Computers in Human Behavior

# Knowledge Discovery of Game Design Features By Mining User-Generated Feedback

**Abstract**

The term “Gamification” is an emerging paradigm that aims to employ game mechanics and game thinking to change behavior. Gamification offers several effective ways to motivate users into action such as challenges, levels and rewards. However, an open research problem is discovering the set of gamification features that consistently result in a higher probability of success for a given task, game or application. The objective of this paper is to bridge this knowledge gap by quantifying the gamification features that are consistently found in successful applications. Knowledge gained from this work will inform designers about the gamification features that lead to higher chances of an application’s success, and the gamification features that do not significantly impact the success of an application. The case study presented in this work leverages demographic heterogeneity and scale of applications existing within mobile platforms to evaluate the impact of gamification features on the success or failure of those applications. The successful game design features identified have the potential to be embedded into interactive gamification platforms across various fields such as healthcare, education, military and marketing, in order to maintain or enhance user engagement.

**Keywords:** Gamification; Game Design Features; Machine Learning; Behavior Change; User Engagement

## 1. Introduction

The term “gamification” is an emerging paradigm that aims to employ game mechanics and game thinking to change behavior. Alternatively, gamification can be defined as the concept of applying game mechanics and game design techniques to engage and motivate people to achieve their goals (Hsu et al., 2013). Google Trends indicates that the term “gamification” was not searched for, prior to the second half of 2010. However, the number of such searches has since increased tenfold since May 2014 (“Google Trends - Web Search Interest - Worldwide"). During the early stages of the video game era in the 1970s, video games were designed to appeal mainly to young males (Janne and Juho, 2012). In the following decades however, the gaming industry began making games that appealed to a wider audience (Terlecki et al., 2010). The success of mobile games such as angry birds and candy crush, has extended the definition of a “gamer” to include a broad range of individuals of all ages and demographics (Heaven, 2014; Terlecki et al., 2010).Statistical evidences obtained from survey data and research studies have discovered that average game is 37 years old and has 12 years of gaming experience (Markopoulos et al., 2015). Moreover, 77% American households own videogames. The percentage of female gamers in United States is 48% (Markopoulos et al., 2015). Forty-five percent of gamers are women, and women of age 18 or older represent 31 percent of the game-playing population. In addition, 68 percent of gamers are adults, with 36 percent over the age of 36 (Bardzell et al., 2008). These statistics provides evidence that the current gamer population is distributed across different age and gender demographics.

The video game industry has been around for over 40 years and has advanced the fundamental understanding of what motivates and engages people. According to Self Determination Theory (SDT) "three innate psychological needs – competence, autonomy, and relatedness – which when satisfied, yield enhanced self-motivation and mental health and when thwarted, lead to diminished motivation and well-being" (Ryan and Deci, 2000). A brief review suggests that video games have developed the ability to provide the basic psychological needs specified by SDT. Over time, video game developers have learned to harness the magnetic engagement and motivational appeal of video games by using the various game design features. Fogg's Behavior Model (FBM) studies the factors that can generate a certain behavior, which is highly applicable for the case of human-computer interactions (Fogg, 2009). "The FBM asserts that for a person to perform a targeted behavior, he or she must (i) be sufficiently motivated, (ii) have the ability to perform the behavior, and (iii) be triggered to perform the behavior. These three factors must occur at the same moment, for the behavior to happen". This temporal convergence of motivation, ability and trigger is why gamification is able to modify, alter and manipulate human behaviors (Fogg, 2009).

The concept of using game design features in non-game contexts to motivate and increase user engagement has rapidly gained traction in interaction design and digital marketing. For instance, Gartner Inc., predicts that by 2015, a gamified service for consumer goods marketing and customer retention will become as important as Facebook, eBay, or Amazon, and more than 70% of Global 2000 organizations will have at least one gamified application (Burke, 2014). Gamification has attracted the interest of marketers, human resource professionals, and others interested in driving user engagement for extended periods time. Some applications of gamification include enhancing employee engagement, creating healthy competition among teams, encouraging customer loyalty, recruiting in military, etc. The applications of gamification have started to gain importance in a variety of fields such as healthcare, education, military, marketing, sales, sustainability, news and entertainment. Gamification is a motivational design problem. From the above discussions, it is evident that understanding the game design features that result in successful user engagement for extended periods of time, is an important facet of motivation. The objective of this paper is to identify the game design features that are common across successful task driven applications, compared to those game features that are found in unsuccessful task driven applications. These identified aspects can then be embedded into interactive gamification user platforms to achieve various goals in a variety of fields. This paper is organized as follows. This section provides an overview of gamification and outlies the motivation for this work. Section 2 reviews research conducted in the past. Section 3 outlines the methodology. Section 4 describes the case study based on mobile games and section 5 discusses the research findings from the study. Section 6 concludes the paper and highlights several possible areas for future research expansion beyond this work.

## 2. Literature Review

Figure 1, along with several peer reviewed publications presented in this section, clearly indicate the popularity of "gamification" as a subject of interest in the research and application domains. In the second half of year 2010, interest in gamification peaked due to studies showing an impact on the efficacy of gamification in non-gaming contexts. Researchers started studying the effect of using gamification strategies in non-gaming environments to motivate users and increase productivity (Lucassen and Jansen, 2014). In the healthcare context, gamification strategies helped patients recover from physical and mental wellness by enabling them to better adhere to their treatment regime (McCallum, 2012). Educators in academia have experienced a change in the behavior of students, based on the application of gamification (Goehle, 2013). Such work has led to the evolution of a variety of gamification applications targeted at augmenting human behavior (Read J and Shortell SM, 2011).

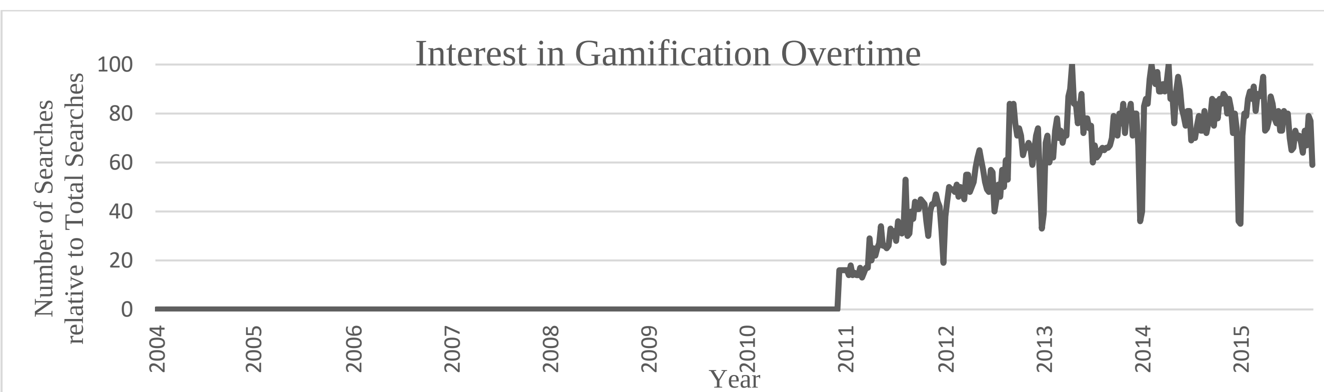


Figure 1: Interest in Gamification over time

*2.1 Application of Gamification in Non-gaming Domains*

In education, gamification has been successfully used to increase student engagement and participation (Denny, 2013; Fitz-Walter et al., 2011; Goehle, 2013) and enhance learning (Li, Grossman, and Fitzmaurice 2012; Cheong, Cheong, and Filippou 2013; Dong et al. 2012). Fitz-Walter et al. investigated the use of game achievements within Orientation Passport, a mobile application designed to help university students learn about their campus during the orientation phase of the semester. Orientation Passport utilizes game achievements to present orientation information in an engaging way and encourage students to visit and learn about various places at the university. In another recent study, Denny investigated the impact of incorporating badge-based achievement systems within an online learning tool for students and concluded that students enjoyed being able to earn badges, in addition to having them available in the user interface (Denny, 2013).

Gamification has been proven to enhance the quality of learning by better engaging students with learning activities. GamiCAD (Li et al., 2012) is a gamified tutorial system for AutoCAD users with real-time audio and video feedback. Users reported faster task completion times and found the experience to be both more effective, engaging and enjoyable with the gamified version of the tutorial. Dong et al. created *Jigsaw*, a learning game that teaches Adobe Photoshop users using image manipulation tasks. Users stated that they were able to explore the application and discover new techniques with this gamified approach (Dong et al. 2012). In a similar study, a gamified multiple-choice quiz application called Quick Quiz, was used by students who reported a positive feedback in terms of the learning effectiveness, engagement and enjoyment generated by the gamified application (Cheong et al., 2013).

There are typically three types of games with respect to health and wellness (i) games improving physical health (Wii Fit, Just Dance, Zumba Fitness, Kinect Sports) (ii) games for cognitive health (e.g., Brain Age) and (iii) games for social and emotional wellbeing (e.g., Nintendo Wii) (McCallum, 2012). In health and wellness, gamification has been able to achieve high compliance and improved quality of life (K. Rose et al., 2013; Stinson et al., 2013). Rose *et al*. studied the effects of a mobile diabetes monitoring app called *mySugr* on the compliance behavior of people with diabetes. Results showed positive effects on testing frequency and blood sugar level and quality of life was subjectively reported to have increased (K. J. Rose et al., 2013). Jibb *et al*. developed *Pain Squad*, a game-based smartphone pain assessment tool for adolescents with cancer. The game-based nature of the application was found to be appealing overall and the built-in virtual reward system was well received by the adolescents, leading to high compliance and satisfaction scores (Jibb et al., 2012).

Marketing is another field where gamification concepts have been successfully implemented in order to induce engagement, brand loyalty and brand awareness. These three key marketing concepts are relevant in the gamification context: engagement – “high relevance of brands to consumers and the development of an emotional connection between consumers and brands” (Rappaport, 2007), brand loyalty – “the relationship between relative attitude and repeat patronage” (Dick and Basu, 1994) and brand awareness, “the rudimentary level of brand knowledge involving, at the least, recognition of the brand name” (Hoyer and Brown, 1990). There has also been work that shows the positive attitude of marketing executives towards adopting gamification in order to improve the above mentioned three marketing concepts (Lucassen and Jansen, 2014).

Literature relevant to gamification in wide range of fields is summarized in Table 1.

Table 1: Gamification Applications in Various Domains

| Domain | Relevant Literature |
|---|---|
| Education/ Learning | (Cheong et al., 2013b; Denny, 2013; Dong et al., 2012; Fitz-Walter et al., 2011; Foster et al., 2012; Goehle, 2013; Li et al., 2012) |
| Health and Wellness | (Cafazzo et al., 2012; Hamari and Koivisto, 2013; Hori et al., 2013; K. Rose et al., 2013; Stinson et al., 2013) |
| Marketing | (Hamari and Järvinen, 2011) |
| Sustainability | (Berengueres et al., 2013; Gnauk et al., 2012; Gustafsson et al., 2009) |
| Commerce | (Hamari, 2013) |
| Crowd Sourcing | (Liu et al., 2011) |

*2.2 Game Design Features*

According to Werbach and Hunter, there are three categories of game features that are relevant to gamification: Dynamics, Mechanics and Components. (Werbach and Hunter, 2012). The authors define the three features as follows:

- *“Dynamics”* are the big-picture aspects of the gamified systems that you have to consider and manage but which you never directly enter into the game. Analogies in the management world would be employee development, creating an innovative culture, etc.
- *“Mechanics”* are the basic processes that drive the action forward and generate player engagement”
- *“Components”* are the specific instantiations of mechanics or dynamics”

Table 2.1 and 2.2 enlist game mechanics and components defined by them (Werbach and Hunter, 2012) and the relevant literature for the successful implementation of each game feature. Table 2.3 presents the mechanics of latent gamification features and their corresponding components. Availability of a wide array of game design features makes it challenging for designers to incorporate all game design features into a single application or game. Though there has been a modest amount of research in evaluating the success of specific game design features, the relationship between successful games and the game design features that they contain, remains an open research question. This paper will focus on identifying the game design features that contribute towards the success of a game. In this paper, *mechanics* and *components* are explored, given that *dynamics* does not directly enter into the design of a game and is more abstract in nature. Knowledge gained from this work will enable designers to incorporate gamification strategies into their decision making processes in order to motivate and enhance user engagement.

Table 2.1: Literature of Various Game Design Features

| Mechanics | |
|---|---|
| Game Design Features | Relevant Literature |
| **Challenges** – Puzzles or other tasks that require effort to solve | (Domínguez et al., 2013; Dong et al., 2012; Flatla et al., 2011) |
| **Feedback** – Information about how the player is doing | (Dong et al., 2012; Gustafsson et al., 2010; Li et al., 2012) |
| **Rewards** – Some benefits that go together for some action or achievement in the game | (Downes-Le Guin et al., 2012; Liu et al., 2011; Li et al., 2012) |

Table 2.2: Literature of Various Game Design Features

| Components | |
|---|---|
| Game Design Features | Relevant Literature |
| **Achievements** – A form of reward attached to performing specific actions | (Fitz-Walter et al., 2011; Liu et al., 2011; Montola et al., 2009) |
| **Avatars** – Visual representations of players' characters | (Berengueres et al., 2013; Downes-Le Guin et al., 2012; Liu et al., 2011; K. Rose et al., 2013) |
| **Badges** – Visual representations of achievements | (Anderson et al., 2013; Denny, 2013; Domínguez et al., 2013; Hakulinen et al., 2013) |
| **Leaderboards** – Visual displays of player progression and achievements | Domínguez et al., 2013; Farzan et al., 2008; Gnauk et al., 2012; Halan et al., 2010 |
| **Levels** – Defined steps in player progression | Domínguez et al., 2013; Dong et al., 2012; Farzan et al., 2008 |

| | |
|---|---|
| **Points** – Numerical representation of game progression | (Farzan et al., 2008b; Halan et al., 2010) |
| **Social graph** – Ability to track progress of friend and enables interaction | (Hamari and Koivisto, 2013; Shi et al., 2014; Simões et al., 2013) |

Table 2.3 Latent Game Design Features

| Mechanics | Components |
|---|---|
| **Chance** – Involvement of luck from a random mechanism | **Boss Fights –** Especially hard challenges at the culmination of a level |
| **Competition** – Getting players to compete against one another | **Collections** – Set of items or badges to accumulate |
| **Cooperation** – Getting players to work together to achieve a shared goal | **Content unlocking** - Unlocks new levels/new features when players reach specific objectives |
| **Resource acquisition** – Obtaining useful or collectible item | **Gifting** – Gives an opportunity to gift things such as lives/points to other players |
| **Transactions** – Buying, selling or trading with other human players or automated players | **Quests** – Predefined challenges with objectives and rewards |
| **Turns** – Sequential participation by alternating players | **Teams –** Defined group of players working towards a common goal |
| **Win states** – The state that defines winning the game | **Virtual Goods –** game assets with perceived or real money value |

## 3. Methodology

This work seeks to discover whether there exists a set of game design features that are common across successful task driven applications. Figure 2 presents an outline of the proposed methodology that includes Data Sampling (3.1), Data Collection (3.2) and Model Generation and Validation (3.3).

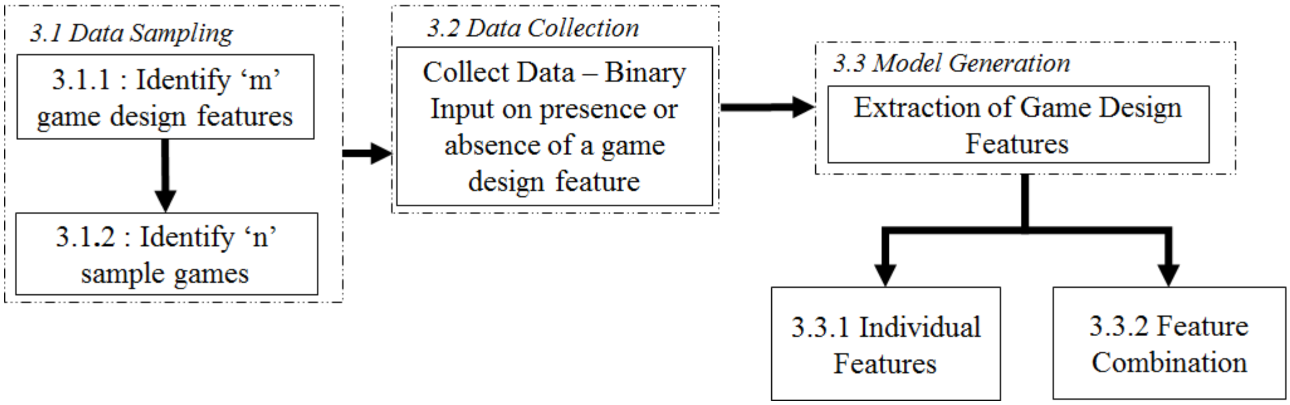


Figure 2: Outline of the Methodology

*3.1 Data Sampling*

*3.1.1 Identification of 'm' game design features*

Game design features are defined as the building blocks or features shared by games and not just mere elements that are necessary for building games (Deterding et al., 2011). In the methodology presented in Figure 2, '*m*' game design features are identified using previously conducted research on gamification and game design. Research on game design features in the past has led to the discovery of a set of game design features. However, there is a knowledge gap between the existence of these game design features and their impact on the success/failure of games. An exhaustive list of game design features is given in Tables 2.1, 2.2 and 2.3. A total of 24 game design features are identified from literature. Due to continuous integration of newly developed features into games, it is possible that the game design features considered in this work are a subset of the total existing game design features that will emerge in the future. The 24 game design features are classified into two main categories: Mechanics and Components. In this work game design features are considered individual entities building a game, in order to avoid preconceived classifications of their functions.

*3.1.2 Sampling of 'n' games to be studied*

To evaluate the impact of extracted game design features, it is essential to identify games that can be played using various gaming platforms such as mobile, PCs, Consoles, etc. Mobile games are becoming ubiquitous in today's society. The number of smartphone users has increased exponentially in the last few years with an increase of over 100 million in a period of one year from 2012 to 2013. Statistics reports in 1990s suggested that 78% of adults in US own a smartphone and according to recent estimates total number of smartphone users was 1.75 billion is 2014 which is expected to grow up to 2.50 billion in 2017 worldwide(Johnson and Maltz, 1996; Munoz et al., 2015). Moreover, a higher percentage of users spend time downloading applications from the platform markets for *iOS* and *Android* (Feijoo et al., 2012; Lee, 2012). Online game or app downloading websites have become popular in recent years due to scalability and ease of use (Purcell, 2011). In this work, games to be investigated are selected based on their ranking in the platform application market. The rank of a game is indicative of its success, compared to other games in the pool (Filho et al., 2014). In an attempt to reduce bias from the end result, it is necessary to select games that are highly successful or ranked and games that are highly unsuccessful. Sampling games in this manner will enable researchers to identify the combination of game features that have an impact on the success as well as failure of a game. The sample games to be studied can either be selected randomly or based on the genre (arcade, action, trivia, etc.) and then classified as successful or unsuccessful based on their respective rankings within the gaming platform market.

### *3.2 Data Collection*

After the identification of game design features and games to be sampled based on the rankings of the games in the gaming market, an '*n* x *m*' binary input matrix is constructed based on the presence or absence of each game design feature (selected in section 3.1.1) on the level of success or failure of a game (selected in section 3.1.2). The binary matrix gets input by analyzing each game for the presence or absence of the game design features identified.

Table 3 Representation of Binary Matrix – State of Game

| Game | Game Design Feature 1 | Game Design Feature 2 | ………. | Game Design Feature 'm' | State of Game |
|---|---|---|---|---|---|
| Game 1 | Present | Absent | ………. | Present | Positive Outcome |
| Game 2 | Absent | Absent | ………. | Present | Negative Outcome |
| . | . | . | ……… | …….. | …………. |
| . | . | . | ……… | …….. | …………. |
| . | . | . | ……… | …….. | …………. |
| Game 'n' | Absent | Present | ……… | Present | Positive Outcome |

Table 3 represents the binary matrix constructed using inputs on game design features and the output of the *state of the game*. The *state of the game* in Table 3, represents whether a game was successful or unsuccessful. A successful game will be a positive outcome and an unsuccessful game will be a negative outcome. The success of a game is based on its ranking in the gaming market (Filho et al., 2014). A higher ranked game is successful, as rankings are governed by the number of users and ratings for the game. Similarly a significantly lower ranked game will be categorized as unsuccessful.

*3.3 Model Generation*

It has been discovered that the market demand of a product is positively correlated with customers' feedback expressed on large scale digital platforms (Tuarob and Tucker, 2015, 2013). It is essential that such feedback is taken into account while designing new products or advanced versions of existing products. Users provide feedback about their experience with a product through ratings. These ratings are aggregated to score the product based on the users' response and ranked in comparison to other products within its domain. Filho *et al*. claimed that rankings of a game are directly related to their success in the gaming market (Filho et al., 2014). Based on the game design features existing in a game, and the success/failure outcome of a game (based on users' feedback measured by the ranking of a game), the impact of i) individual game design features and ii) combinations of game design features on the success/failure of a game can be quantified.

*3.3.1 Model Generation using Individual Features*

The relationship between the presence/absence of the game design feature and the success/failure of the game, is quantified based on a confusion matrix.  Table 4 illustrates a confusion matrix, where the columns represents the presence and absence of a particular game design feature and the rows represents the success/positive outcome and failure/negative outcome of a game, determined based on its ranking. Performance of a classification is evaluated using a confusion matrix, with measures such as *precision*, *recall* and *F-Score*, employed to evaluate the robustness of a classification (Buckland and Gey, 1994). In this work, *precision* (Powers, 2011) represents the ratio of the number of successful games that have a game design feature to the total number successful games with and without that particular game design feature usually expressed as percentage (equation 1).

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{1}$$

*Recall* (Powers, 2011) is the ratio of the number of successful games that have a game design feature, to the total number successful and unsuccessful games with that particular game design feature (equation 2).

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{2}$$

Table 4 Representation of Confusion Matrix

| | | *Game Design Feature* | |
|---|---|---|---|
| | | Present | Absent |
| | Positive Outcome | True Positive(TP) | False Positive(FP) |

| | | | |
|---|---|---|---|
| *Class Variable* | Negative Outcome | False Negative(FN) | True Negative(TN) |

The confusion matrix in Table 4 shows the presence or absence of a game design feature and the categorized state of a game (i.e., positive or negative), based on its rankings. A confusion matrix defines the relation between the true condition (i.e., the presence of a given game design feature) and the predicted condition (i.e., the positive or negative outcome of a game). In this case, True Positive (TP) will be defined as "positive outcome for a game when a game design feature is present". False Negative (FN) will be defined as "negative outcome for a game when a game design feature is present". False Positive (FP) will be defined as "positive outcome for a game when a game design feature is absent" and True Negative (TN) will be defined as "negative outcome for a game when a game design feature is absent".

The *F-Score* is a metric that characterizes the combined performance of both *precision* and *recall*. It is the harmonic mean of *precision* and *recall* (equation 3). The *F-Score* provides a statistical measure of the agreement between the ground truth and class variable. The *F-Score* enables the assessment of a classification algorithm's ability to correctly distinguish between features relevant to a class variable and features irrelevant to a class variable (Huang et al., 2005). An F-Score of 1.0 means that a particular game design feature consistently predicts the success/failure of a game (i.e., with no type 1 or type 2 error). Literature suggests that the *F-Score* is a composite measure that favors algorithms with higher sensitivity and specificity. Classical measures such as *precision, recall* and *F-Score* are frequently used to evaluate the capabilities of algorithms (Sokolova et al., 2006) and will therefore be employed in this work to assess the veracity of the game design feature classification models.

$$F\ Score = 2\left(\frac{Precison * Recall}{Precision + Recall}\right) \tag{3}$$

*3.3.2. Model Generation using Combination of Game Design Features*

While individual gamification features may impact the success or failure of a game, there may be unique game design feature combinations that are better predictors of a game's success or failure. Exploring game design feature combinations requires more complex mathematical approaches beyond single feature confusion matrix models presented in section 3.3.1. If an individual game design feature obtains an *F-Score* of 1.0, it has the potential to drive the outcome of a game to success. However, the complexity of modern games means that more than one feature is typically found in a game. Therefore, it is important to explore feature combinations, in order to quantify their impact on increasing or decreasing the *F-Score* metric. This combination could be the simultaneous implementation of two or more game design features in order to increase the probability of a game being successful. For example, to analyze the impact of a combination of features on the *F-Score*, the confusion matrix in Table 5 is presented.

Table 5 Confusion Matrix for two game design features together

| | | (Game Design Feature 1) U (Game Design Feature 2) | |
|---|---|---|---|
| | | Present | Absent |
| *Class Variable* | Positive Outcome | True Positive(TP) | False Positive(FP) |
| | Negative Outcome | False Negative(FN) | True Negative(TN) |

Table 5 shows the confusion matrix for two game design features being analyzed together. This confusion matrix could be constructed for more than two game design features. The confusion matrix will result in an *F-Score* for the selected game design features, based on the *precision* and *recall* measures. However, selection of these game design features itself poses a computational problem because of the number of permutations generated based on the number of features. From an optimization perspective, the aim is to maximize the *F-Score* by selecting an optimal combination of two or more game design features. For a set of *n* game design features, the total number of permutations will depend of the number of features *r* considered at a time (equation 4).

$$total\ number\ of\ permulations\ P\ (n, r) = \frac{n!}{(n-r)!} \tag{4}$$

It is essential to explore the impact of each feature on every other feature, as there may exist interaction effects between features shared by games (Filho et al., 2014). This process will terminate after obtaining the maximum *F-Score* possible, based on a given combination of game design features. Therefore, as the number of game design features increases, it becomes difficult to sequentially analyze the interactions between various feature combinations. Furthermore, it is difficult to determine the order in which these feature combinations should be evaluated, towards maximizing the *F-Score*. Hence, computationally efficient methods are necessary to generate a model for analysis of these interactions. Machine learning algorithms have the ability to build relations between features while computing the importance of each feature in the resulting predictive model. There are a number of machine learning classification algorithms that can be employed to determine optimal feature combinations, relative to an output variable (i.e., in this case, successful or unsuccessful games). Table 6 presents a comparison of various classification algorithms, based on certain metrics. These algorithms have been shown to perform exceptionally well across a wide variety of classification tasks (Behoora and Tucker, 2015). In Table 6, four stars represent the best performance attainable, while a one star represents the worst performance attainable. The SVM, Naïve Bayes, IBK, Decision Trees and Random Forest are presented in Table 6, based on a comparison presented by (Kotsiantis, 2007).

Table 6 Comparison of Classifiers used (Kotsiantis, 2007), where **** represents the best and * represents the worst performance.

| Algorithms | Decision Tree (C4.5, Random Forest) | Naïve Bayes | SVM | IBK |
|---|---|---|---|---|
| Model Accuracy | ** | * | **** | ** |
| Explanation Ability of Classification | **** | **** | * | ** |
| Dealing with danger of overfitting | ** | *** | ** | *** |
| Tolerance to Independent Attributes | ** | * | *** | * |

Classification algorithms are evaluated based on a variety of metrics such as *accuracy*, *F-Score* and *relative error* between the actual and predicted variables. Each of the above classification algorithms will be employed to efficiently discover relevant game design feature combinations that predict the success or failure of games.

## 4. Case Study

Casual gaming is considered to be a popular activity during leisure time and has gained in popularity, primarily due to the widespread use of mobile phones (Khan et al., 2015). Research suggests that such games have the potential to reach a broader range of individuals, as they are designed to be used among all age groups and are targeted for mass audience appeal (Gerling et al., 2011; Khan et al., 2015). A case study using games from the android market (Google Play Store) (Khan et al., 2015) is used to discover the gamification features that impact the success or failure of a game.

### *4.1 Data Sampling*

#### *4.1.1 Identify Game Design Features in Mobile Games*

Based on the gamification literature, there are a total of $m$=24 game design features that have been identified. Given that different game design features have been employed in the design of different games, tasks and applications, a knowledge gap exists in terms of which game design feature (s) has the highest impact on predicting the success or failure of a game. Therefore the entire set (i.e., 10 mechanic features and 14 component features given in Tables 2.1, 2.2, 2.3) of gamification features are considered for the purpose of this study ($m$=24).

#### *4.1.2 Game Platform and Sample Games*

In this paper, a mobile platform is considered since it is used across different age and gender demographics, when compared to other gaming platforms such as Consoles and PC's (Gerling et al., 2011; Hui-Yi and Ling-Yin, 2010; Khan et al., 2015). Android is one of the most popular mobile platforms for gaming (Butler, 2011). The rankings provided by the Google Play Store are considered as the basis for classifying games as successful and unsuccessful (Filho et al., 2014). The rankings of games in the Google Play Store are classified into three categories; "Top Free Games", "Top Grossing Games" and "Top Paid Games". The Google Play Store displays 540 games under each category, where the top games are successful and the bottom games are relatively unsuccessful. For the purpose of this paper, the top 10 and bottom 10 ranked games in each of three categories (as on 12/07/2014), is considered as shown in Figure 3. Thus, a total of *n*=60 games are selected for the study (please see the appendix section for the actual name and ranking of each game).

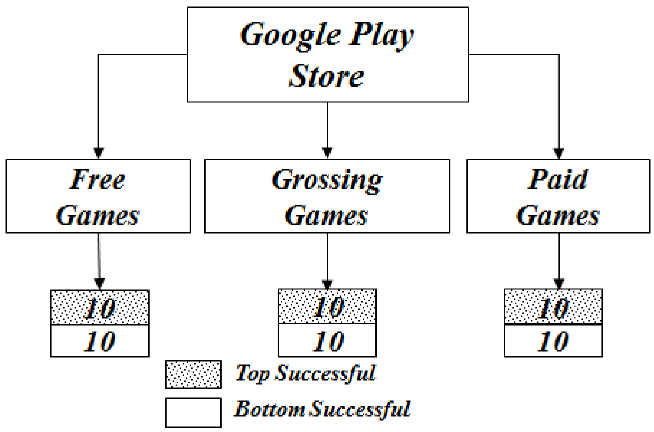


*Figure 3 Game Sampling from Google Play Store based on rankings*

*4.2 Data Collection (Binary Matrix)*

A binary matrix (60X24) is constructed by the authors after investigating the presence/absence of each of the 24 game design features found in the 60 games. Table 7 shows the sample of the binary matrix, based on the performance of the game in the Google Play Store.

Table 7 Sample of Data Collected - Binary Matrix

| Game | Challenge | Chance | ……. | Teams | Virtual Goods | Successful vs Unsuccessful |
|---|---|---|---|---|---|---|
| Game 1 | Present | Absent | ……. | Absent | Present | Successful |
| Game 2 | Absent | Present | ……. | Absent | Absent | Successful |
| . | . | . | . | . | . | . |
| . | . | . | . | . | . | . |
| . | . | . | . | . | . | . |
| Game 59 | Present | Present | …… | Absent | Present | Unsuccessful |
| Game 60 | Absent | Absent | …… | Present | Absent | Unsuccessful |

*4.3. Model Generation*

*4.3.1. Model generation using individual game design features*

For each individual game design feature, a confusion matrix is generated that contains information about whether this feature is present or absent in a game, and whether the game is successful or unsuccessful in the market. In this case, *success/failure* of a game is what is to be predicted and is based on the rankings of the game in gaming market. It is necessary to tie success or failure of a game to the presence or absence of a game design feature. A sample confusion matrix for the game design feature ‘points’ is shown in Table 8.

Table 8 Confusion Matrix for 'Points' - Presence of 'Points' Vs. Success of Game

| | | **GAME DESIGN FEATURE – ‘POINTS’** | |
|---|---|---|---|
| | | **YES** | **NO** |
| **STATE OF THE GAME** | **SUCCESSFUL** | 25 | 5 |
| | **UNSUCCEESSFUL** | 12 | 18 |

From Table 8, we can conclude the following:

- 25 games having ‘points’ as a game design feature are successful
- 12 games having ‘points’ as a game design feature are unsuccessful
- 5 games not having ‘points’ as a game design feature are successful
- 18 game not having ‘points’ as a game design feature are unsuccessful

The *precision*, *recall* and *F-Score* of ‘points’ is calculated as shown below:

Using equation (1), (2) and (3), we get

$$Precision = \frac{25}{25+5} = 0.833$$

$$Recall = \frac{25}{25+12} = 0.675$$

$$F\ Score = 2\left(\frac{Precison * Recall}{Precision+Recall}\right) = 0.746$$

*Precision* measures the ratio of correctly found correspondences or games that were successful with *"Points"* as a game design feature with the total number of successful games with and without *"Points"* as a game design feature. *Recall* measures the ratio of correctly found correspondences or games that were successful with *"Points"* as a game design feature with total number successful games with *"Points"* and unsuccessful games with *"Points"*. Each quadrant in the confusion matrix is defined with values such as True Positive, True Negative, False Positive and False Negative. Type I error is denoted by the occurrence of False Positives and Type II error is denoted by occurrence of False Negatives. In Table 8, Type I error is absence of *"Points"* as a game design feature and a positive outcome "Successful" and Type II error is presence of *"Points"* as a game design feature and a negative outcome "Unsuccessful". Similarly, the confusion matrix is constructed, with the *F-Score* calculated for the remaining 23 game design features. Table 9 presents a summary of results obtained after evaluating *precision*, *recall* and *F-Score* measures for each game design feature. The results obtained are representative of the importance of the game design feature in predicting the success/failure of a game.

Table 9 Summary of Precision, Recall and F-score at Step 4.3.1

| **Game Design Feature** | **Precision** | **Recall** | **F-Score** |
|---|---|---|---|
| Points | 0.833 | 0.676 | 0.746 |
| Challenge | 0.933 | 0.56 | 0.7 |
| Feedback | 0.733 | 0.595 | 0.657 |
| Virtual goods | 0.7 | 0.583 | 0.636 |
| Leader Boards | 0.667 | 0.606 | 0.635 |
| Content Unlocking | 0.633 | 0.576 | 0.603 |
| Social Graph | 0.667 | 0.541 | 0.597 |
| Win States | 0.667 | 0.526 | 0.588 |
| Rewards | 0.667 | 0.513 | 0.58 |
| Levels | 0.667 | 0.5 | 0.571 |
| Avatars | 0.567 | 0.567 | 0.567 |
| Chance | 0.5 | 0.652 | 0.566 |
| Transaction | 0.5 | 0.556 | 0.526 |
| Gifting | 0.367 | 0.688 | 0.478 |
| Resource Acquisition | 0.5 | 0.441 | 0.469 |
| Collection | 0.433 | 0.5 | 0.464 |
| Competition | 0.333 | 0.625 | 0.435 |

| | | | |
|---|---|---|---|
| Achievements | 0.433 | 0.382 | 0.406 |
| Quests | 0.2 | 0.545 | 0.293 |
| Turns | 0.167 | 0.625 | 0.263 |
| Cooperation | 0.133 | 0.8 | 0.229 |
| Boss Fights | 0.133 | 0.4 | 0.2 |
| Badges | 0.1 | 0.429 | 0.162 |
| Teams | 0.067 | 0.4 | 0.114 |

The results in Table 9 are obtained by analyzing each game design feature on an individual basis. Therefore, no interaction effect is being considered among game design features in Table 9. From Table 9, it can be observed that the game design feature, *"Points"*, obtained the highest *F-Score*, indicating that *"Points"* has the maximum predictive power for an outcome of a game amongst 24 the game design features. However, game design features are building blocks of a game and are shared by a game. Thus, there may be interaction effects that are better indicators of the success or failure of a game.

*4.3.2 Model generation using combination of design features*

Evaluating games on an individual design feature basis reveals that '*Points'* has the highest predictive power. However, none of the features could achieve an F-Score of 1.0. This indicates that a single game design feature does not exist that can solely be used to predict the success or failure of a game. In order to explore the confounding effects of multiple game design features, a pair of game design features is evaluated using the confusion matrices presented below. The confusion matrices constructed with a combination of features evaluate a subset of the total number of games.

Table 10 Confusion Matrix for Points and Challenge as a Feature Combination

| | | GAME DESIGN FEATURES – 'POINTS' and 'CHALLENGE' | |
|---|---|---|---|
| | | **YES** | **NO** |
| **STATE OF THE GAME** | **SUCCESSFUL** | 24 | 1 |
| | **UNSUCCEESSFUL** | 12 | 8 |

From Table 10 we can conclude the following:

- 24 games having 'points' and 'challenge' as a game design features are successful

- 12 games having ‘points’ and ‘challenge’ as a game design features are unsuccessful
- 1 games not having ‘points’ and ‘challenge’ as a game design features are successful
- 8 game not having ‘points’ and ‘challenge’ as a game design features are unsuccessful

Table 11 Confusion Matrix for Points and Resource Acquisition as a Feature Combination

| | | GAME DESIGN FEATURES – ‘POINTS’ and ‘RESOURCE ACQUISITION’ | |
|---|---|---|---|
| | | **YES** | **NO** |
| **STATE OF THE GAME** | **SUCCESSFUL** | 13 | 3 |
| | **UNSUCCEESSFUL** | 7 | 6 |

From Table 11 we can conclude the following:

- 13 games having ‘points’ and ‘challenge’ as a game design features are successful
- 7 games having ‘points’ and ‘challenge’ as a game design features are unsuccessful
- 3 games not having ‘points’ and ‘challenge’ as a game design features are successful
- 6 game not having ‘points’ and ‘challenge’ as a game design features are unsuccessful

Table 12 F-Score for feature combination with 'Points'

| **Feature Combination** | **F-Score** |
|---|---|
| Points and Challenge | 0.78 |
| Points and Resource Acquisition | 0.72 |

Table 12 shows the *F-Score* obtained by combining the game design feature *‘Points’* with two different game design features: ‘*Challenge*’ and ‘*Resource Acquisition’*. In the original evaluation of individual game design features (Table 9), the game design feature, *‘Points’*, obtained an *F-Score* of 0.746. From Table 12, it is evident that the *F-Score* increases above 0.746 when *‘Points’* and *‘Challenge’* are considered to be a set of features and decreases when *‘Points’* and *‘Resource Acquisition’* are considered to be the basis for evaluation of games. Many such combinations exist and each of the combinations would result in a different *F-Score*. Furthermore, it becomes challenging to make a decision on the order in which these features should be selected. It is quite possible that a feature selected first may not result in a better F-Score than the individual feature. Moreover, after achieving an F-score of

0.78 with *'Points'* and *'Challenge'*, the objective would be to explore other candidate game design features that could potentially increase the *F-Score*, towards a value of 1.0. With a set of 24 features and 2 features being considered at a time, a total of 552 confusion matrices are needed (24! / (24-2)!). Machine learning algorithms are proven to be efficient at handling such computationally complex problems. To evaluate the interaction effects of the game design features in an efficient and effective manner, machine learning algorithms are employed to generate the game design feature model. The results of the selected machine learning algorithms are presented in Table 13. When exploring game feature design combinations, the Sequential Minimal Optimization (SMO) algorithm performed the best, with the highest *F-Score* for classification and lowest relative error.

Table 13 Classification Algorithm comparison design feature data for games

| Sr. No. | Algorithm | F-Score | Relative Error |
|---|---|---|---|
| 1 | SMO | 0.749 | 50.00% |
| 2 | J48 | 0.700 | 73.66% |
| 3 | Naïve Bayes | 0.667 | 80.09% |
| 4 | Random Forest | 0.650 | 84.83% |
| 5 | IBK | 0.633 | 73.17% |

SMO is a modified Support Vector Machine (SVM) algorithm well suited for regression problems. It is computationally efficient and generally used for classification problems (Joachims, 1999; Platt, 1999; Shevade et al., 2000). Table 14 shows the results for design features obtained after running the SMO algorithm. Out of a set of 24 game design features, 15 features obtained a positive coefficient, indicative of their impact in predicting the outcome of a game. The game design features listed in Table 14 are arranged in decreasing order of their coefficient obtained from the SMO Model.

Table 14 Features extracted by SMO model

| Ranking | Coefficient | Game Design Feature |
|---|---|---|
| 1 | 1.4883 | Points |
| 2 | 1.3653 | Avatars |
| 3 | 0.6504 | Challenges |
| 4 | 0.6364 | Virtual goods |
| 5 | 0.5151 | Competition |
| 6 | 0.5123 | Boss Fights |
| 7 | 0.4572 | Teams |
| 8 | 0.3805 | Leader Boards |
| 9 | 0.3366 | Gifting |

| | | |
|---|---|---|
| 10 | 0.3348 | Content Unlocking |
| 11 | 0.3212 | Transaction |
| 12 | 0.3141 | Turns |
| 13 | 0.3086 | Quests |
| 14 | 0.2116 | Cooperation |
| 15 | 0.191 | Feedback |
| 16 | -0.0137 | Badges |
| 17 | -0.1312 | Win States |
| 18 | -0.1325 | Levels |
| 19 | -0.2655 | Rewards |
| 20 | -0.4589 | Collection |
| 21 | -0.5739 | Resource Acquisition |
| 22 | -0.6374 | Chance |
| 23 | -0.8975 | Social Graph |
| 24 | -1.1006 | Achievements |

The coefficient obtained by each of the game design feature is a normalized value, indicating the power of each feature in determining the outcome of a game. From Table 14, we can conclude that 'Points' has the highest coefficient in the SMO Model, indicating that it has the highest impact in the predicting outcome of a game (consistent with the discovery presented in Table 9).

**5. Results and Discussion**

The authors of this work proposed a methodology to identify a set of game design features that are common across task-driven applications, based on rankings as a measures of success/failure. 60 android games (*see Appendix A*) were sampled based on their ranking in the Google Play Store to reduce bias in the results. Individual game design features were evaluated in order to determine their power in predicting the success/failure of a game, with the *Points* feature found to be the strongest predictor of the outcome of a game, with an *F-Score* of 0.746. However, none of the features by themselves, obtained an *F-Score* of 1.0 and thus, combinations of features were evaluated in order to quantify the impact of feature combinations on the outcome of a game. However, the complexity of this task being done sequentially motivated the use of machine learning algorithms. Certain machine learning algorithms are best suited to deal with discrete features such as the presence or absence of a game design feature. Five such machine learning classification algorithms were tested on the dataset collected to extract the impact of each of the game design features (and their interactions) on the success/failure of a game. Out of these five machine learning algorithms, SMO performed best, with an *F-Score* of 0.749. SMO's regression model with a 10-fold cross validation assigned a coefficient to each of the game design features in the model. Comparing the rankings of game design features obtained from both the i) individual feature results (Table 9) and the ii) feature combination results (Table 14), it is discovered that in spite of a small shift in the ranks, the results are consistent. Table 15 illustrates this consistency in the features obtained using each approach.

Table 15 Comparison of features obtained based on the individual feature model and feature combination model

| Ranking | SMO Algorithm Model | Individual Feature Model |
|---|---|---|
| 1 | Points | Points |
| 2 | Avatars | Challenges |
| 3 | Challenges | Feedback |
| 4 | Virtual goods | Virtual goods |
| 5 | Competition | Leader Boards |
| 6 | Boss Fights | Content Unlocking |
| 7 | Teams | Social Graph |
| 8 | Leader Boards | Win States |
| 9 | Gifting | Rewards |
| 10 | Content Unlocking | Levels |
| 11 | Transaction | Avatars |
| 12 | Turns | Chance |
| 13 | Quests | Transaction |
| 14 | Cooperation | Gifting |
| 15 | Feedback | Resource Acquisition |

From Table 15, it is evident that 8 of top 15 game design features consistently shows up in each model. Individual features were ranked, based on the *F-Score* obtained by each of the features separately. Each confusion matrix was constructed based on the presence or absence of a game design feature in a successful or unsuccessful game. The analysis of individual features (right side of Table 15) led to determination of a feature with highest predictive power (i.e., *Points* with an *F-Score* of 0.746). The benefits of exploring feature combinations in this work (left side of Table 15) are threefold: i) machine learning algorithms eliminated the need for a manual exploration of an enumerative test of feature combinations, ii) the results generated by the SMO algorithm represents a general case of the 15 game design features (out of the total 24 game design features found in the literature) that should be considered when designing gamification tasks, with *Points* representing the most significant game design feature, iii) the feature combination results (Table 13) yielded a slightly higher *F-Score* than exploring the game design features individually (Table 9). This work lead to the discovery of game design features that can increase the probability of a game being successful across users.

**6. Conclusion and Future Work**

The objective of this research is to identify the game design features that are common across all success driven task applications and enable users to get motivated while increasing user engagement. Individual game design features were evaluated in order to determine the predictive power of each feature. None of the individual features could predict the outcome of a game on an individual basis and thus, combination of features were evaluated utilizing the efficiency of machine learning algorithms. Game design features responsible for an increase in the probability of a game being successful were identified using the Sequential Minimal Optimization (SMO) algorithm. This modified SVM algorithm was discovered to be the best suited algorithm while dealing with such a dataset. Consistency observed in the results based on individual features and combination of features, supports the claim that there exist a set of features that are common across all success/unsuccessful driven applications. However, the order in which these features must be incorporated is discovered through the SMO algorithm. This work was based on features extracted manually after playing games downloaded from the Google Play Store and thus, had limited number of instances (i.e., 60 games). Future work in this direction will focus on conducting a study with a sufficiently larger dataset. Furthermore, the presence or absence of a game design feature was assumed to be a binary variable in this work. However, in addition to the presence or absence of a game design feature, the quality of a game design feature when it is present, may also influence the success or failure of a game. In this work, the authors abstained from exploring the quality of a game design feature due to the qualitative nature of measuring quality, given a game design feature. However, future work will explore metrics that define quality, so as to explore the impact of the quality of a game design feature on the success or failure of a game. The importance of such work lies in the fact that application designers can optimize application designs to enhance user experience and achieve prolonged user engagement. There is a need to design learning, healthcare, and enterprise environments in such a way that they are inherently motivating in order to engage individuals who are characterized as having low interest or lacking in motivation due to switch from one type of medium (for example, traditional physical therapy protocols ) to another (for example, gamified physical therapy intervention). Game design features built into the video games that contribute towards their respective success (i.e. game design features that are responsible for motivating and engaging users) were identified by mining game design features. The healthcare domain is a potential application for such a strategy to motivate patients undergoing therapies and facing issues with adhering to the protocols. Such strategies can bring change in human behavior and essentially provide enhanced wellness outcomes as compared to the traditional healthcare management systems. A limitation of this study is that it explored the game design features in casual games on the mobile platform. In the future, similar studies using other types of games such as serious games on different gaming platforms can be explored.

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## Appendix A. Games and rankings obtained from Google Play Store

| Sr.No. | Category | Name of the Game | Rank within Category |
|---|---|---|---|
| 1 | Top Grossing | Clash of clans | 1 |
| 2 | | Candy Crush Saga | 2 |
| 3 | | Candy Crush Soda | 3 |
| 4 | | Game of Wars Fire Age | 4 |
| 5 | | Farm Heroes Saga | 5 |
| 6 | | Hay Day | 6 |
| 7 | | Family Guy The Quest of Stuff | 7 |
| 8 | | Slotomania - Free Slots | 8 |
| 9 | | Big Fish Casino - Free Slots | 9 |
| 10 | | Castle Clash | 10 |
| 11 | Top Free | Bubble Shooter Galaxy | 1 |
| 12 | | Trivia Crack | 2 |
| 13 | | Bee Bubble Shooter | 3 |
| 14 | | Deck Heroes | 4 |
| 15 | | Subway Surfers | 5 |
| 16 | | Stick Hero | 6 |
| 17 | | New Words with Friends | 7 |
| 18 | | Chick Fly Chick Die 2 | 8 |
| 19 | | Monsters Busters | 9 |
| 20 | | Don’t Tap the White Tile | 10 |
| 21 | Top Paid | Minecraft - Pocket Edition | 1 |
| 22 | | Five Nights at Freddy's 2 | 2 |
| 23 | | Five Nights at Freddy's | 3 |
| 24 | | Kingdom Rush Origins | 4 |
| 25 | | Worms 3 | 5 |
| 26 | | Scribblenauts Remix | 6 |
| 27 | | Geometry Dash | 7 |
| 28 | | THE GAME OF LIFE | 8 |
| 29 | | True Skate | 9 |
| 30 | | Bloons TD 5 | 10 |
| 31 | Top Grossing | Odd Socks | 531 |
| 32 | | Texas HoldEm Poker Deluxe Pro | 532 |
| 33 | | Restaurant Story: Christmas | 533 |
| 34 | | My Talking Angela | 534 |
| 35 | | NBA All net | 535 |
| 36 | | GraalOnline Era | 536 |
| 37 | | Sky Force 2014 | 537 |

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|---|---|---|---|
| 38 | | Slots Casino 1Up Slot Machines | 538 |
| 39 | | Motor World Car Factory | 539 |
| 40 | | Final Fantasy VI | 540 |
| 41 | **Top Free** | Knights and Dragon | 531 |
| 42 | | Farm Slots - Free Vegas Casino | 532 |
| 43 | | Swamp Attack | 533 |
| 44 | | Make Them fall | 534 |
| 45 | | Free Car Driving | 535 |
| 46 | | Dead Target: Zombie | 536 |
| 47 | | Who wants to be a millonaire | 537 |
| 48 | | Amazing Brick | 538 |
| 49 | | Slots - Journey of Magic | 539 |
| 50 | | SAS - Zombie Assault 4 | 540 |
| 51 | **Top Paid** | Speedway masters | 531 |
| 52 | | TNA wrestling Impact | 532 |
| 53 | | Mike V: Skate Board Party | 533 |
| 54 | | Jelly Defense | 534 |
| 55 | | Rise Wars (Risk Game) | 535 |
| 56 | | Deadly Dungeons RPG | 536 |
| 57 | | Undead Residence: Terror Game | 537 |
| 58 | | Random Heroes 2 | 538 |
| 59 | | Craps Trainer Pro | 539 |
| 60 | | Flick Golf | 540 |