A Data-driven Model for Mobile Game New Version Update Evaluation

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ABSTRACT
Game analytics has been used in game development and game research. However, less work focus on the game publishing side, especially on the new version update evaluation. This paper shows how game analytics can be used to guide game version updates. We innovatively view mobile game publishing as maintaining a fish tank and use our Fish Tank Model (FTM) to evaluate how game version updates improve players' activation and game revenue. First, we define some key metrics for evaluating mobile game performance based on FTM. Second, we introduce a real game project to develop and apply FTM to the new version update. Third, based on analyzing the changes before and after the game version update, we provide suggestions on how to improve the new version. Finally, we summarize how to use our data-driven model to guide the mobile game new version update evaluation and continue to improve the game content.

Keywords
Business Intelligence, Game analytics, Fish Tank Model, Metrics, Indie game developer, New version update

INTRODUCTION
Game publishing is an important part of the game promotion using effective ways of connecting games with their target users. Traditionally, publishers handle advertising, marketing and also distribution efforts (Peitz, 2012). After the game is developed, the game developer delivers the game to a publisher to promote it to the target user. From the game industry side, the traditional game value chain has been complemented with the mobile value chain and online value chain (European Games Developer Federation, 2011). The mobile value chain makes game developers self-publishing possible as the game developers can submit their games to the distribution channels, such as Google Play and App Store, themselves. However, they are facing the same publishing issues after the game launch. They need to continuously update the game content to maintain hardcore players and increase revenue (Macgregor, 2019). This means that many developers have to keep developing the game and releasing new versions. However, how to make sure the new version is better than the previous one and how to make sure

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that it stands for the desired game development direction is vital throughout the entire publishing process.

Analytics means the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions (Davenport and Harris, 2007). Analytics is a subset of business intelligence that uses data to understand and analyze business performance. It ensures that the money and resources devoted to the marketing focus on the most effective campaigns and channels (Davenport et al., 2010). Game analytics has already been used in the game industry for many years including identifying in-game design issues (Kim et al., 2008), visualizing players' behavior on the map (Moura et al., 2011) and also driving the game development process (Hullett et al., 2011). However, until now, most studies focus on game development and game research. Less research focuses on the game publishing side. As for mobile game analytics, Drachen et al. (2016, p. 1) point out that "*In essence, the field is in its infancy and the available knowledge is heavily fragmented*." This is to be expected in the explorative phase of a new domain such as mobile game analytics. In addition, as more and more mobile games appear, we also see an increasing number of independent (indie) game development studios. Many indie game developers are good at game development, but most of them lack experience in game publishing (Guevara-Villalobos, 2011). They do not know how user acquisition works and how to transfer users into loyal and also paying players (Mendez, 2011). In short, as many game developers lack experience in publishing and they do not know how to evaluate new game versions and how to use game analytics to guide new version updates.

In this paper, we explore how to use game analytics for new version update evaluation based on our data-driven Fish Tank Model (FTM) (Su et al., 2019). It is crucial for mobile game developers to make the right decisions about version updates during the game publishing process. They need to evaluate if the recent game development for the new version update is right or not, and also what needs to be improved for the next new version update. Therefore, we aim to provide guidance on how to evaluate new game versions according to the FTM. Our contribution includes a procedure to guide the game developer on how to use the data-driven FTM to drive their game publishing with respect to new version update evaluation.

RELATED WORK

Initially, game analytics focused on game development and game research (Drachen et al., 2013). Drachen et al. (2018) through a case study of more than 200,000 players, present an analysis of the relationship between the social features in free commercial casual mobile games and their revenue. The final results show that social activities will be valuable for improving game revenue. Drachen et al. (2016) provide a heuristic-based approach to quickly predict player retention. This fast prediction uses the first session from the player's activity and also the day and week of information to achieve reasonable and comparable performance. Petersen et al. (2017) developed a lab-based mixed approach to provide an evaluation of the user experience of the mobile game onboarding phase. It was also applied across 28 participants to three F2P mobile games from different genres. This research brings two contributions for the game user research, including evaluating different research techniques for mobile games and also providing an empirically based recommendation for mobile game design. Isaksen and Nealen (2016) provide a statistic analysis of player improvement and achieving single-player high scores based on game analytics. By analyzing the probabilities of two popular mobile games, they found that the more players play, the faster the chances of getting a high score. In order to deeply understand the players' behavior through space and time analysis, Canossa et al. (2016) proposed the G-Player which is a tool to assist in the analysis of players' behavior allowing users to gain a level of insight rather than simply descriptive statistics. So effective game analytics can not only help the success of game publishing and marketing promotion but also optimize the game in a targeted manner and extend its life cycle and increase revenue (Fields, 2011). However, the application of game analytics in the mobile game area is heavily fragmented and lacks systematic studies (Drachen et al., 2016). To the best of our knowledge, by now there is a lack of research focusing on mobile game publishing, especially for mobile game new version update performance evaluation.

Moreira et al. (2014) use the ARM (acquisition, retention, and monetization) funnel model as the basic analysis for the game publishing process. However, the ARM funnel model is originally developed for social games by the company Kontagent (Aaron, 2011). It just visualizes the process of how gamers pass through a funnel. It is used for visualizing the game publishing process by the three stages: acquisition, retention, and monetization. However, as the ARM funnel model only shows the players' changes in three stages, the relationship between the players and channels, new game versions and performance cannot be captured. The potential issues beyond acquisition, retention, and monetization cannot be solved by the ARM funnel model. So we propose a new model called the FTM (Su et al., 2019) which can be used to capture these potential issues and drive the mobile game publishing process towards solutions about the channels, new game content, in-game system, players' behavior changes and also revenue performance evaluation, as shown in Figure 1.

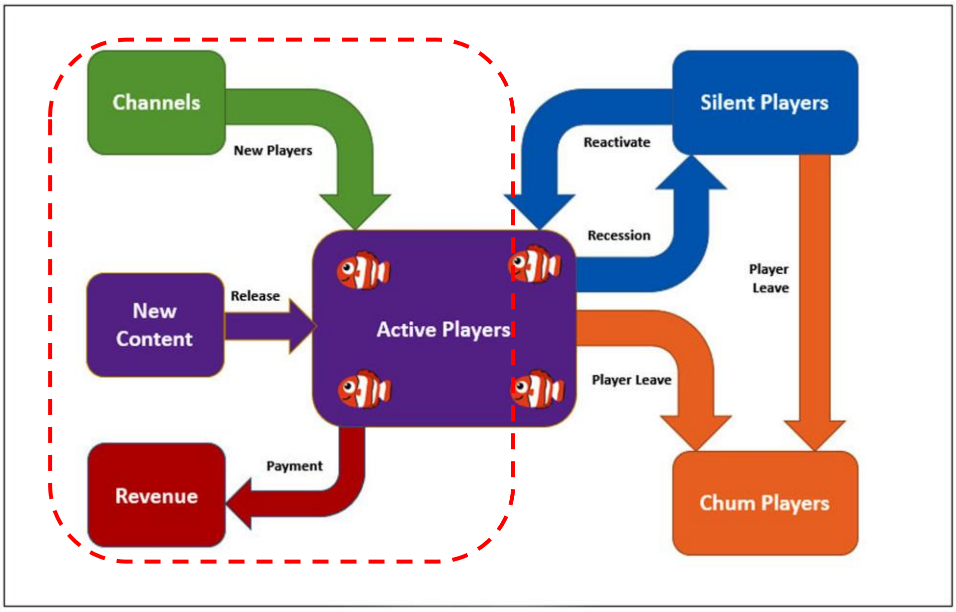


Figure 1: FTM for mobile game publishing (Su et al., 2019). The dotted line marks the parts that are in focus in this paper.

The FTM supports the publishing process taking the specific requirements of mobile game publishing into account. The main publishing tasks such as new user acquisition, maintaining the hard-core players and delivering more revenue can be tracked from each link through the construction of the FTM. We can recognize the mobile game publishing process as an analogy of maintaining a fish tank. How to make more fish survive, grow and multiply are key issues in a fish tank which explains the metaphorical meaning for mobile game publishing.

The red dotted line in Figure 1 marks the focus area of this paper. It is to explore the relationship between new content, active players and also the output revenue in FTM, including the IOS and Android Channels, and then based on the FTM, provide an evaluation method for mobile game version updates. In order to keep iterating our FTM for driving the indie mobile game publishing process, we apply it to an indie mobile game project.

THE LIFETIME VALUE OF FREE-TO-PLAY GAMES

In this paper, we focus on providing an evaluation method for mobile game developers to guide their new game version updates and performance evaluation based on the FTM. Constant new version updates can extend the game lifetime (Bratuskins, 2018). The mobile game lifetime value determines the final business performance. This is of particular importance for the Free-to-play (F2P) games. It specifically refers to free download and in-game payment mode. During the mobile game publishing process, game developers usually need to keep releasing new versions to attract and maintain game players and extend the mobile game lifetime value. Combined with our FTM, especially for the new content part, the new version update performance can be recognized as new content input. What we need to do is to find out the relationship between the new content input, in-game active players and also the revenue output. As shown in Figure 2, we can measure the changes from two sides by metrics. On one side, we define the New Version Rating (NVR) metrics which can be obtained from the App Store new version rating or the Google Play new version rating. These kinds of ratings are based on the players' reviews about each version which are suitable for measuring the new content performance. On the other side, we add the new metric New Version Change Rate (NVCR) to measure the new version update performance including the install change rate, paying user change rate, revenue change rate and also the Daily Active User (DAU) change rate. If the change rate is positive, it means the new content is favored by players, otherwise, the new content needs to be improved.

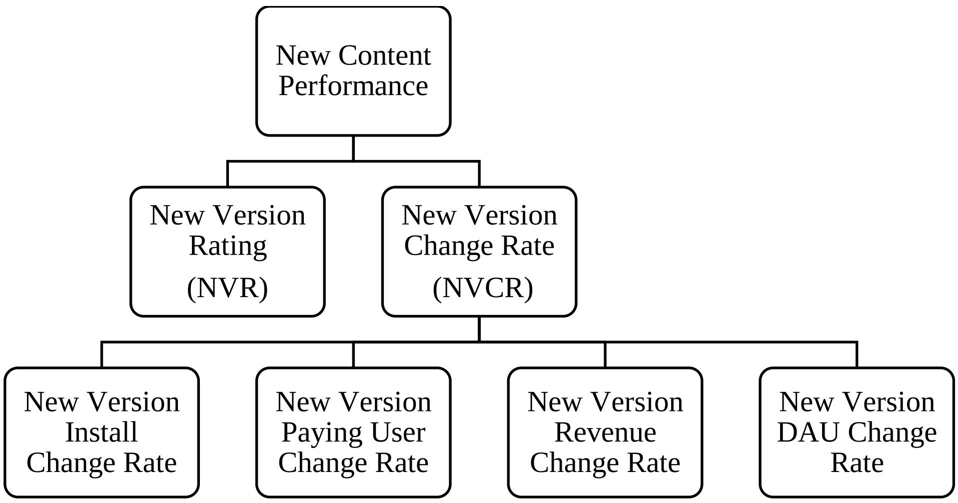


Figure 2: New version update performance evaluation metrics.

The New Version Rating (NVR) is the general method to evaluate the new version performance which mainly comes from the players' comments through the collection of mobile game distribution platforms, such as the App Store and Google Play. Usually, players just give intuitive feedback on the evaluation of different game versions if they like or dislike the new version update. However, in the process of new game version update, as not all players are willing to participate in the evaluation of the new version, and may not give comments in App Store and Google Play, we cannot rely solely on the NVR. Therefore, considering the in-game changes, we introduce the new metrics called NVCR by analyzing the changes in-game revenue after the new version update and also the changes in the DAU, install and paying user. By combining the NVR NVCR, we can give a more comprehensive evaluation of the game version update for different mobile games.

METHODOLOGY

The research aims to use game analytics for the new version update evaluation based on the FTM. In order to solve some challenges and pain points for indie game developers, we create and apply the FTM to guide mobile game publishing by a Design Science Research Method (DSRM) (Vaishnavi and Kuechler, 2013). As Hevner et al. (2004) point out, design science is the creation of artifacts that satisfy a given set of functional requirements by the knowledge expressed in the form of constructs, techniques and methods, models, or mature theories. As our research provides a new artifact, namely a set of guidelines to drive mobile game publishing, a design science research method should be suitable. In this project, we cooperate with an indie game studio and participated in their specific mobile game publishing project, where we applied our FTM to their indie mobile game project for a case study.

From the research ethics side, we got approval from the indie game developer to use related materials for our research as long as we provide free guidance. As for the in-game data collection, we also follow the General Data Protection Regulation (GDPR, 2018) and only collect the data related to our research metrics.

RESEARCH PROCESS

We apply the FTM and its related metrics to evaluate the performance of a casual game released by the cooperating indie game studio. Through the collection and analysis of the related data before and after the new version update, we can demonstrate how our FTM can be used for mobile game updates evaluation. The whole research process includes four parts which are shown in Figure 3.

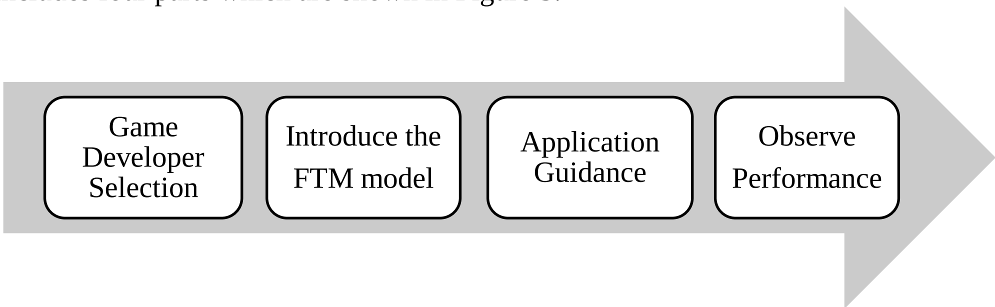


Figure 3: The whole research process.

- **Game Developer Selection.** According to the research goal, we need to apply the FTM for the new version update performance evaluation. Based on this research goal, we wanted to choose an indie game developer who mainly targets the mobile platform and already has launched games. Based on these screening criteria, we found an indie game studio with a casual mobile game that matched well. The game mainly provides fun for players by raising pets. Although this game had been launched two years ago, the team has been constantly developing new versions and new content to maintain the players.
- **Introduce the FTM.** In the early stage of communication, in order to ensure that the indie game developer is interested in the FTM, the first author visited their studio three times and held meetings and gave an introduction about the FTM and how it can be used for guiding mobile game publishing. They planned a new game version update soon, called version 2.7, which constituted a suitable case. The indie game studio was not clear about how to evaluate the performance of this new version update, especially for what kind of data to collect and how to do the data analysis. They needed to evaluate if the new version update would be welcomed by players and also what needed to be improved for the next new version update. So, we introduced the FTM as guidance to them to collect the related data. Based on the FTM data analysis method, we guided them with the new version update performance evaluation

to explore the relationship between the input of new content, active players and the output revenue.

- **Application Guidance.** In order to solve the specific issues faced by indie game developers, the first author worked with the indie game studio and guided them to use the FTM in their game publishing to measure the new version update performance. It included the game metrics and also the analysis methodology for the new version update. The metrics give the definition of what kind of data needs to be collected for the new version update. The analysis methodology gives guidance on how to analyze data and what kind of analysis methods we can choose. In order to collect the related data, we suggested the indie game studio to use the third-party data statistics tool *GameAnalytics* (GameAnalytics, 2019). We also defined the metrics for the new version update data collection. Besides, we adopted a reliable approach, not only collecting one or two days data but also focusing on the whole data collecting from the week before the new version update and the week after the update, laying the foundation for subsequent detailed analysis.
- **Observe Performance.** We observed the performance after using game analytics for the new version update evaluation based on our data-driven FTM. Based on the collected data, we used different data analysis methods to evaluate the new version update performance. We also compared the performance from the IOS and Android channels for the same version update and suggested improvements. At last, we summarized the four steps about how to apply our FTM for the new version update evaluation and make a conclusion.

DATA COLLECTION AND ANALYSIS

In the specific data collection, we take two approaches including inside game data collection and outside game data collection according to the metrics as shown in Figure 2. Based on these data, we can make a comprehensive evaluation of the new version update performance. For the data analysis, we provide comparative analysis methods for NVR, revenue analysis, DAU analysis, install analysis and paying user analysis and also correlation analysis for analyzing all variables related to the game version update to explore the consequences of the update.

Data collection

First, concerning the game rating for different game versions, we adopted App Annie (App Annie, 2019) which is a third-party tool to collect the data about the game rating from App Store and Google Play directly. All the rating data come from the App Store and the Google Player platform. We collect and compare the new version rating with the old version rating according to the player's feedback. Second, for the NVCR, we need to collect the related in-game data before the update and after the update. The third-party analytics tool, *GameAnalytics*, is used to make sure that the metrics definitions are the same without any errors both for the IOS and also the Android channels. Besides this, in order to make it easy for the developer to monitor game data changes and collect related data, we need to integrate the *GameAnalytics SDK* into the games for data collection in advance.

Figure 4: App Store new game version rating before (lower) and after (upper) the update.

As shown in Figure 4, after the release of the new version 2.7, the average score of players in the IOS App Store was 4.7, which is higher than the previous version 2.6.3. It seems that the new version update performance for the IOS version is better than the old version. However, as shown in Figure 5, for the Android version, the rating in the Google Play is 4.7 both before and after the update. As the rating for Android is the same, if we only rely on the new version rating, it is hard to make a conclusion for the Android version. So that means we also need to collect in-game data to do further evaluation.

Figure 5: Google Play new game version rating before (lower) and after (upper) the update.

For the in-game data collection, considering the input and output after the new version update, we bring and create new game metrics for FTM and collect the related data for measuring the new version update performance, such as game revenues, install, paying user and DAU. In the specific data collection, we collected all the data seven days before and also seven days after the new version update to ensure that the changes can be represented clearly.

Comparative analysis

The comparative analysis focuses on similarities and differences in values of variables which is usually broken down into two types according to whether the aim is to explain differences or similarities (Pickvance, 2001). As for our comparative analysis, we mainly focus on explaining the differences before the new version update and after the new version update.

Following the two data collection methods mentioned above, we obtained all the data to evaluate the new game version update performance according to the metrics defined by the FTM as shown in Figure 2. Through the comparative analysis of these data, we can analyze the IOS App Store and Google Play new version update respectively, and provide a comprehensive evaluation for the new version update. Since the player attributes from Google Play and the App Store are different, we plan to further analyze how much of a difference the same new version update makes.

New version rating analysis

According to the evaluation proportion analysis of the new version, as shown in Table 1, after the release of new game version 2.7, the average evaluation score of the IOS App Store is 4.7, which is 0.3 higher than that of the previous version 2.6.3 with an improvement of 7%. Therefore, the update of the new IOS version is well received by the IOS players. It can be seen that the content of the new version has a good attraction to IOS players and also a good reputation among the IOS players.

Contrast Items	IOS Before Update	IOS After Update	IOS NVCR
IOS Install	2,608	2,739	5%
IOS AVG DAU	6,529	6,745	3%
IOS Net Revenue	2,311	3,655	58%
IOS Paying User	225	282	25%
App Store NVR	4.4	4.7	7%

Table 1: Game IOS new version update contrast.

However, there is no difference between the players' rating of the new version and the old version in the Google Play channel, which both are 4.7 (Table 2). From this case, we can see based on this rating that it is difficult to determine whether the players on Google Play hold a positive attitude towards the new version update. The main reason for the existence of the difference is that the players' rating on any of the mobile platform has certain randomness. Compared to all players, only some of the players will take the initiative to give comments to the new version, so there are still players who didn't participate in the reviewing. Therefore, we can hardly draw a correct conclusion for the evaluation of the new version update only through channels' ratings. So in order to solve this problem, we provide the guideline on how to use our FTM to evaluate the new game version performance. According to our FTM metrics, we need to combine the ratings with the in-game data for comprehensive evaluation such as the install, paying user, DAU and revenue. These metrics are shown in Table 1 and Table 2 for IOS and Android respectively.

Contrast Items	Android Before Update	Android After Update	Android NVCR
Android Install	13,911	14,727	6%
Android AVG DAU	41,596	42,075	1%
Android Net Revenue	7,365	11,307	54%
Android Paying User	910	1,484	63%
Google Play NVR	4.7	4.7	0%

Table 2: Game Android new version update contrast.

Install analysis

We can see from Table 1, after the release of the new game version 2.7, the new install player of the IOS App Store reaches 2,739, which is 5% higher than the previous version 2.6.3. For the Android Google Play, as shown in Table 2, the new install player reaches 14,727, which is 6% higher than the previous version 2.6.3. It seems the update of the new version has a good attraction to the new install players. However, the increase in new install is also related to marketing promotion efforts. It is difficult to evaluate the overall new version update performance only through this change, so we also need to consider the changes from other related metrics.

Paying user analysis

As for the paying user analysis, we can see from Table 1, after the release of the new game version 2.7, the paying users for IOS App Store reach 282, which is 25% higher than the previous version 2.6.3. For the Android Google Play, as shown in Table 2, the paying users reach 1,484, which is 63% higher than the previous version 2.6.3. It can be seen that the new version update has contributed to the payment with more paying users. However, it still needs further analysis of whether these paying users are mainly the new install users or old users.

Revenue analysis

Revenue analysis is an important metric to measure the effectiveness of new versions of the game. We evaluate the impact of version updates on game revenue. Specifically, from the perspective of whether users pay for new versions of content, i.e. to explore whether the new version of the content is enough to attract players to pay. Besides, in the new version update of mobile games, usually, there are some in-game discounts and promotions around the new version update. These events play an important role in maintaining active players and promoting the players' payment. To ensure the new content is welcomed by players and attract more players to pay, the analysis of revenue changes are also meaningful for guiding game development. In order to evaluate the effectiveness of this new version update, especially in terms of revenue performance, we collected daily revenues. These revenues include seven days before the new version update and also seven days after the update. These revenues include IOS App Store revenue and also the Google Play net revenue after deducting the channels' 30% share.

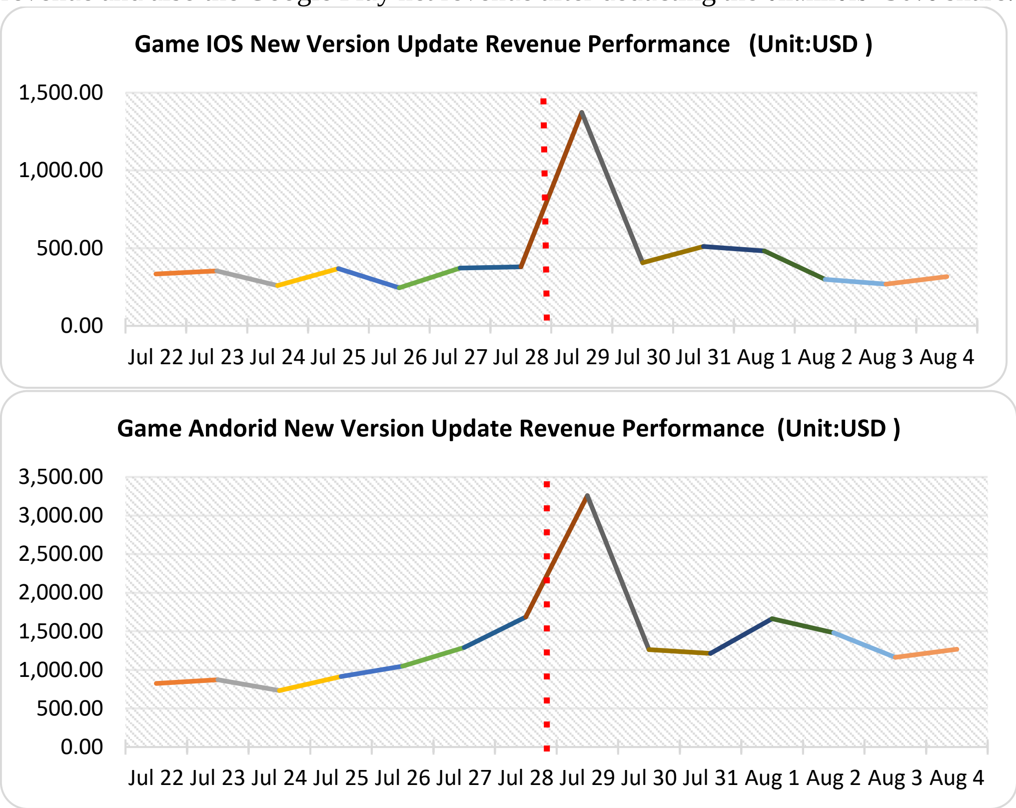


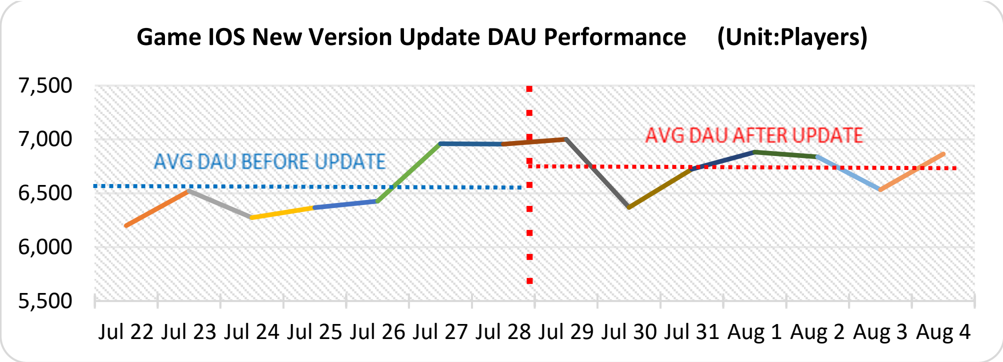
Figure 6: New version update revenue performance on Android (lower) and IOS (upper).

As shown in Figure 6, through the changes in the revenue curves, it shows that after the new game version update on July 28th, the overall game revenue increased. Especially on the second day after the version update, the revenue growth was significant. In short, the revenue for the IOS channel increased by 58% after the new version update, and the revenue for the Android channel increased by 54% after the new version update.

DAU analysis

In addition to the revenue analysis, in order to analyze to what extent the increase in revenue depended on few highly active players, we introduce the DAU metrics to measure how many players are attracted after the new version update. DAU represents how many players are active every day in the game, where active is defined as how many players access the game every day. DAU can faithfully reflect the players' activity in the game. Generally, during the mobile games publishing process, with the continuous iteration of new versions, DAU will change dynamically. It also objectively reflects the players' attitude for the new version update.

As with the revenue analysis, we collected the DAU values for the game, seven days before the version update and seven days after the version update, as shown in Figure 7. By comparing the average DAU changes, we can conclude that the new version update has an overall impact on the DAU.



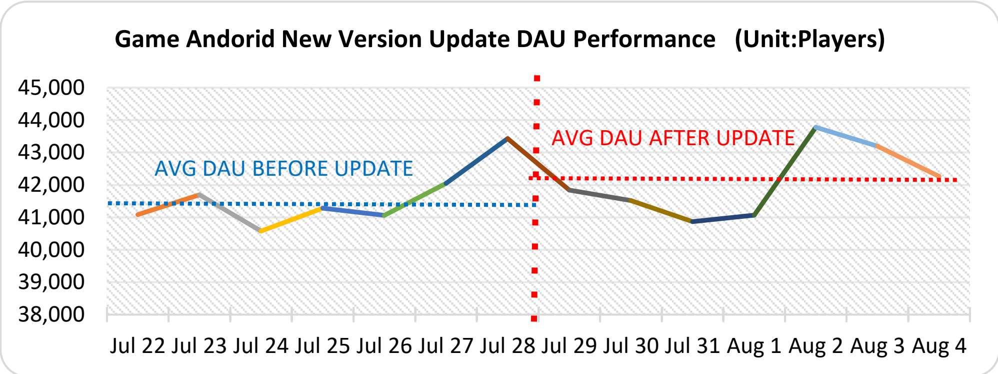


Figure 7: New version update DAU performance on Android (lower) and IOS (upper).

As shown in Figure 7 and Table 1, the IOS channel's new version update leads the average DAU to increase and reaches 6,745 (the red dotted line) compared with the previous version of 6,529 (the blue dotted line). This is an increase of 3%. However, from the Google Play channel, the new version update makes the average DAU reach 42,075 (the red dot line) which is 1% higher than the previous version of 41,596 (the blue dot line). It can be seen that the new version update also increased the DAU both for the IOS and Android channels.

Correlation analysis

As comparative analysis only focuses on similarities and differences in the values of individual variables it is really hard to see the relationship between different variables. Based on the FTM and also the related metrics, we need to take our data-driven FTM and the corresponding analysis method to a higher level and deeply explore the relationship between new game content, active players and the revenue. We choose the correlation analysis method to do this. The correlation analysis can help the game developer to deeply analyze variables related to the game version update.

Correlation is a way of assessing the relationship between variables. It measures the relationship between two variables. It uses the linear product-moment correlation coefficient known as Pearson's correlation coefficient γ, to express the strength of the relationship (Lee Rodgers and Nicewander, 1988). Based on the value of γ, we can figure out the relationship between variables X and Y.

We calculate the Pearson's correlation coefficient for the new version update variables both for the IOS and Android versions and plot the correlation figures shown in Figure 8 and Figure 9 using the R language. For the new version update correlation analysis, if the correlation between two variables is stronger, the graph formed by them is closer to a linear distribution. Conversely, the graph is closer to the circular distribution when the variables are uncorrelated. The darker the graph, the stronger the correlation. Blue indicates a positive correlation and red indicates a negative correlation. The graph composed of two variables corresponds to the correlation coefficient between the two variables.

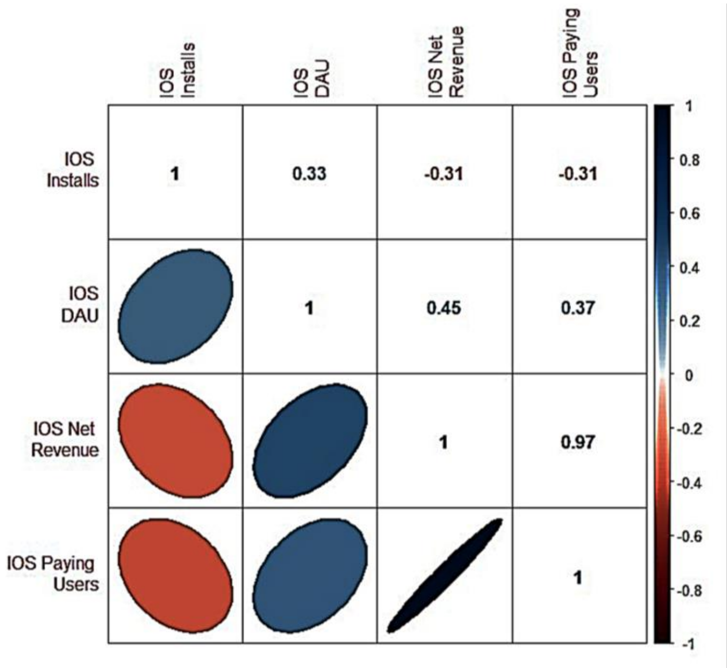


Figure 8: IOS new version update correlation analysis.

For the IOS channel, as shown in Figure 8, the installs variable has a poor relationship with in-game DAU and also the revenue. As the correlation coefficient γ between the IOS installs and IOS DAU only reaches 0.33 and the correlation coefficient γ between the IOS installs and IOS revenue is -0.31. So based on the correlation analysis, we find out a potential issue for IOS that the new install players have less contribution to this new version update, both for the DAU and revenue.

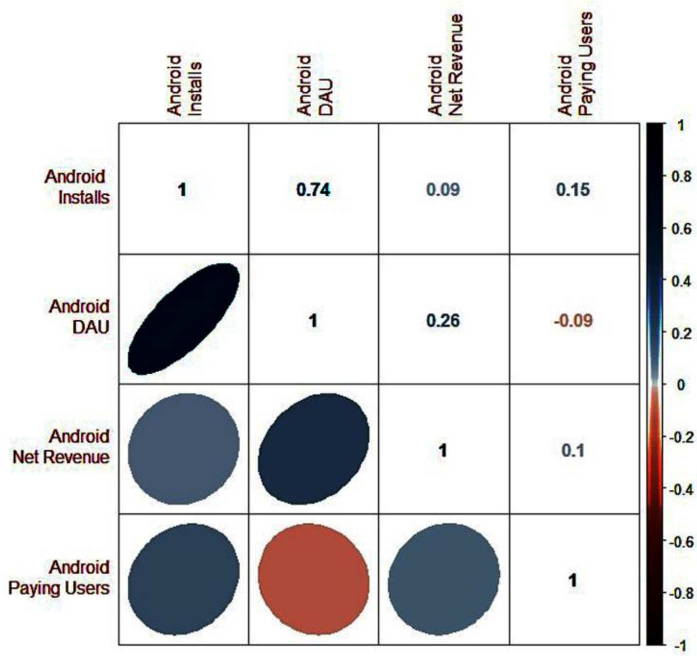


Figure 9: Android new version update correlation analysis.

For the Android channel, as shown in Figure 9, the correlation coefficient γ between Android installs and Android DAU reaches 0.74. This means that the Android installs and DAU have a strong relationship, as most of the DAU from the Android channel is new installed players. However, the correlation coefficient γ between Android install and Android revenue only reaches 0.09 and the correlation coefficient γ between Android DAU and Android revenue reaches 0.26. The same issue for Android new version update, that the new install players have less contribution to the revenue of this new version update. So we suggest the indie game developer to improve the new content and attract more new install players to get more revenue for the next version update. To be specific, we suggest the indie game developer to add a first payment reward for the next new version update which mainly targets the new install players and improves the payment.

However, for the same new version content, we also found some differences between IOS and Android channels. Through correlation analysis, we found that the correlation coefficient γ between installs and DAU in the IOS channel was only 0.33. The correlation coefficient γ between installs and DAU in the Android channel reached 0.74. As the definition of DAU includes the new install users, so it can be seen that most active users in the Android channel are new users, while only a small proportion of active users in the IOS channel are new users. Therefore, we suggest increasing the new user acquisition for the IOS channel in the future version update.

In short, based on the correlation analysis, we find out the potential publishing problems behind the data related to the new version update. We also provide the suggestion to the indie game developer to improve the new install players' performance for the next version update. Such as adding the first payment rewards for the new install players to improve the payment and increase the new user acquisition for the IOS channel. Besides this, for this new version update, the install and DAU have no obvious relationship with revenue, both for Android and IOS channels. So that is also the main reason why we need to consider the install, DAU and revenue separately for the new version update performance evaluation.

CONCLUSION

In this paper, we propose a procedure for how to use the FTM to evaluate new version update performance. We involve an indie game studio publishing project and give guidance about how to use FTM to evaluate their new version update. *Step 1*, based on the FTM metrics, we collect the new version update performance evaluation data. It includes the in-game data such as the install, DAU, paying user, revenue data and also the players' rating data from App Annie. *Step 2*, after receiving the relevant data from the previous step, we provide the solution to do the data analysis for the new version update including the comparative analysis and also the correlation analysis. The comparative analysis is used for comparing the data changes before the new version update and also after the new version update. The correlation analysis is used for finding out all the variables relationships with the new version update. *Step 3*, based on the FTM, we also discuss the reason why we need to do the correlation analysis and find out the relationship among the input new content, active players and the output revenue. *Step 4*, based on the analysis result, we finally point out the weak performance of the new install players and suggest the indie game developer to improve the new install players' performance for the next version update which includes adding first payment rewards for the new install players to improve the payment and also increasing the new user acquisition for the IOS channel.

As for the indie game developers, most of them lack experience in game publishing (Guevara-Villalobos, 2011) and they do not know how to transfer users into loyal and also paying players (Mendez, 2011). Based on our data-driven model, we provide a guideline about the mobile game publishing new version update performance. It is crucial for mobile game developers to make the right decisions about version updates during the game publishing process. So for new features, new functions, new systems and the new events in the mobile game new version update, if welcomed by the players, developers can continue to develop along the ideas and directions to enhance the game fun. If the players dislike the updates, mobile game developers can change instantly. We apply our model to the indie mobile game project and the result shows that from the install, paying user, revenue and DAU side, the new version update performance is good both for IOS and Android channels. However, based on the correlation analysis, we also find out that the new install players' performance for the next version update still needs to be improved by game development, especially for the new install players' payment.

As for the launched games, the key tasks for publishing are maintaining active players and increasing revenue (Macgregor, 2019). Through our case study, we can see that the evaluation of mobile game new version updates is a comprehensive evaluation process. If game developers rely on only certain metrics and ratings, it is difficult to get a trustworthy evaluation result. The players' rating is the general method to get feedback about the new game version. However, considering the shortcomings of the players' rating, such as that not everyone will give comments and ratings for the new version update, we need to consider other relevant metrics as well. It is necessary to combine the changes of in-game data for comprehensive analysis. In accordance with our proposed FTM and corresponding metrics, we consider the App Store and Google Play rating for the mobile game new version update separately, as player attributes from these channels are different. We also introduced in-game core data such as install, paying user, revenue and DAU changes before and after the update for the evaluation. Besides these, we also provide the comparative analysis method for New Version Rate, install analysis, paying user analysis, revenue analysis, DAU analysis and also the correlation analysis for analyzing all variables related to the game version update. By combining the two analysis methods, we find out the reason behind the data, especially that the new install players have less contribution to this new version update. This indicates that our data-driven model can give guidance to the new version update performance evaluation and provide the suggestion to the new version development.

FUTURE WORK

In this paper, based on the previously proposed FTM, we propose a set of metrics that we combine for a specific mobile game new version update case study and give evaluation guidelines. This research can help indie game developers to evaluate their mobile game new version updates performance by using several in-game data and Google Play and App Store version ratings. In the current case, our data-driven model FTM has been used for F2P games. However, for Pay-to-play (P2P) model games, as game developers only focus on download data, it is difficult to get more in-game data. So there is a need for future research on how to evaluate the effect of the new version update for P2P games. Besides this, in the future, we plan to further optimize and iterate our model for indie mobile game publishing including new metrics and data analysis methods. Our data-driven model can help indie game developers to understand the essence of game publishing in-depth and find out the relationship between the input, in-game players and output. Through our research, indie game developers can use the simplest method to evaluate the performance of their game publishing and solve the potential problems encountered in mobile game publishing.

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