Multimedia Tools and Applications (2023) 82:25403–25425
https://doi.org/10.1007/s11042-023-14366-5

Proxies to the monthly active user number of Geo AR Mobile games – online search volume as a proposal

Hugh Xuechen Liu [1] · Christian Wagner [1]

Received: 24 May 2022 / Revised: 19 November 2022 / Accepted: 2 January 2023 /
Published online: 13 January 2023

Abstract
Mobile game metrics have received attention since the emergence of big data technology and data-based decision-making. Among different metrics, the monthly active user number is usually significant because it shows the level of players' engagement and the profit of this game as a business. Therefore, the monthly active user number is valuable for researchers, analysts, and decision-makers interested in the mobile game industry. However, the actual monthly active user number data typically have the accuracy, accessibility, granularity, and cost problems. Therefore, a proxy to the monthly active user number would be helpful to facilitate the decision-making process. This paper proposes to capture user activity through the searches on the Internet from an information-seeking perspective. And the online search volume, wiki page view, social media posts and views are proposed as potential proxies. This paper proposes that the online search volume is an acceptable proxy for the monthly active user number in the context of Geo Augmented Reality (AR) mobile games through data analysis.

Keywords Game metrics · Geo AR mobile games · Online search volume · Proxy · Google trends · Correlation

1 Introduction

Metrics of mobile games, namely the particular bits of data that the client reports back to the server, have gradually become crucial since they convey information about the players' behavior and the game's performance. Multiple metrics have been proposed in the current era of data-driven decision-making and are commonly used in practice. These metrics are

✉ Hugh Xuechen Liu
hugh.liu@my.cityu.edu.hk

Christian Wagner
c.wagner@cityu.edu.hk

[1] School of Creative Media, City University of Hong Kong, Hong Kong, SAR, China

typically interpreted by academic researchers, business analysts or game designers and used to guide the game design or profit strategy [34]. For other decision-makers in the mobile game industry, the metrics are also crucial for them to grasp the current situation of the games and possibly, participate in the value co-create process [3, 17, 24]. The monthly active user number (MAU) usually receives more attention among varied metrics. It grasps the level of players' engagement with the game and plays a vital role in reflecting the level of profits of this game [16, 64].

Typical channels to get the data include game developers, business intelligence companies, direct sampling and direct observation. However, each channel has some advantages and disadvantages. Game developers, who usually have the accurate number of their games' MAU, see these data as their business secrets and are unwilling to share them with others. If they are willing to share it with others, they may only share static and aggregated data. The data granularity is therefore given and rigid. They may also charge a lot for the data. Business intelligence companies routinely publish industrial reports that possibly include interest data. But similarly, these data are static and aggregated. The customized service is supported but may cost much money. The MAU data may be collected through direct sampling, especially on crowdsourcing platforms. There the data of favorable granularity may be attained at a reasonable price. But the data would depend heavily on the sampling method and the demographic structure of the samples. Lastly, the MAU data can be estimated through direct observations in the game. But that would cost a lot of time and money.

All these typical channels of MAU data have drawbacks and somehow hinder the usage of the MAU data in decision-making. Therefore, this paper would like to propose a proxy for the game's MAU. This proxy should be accessible to the decision-makers, provide flexible data granularly, cost little and convey the core messages in the MAU data. From the information-seeking perspective, this paper proposes that the user activity in a game can be captured by the information-seeking around the game on the Internet, especially the queries and searches on the Internet. Four potential proxies are proposed: online search volume, wiki views, and social media posts and views counts. This paper tests the validity of these four proxies in the context of Geo AR mobile games through a correlation analysis using the data of two games.

The following sections are organized in this way. Section 2 provides the background information of the MAU as a mobile game metric and Geo AR mobile games. Then, from the perspective of information seeking, the proxies and their hypothesis are proposed. Section 3 demonstrates the methods of data collection and analysis. Section 4 shows the results, especially the correlation coefficient between the actual MAU and the proxies. Section 5 reports the discussions based on the results. Finally, Section 6 includes the conclusion of this paper.

2 Background

2.1 Monthly active user number as a metric of Mobile games

With the development of online gaming and big data technologies in the mobile game industry, game devices can send information across a network. Metrics, namely particular bits of data that client software reports back to the server, indicate game players' dynamic behavior with the game. It's understandable why it has become more critical for game companies since the evolving players' tastes demand the variety and quality of marketplace offerings to expand.

To meet players' expectations and survive in the market competitions, the game developers have their business intelligence unit interpret the metrics collected, modify their game or adjust the business strategy accordingly, issue patches or updates to the game, and see players' responses. This current situation has forced game developers to stop thinking of their games as ever truly finished. Therefore, it becomes more and more important to continuously monitor players' engagement and the business performance of a mobile game. These data would be necessary for the data-driven decision-making process related to the game design and marketing strategy [56, 62].

So far, diverse metrics have been proposed to capture game players' dynamic behaviors with the game. Generally, these metrics directly measure the player population, monetization and online advertising. Table 1 below lists player population metrics frequently used in mobile game analysis and their definitions [16, 19, 34]. These metrics stand out because they can be used in almost all games. Even if a game has not been monetized yet, many users can be plausible. A large user base is a foundation for monetization and online advertisement in the future. Among the three metrics of the player population, the monthly active user numbers (MAU) are the most frequently used metric. On the one hand, it captured the whole level of players' engagement rather than the peaks and a month is also relatively more extended and more stable than a day. That means MAU captures the players' engagement more reliably and comprehensively. On the other hand, MAU can estimate other metrics such as revenues of a game. Whether one mobile adopts a freemium or premium business model, knowing the situation of the player's population is always helpful for the decision-making around the game. That means MAU lies in the center of the mobile game metrics. Therefore, the data of MAU is crucial for data-driven mobile game decision-makers.

As common practices, there are three typical approaches to getting the MAU data of a game and the data provided by each way has each's characteristics. Table 2 below summarizes the three typical approaches to collecting the MAU data of a game and the characteristics of the data.

The first way is to ask the game developers to provide data. In the mobile game software engineering process, *instrumentation* means game developers put functions into a piece of software to collect and report back metrics to their business intelligence department. It is technically possible and will be implemented as long as the game developers realize the importance of the metrics. A game company may arbitrarily determine the criteria of an "active player." For example, the company may treat a game account, a device, or a play session as a

Table 1 Player population metrics of mobile games

Name	Abbreviation	A Brief Explanation
Daily Active User Numbers	DAU	• DAU is the number of *active users* in a day. • Most social networks consider users active when they view or engage with the application or its content. But there is usually no minimum play time or further interaction required to qualify as a "daily user."
Monthly Active User Numbers	MAU	• MAU is the number of active users in a month. • It is the aggregation of the DAU over a month. • *MAUU* (Monthly Average Unique User Numbers) is an alternative if unique users are interested.
Peak Concurrent User Numbers	PCU	• PCU is the maximum number of active users at the same moment (i.e., "concurrent user"). • This metric is useful for games with a vital backend server component.

Table 2 Three approaches to obtain MAU data

Approaches	Examples	Accuracy	Accessibility	Granularity	Cost
Enquire game developers	Open access reviews and financial reports	Possibly the most accurate	Usually inaccessible because they are seen as business secrets; Determined by the developers	Can be the highest with little aggregation; Usually quarterly data; determined by the developers	From free to expensive, determined by the developers
Directly Collect	Direct sampling on game forums (e.g., *Reddit*) or crowdsourcing platforms (e.g., *MTurk*)	Mediate accuracy; may have representativeness problem	Open access	Can be the highest with little aggregation; determined by the investigator	May cost money and time
	Direct observation	Low accuracy	Open access	Can be the highest with little aggregation	Cost little money, but a lot of time
Consult business intelligence companies	Open access report	High accuracy	Open access	Can be low or high; Usually annual data; determined by the companies	Free
	Customized services	High accuracy	For paid customers	Can be low or high; determined by the customer and the company	May cost money and time

player. A player may be seen active if the game account is logged in or a play session was started. Drachen, et al. [16] correctly criticized that MAU has been controversial because of the unclear criteria to qualify a user as a "monthly user." The specific behavioral definition of "engagement" is also worried. Nevertheless, the game developers have a definition in their mind and use the resulted MAU as a metric.

The MAU data collected by the game developers through instrumentation is usually the most accurate. The data granularity is typically high, which means one can know the exact MAU of each month. However, the MAU data from game developers is usually inaccessible because it's seen as a business secret. For example, in a Q&A session of the game *Ingress*, the development team directly refused the inquiry of the game's MAU [31]. Even if developers are willing to share the data, they won't give the data with the highest granularity but aggregated ones, like the MAU of a quarter or a year. Requests to access the MAU data from game developers may demand long-time negotiations. The data may be given free or charged high. Therefore, the costs of the MAU data from game developers can vary greatly and are determined by the game developers. In the previous studies, Ljepava, et al. [45] used the *Facebook* MAU data in reports given by the company. Lien and Cao [42] referred to Tencent's annual announcement report for the MAU data of *WeChat*.

The second way is to collect data on one's own. For example, it is possible to launch a poll and send questionnaires on the game forums (e.g., *Reddit*) or crowdsourcing platforms (e.g., *MTurk*). It is also possible to play the game and see the user's activity in the game. Although highly accessible and provide high data granularity, these approaches cost a lot of time or money. They may have representativeness problems as well. The quality of data heavily depends on the technique of sampling and research design. This approach is relatively straightforward and feasible. Although this approach can provide intelligence for practical uses, it's not often utilized in academic contexts.

The third way is to consult the business intelligence companies. Some examples are *App Annie*, *SensorTower* and *Statista*. These companies provide reports on mobile game metrics open to the public and paid customized services [48]. In open-access reports, the data is usually a vague estimation and aggregated depending on the data collection technique. However, these open-access reports are widely accepted in the literature (for example, Al-Haija, et al. [1] used the reports of *Statista* to get the monthly active user of *Facebook* and *Twitter*). The data in the report may not be precisely what the decision-makers care about. Customized services may make data with higher accuracy and higher granularity attainable. But it is usually expensive and time-costing.

It's important to notice that business intelligence companies may also use the first two ways to collect data. For instance, a company can ask the game developer for the data like any other ordinary researcher. A company may also hire a large group of people to complete questionnaires. However, business intelligence companies can still provide original knowledge. For example, *SensorTower* describes its "App Intelligence Methodology" as follows:

> "App Intelligence data is pulled directly from both iOS and Google App stores via API on a daily basis. This helps ensure a high level of data accuracy for ratings, rankings, reviews, metadata, etc. A smaller subset of data (such as keyword difficulty scores) are compiled through data science and modeling, which are regularly updated in line with app store algorithm changes. [59]".

On the one hand, the data pulled from app stores via API (Application Programming Interface) are later included in their business intelligence report. These are second-hand data. At this very moment, these companies provide a synthesis of the knowledge available from other sources instead of providing primary information. Therefore, it's reasonable to argue these companies may not be comparable to the other two sources. However, on the other hand, the data "compiled through data science and modeling" seems first-hand data because they use the company's unique algorithms. A company may also get "exclusive data" from game developers that are not accessible to ordinary people. Therefore, it's still reasonable to see business intelligence companies as an independent way to get a game's MAU data.

In practice, choosing what approach to collect the MAU data calls for a comprehensive understanding of the task and the resources. It needs a balance between the accuracy, accessibility, granularity, and cost of data. Ideally, data with the highest accuracy is most wanted. A high accuracy guarantees the validity of the data and therefore makes the data convincing. Consequently, it's reasonable to ask developers to share the data first, then triangle it with business companies' data or data collected by oneself. But at the same time, accessibility, granularity, and cost are also critical dimensions to be considered by researchers and analysts. As shown in Table 2, each of the current three approaches has advantages and disadvantages in the dimensions. However, none of these approaches can meet the requirements of high accessibility, high data granularity and low cost at the same time. Therefore, a proxy to the MAU data of mobile games is necessary.

2.2 Monthly active user numbers of Geo AR Mobile games

Geo AR mobile games, aka location-based augmented reality mobile games, refer to the location-aware mobile game that combines live surrounding-based experience with sensory virtual information [44]. This mobile game came out early in 2000, but it didn't enter the mass market or receive broad monetization until 2016 with *Pokémon GO*'s release [52]. Here are some illustrations of the impressive performance of *Pokémon GO*: it peaked at 100 million users worldwide, 45 million daily unique visitors with 28.5 million in the U.S. alone. It had $832 million in revenue in the launch year, with $2 million in daily revenue estimated [13, 35]. Players flocked into parks and streets as they played the game [20, 21, 40].

Geo AR mobile games were expected to redefine how players engage with a game and disrupt the video game industry based on the media or analysts in 2016 [25, 39]. Since then, multiple Pokémon-GO-like Geo AR mobile games have emerged. And all these games adopted a freemium business model like *Pokémon GO*. Moreover, since 2017, diverse research on the Geo AR mobile game has emerged, covering fields like physical activity, tourism, culture, learning activities, etc. [2, 27, 28, 30, 47, 53, 68].

However, these Geo AR mobile games are usually short-lived and not sustainable. Three have been confirmed discontinued among eight Geo AR mobile games released in 2018 and 2019. Four alive games have struggled with only 1% of their peak MAU. Only the last one alive has maintained a level of 10% of its peak. In 2021, three Geo AR mobile games were released. One of them (i.e., *Arabian Nights: Genie's treasures*) was discontinued merely two months after its release. The other two games released in 2021, namely *The Witcher: Monster Slayer* and *Pikmin Bloom*, also have less than 10% of their peak MAU and seem to keep losing them without any signs of turning the tide. All these Geo AR mobile games are freemium. Hence, MAU is crucial for monetization approaches, including in-game purchases, subscriptions and advertisements [19, 32]. Therefore, the sustainable survival of Geo AR mobile games, represented by the MAU, is in a crisis [44]. This MAU crisis has again brought the argument whether Geo AR mobile games or augmented reality technology is just hype [9, 15].

Since the MAU of Geo AR mobile games is a trendy and urgent topic, it's appropriate for this paper to join the conversation. Moreover, compared with other new forms of mobile games (e.g., cryptogames), Geo AR mobile games have a long history with relatively adequate data expected. Therefore, it's both meaningful and feasible to investigate the MAU proxy of Geo AR mobile games [37, 58].

2.3 The uses and gratification theory

As one of the player population metrics, MAU embodies the *engagement* of players in the game. It's helpful to look for theories indicating constructs that have relationships to players' engagement for potential proxies. This paper proposes that the uses and gratification theory can be a proper perspective.

The uses and gratification theory is a classic theory to understand why and how individuals actively seek out and use specific media to satisfy specific needs [14, 70]. For example, one user may want to seek information or educate themselves. This is called *information-seeking* or "information motivation." [36] Also, one may use certain media for hedonic use, called entertainment. Since the uses and gratification theory has been proposed, various gratifications have been developed and identified in different media contexts. This theory has been used and verified in multiple contexts, including online games [71], social media [70], and Geo AR mobile games [27, 57]. Therefore, it's reasonable to use this well-examined theory to look for potential proxies.

The information-seeking gratification matches the topic of this paper. This paper is highly interested in the information about games and may be counted in the field called "game data science [18]." As mentioned, information-seeking is driven by one's desire to increase awareness and knowledge of oneself, others, and the world. This logic may also be supported by considering the conversation perspective. Levine, et al. [41] propose that markets are conversations. The Internet has enabled networked conversations as information seeking, which was previously impossible in the mass media era. Technology has enabled people to collect information before making decisions to engage truly. According to a survey by *Google*, 85% of shoppers find product information and pictures essential for deciding which brand or retailer to buy from. 53% of shoppers always research before purchasing to ensure their choice is the best possible [23]. This "YouTube it before you buy it" trend indicates a strong connection between the information-seeking gratification desired and the actual engagement with one product [55].

2.4 Propositions and hypothesis

Given the relationship indicated by the uses and gratification theory, this paper proposes that the measures of information-seeking motivation may be the proxies needed to represent the engagement of players. Literature finds that people tend to visit wikis to get some information about interesting subjects, use social media to "learn how to make sense of things from their peers on just about any subject [4]" and send queries to search engines [60]. Therefore, wiki views, social media views, the number of social media posts (i.e., contents), and online search volume can be treated as measures of information-seeking. And this paper proposes these measures can be used to predict engagement. The relationships between concepts and variables are proposed in Fig. 1 below based on these previous studies.

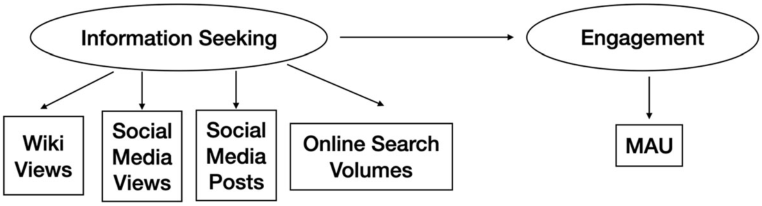

Fig. 1 Proposing potential proxies of MAU from the information seeking perspective

Using the measures of information-seeking to predict engagement is frequent. Goel, et al. [22] used the online search volume to predict consumer behaviors in diverse genres, including box-office movie revenue, first-month video game sales, and songs' Billboard rank. Liikkanen and Salovaara [43] used data from *YouTube* videos to demonstrate user engagement in different types of music videos. These precedents provide justifications for the potential proxies. Based on that, here is the proposition of this paper:

Proposition: When a Geo AR mobile game receives more engagement from the players, more information-seeking about the game occurs.

Based on the proposition, four hypotheses are developed:

Hypothesis 1: The Wiki views of a Geo AR mobile game have a strong positive correlation with the game's MAU.
Hypothesis 2: The social media views of a Geo AR mobile game have a strong positive correlation with the game's MAU.
Hypothesis 3: The number of social media contents of a Geo AR mobile game has a strong positive correlation with the game's MAU.
Hypothesis 4: The online search volumes of a Geo AR mobile game have a strong positive correlation with the game's MAU.

3 Methods

3.1 Data collection

The Geo AR mobile games considered are those launched after 2016. Geo AR mobile games since then broadly adopted a monetization of freemium. That is the prerequisite to looking for business metrics data on the Internet. LIU [44] pointed out there are twelve games to consider. As inspired by previous studies, the name of each game is used as part of the keyword for inquiry in the search engine *Google*. For example, when looking for the actual MAU data of *Pokémon GO*, the keyword for inquiry would be "Pokémon GO monthly active user number," "Pokémon GO monthly active user," "Pokémon GO metrics," "Pokémon GO active users" that are commonly used in the media. This paper aims to obtain the actual MAU data of these twelve Geo AR mobile games possibly available on the Internet. The data can be obtained for free. The targeted time range and granularity can be determined based on the actual MAU data obtained.

For wiki views, this paper chooses *Wikipedia* (https://en.wikipedia.org/wiki/Main_Page) as it's the most representative wiki in the world. The views of each page are collected through the

Pageview Analysis tool (https://meta.wikimedia.org/wiki/Pageviews_Analysis). It is a tool to analyze page view statistics [54]. Users of *Pageview Analysis* can customize the dates, date type (i.e., the granularity of the data to be collected), and the specific *Wikipedia* project to obtain the data of views of the Geo AR mobile game's *Wikipedia* page. The data can be directly exported as a .csv file.

This paper chooses *Google* as the context for online search volumes since it's the most representative search engine. *Google* is the most popular search engine globally, with a 70% market share [61]. The online search volume is obtained through *Google Trends*, a free keyword research tool that provides near real-time trend data regarding interest as operationalized by the internet search volume. It shows the changes in online interest for time series in any selected term in any country or region over a selected period. It should be noted that *Google Trends* is not the actual amount of the queries in *Google*. The returned result is a relative value ranging from 0 to 100 based on the proportion. This paper uses the game name as the keyword in *Google Trends*. The actual MAU data determine the date range. When the *Google Trends* data is of higher granularity than the actual MAU data, the aggregation is conducted by adding the *Google Trends* data for each period.

For social media views, this paper chooses *YouTube* as a representative example. *YouTube* is the second-largest search engine globally [12, 67]. It is a social media featuring videos resonating with the multimedia characteristic of Geo AR mobile games. Using the game name as the keyword and the date range revealed by the actual MAU data collected, *YouTube Data API* would return a list of the videos searched with the views. The counts and views of videos will be aggregated to match the data granularity embodied in the actual MAU. This paper used *Python* to unitize the *YouTube Data API*. We are aware that there are specific game-based social platforms like *Discord* or *Steam*. Some studies already utilized the valuable data there to inform game design and player's psychographic characteristics (e.g., [26]). This study sticks with *YouTube* because little Geo AR mobile games have their pages on *Steam*. *Discord*, however, are used by only a fraction of players compared to *YouTube*.

3.2 Data analysis

There are three steps of data analysis in this paper. The first step is data aggregation. The second step is correlation analysis. The third step is bootstrap.

After cleaning the data, the data of potential proxies may be aggregated if the original data does not match the granularity of the actual MAU. For example, suppose the actual MAU of a game is presented as the annual data and the data of the potential proxy is monthly. In that case, the monthly data of the potential proxy will need to be added to get the annual result. It's not a problem with *Wikipedia* page views since *Pageview Analysis* supports customizing the data granularity. It's not a problem with *YouTube* video views since the views of each video published at any second are known. The problem may happen in the online search volumes. For example, *Google Trends* could be a weekly data unmatched by the monthly actual MAU data. At this moment, the concerned weekly *Google Trends* data would be added to get a monthly aggregation. For a week with some days in one month and the other days in the other month, the weekly *Google Trends* is averagely divided into the days. The second step is correlation analysis, calculating the Pearson correlation coefficient between the actual MAU and each potential proxy (possibly aggregated). Using the rule of thumb for interpreting the size of a correlation coefficient shown in Table 3, the hypothesis would be tested [49].

Table 3 Rule of thumb for interpreting the size of a correlation coefficient

Size of Correlation	Interpretation
.90 to 1.00 (−.90 to −1.00)	Very high positive (negative) correlation
.70 to .90 (−.70 to −.90)	High positive (negative) correlation
.50 to .70 (−.50 to −.70)	Moderate positive (negative) correlation
.30 to .50 (−.30 to −.50)	Low positive (negative) correlation
.00 to .30 (.00 to −.30)	Negligible correlation

Nevertheless, given the scarcity of the actual MAU data, the sample for calculating the correlation coefficient may be small. A correlation relationship between the MAU and a proxy identified in a sample may be partly impacted by the approach to collect MAU or sampling variability. Therefore, it's necessary to eliminate the variability and approximate the correlation coefficient in the population as closely as possible. For this purpose, the bootstrap method is used. Bootstrap is a resampling method where large samples of the same size are repeatedly drawn, with replacement, from a single original sample [72]. This way, bootstrap creates the resulting distribution of massive samples as a Gaussian distribution, making statistical inference like constructing a Confidence Interval possible [7]. A confidence interval can be described as the range of values one variable may have under a given confidence level. It's a widely used technique for parameter estimation in fields like medicine [29] and environmental science [65].

In this manuscript, the bootstrap method will be used after the discussions on the sample data have been made. The confidence interval of the correlation coefficient between the MAU and each proxy will be made to allow further analysis of the correlation relationship. The bootstrap will be conducted using the "boot" package in R Programming Language [6]. As suggested by Davidson and MacKinnon [11], 399 would be the minimum number of bootstrap samples for testing at the .05 level. Therefore, the size of bootstrap samples is determined as 500.

4 Results

Only two games' actual MAU are found among the twelve Geo AR mobile games. This scarcity of actual MAU data resonates with the argument of this paper that the actual MAU data is usually scarce and seldom open on the Internet. These two games are *Pokémon GO* and *The Walking Dead: Our World*.

4.1 Pokémon GO

Table 4 shows the data collected, and Table 5 shows the result of the correlation analysis on the full data set of *Pokémon GO*. The data of MAU comes from the open-access reports of the business intelligence companies [46, 66]. The actual MAU data of *Pokémon GO* is annual. And there is no data available with higher granularity (e.g., MAU of each month or each quarter). It's noted that there is a significant correlation between the Actual MAU and *Google Trends*. Since the correlation coefficient is 0.919 > 0.9, the rule of thumb would suggest a very high positive correlation. The correlation coefficients of the other three potential proxies are all larger than 0.7 and smaller than 0.9, seemingly indicating a high positive correlation.

Table 4 Full data set of the actual MAU and potential proxies of *Pokémon GO*

Time	Actual MAU (in millions)	Google Trends	Wikipedia Views	YouTube Video Counts	YouTube Video Views
2016	232	595	11,183,176	196	1,676,939,819
2017	65	193.429	725,698	84	211,322,263
2018	104	241.571	507,306	55	179,018,151
2019	153	275.143	473,363	78	93,600,948
2020	166	491	442,753	130	80,653,860

However, their p value is all larger than 0.05, which means the correlations are not significant in the common sense.

There are two expected significant correlations. One is between *Google Trends* and *YouTube* Video Counts. The correlation coefficient is 0.934, indicating a very high positive correlation. The p value of the correlation is $0.02 < 0.05$, indicating the correlation is significant. The other one is between *Wikipedia* views and *YouTube* video views. The correlation coefficient is 0.998, indicating a very high positive correlation. The p value of the correlation is $0.000 < 0.05$, indicating the correlation is significant.

Table 6 below reports the results of the bootstrap correlation coefficient between the actual MAU and potential proxies of Pokémon GO in the full data set. Based on 500 bootstrap replicates, the correlation coefficient between the actual MAU and Google Trends has a mean of 0.922. Its confidence intervals are (0.756, 1.076), although a correlation coefficient is a maximum of 1. That means, with a 95% confidence level, the correlation coefficient is higher than 0.7, indicating the high positive correlation relationship found in the small sample is steady and therefore convincing in the population. In contrast, the correlation coefficients of other proxies in the sample don't demonstrate a high mean as that of Google Trends. Their confidence intervals are also wider, indicating a correlation with fewer precisions.

Table 5 Correlations analysis of the actual MAU and potential proxies of *Pokémon GO* in full data set

Time		Actual MAU (in millions)	Google Trends	Wikipedia Views	YouTube Video Counts	YouTube Video Views
Actual MAU (in millions)	Pearson Correlation	1	0.919*	0.760	0.842	0.721
	Sig. (2-tailed)		0.027	0.136	0.073	0.169
Google Trends	Pearson Correlation		1	0.746	0.934*	0.712
	Sig. (2-tailed)			0.148	0.020	0.177
Wikipedia Views	Pearson Correlation			1	0.870	0.998**
	Sig. (2-tailed)					0.000
YouTube Video Counts	Pearson Correlation				1	0.847
	Sig. (2-tailed)					0.070
YouTube Video Views	Pearson Correlation					1
	Sig. (2-tailed)					

*. Correlation is significant at the 0.05 level (2-tailed)

**. Correlation is significant at the 0.01 level (2-tailed)

Table 6 Results of bootstrap correlation coefficient between the actual MAU and potential proxies of *Pokémon GO* in full data set

	Google Trends	Wikipedia Views	YouTube Video Counts	YouTube Video Views
Mean	0.922	0.252	0.760	0.221
Standard error	0.0815	0.852	0.374	0.861
Confidence Intervals (95% Level)	(0.756, 1.076)	(−0.4002, 2.9378)	(0.191,1.659)	(−0.466,2.909)

The finding of the significant strong correlation between the actual MAU and *Google Trends* of *Pokémon GO* in the full data set is encouraging. So do the correlations between *Google Trends* and *YouTube* video counts besides *Wikipedia* views and *YouTube* video views. However, these specific correlation relationships come from all the five annual data of *Pokémon GO*. To increase the rigor and relevance of the correlation between the actual MAU and *Google Trends*, it's necessary to conduct the correlation analysis in the subsets of data of *Pokémon GO*. On the one hand, if the correlation remains significant and strong even in short periods of observation, the correlation is more rigorous and convincing than a coincidence of the data.

On the other hand, the usefulness of MAU and its proxy can hardly be achieved if the year-by-year results are neglected. In real life, hardly a game may survive five years. Therefore, if proxies are expected to function, they must have consistent correlation relationships with the actual MAU even in possibly shorter periods. Therefore, the correlation analysis has been conducted in the subsets of data.

The data for shorter periods are subsets of the full data set. Meaningful subsets should meet two requirements. First, given that the full data are continuous in chronological order, the subset data shall be continuous and in chronological order. Second, a subset must have at least three data points for correlation analysis to determine the relationship's significance, direction and strength. Although it's feasible to conduct correlation analysis on subsets with merely two data points, it's hardly meaningful in practice. Their significance level would always be 0.000, and the coefficient would be either 1 or − 1. Based on these two criteria, subsets are picked up and analyzed. Table 7 below shows subsets picked up and the correlation analysis results.

There is no significant correlation between the actual MAU and each proposed proxy in subsets. The only exception is "Actual MAU – YouTube Video Views" in the subset [2017, 2018, 2019, 2020]. The correlation coefficient is −0.989 with a Sig. (2-tailed) of 0.011 < 0.05. Besides, there are two scenarios with a marginal significance value. One is "Actual MAU – Google Trends" whose correlation coefficient is 0.942 with a Sig. (2-tailed) of 0.058. The other is "Actual MAU – YouTube Video Views" whose correlation coefficient is −0.997 with a Sig. (2-tailed) of 0.050. Therefore, the significance and strength of correlation in these data subsets are inconsistent with those found in the full data set. To put it another way, significant correlation relationships only exist in a data set with five data points.

4.2 The walking dead: Our world

Table 8 shows the full data set of *The Walking Dead: Our World* with ten data points of quarterly data. The actual MAU data comes from the game developer's financial statements and audio cast presentations [50, 51]. Since there is no independent *Wikipedia* page for this

Table 7 Correlation coefficient between actual MAU and proxies in *Pokémon GO* data subsets

Data Subsets		Google Trends	Wikipedia Views	YouTube Video Counts	YouTube Video Views
[2016, 2017, 2018, 2019]	Pearson Correlation	0.942	0.856	0.836	0.832
	Sig. (2-tailed)	0.058	0.144	0.164	0.168
[2017, 2018, 2019, 2020]	Pearson Correlation	0.806	−0.914	0.539	−0.989*
	Sig. (2-tailed)	0.194	0.086	0.461	0.011
[2016, 2017, 2018]	Pearson Correlation	0.993	0.971	0.913	0.970
	Sig. (2-tailed)	0.073	0.155	0.268	0.155
[2017, 2018, 2019]	Pearson Correlation	0.986	−0.894	−0.131	−0.982
	Sig. (2-tailed)	0.107	0.296	0.916	0.121
[2018, 2019, 2020]	Pearson Correlation	0.750	−0.957	0.856	−0.997
	Sig. (2-tailed)	0.460	0.187	0.346	0.050

*. Correlation is significant at the 0.05 level (2-tailed)

**. Correlation is significant at the 0.01 level (2-tailed)

game, only the actual MAU, *Google Trends* and *YouTube* video data are collected and analyzed. The correlation analysis results are shown in Table 9. Three potential proxies all have a correlation coefficient larger than 0.9, indicating that each has a strong positive correlation with the actual MAU. The p value of each potential is 0.000 < 0.05, indicating the correlation is significant. The correlation coefficient between the actual MAU and *Google Trends* is the largest among the three, indicating the highest correlation. The correlation coefficients between potential proxies are all larger than 0.9, indicating a strong positive relationship. These correlations are significant since the p values are all 0.000 < 0.05.

Table 10 shows the results of the bootstrap correlation coefficient between the actual MAU and potential proxies of *The Walking Dead: Our World* in the full data set. The mean of the correlation coefficient between the actual MAU and *Google Trends* is 0.953, with a 95% confidence interval of (0.896,1.064). That means on 500 bootstrap replicates, the correlation

Table 8 Full data set of the actual MAU and potential proxies of *The Walking Dead: Our World*

Code	Time	Actual MAU (in millions)	Google Trends	YouTube Video Counts	YouTube Video Views
A	07–09/2018	2096.120	442.429	274	16,729,712
B	10–12/2018	758.542	108.857	62	930,822
C	01–03/2019	982.345	87.143	25	241,160
D	04–06/2019	602.486	59	31	23,013
E	07–09/2019	528.751	44.714	16	26,934
F	10–12/2019	591.469	36.714	12	15,605
G	01–03/2020	309.333	22	14	17,477
H	04–06/2020	246.170	23.571	23	20,070
I	07–09/2020	245.716	14.143	14	43,686
J	10–12/2020	231.433	13.857	17	9989

Table 9 Correlations analysis of the actual MAU and potential proxies of *The Walking Dead: Our World* in full data set

Time		Actual MAU (in millions)	Google Trends	YouTube Video Counts	YouTube Video Views
Actual MAU (in millions)	Pearson Correlation	1	0.967**	0.922**	0.909**
	Sig. (2-tailed)		0.000	0.000	0.000
Google Trends	Pearson Correlation		1	0.990**	0.979**
	Sig. (2-tailed)			0.000	0.000
YouTube Video Counts	Pearson Correlation			1	0.991**
	Sig. (2-tailed)				0.000
YouTube Video Views	Pearson Correlation				1
	Sig. (2-tailed)				

*. Correlation is significant at the 0.05 level (2-tailed)

**. Correlation is significant at the 0.01 level (2-tailed)

coefficient is almost always no less than 0.9, which indicates a steady, very high positive correlation. In contrast, the other two potential proxies (i.e., YouTube Video Counts and YouTube Video Views) have lower means and wider confidence intervals. That means their correlations are not as strong nor precise as that of *Google Trends*.

Similarly, the correlation analysis is conducted on the subsets of the data. Table 11 shows the results of each subset. The findings from these results are listed below:

1) Among subsets with at least six consecutive data points, there is always a significant positive correlation between the actual MAU and Google Trends at the 0.05 level (2-tailed) at least. Therefore, it's reasonable to say the correlation is robust and consistent in these subsets. Moreover, these robust significant correlations between the actual MAU and *Google Trends* are all high. As shown in Table 11, the correlation coefficients derived from data subsets with at least six consecutive data points are all larger than 0.8. Based on the rule of thumb in Table 3, these results show a high positive correlation since the correlation coefficients are all larger than 0.7. In contrast, neither the correlation between the actual MAU and YouTube Video Counts nor that between the actual MAU and YouTube Video Views demonstrates a similar consistency.
2) Among all six subsets with five consecutive data points, *Google Trends* demonstrated a significant and strong correlation with the actual MAU in four subsets. In these four scenarios, the correlation coefficients are all larger than 0.7, indicating a high correlation.

Table 10 Results of bootstrap correlation coefficient between the actual MAU and potential proxies of *The Walking Dead: Our World* in full data set

	Google Trends	YouTube Video Counts	YouTube Video Views
Mean	0.953	0.787	0.813
Standard error	0.043	0.249	0.222
Confidence Intervals (95% Level)	(0.896,1.064)	(0.570,1.544)	(0.570,1.438)

Table 11 Correlation coefficient between actual MAU and proxies in *The Walking Dead: Our World* data subsets

Data Subsets		Google Trends	YouTube Video Counts	YouTube Video Views
[A,B,C,D,E,F,G,H,I]	Pearson Correlation	0.968**	0.927**	0.916**
	Sig. (2-tailed)	<0.001	<0.001	<0.001
[B,C,D,E,F,G,H,I,J]	Pearson Correlation	0.896**	0.494	0.532
	Sig. (2-tailed)	0.001	0.177	0.140
[A,B,C,D,E,F,G,H]	Pearson Correlation	0.969**	0.932**	0.927**
	Sig. (2-tailed)	<0.001	<0.001	<0.001
[B,C,D,E,F,G,H,I]	Pearson Correlation	0.881**	0.473	0.513
	Sig. (2-tailed)	0.004	0.236	0.194
[C,D,E,F,G,H,I,J]	Pearson Correlation	0.967**	0.442	0.780*
	Sig. (2-tailed)	<0.001	0.297	0.022
[A,B,C,D,E,F,G]	Pearson Correlation	0.976**	0.950**	0.945**
	Sig. (2-tailed)	<0.001	0.001	0.001
[B,C,D,E,F,G,H]	Pearson Correlation	0.853*	0.413	0.502
	Sig. (2-tailed)	0.015	0.357	0.251
[C,D,E,F,G,H,I]	Pearson Correlation	0.962**	0.409	0.774*
	Sig. (2-tailed)	<0.001	0.362	0.041
[D,E,F,G,H,I,J]	Pearson Correlation	0.913**	0.234	−0.088
	Sig. (2-tailed)	0.004	0.614	0.852
[A,B,C,D,E,F]	Pearson Correlation	0.982**	0.962**	0.966**
	Sig. (2-tailed)	<0.001	0.002	0.002
[B,C,D,E,F,G]	Pearson Correlation	0.825*	0.450	0.477
	Sig. (2-tailed)	0.043	0.371	0.339
[C,D,E,F,G,H]	Pearson Correlation	0.954**	0.315	0.828*
	Sig. (2-tailed)	0.003	0.543	0.042
[D,E,F,G,H,I]	Pearson Correlation	0.894*	0.223	−0.379
	Sig. (2-tailed)	0.016	0.671	0.459
[E,F,G,H,I,J]	Pearson Correlation	0.910*	−0.496	−0.120
	Sig. (2-tailed)	0.012	0.317	0.822
[A,B,C,D,E]	Pearson Correlation	0.980**	0.959**	0.966**
	Sig. (2-tailed)	0.003	0.010	0.007
[B,C,D,E,F]	Pearson Correlation	0.728	0.324	0.428
	Sig. (2-tailed)	0.163	0.595	0.472
[C,D,E,F,G]	Pearson Correlation	0.951*	0.515	0.879*
	Sig. (2-tailed)	0.013	0.374	0.050
[D,E,F,G,H]	Pearson Correlation	0.855	0.094	0.236
	Sig. (2-tailed)	0.065	0.881	0.702
[E,F,G,H,I]	Pearson Correlation	0.894*	−0.489	−0.402
	Sig. (2-tailed)	0.041	0.403	0.503
[F,G,H,I,J]	Pearson Correlation	0.915*	−0.581	−0.262
	Sig. (2-tailed)	0.030	0.304	0.670
[A,B,C,D]	Pearson Correlation	0.979*	0.956*	0.973*
	Sig. (2-tailed)	0.021	0.044	0.027
[B,C,D,E]	Pearson Correlation	0.705	0.209	0.363
	Sig. (2-tailed)	0.295	0.791	0.637
[C,D,E,F]	Pearson Correlation	0.918	0.373	0.982
	Sig. (2-tailed)	0.082	0.627	0.018
[D,E,F,G]	Pearson Correlation	0.822	0.418	0.266
	Sig. (2-tailed)	0.178	0.582	0.734
[E,F,G,H]	Pearson Correlation	0.874	−0.701	0.108
	Sig. (2-tailed)	0.126	0.299	0.892
[F,G,H,I]	Pearson Correlation	0.912	−0.576	−0.525
	Sig. (2-tailed)	0.088	0.424	0.475
[G,H,I,J]	Pearson Correlation	0.556	−0.425	−0.103
	Sig. (2-tailed)	0.444	0.575	0.897
[A,B,C]	Pearson Correlation	0.978	0.957	0.981

Table 11 (continued)

Data Subsets		Google Trends	YouTube Video Counts	YouTube Video Views
	Sig. (2-tailed)	0.135	0.188	0.123
[B,C,D]	Pearson Correlation	0.475	−0.252	0.129
	Sig. (2-tailed)	0.685	0.838	0.971
[C,D,E]	Pearson Correlation	0.983	0.264	0.986
	Sig. (2-tailed)	0.118	0.830	0.107
[D,E,F]	Pearson Correlation	0.296	0.445	−0.669
	Sig. (2-tailed)	0.809	0.706	0.534
[E,F,G]	Pearson Correlation	0.843	−0.212	0.155
	Sig. (2-tailed)	0.362	0.864	0.901
[F,G,H]	Pearson Correlation	0.964	−0.763	−0.903
	Sig. (2-tailed)	0.172	0.448	0.283
[G,H,I]	Pearson Correlation	0.365	−0.495	−0.581
	Sig. (2-tailed)	0.762	0.671	0.605
[H,I,J]	Pearson Correlation	0.545	0.216	0.712
	Sig. (2-tailed)	0.633	0.862	0.496

*. Correlation is significant at the 0.05 level (2-tailed)

**. Correlation is significant at the 0.01 level (2-tailed)

YouTube Video Counts and YouTube Video Views have less than two scenarios demonstrating a significant correlation.

3) In data sets with less than five data points, there is no significant correlation between the actual MAU and any proxies. The only exception is the scenario [A, B, C, D], where three proxies demonstrated a significant correlation with the actual MAU.

In summary, only *Google Trends* demonstrates a very high and significant correlation with the actual MAU in both games in the full data set. *Wikipedia* views, *YouTube* video counts and views are high and significant in the case of *The Walking Dead: Our World* but not significant in the case of *Pokémon GO*. In data subsets of *Pokémon GO,* none of the correlation relationships remain significant. However, in subsets of *The Walking Dead: Our World*, the correlation between the actual MAU and *Google Trends* remains significant and strong if more than five quarterly data are included. Table 12 below summarizes the hypotheses and the results. The findings of this paper give confidence in using the online search volume as a proxy for the MAU of a game based on the high and significant correlation.

Table 12 Summary of hypothesis and results

Hypothesis	Results
Hypothesis 1: The Wiki views of a Geo AR mobile game have a strong positive correlation with the game's MAU	Not supported
Hypothesis 2: The social media views of a Geo AR mobile game have a strong positive correlation with the game's MAU.	Not supported
Hypothesis 3: The numbers of social media contents of a Geo AR mobile game have a strong positive correlation with the game's MAU.	Not supported
Hypothesis 4: The online search volumes of a Geo AR mobile game have a strong positive correlation with the game's MAU	Supported

5 Discussions

5.1 Reflections on the findings

The actual MAU of *The Walking Dead: Our World* is highly reliable since it's in the reports directly provided by the game developers. In that case, all three potential proxies have a high, positive and significant correlation with the actual MAU. Also, these three potential proxies are correlated with each other in a high, positive and significant way. That confirms the expectation conceptualized from the uses and gratification theory and previous studies about these potential proxies. All these three potential proxies reflect the general level of the information-seeking behavior of the players. Therefore, they are expected to be closely related, as shown in the result. Since information-seeking and engagement are related, it's no wonder each of the potential proxies has a strong correlation with the actual MAU. *Wikipedia* and *Google Trends* have been widely used to forecast for a long time. *The Walking Dead: Our World* investigation confirmed that both are still good indicators of information-seeking in the context of Geo AR mobile games [22]. Surprisingly, *YouTube* video counts and views have a high, positive, and significant correlation with the actual MAU of the game. These results about *YouTube* videos may suggest the importance of video social platforms in terms of the multimedia objects like video games.

The actual MAU of *Pokémon GO* comes from the business intelligence companies and is second-hand. Only the online search volume has a high, positive and significant correlation with the actual MAU among the four potential proxies. Wiki and social media views don't pass the statistical test, but the p-values are relatively marginal. This paper tends to interpret this because of the poor quality of the actual MAU data. However, it's confirmed that the online search volume is a robust proxy to the MAU of a Geo AR mobile game. This paper responds the two problems of game player analytics challenge proposed by Su, et al. [62]. With the results from the samples and bootstrap analysis, this study suggests that using the online search volume as a proxy can save the data collection cost with a still high validity.

Furthermore, it's noted that *Google Trends* has a high, positive and significant correlation with the *YouTube* video counts. That may indicate that the *YouTube* content creators notice people's queries about the game and upload related videos to go with the tide. These *YouTube* videos may reversely attract onlookers and elicit more queries in the search engine. Similarly, there is a high, positive and significant correlation between *Wikipedia* views and *YouTube* video views. This may suggest a general interest in seeking information about *Pokémon GO* among the public.

These correlations are identified in the aggregated data covering a long time range. In the context of *Pokémon GO*, it is annual data covering five years. In the context of *The Walking Dead: Our World*, it is the quarterly data covering two and a half years. However, for both the rigor and relevance of the research, these correlations are tested in subsets of data. On the one hand, in the context of *The Walking Dead: Our World,* the correlation between the actual MAU and *Google Trends* remains significant and high even in a smaller range of observations, namely six quarterly MAU data covering one and a half years. The correlations between the actual MAU and other proxies are also significant to a different level in the data subsets. On the other hand, however, the correlation between the actual MAU and *Google Trends* is not significant in any subsets of data. Reflections on these results on the subsets are listed below:

1) The reason why correlation is significant in data subsets of *The Walking Dead: Our World* but not significant in data subsets of *Pokémon GO* may be the difference in data quality. The actual MAU of *The Walking Dead: Our World* originated from the game developer's financial statements and audio cast presentations [50, 51]. Therefore, the correlation can be consistent and robust even in smaller data subsets. But the actual MAU data of *Pokémon GO* used is from business intelligence companies which are not as accurate as the ones directly given by the game developer. Therefore, although the correlation pattern is significant if one aggregates all the data, it cannot remain significant in subsets of data.
2) There seem to be some conditions for *Google Trends* to function as an ideal proxy to the actual MAU. For example, even in the context of *The Walking Dead: Our World*, the significant correlation doesn't firmly exist in subsets with less than six data points covering one and a half years. To put it another way, a Geo AR mobile game may have to survive at least one and a half years for the correlation pattern between the actual MAU and *Google Trends* to emerge, facilitating the use of *Google Trends* as a proxy to the actual MAU. This interpretation is also plausible in the context of *Pokémon GO*. Over the five years of *Pokémon GO*, only 32 game updates contributed to the increase and the stop of decrease in the active user base. It's not likely that every week something changes in the game. Players also need time to recognize what has changed in the game, which is later reflected in their information-seeking behavior. That said, the conditions for using *Google Trends* to represent the actual MAU of a Geo AR mobile game may be subject to the minimum requirements of game release time, the number of updates implemented in the game and the general level of players' recognition of what's happening in the game. Enough data points may be really necessary for both analysis and prediction.

5.2 On the specificity and generalizability of findings

The "specificity – generalizability" issue (or called the "context – generalizability" issue) has been widely discussed in fields like information systems and psychology research [8, 10, 63]. In this paper, it's about to what extent the findings are specific to the Geo AR mobile game context and to what extent it is general to any other kinds of video games or even software. This paper argues that the proxies of the actual MAU are specific in terms of the AR and geolocation functions in the game. These functions, enabled by the AR engine (e.g., *ARCore* and *ARKit*) and geolocation engine (e.g., *Google Maps*), are distinctive characteristics of Geo AR mobile games [44]. However, these proxies can also be applied to general video games and software.

Geo AR mobile games are "location-aware mobile games that combine live surroundings-based experience with sensory virtual information" [44]. Currently, the common way is to use the AR engine and geolocation engine to create such a game experience. Therefore, it's reasonable to say AR and geolocation engines are where Geo AR mobile games are distinct from other kinds of video games. With that, the actual MAU and proxies of a Geo AR mobile game can be influenced by changes in the in-game events or settings related to AR and geolocation. For example, COVID-19 has caused great discontinuance to the settings and events in Geo AR mobile games [38]. For these games, their geolocation feature by nature demands outdoor activities. But in the pandemic era, the governments strictly regulate outdoor activities and, therefore, damage players' engagement with the game. As a result, multiple Geo AR mobile games blamed the pandemic for their discontinuance [5, 69]. However, some games took adaptive actions in the game as a response to the pandemic regulations and increased the number of active players. For example, *Pokémon GO* used the legendary Pokémon Darkrai in raids and its shiny form (available 6–8 March and again 28 April–5 May) to attract players and counter the effect of self-regulation about COVID-19 in Finland. These actions managed to increase players' motivation to play the game even in the pandemic era [38]. Similarly, if there were regulations on the use of cameras in the public area, namely limiting the use of AR function, players' information-seeking and engagement in Geo AR mobile games is expected to decrease. That will also be reflected in the volume of proxies and the actual MAU. Therefore, a general limitation or encouragement on people's use of video games should impact the proxies and the actual MAU level of Geo AR mobile games as well.

However, individuals' information-seeking and engagement are not limited to Geo AR mobile games or other video games, as suggested by the uses and gratification theory. Different contexts can include social media and movie box offices [22, 43]. Therefore, the findings of the paper can be generalized to a different context. The difference may be the factors that may bring change in the proxies and the actual MAU. For example, the correlation between *Google Trends* and the actual MAU of a game featuring virtual reality (VR) could also be significant and strong, like the Geo AR mobile game in this paper. However, their metrics may be sensitive to the events related to VR instead of AR or geolocation.

The findings of this paper, namely using the proxies to represent the actual MAU, could be a technique used in the context of Geo AR mobile games and others. With this technique, it's possible to know the general performance of a game. Especially by focusing on the discontinuance in the data, it's possible to locate factors that contribute greatly to the game. These factors can be changes in the game (e.g., an update in the geolocation and AR engine in *Pokémon GO*) or some environmental change (e.g., pandemic regulations on outdoor activities). In this way, game designers and researchers could identify patterns between these factors and players' engagement. These patterns may be used to further polish the distinct characteristics of Geo AR mobile games or make a game "complete" to capture a larger group audience [44].

6 Conclusion

This paper starts from the proposition that players' engagement with a Geo AR mobile game can be captured through the information-seeking phenomenon about the game on the Internet. Precisely, players' engagement is measured through MAU. The information-seeking phenomenon is measured with wiki views, social media views and online search volumes. This paper further proposed four hypotheses of correlations between the actual MAU and each potential proxy. Only two games' actual MAU data among twelve Geo AR mobile games are obtained, confirming the scarcity of the data. The four hypotheses are tested. Only the online search volume demonstrates a robust, high, strong, and significant correlation with the actual MAU data of the games. Therefore, the online search volume is validated as a proxy to the MAU of a Geo AR mobile game.

The contributions of this paper are three-folded. First, this paper validates the online search volume as a proxy of the MAU. Researchers and analysts now may use the online search volume to track, monitor and forecast the players' engagement with a Geo AR mobile game without being hampered by the scarcity of the actual MAU data. Given the high and significant correlation, the online search volume may be used to demonstrate the pattern and discontinuity of the engagement over time compatible with typical analysis techniques. In other words, this paper validates the online search volume as a tool to investigate the players' engagement. Second, this paper validates the traditional engagement indicators in the new technology context, namely the Geo AR mobile games. Wiki views, social media posts and views are long-established indicators of users' engagement in public opinions, commerce and traditional entertainment. This paper shows they are still good indicators in the Geo AR mobile games context. Some of the findings are not as ideal as expected because of the data quality. Future studies may collect more data with better reliabilities to test. Third, this paper points out that the online search volume could be a potentially disruptive innovation. This discussion may suggest an emerging market of business intelligence.

This paper is not without limitations. First, only four potential proxies are proposed and tested. This paper focuses on wikis, social media and search engines, given their reliability and validity in previous studies. But it's reasonable to argue that more measurements of information-seeking can be proposed as a proxy to the MAU, capturing the players' engagement. Second, there should be more alternatives for each potential proxy. To capture the social media views and posts, one may use the data of posts on other social media platforms like *Facebook* and *Twitter*. Third, this paper only examined two Geo AR mobile games. Although both games are representative, more data of different games (not only Geo AR mobile games) are welcomed to enlarge the test data set. Fourth, this paper's analysis results of data subsets are not ideal. This paper tends to be quick to propose the idea of proxying the actual MAU with the online search volume. Further investigations on "small data," namely a shorter period of observation, are encouraged to enhance the rigor and relevance of the research. Fifth, this paper only provides a primary discussion on the role of business intelligence companies. As pointed out, these companies may function as both a synthesizer of present data and a provider of original knowledge. It's valuable further to differentiate these two roles of business intelligence companies.

Future research may consider the following directions to overcome the limitations of this paper and extend the findings. First, more measurements of information-seeking or other constructs suggested by theories could be examined as a proxy to the MAU. For example, for games built on the blockchain, it's possible to use the blockchain transaction network information to estimate the level of the game's popularity [33]. Second, more sources and approaches to collecting data are encouraged. Scholars and analysts can compare their data and grasp a game's player engagement more accurately with more options. Especially the three approaches to obtaining a game's MAU data are compared based on limited empirical findings in this paper. In fact, it's noted that the confidence intervals in the case of *The Walking Dead: Our World* are generally narrower than those in the case of *Pokémon GO*. This may suggest a difference in data reliability between using developers' data and business intelligence company data. Future studies are recommended to further evaluate these approaches, including online search volume as the proxy, in terms of accuracy, accessibility, granularity and cost of their data. Third, the findings of this paper can be tested in more and diverse contexts-for example, other Geo AR mobile games, other video games or other software. Fourth, data from shorter period observation are welcome to increase the rigor and relevance of this paper's findings. It's possible that to use the proxies to represent a game's actual MAU, a minimum level of time and update volumes are necessary. If so, it would be meaningful to find these requirements to facilitate the proxies. Fifth, case studies on the roles of business intelligence companies are necessary. How could one differentiate its role as a primary source and a synthesizer? How do these companies see themselves? These questions can be meaningful.

Data availability The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests The authors have no competing interests to declare that are relevant to the content of this article.

Funding: The preparation of this manuscript was funded by the project "Opportunities in Contemporary Digital Game Design," Start-up Grant for New Faculty, City University of Hong Kong.

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