principle, or generate their revenue in an even more equitable manner than the Pareto principle suggests: in Quasi-Pareto games, 20% of spenders generate 79.27% of spending; in Sub-Pareto games, spending is distributed more equitably than even this; in Uniform games, spending is distributed almost equally across percentiles. However, a distinct minority subset of games exist that generate their revenue in a fundamentally different manner: Hyper-Pareto games. In these games, revenue generation is almost exclusively the province of top percentiles: the top 1% of spenders in Hyper-Pareto games tend to generate approximately more than 38% of total revenue. Such an extreme distribution of revenue in a distinct subset of games (11.8% of our sample, $n = 338$ games) has not been previously suggested in the academic literature.

What might the causes and consequences be of such skewed revenue generation strategies? An interesting comparison may be made via the field of gambling studies, in which similar distributions of revenue are commonly seen. Within the field of gambling, such distributions are often conceptualised as a product of disordered spending. Could a similar pattern of disordered engagement be occurring here, within Hyper-Pareto games? The extent to which in-game spending is harmoniously aligned with an individual's overall life, or the extent to which in-game spending provokes disorder in that individual's life is beyond the scope of this research: however, these results highlight that these topics must be a key priority for future work in games research.

### 6.2 High Spending Exists in a Subset of Mobile Games

Concerns regarding overspending or financial harms in video games are further sharpened by the outputs of Study 2, which show that Hyper-Pareto games are typified by systematically extracting meaningful amounts of money from the top 1% of spenders on which a substantial portion of their revenue relies. Contrary to speculation by some academic literature that IAP spending may potentially be mild, the top 1% of spenders in these games systematically expend four-figure sums during the period under study: In the average Hyper-Pareto game, the top 1% of spenders spent a median of \$1,711. In many games, the top 1% of individuals systematically spent tens of thousands of dollars in-game. What does this mean for potential financial harms associated with gaming? Again, providing a definitive answer is beyond the scope of this article, and there is a deep complexity associated with finding answers, not the least given variance in game design. Industry perspectives suggest that the heaviest spending gamers tend to be wealthy, and thus can afford their substantial levels of in-game purchasing [46]. However, what little previous academic research that exists on the topic has found no correlation between an individual's income and their in-game spending, suggesting that the heaviest spending gamers may not necessarily be the most financially secure [18]. Thus, whilst none of the data in this study can directly show whether any specific group of gamers can afford the \$2,000, \$10,000, or—indeed—\$2M that they have spent in-game on a specific title, it is possible that at least some of these transactions may lead to poor financial health. This point has two corollaries:

- *Concentration of financial harm:* Since the top 1% are responsible for such a large proportion of all of the revenue in Hyper-Pareto games (and to a lesser extent in other categories of mobile games), any financial harm is plausibly concentrated most strongly in this minority of games.
- *Noise in datasets:* The disparity in engagement within Hyper-Pareto games suggest that large, population-level studies of financial and wellbeing impacts may fail to find real effects even when they exist: After all, if 99% of a game's players engage much less heavily than a top percentile, then a real effect occurring within this subgroup will be diluted by noise originating from the majority of players.

Further work must focus on unpicking who these heavy spenders are and how their financial involvement in games affects their overall lives. This concern is sharpened by the extremes that were observed within this study: for example, the highest-spending individual in our sample spent \$2,233,935. The ability for such very highly involved individuals to transfer such a large amount of money to the makers of a game (more than \$3,000 per day under analysis) suggests both the potential for significant harm (but, importantly, not direct evidence of harm), and the need for greater appreciation of games as a site (or market) involving meaningful financial exchange.

### 6.3 Massive-scale Population Data Analysis Prevents False Negatives Regarding Extreme Subgroups

A related contribution of the work relates to its usage of the true distribution of spenders. This is due to its utilisation of large-scale secondary data. Significant prior work has dealt with understanding the importance of variables such as playtime and in-game spending using primary data collection that involves convenience sampling [31, 79]. Even when used in tandem with access to limited industry data as in Reference [42], such data will naturally afford only a biased and distorted view of the true distribution of these variables: Studies that rely on convenience sampling to study playtime may naturally undersample or oversample very heavily involved players, for example, as these individuals may be too busy with playtime to involve themselves in a study. Such studies will not be able to correct for this bias, and may not even be able to detect it given a prior lack of knowledge regarding the overall distribution of these variables. This is not an issue when large-scale secondary data are directly used by independent researchers. Furthermore, even if such a study were to use a representative sampling strategy to avoid any possible distortion to the individuals taking part in a study, it would still likely be inadequate for modelling phenomena that take place at the tail end of distributions. Even if a perfectly representative sample was obtained, in a study with a large sample size of $n = 10{,}000$, for example, only 100 individuals would be drawn from a top percentile of spenders or players. This highlights the importance of the approach taken here: In our sample of size $n = 69{,}144{,}363$, we have more than 69,000 individuals drawn from the top 1%. This allows us to model phenomena that would otherwise be missed. A good example of this may be observed through reference to Table 2. In Table 2, we report the median revenue per paying user for each of our cluster. There is little difference in this statistic between Uniform and Hyper-Pareto games. The average spender in a Uniform game paid \$4 over the period in question; the average spender in a Hyper-Pareto game paid approximately twice this amount during the same period (\$8). However, when one compares these values with similar statistics calculated over the top 1% of spenders, clear differences between groups emerge: The average Uniform game has its top 1% spend an average of \$19; by contrast, the average Hyper-Pareto game has its top 1% spend \$1,711—almost one hundred times more. This highlights the largely unique ability of datasets such as this one to model phenomena that may only occur toward the extreme ends of distributions, and suggests that research into the social impact of gaming may need to utilise similarly large data in future to avoid systemic “false negatives” regarding potential impacts of gaming.

It is crucial to note that such knowledge cannot be gleaned from “grey literature” reports associated with industry think tanks, consultancies, and aggregators given the opacity of both their datasets and analysis procedures. Whilst we may be unable to share the commercially sensitive raw data under test here, we can nonetheless transparently report what kind of data were used, how they were obtained by the industry, and how they were analysed.

### 6.4 IAP Spending in Mobile Games Is Highly Varied, Both between Games and between Gamers

An additional contribution of this work relates to within and between-group heterogeneity. To the best of our knowledge, no previous study has had the ability to simultaneously model spending behaviour across thousands of games (or even a few, given the previous paucity of available data on in-game spending). The sample size of 2,873 games analysed here means that this study affords a unique lens into how patterns of spending differ between games. The scope of this analysis is substantially closer to the level of the global market than any prior work thanks to the number of game creators using Unity Technologies game engine. We find that there are large and important differences in spending between the games within our sample. For example, one casino game in our dataset had its top 1% spend an average of $16,679; another had them spend $49 (see Table 6). The lowest-spending gamer in our dataset spent less than a cent in-game; the highest, more than $2M. This degree of heterogeneity suggests that the impacts of gaming—and the financial impacts of gaming—are likely to not be consistent across different products. Factors such as design quality, marketing budgets, cultural differences and similar issues mean that games may not be directly comparable within genres or categories. Further work that addresses the wellbeing impacts of games (either positive or negative) must take this heterogeneity into account in terms of both their designs, and the discussion of the generalisability of their results. The results of a study that investigates wellbeing impacts in a Sub-Pareto or Uniform simulation game where the top 1% invest $2 are unlikely to generalise to players of a Hyper-Pareto puzzle game where the top 1% tend to spend over $60,000 each.

### 6.5 Laying the Foundation for a Data-driven Literature on Monetisation

A summative contribution of the work presented here is its ability to provide a public benchmark of the diversity and extremity of spending in video games. This provides impetus for future research on the potential impact of this factor on gaming audiences—which are substantial and global, as evidenced by the almost 70M players involved in just the work presented here.

Prior work in this space has always been forced to rely on estimates or inferences of revenue from analytics companies and other producers of grey literature. The basis for such projections and specific details about how the market size is inferred within them is not disclosed by such companies. Neither do such estimates typically provide details about inclusion criteria for products: for example, a definition of what a game is, and the boundary between "gamified applications" and "games."

Furthermore, such projections and estimates vary across companies operating in the space. Due to data confidentiality and reasonable constraints associated with doing business, the estimating procedures underpinning these analytics bureaus are opaque, and it is challenging to evaluate the quality of such estimates. Whilst, in the future, it is possible that collaboration with academic researchers using independent clearing houses as intermediaries could establish quality evaluations, such work is not yet underway.

Thus the work presented here represents a step-change in trustworthy marketplace analysis, and provides the first detailed breakdown of individual–level spending in mobile games across a substantial section of the mobile games market. Previous work across academia and industry has not had the kind of data to back up conclusions as is utilised here. The debate about video game monetization has thus gained much-needed foundational evidence to guide future research, and there is now analysis available to benchmark future developments within the industry against.

## CONFLICTS OF INTEREST STATEMENT

Data for this study were provided by Unity Technologies. Unity Technologies played no role in the design of the study, its reporting, or its execution. No funds were disbursed to the research team for the work incorporated into this manuscript. This includes data access fees for the serverless data warehouse from which the data under analysis were accessed, which were paid by the lead author out of a research stipend he receives from his host institution. Access to the data used in this study were contingent on a data sharing agreement between unity technologies and DZ's host

university. Legal approval was sought from Unity for the sharing of the data in this paper prior to its submission for peer review.

DZ has never received any form of funding from the games industry. He has worked as a paid consultant for governments and charities seeking to understand the effects of video gaming. He has worked as an expert witness in cases relating to the video game industry, but has never represented the games industry legally or been formally affiliated with any games industry body in any way. DZ has been involved in brokering data sharing agreements with industry stakeholders in the past. He acknowledges that such data sharing agreements constitute a conflict of interest as important as financial awards, and wishes to highlight that he has used such data brokerage in ways that are likely to give him indirect financial advantage: He has used them as evidence for excellence in promotion applications; he has used them as evidence in grant applications. No such applications have been funded at the time of writing this manuscript. He has no further conflicts to declare.

AD, CF are associate editors of ACM Games: Research and Practice. SD is co-editor-in-chief.

CF has received funding from the Tides Foundation on the recommendation of the Unity Charitable Fund [grant number TF2201-105180] for a separate project. They have no other conflicts to declare.

AD has previously worked in a paid capacity within the video games industry as a game analytics consultant. He has worked on multiple industry-focused projects with a focus on knowledge transfer. He has received funding from the Tides Foundation on the recommendation of the Unity Charitable Fund [grant number TF2201-105180] for a separate project.

SD has worked as a paid design consultant for game studios and startups, though never for Unity Technologies. He is currently working part-time as an Amazon Scholar, but not on games. He has no other conflicts to declare.

All other authors have no conflicts to declare.

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