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A METHOD FOR CHURN ANALYSIS OF NEW USERS OF MOBILE GAMES USING PROCESS MINING

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Abstract. *These days most mobile game applications (apps) can be downloaded for free by users. That is to say that basically users can play games without payment. Revenue from mobile games is generated primarily from additional payments for items by in-app purchasing. However, it is not easy to lock new users into a mobile game, as it is a highly competitive market with a large range of mobile games available. Currently, mobile game companies in Korea are trying to analyze the leaving behaviors of new users using funnel analysis, a type of churn analysis. In particular, in the mobile game industry, the initial game play patterns of new users are very important as most new users leave the game on the day that they join it. In this study, we propose a new framework for analyzing users' initial churn patterns using process mining techniques. The framework consists of 3 steps: data preparation, comparative user behavior analysis, and discussion. In the comparative user behavior analysis step, users' game play processes are analyzed in order to detect game playing patterns. In addition, users are classified into either a churn user group or a retention user group. The churn user group is defined as the user group who leaves the game on the day of joining. The retention user group is defined as the user group who plays the game continually. We suggest a method for comparing the differences in performance between the two groups.*
Keywords: Churn analysis, Funnel analysis, Mobile game, Process mining, User pattern analysis

1. **Introduction.** The mobile game industry in Korea has gained increasing attention since the establishment of the first domestic mobile game company COM2US in 1998. With the advent of smartphones, the mobile game industry has grown explosively, and it has now been combined with social platforms such as KakaoTalk, Band, Facebook, and others.

The market size of the Korean mobile game industry in 2015 was estimated to be about 4.0 trillion Korean won, and to have grown by 23.3% over the previous year (from 2.9 trillion Korean won). It is also expected to record a growth of over 10% in both 2016 and 2017 [9]. According to Newzoo, a specialized research company, the compound annual growth rate (CAGR) of the global mobile gaming market from 2014 to 2018 is estimated to be 15.9% [10].

People who have a mobile device can play mobile games anytime and anywhere with portability, accessibility, and simplicity that is not available with other platforms such as a PC, or with online and console games [4]. Users can also download almost any mobile games for free on their own mobile devices, unlike the app purchasing of the past. Mobile games come in a variety of genres including RPG (role-playing games), MMORPG (massively multiplayer online role-playing games), FPS (first-person shooter), puzzles, sports, adventure, strategy/simulation games, and so on.

However, these advantages lead to intense competition for user acquisition between the mobile games. Users of a particular game can quickly lose interest because they can easily play and enjoy other mobile games. The initial churn rate is very high due to the wide accessibility of mobile games [3]. In most mobile games, new users leave games at a rate of approximately 60%-70% within one hour of the day of app installation. Therefore, to better retain these novices who are leaving games, it is necessary to analyze their playing processes and to try and discover any playing patterns.

Many mobile game companies conduct a funnel analysis to analyze user churn behavior. Funnel analysis is one of the analysis techniques used to analyze customer churn. It allows analysts to track users according to a defined set of steps, and it enables the checking of how many users stay on each of these stages. Further, it allows churn users who did not complete the pre-defined whole process to be found [18].

However, funnel analysis has limitations as it relates the churn frequency and ratio only to a set of steps that must be defined before it begins. Process mining can more accurately discover the behavior of players as it can discover a process model from actual whole logs. In addition, the process mining technique discovers process models via a variety of algorithms, and it also makes it possible to visually replay extracted logs by animation [14,15].

In this study, we present a framework for analyzing user churn by exploring the process of initial users' behavior. According to the framework, we can find the causes of the churn from the perspective of the process.

The remainder of this paper is organized as follows. Section 2 presents related work on process mining and churn analysis. Section 3 describes the churn analysis framework in mobile games using process mining. Finally, Section 4 offers conclusions.

2. Related Work.

2.1. Process mining.
Process mining is a process perspective technique that allows the discovery of the as-is operation processes from event logs [14,15]. It extracts meaningful information from real event logs generated by information systems [16]. Recent process mining case studies are available from a variety of industries including such diverse areas as health checkups [6], ship building [2], web server logs [19], and accommodation [5], amongst others [17].

As shown in Table 1, there are three main types of process mining: discovery of process models, conformance checking, and enhancement [14].

TABLE 1. Types of process mining

Type	Description
Discovery of process model	End-to-end process models can be visually discovered. Generally, a business process may be very complex. Nevertheless, it can be discovered and presented by various notations such as petri-net, and BPMN using α-algorithm, heuristic, and fuzzy algorithm [14,16].
Conformance checking	This checks the compliances between actual discovered processes and applied standard processes on the current information system [14,16].
Enhancement	The current process model can be improved or extended using analysis results of the above two types of performance analysis. It can be further divided into two sub types: repair and extension [14,16].

In this paper, we suggest a framework for establishing countermeasures about new users' churn of the mobile game. It involves 3 steps for the churn analysis: process discovery, pattern analysis, and performance analysis.

2.2. **Churn analysis.** Churn analysis is an important analytical method for preventing customer churn and it has mainly been applied to banking, insurance, finance, telecommunications, and so on [7,12]. Some research about churn analysis and prediction has been conducted in the PC online game area. Feng et al. analyzed user churn and update effect using individual characteristics, and login patterns based on plot analysis of UV (unique visitor) over time [13]. Kawale et al. studied social influences on predictions of user churn using the modified diffusion model [7]. However, existing researches were not analyses of churn users' behavior patterns from the perspective of process in games, but rather analyses or predictions of UV such as DAU (daily active user), WAU (weekly active user), and MAU (monthly active user) over time. There also exist researches on churn analysis and prediction using an HMM (hidden Markov model) in mobile games and online social games. However, applying different churn analysis and predictions depending on the usage environment of different game platforms remains the domain of future research [8]. In this study, we present a scheme to analyze the churn reasons of new users by exploring the lifecycle of their game playing in the mobile environment. Most existing studies have focused on churn analysis based on UV overtime, but this study differs from these existing studies at this point.

3. **Churn Analysis in Mobile Games Using Process Mining.** To analyze churning (or exit) patterns of new users on the day of joining in a mobile game, it is necessary to classify two groups: a churn users group and a retention users group. As shown in Figure 1, the proposed framework for churn analysis is composed of 3 steps (data preparation, comparative user behavior analysis, and discussion).

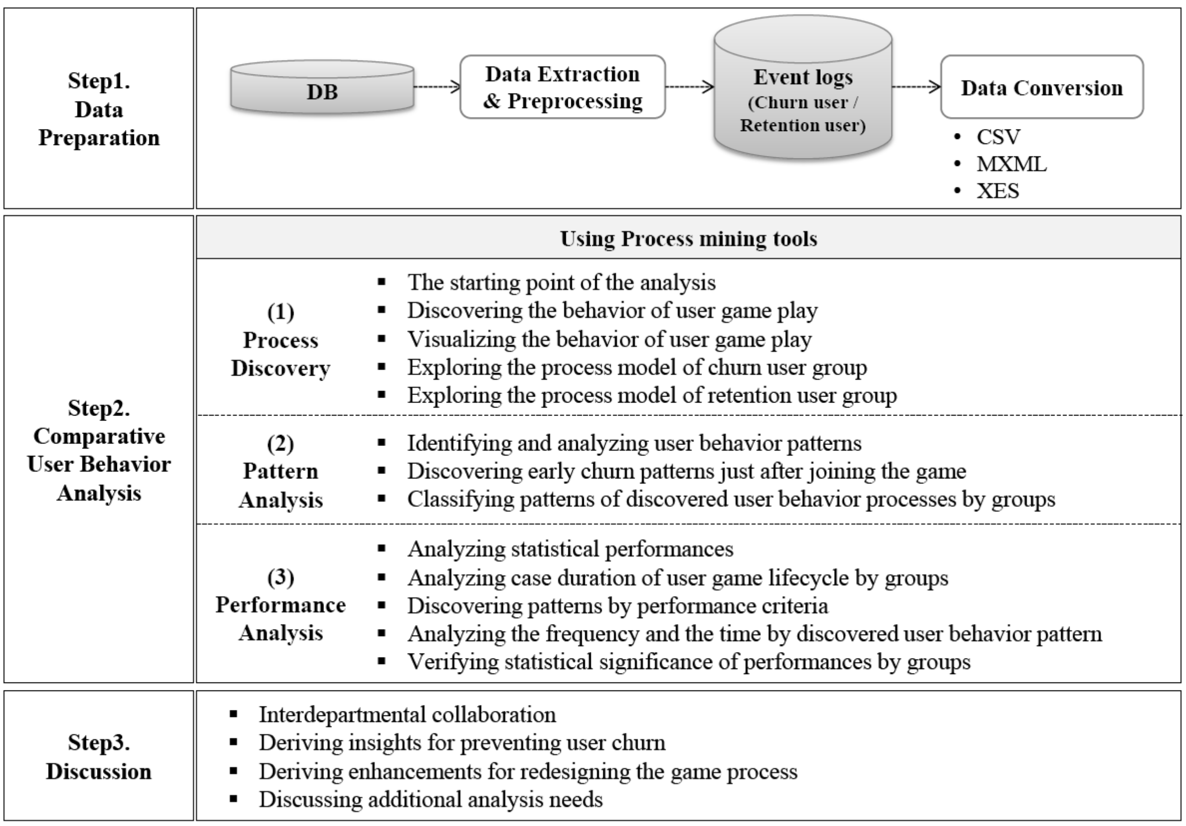


Figure 1. Churn analysis framework in mobile games using process mining

3.1. **Data preparation.** This step is composed of data extraction, preprocessing, grouping sets of event logs, and data conversion according to the analysis criteria. To analyze the churn in this framework, prior to the analysis, some pre-defined analysis criteria considering mobile game characteristics are required: churners (or churn users), activity, and logout [8].

3.1.1. *Defining churners.* User churn can be generally defined as a state of leaving the game permanently [8]. However, if a mobile game is continuously serviced, churn users can return to the game by special updates, events, or friends' invitation.

Therefore, in order to properly analyze churn by this framework, churn users should be defined as being in an inactive condition from the day of joining for a period of 7 days, 14 days, 30 days, or 100 days respectively on that game for the analysis needs. These are the criteria of churn used by almost all mobile game companies. For example, users who have no access to the game for 14 days after the day of joining can be defined as churners and if they reconnect to the game once more after the day of joining they will be defined as retention users. With the adoption of such definitions of churners and retention users, comparative user behavior pattern analysis can be conducted using process mining.

3.1.2. *Defining activity.* In this framework, we do not consider all of the log data of touch streams in order to basically discover the cause of churners in their behavior pattern in the game. Therefore, an activity is defined and recorded when there are any value changes in the game such as goods, paid items, levels, and experience points by user action. Further, the definition of an activity can be modified by analysis needs such as stages, levels, and stages with levels.

3.1.3. *Defining logout.* Commonly, end activity may not be recorded as 'logout' on the event logs according to the features of mobile devices and games. When the user ends the game, 'logout' should be recorded on the event logs after a certain time but there are no 'logout' activities in many cases. In this study, we define the last event of each user as 'logout' activity for the churn analysis of new users who leave the game on the day of joining.

3.2. **Comparative user behavior analysis.** In order to perform effective churn analysis in mobile games using this framework, it is necessary to set the following basic analysis goals:

1) Are the new users playing the game in the manner intended by the game designer?
2) Are there differences of play patterns between churners and retention users?
3) What are frequent play patterns that lead to leaving the game on the day of joining?
4) Which activities influence the churning of churners?
5) Are there differences in the performance of users such as play duration, events, and frequency between churners and retention users?

Step 2 in Figure 1 is composed of process discovery, pattern analysis, and performance analysis for comparative user behavior analysis. Figure 2 shows comparative analysis results between churn group and retention group of an example case. Here, the churning point is the end activity of the churn group, and the end activity of the retention group is the point of exiting the game on that day.

Analysts can find some implications or answers about the first and second of the above analysis goals from the "Process Discovery" phase (labeled (1) in Figure 2). The second, third, and fourth analysis goals can be partially solved at the "Pattern Analysis" phase (labeled (2)). Finally, the fifth analysis goal can be achieved by exploring the dotted chart in the "Performance Analysis" phase (labeled (3)).

Process discovery is the starting point of churn analysis. Here the analyst can discover and visualize user behaviors in mobile games. Further, it is possible to discover core processes and make a comparative analysis by defining activities at stage, level, stage

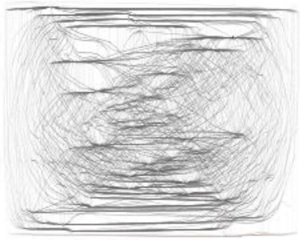
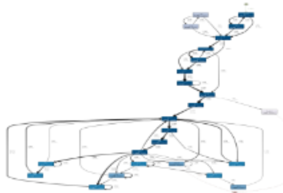
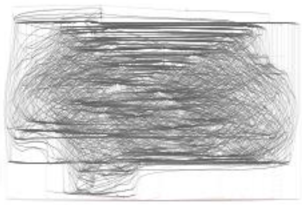
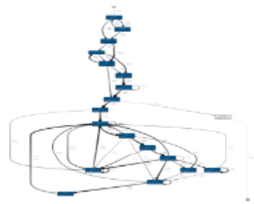
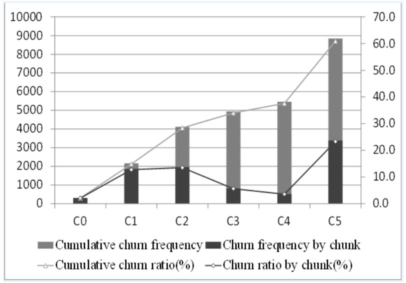
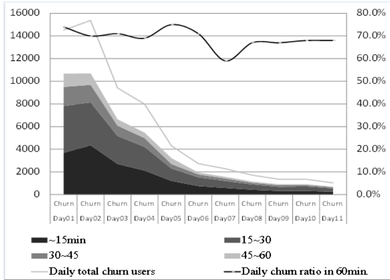
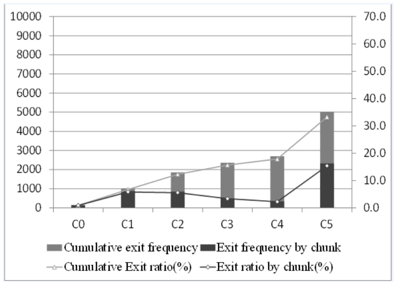
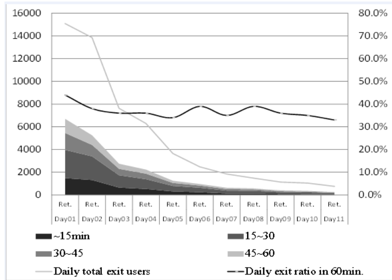
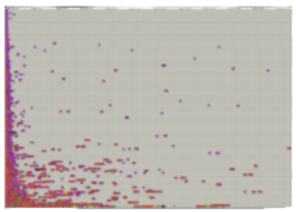
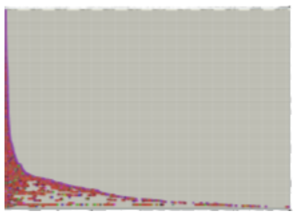
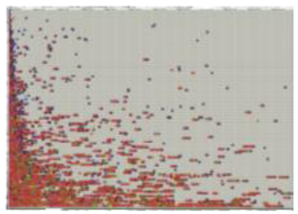
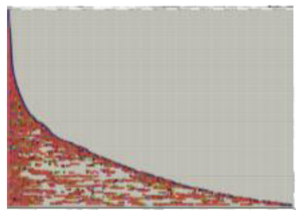
Analysis examples	Churn group		Retention group	
(1) Process Discovery (Users behavior on the mobile games)	 Discovered behavior of whole churners	 The most common churners behavior	 Discovered behavior of whole retention users	 The most common retention users behavior
(2) Pattern Analysis (stage, level, time, etc.)	 Discovered pattern by activity chunk	 Churn ratio by time Every 15mins (up to 60mins)	 Discovered pattern by activity chunk	 User exit ratio by time Every 15mins (up to 60mins)
(3) Performance Analysis	 Dotted chart by the number of events	 Dotted chart by the play duration	 Dotted chart by the number of events	 Dotted chart by the play duration

FIGURE 2. The examples of comparative user behavior analysis

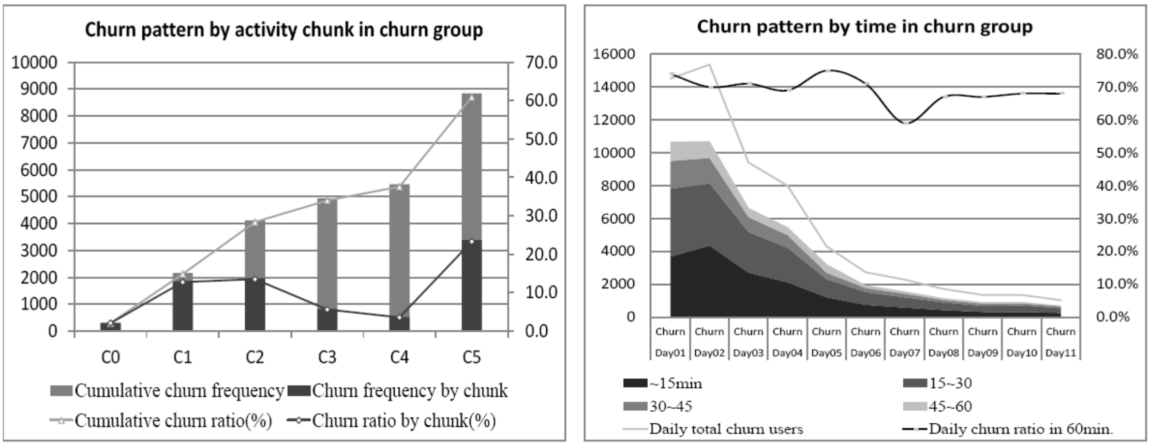


FIGURE 3. The examples of churn pattern analysis (left: by chunk, right: by time)

with level, and so on within the groups. In particular, if the analyst defines the activity as level, it is possible to analyze huddles on level growing process of user characters. And if the activity is defined as stage, information about the stages causing users churn will be discovered. These are very important factors causing the churn of new users. Churn analysis can also be conducted by counting the frequency of the end activity's chunk and by connecting relationships between activities as paths.

The pattern analysis phase explores some of the patterns from the discovered process. Activities should be well defined according to the analysis purposes in order to detect the causes of churn effectively.

Currently, most mobile games provide tutorials and an initial guide for the adaptation of new users. Despite such efforts, about 60%-70% of new users leave the game after the end of the tutorial or initial guide stage. Therefore, it is important to discover patterns of churn on the beginning processes of account joining, tutorials, and initial guides and to check the causes of users churn. Further a comparison between groups at the process of the same level also needs to be performed.

In Figure 3, we expand some examples of the pattern analysis in the churn group in Figure 2. In the chart on the left side of Figure 3, each chunk is set by related activities such as stage start, stage end, or level up. It is possible to analyze the causes of users churn from activities. At the very beginning of the games, some slopes have a steep angle. If the churn ratio rises suddenly, chunks such as C2 and C5 in Figure 3 need to be checked, and these are considered points of churn. This pattern analysis can be used to analyze churn causes from all types of user behavior, which is different from funnel analysis used for tracking a defined set of steps.

In the chart on the right side of Figure 3, we can analyze the time slots when many users are leaving the game. About 70% of new users in the churn group leave the game within one hour. While the daily total number of new users in the churn group is rapidly reduced, the user churn ratio for the first hour is maintained at about 70%.

Finally, in the performance analysis phase, the performances of users in areas such as case frequency, case duration, and play duration are analyzed and compared between the two groups. Performance analysis using dotted charts shows visually frequency and duration in the game from the perspectives of absolute time and relative time. In particular, if the dots are selected as new users, the whole new users' lifecycle can be shown effectively from the perspective of relative time. When the dots are selected as activities, how many users play or use the activities can be checked, and the effects of game updates can be analyzed.

3.3. **Discussion.** In this step, insights for preventing churn of new users should be derived based on the results of the analysis. Discussions on answers to the specific analysis goals mentioned in Section 3.2 should be conducted. Interdepartmental collaboration between business, development, and operation teams is vital. In addition, discussions may be required about further analysis according to additional needs that may arise.

4. **Conclusions.** In this study, we proposed a framework for churn analysis of new users who leave mobile games on the same day of joining using process mining. Process discovery of user behavior in mobile games plays an important role for understanding as-is operation level. And also, depending on the definition of an activity, it is possible to analyze contents which users like or dislike. Especially, by performing the pattern analysis on a longer time period, it can extend the life cycle of the mobile game.

In this paper, due to the concerns on enterprise information security we could not present a detailed case study based on our framework. We hope to present the results of such an analysis in the future. Future research includes the design of a mining algorithm for automatic churn analysis and implementation of a plug-in module on the ProM [1,11,16].

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