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# User segmentation for retention management in online social games

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ABSTRACT

This work proposes an innovative model for segmenting online players based on data related to their in-game behaviours to support player retention management. This kind of analysis is helpful to explore the potential reasons behind why players leave the game, analyse retention trends, design customised strategies for different player segments, and then boost the overall retention rate. In particular, a new similarity metric which is driven by players' stickiness to the game is developed to cluster players. Three feature dimensions, namely engagement features (e.g., log-in frequency and length of log-in time), performance features (e.g., level, the number of completed tasks, coins and achievements), and social interactions features (e.g., the number of in-game friends, whether or not to join a guild, and the guild role), are employed and aggregated to derive the stickiness metric. The applicability and utility of this new segmentation model are illustrated through experiments that are conducted on a realistic MMORPG dataset. The derived results are also discussed and compared against two benchmark models. The results reveal that the new segmentation model not only achieves better clustering performance, but also improves player's lifetime prediction by better distinguishing between loyal customers and churners. The empirical results confirm the effects of social interaction, which is usually underestimated in the current research, on player segmentation. From an operational perspective, the derived results would help game developers better understand the different retention-behaviour patterns of players, establish effective and customised tactics to retain more players, and boost product revenue.



## 1. Introduction

With the development and growing popularity of online social games, game data mining has become an increasingly significant topic for researchers, game designers, and game developers. Mining in-game data provides a meaningful way for understanding players and their behaviours, preferences, interests, and game life cycles. This knowledge is beneficial for optimising the game design, improving player experience, and maximising game revenue. Although there is a wealth of information hidden in game telemetry data, discovering and extracting useful knowledge and behavioural patterns are not easy tasks. Because the scale of game telemetry data increases exponentially, and the number of variables related to player behaviour analysis are often very large. Some research has been conducted in this area to address questions regarding the classification and clustering of players, player lifetime predictions, and in-game social network analysis. However, scant research has been done on player retention management for online social games.

Retaining players has been considered one of the most critical challenges in online social games. The retention rate is one of the key performance indicator (KPI) used in the gaming industry to evaluate the success of a game. Normally, to attract new players, game operators spend enormous amounts of effort and money to advertise and promote the game before its official launch. It has been well-recognised that acquiring new customers can be much more expensive than retaining existing ones [24]. On the other hand, churners may create negative impacts through unfavourable word-of-mouth reports, and this may result in a further loss of potential and existing players. Effective retention analysis and management can help understand the behaviours of players and reveal the diverse influential factors that cause player attrition, ranging from personal commitment, competing products and services, or shifting interests to social influences. Different players may leave the game for different reasons. By understanding such reasons, game producers can design and implement customised retention campaigns targeted to different player segments.

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Besides having important managerial consequences, retention management of online social games is also of great theoretical importance. Currently, conducting retention analyses in online social games is still at its early stage. Compared to other application domains, one of the most characteristic features of online social games is that it often has a relatively low retention rate [8]. For this reason, the class distribution of churners and non-churners is typically very skewed. The existing work of game retention analysis mainly focuses on player churn predictions [24] and player lifetime predictions [2,45]. For player churn predictions, because of the skewed class distributions, it is more challenging to employ conventional data mining techniques to build useful predictive models, and the high classification accuracy does not necessarily capture the true picture of player churn. Also, the current classification model only segments the players into churn and non-churn groups. In reality, the players' churn behaviour can be more complicated. Different types of players leave the game at different time points and for various reasons. The conventional classification models are incapable of detecting various churn behaviour patterns. Therefore, it is challenging to draw insightful managerial implications for game operators from the classification prediction results. For player lifetime predictions, the approach focuses on the retention behaviour of individual players because it predicts when a certain player will leave the game. From an operational point of view, it is impractical and inefficient to design customised marketing strategies at the individual level. In practice, game operators often employ a general model to analyse the retention behaviours of all players. However, because churners constitute the majority of a social game's player population, their retention behaviours would dominate the analysis if a general model were to be used. This makes it difficult for game operators to analyse the different reasons behind churn and then conduct retention campaigns targeted to prevent different types of churn. In addition, in the gaming industry, a popular way of conducting a retention analysis is to calculate game retention rates at some key time points (e.g., Day-1, Day-7, and Day-28), using such isolated data points makes it difficult to depict the true picture of players' retention behaviour.

To complement the existing literature on retention management for online social games and to do so without creating a general retention model or focusing on individual players, the current study proposes an innovative player segmentation model to support retention management for online social games. The characteristics of retention management in online social games are analysed, and a new metric, termed stickiness, which integrates game engagement, in-game performance, and social interaction feature dimensions, is proposed to cluster players. Extant research only considers the engagement- and performance-related features in clustering players, and the merits of incorporating social interaction attributes in player retention management have not been studied thoroughly. This research overcomes this limitation by proposing a stickiness-based fuzzy C-means (FCM) clustering algorithm that is used to segment players into five different groups from the given dataset. Each player segment has its own characteristics, and the captured retention behaviours are different. Hence, precise retention management strategies can be made accordingly, and precious resources can be devoted to the right player segments to prevent player churn and boost game revenue. In addition, rather than calculating isolated retention rates at certain time points, this approach monitors the retention trends of different player segments continuously over time. This is beneficial for understanding different types of retention behaviours. To further validate this, the proposed model is ompared against two benchmark models, and the results reveal that the new model not only achieves better clustering performance, but also improves players' lifetime predictions by better distinguishing between loyal customers and churners.

The remainder of this paper is organised as follows: Section 2 reviews the related existing works of customer retention and the segmentation of online gamers. In Section 3, a new approach is proposed to manage the retention of players of online social games. Through an empirical study, the effectiveness and utility of the proposed framework is demonstrated in Section 4. The obtained results are analysed and discussed in Section 5. The final section gives a conclusion and indicates future research directions.

## 2. Background

### 2.1. Customer retention

Customer retention is a core dimension of customer relationship management (CRM), and it is gaining particular attention from companies in today's competitive environment. In general, it is assumed that there is a strong association between customer retention and company profitability. The longer a customer stays with a company, the more loyal and valuable that customer becomes. Long-term customers are beneficial to the company in several ways. For example, the cost to serve long-term customers is usually less than serving new ones, and long-term customers can bring in new customers and are usually less sensitive to price differences [6]. Customer retention has been widely studied in several domains, such as insurance, banking [2], online gambling [7,22], retailing [34], telecommunications [6,43,49], service provider-hosted online communities [23], and other areas. Customer retention consists of three stages:

- Stage 1: analyse the important determinants of customer retention
- Stage 2: apply the determinants to predict customer retention (including customer churn and customers' lifetime)
- Stage 3: design and implement policies to improve customer retention and prevent customer attrition.

Most of the existing studies on customer retention mainly focus on Stage 1 (e.g., [22,23,26,37,45]) and Stage 2 (e.g., [2,6,7,24,25,34,43,49]). However, little research has been conducted on Stage 3, such as applying the resultant analysis that is drawn from Stage 1 and Stage 2 to improve customer retention. Kim and Moon [25] claimed that predicting churn probability is not sufficient to build optimal retention management models, and the probability of retention and expected revenues from target customers should also be taken into account. In addition, Chu et al. [6] proposed a hybrid data mining model for customer retention in the telecommunication domain. Unlike previous research, the proposed model in [6] not only predicts possible churners, but also proposes proactive policies to retain these customers. In existing literature, a variety of retention-analysis techniques have been developed for detecting important determinants of customer retention and for predicting potential churners. However, conducting retention analyses in online social games is still in its infancy.

#### 2.1.1. The determinants of customer retention

It is well-recognised that customer retention can be affected by a number of factors; therefore, identifying and analysing the important determinants are crucial to improve customer retention. For example, although competitive pricing may typically drive churn for price-sensitive customers, factors such as service quality, conversion cost, and social ties can also cause customer defection. In addition, the influential factors can be quite diverse in different application domains. For example, Jolley et al. [22] conducted an online gambling experiment to reveal that habit, rather than satisfaction, had a strong impact on customer retention. Weber et al. [45]