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A regression-based rating prediction model for mobile-based puzzle games

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A B S T R A C T

Cell phones, nowadays, are used for not only making phone calls and sending messages but also for entertainment. Mobile-based games of various kinds are instrumental in acting as a source of entertainment. Player enjoyment is one of the major motivations in playing any kind of mobile game. The first model proposed for player enjoyment was Flow, which used eight different elements of enjoyment. GameFlow, a later model, was derived through mapping with the Flow model. Each element of GameFlow consists of a set of criteria for experiencing enjoyment while playing mobile games. Prediction of mobile games' rating using aspects of player enjoyment can be extremely beneficial to mobile game designers. This work first provides a Regression-Based Rating Prediction Model (RBRPM) for Android-based puzzle games using elements of the GameFlow model. RBRPM is derived by applying Forward Stepwise Multiple Linear Regression on a data set consisting of 80 puzzle games. The data set is compiled by playing these games considering the criteria of all elements of the GameFlow model. RBRPM relies on five predictors, namely feedback, social interaction, concentration, clear goals, and player skills for predicting a games' rating. Next, this work extends RBRPM by including not only additional criteria in the already identified elements but also adds three new elements i.e. fantasy, mystery, and thrill. The improved model (IRBRPM) uses 8 predictors. MMRE and PRED(x) are used as prediction accuracy metrics for assessing this model and K-fold cross-validation is used for model validation. These two steps provide encouraging results.

1. Introduction

The availability of high computing power and better graphics in mobile devices allows people to make use of these devices for tasks unrelated to communication. Modern mobile devices are acting as a major source of entertainment to nomadic users. A major chunk of this entertainment comes from mobile games that can be played anywhere at any time.

The popularity and demand for mobile games has increased manifold. This has led to the establishment of a specialized industry for developing mobile games. Mobile games fall into different categories such as action, puzzle, adventure, role-playing, racing, sports, simulation, and strategy [1]. These main categories have further sub-categories. For example, puzzle games are classified as action, general, hidden object, logic, matching, and stacking. Mobile games are mainly played with the motive of enjoyment and entertainment. If the players don't find any element of enjoyment in a mobile game, then its rating may suffer. Rating is a numerical value assigned to an object on the basis of some desirable criteria [2].

Google Play Store [3] motivates game players to rate games and to write review text. The purpose of review text is to indicate why a user assigns a particular rating to a game. Needless to say the more enjoyable a game is the higher will be its rating and the better will be its reviews.

A number of models such as Flow [4], GameFlow [5], and their derivatives have been proposed to judge the user experience of games. However, prediction of games rating still requires due attention from the research community. This research work aims to fill this gap by providing a rating prediction model for Android-based puzzle games. This model is derived from the elements of the GameFlow model using Forward Stepwise Multiple Linear Regression (FS MLR). The initial proposed model uses five predictors. Then, this work proposes an improved model by adding three new elements (predictors) and a few criteria in the already identified predictors. The improved model uses 8 predictors. MMRE and PRED(x) are used as prediction accuracy metrics in order to assess this model while K-fold cross-validation is used to validate the model. These two steps provide encouraging results.

Section 2 presents the problem statement and a brief summary of related work is presented in Section 3. Section 4 presents our complete research methodology which consists of identification of games' rating predictors, data collection, analysis of predictors using Simple Linear Regression (SLR), analysis of predictors using Multiple Linear Regression (MLR), comparison of RBRPM with GameFlow model for ratings, Improved Regression-Based Rating Prediction Model (IRBRPM), model assessment and validation. Finally, Section 5 summarizes the major conclusions and mentions ways in which this work may be extended in the future.

2. Problem Statement

The research community has focused a lot on the GameFlow model in order to evaluate different types of games and applications. However, the prediction of games' rating has not been paid much attention by the research community. A systematic approach for prediction of mobile games rating is vital for improving game design. In this work, we have made an effort to address the following question. Can we develop a rating prediction model for Android- based puzzle games that provides better prediction accuracy in comparison to the general-purpose GameFlow model?

3. Related Work

The design of any product should not only focus on improving the efficiency and effectiveness, but also consider the user experience in order to design a product which is enjoyable and pleasurable to users [6]. According to Norman [7], 'technology should bring more to peoples' lives than the improved performance of the tasks; it should add richness and enjoyment'. This philosophy applies equally well to computer games.

Many theories and models have tried to analyse media enjoyment with respect to one specific concept such as attitude theory and parasocial interaction [8], transportation theory [9], and disposition theory [10]. Apart from media content, Denham [11] identified social situations as a contributor towards enjoyment of viewers. These models are very specific and narrow. However, the Flow model for enjoyment [4] proves that enjoyment elements are global. It presents a general model for everyone's experience of enjoyment. In subsequent sub- sections, we first describe the Flow and GameFlow models [5] that act as a base for our proposed rating prediction model. Later, past research related to rating prediction is briefly discussed.

3.1 Flow and GameFlow

Sweetser and Wyeth [5] reviewed the existing literature on user experience with respect to games comprehensively in order to find the main enjoyment factors for players of video games. As a result of this comprehensive review, the authors determined eight major factors/elements influencing enjoyment of players in games, i.e. (i) concentration, (ii) challenge, (iii) player skills, (iv) control, (v) clear goals, (vi) feedback, (vii) immersion, and (viii) social interaction. These elements were found to be closely overlapped with the elements provided in Flow [4]. Therefore, a mapping of these elements to the elements of Flow was provided and the resulting model was called GameFlow. The first element of Flow being the game itself is not depicted clearly in the elements of GameFlow. However, all elements except social interaction of GameFlow are all closely interconnected and inter-related.

The last element of player enjoyment (namely, social interaction) does not map to any of the elements of Flow. However, the same is very much highlighted in the literature with respect to user experience in games. According to a research carried out with a large

Australian sample [12], among people who play games, 70% of people play mainly to enjoy with others. Thus, there is a rationale for each element of the GameFlow model [5].

Each element of the GameFlow model of player enjoyment consists of a set of criteria derived from literature concerning user experience. Subsequent subsections provide a short description of each element along with a set of criteria (refer to Table 1).

3.1.1 Concentration

A player must concentrate on the game and pay more attention in order to enjoy the game. In fact, the player's attention must be engaged totally in the game and he/she should not be able to process any other activity [4]. Moreover, it is very important that the player's burden should not be increased with unimportant activities/tasks in the game [13].

3.1.2 Challenge

Challenge is considered as one of the most critical aspects for the design of a good game. Games produce enjoyment for the players by challenging their memory and performance bounds [14]. Therefore, games must test the player with a series of distinct and challenging but appropriate activities.

3.1.3 Player skills

If a player really wants to enjoy the game, it is compulsory that he/she develops skills at playing the game. Therefore, player should be educated through interesting and understandable tutorials allowing he player to get involved in the game effortlessly [14]. Both challenge and skills of player associated with an activity must be over a certain level and matched as well [15-16].

3.1.4 Control

Players must feel a strong sense of control over their movements. For promoting such sense of control, games should provide a basic and essential set of buttons for quick learning [15]. Moreover, games should allow the player to customize these controls [17].

3.1.5 Clear goals

Players should be presented with clear objectives or goals at suitable times. Moreover, goals should be delivered to the player clearly and openly [4, 15].

3.1.6 Feedback

Players must be provided with proper feedback at appropriate times. Concentration can be achieved through immediate provision of feedback [4]. When players fail, they should be provided feedback about it and be told about ways to move on the right track [18]. Games should allow players to find their scores and standing in the game and provide constructive feedback to motivate mastery of the game [19].

3.1.7 Immersion

The concept of immersion is often discussed in design and research of games. It is the deep but effortless involvement of players in the game [4].

3.1.8 Social interaction

Games should provide and offer prospects for social interaction. People play games to intermingle with others (irrespective of the task), even without any liking for them or even when they don't like games altogether [5, 20-21]. In the original GameFlow model, expert reviews of two mobile games were carried out considering the GameFlow criteria in order to probe the usefulness and validity of this model. It was established that some of the criteria of GameFlow are more associated with different types of games and some are hard to assess through expert reviews and they need player testing.

Since its publication, the GameFlow model has been used extensively by games research and development communities. This has resulted in derivation of several additional models like EGameFlow [22], RTS GameFlow [23], Pervasive GameFlow [24], etc.

3.2 Mobile Games Rating Predictors

On account of rapid growth of mobile gaming industry, analytics are monitored in order to provide suitable games for the customers.

There is a growing competition in this industry for the development of the most downloaded games in the world. Machine learning has been used for predicting the most downloaded games. Recent research focuses on analysing some research questions for discovering top mobile games. A machine learning approach, namely Learning to Rank [25, 26], is normally used for ranking purpose. Many companies such as Appannie [27] and MopApp [28] provide analytics related to mobile games. Appannie, for instance, updates data about top mobile games on hourly basis and presents analytic reports [27].

Ramadhan and Khodra [29] provided MGPrediction model for top mobile games by extending the Learning to Rank technique. The proposed system makes an effort to help the mobile game industry in deciding suitable and favourable mobile games as the most downloaded ones.

Ramadhan and Khodra [30] proposed MGPrediction+ model by considering Learning to Rank and time series data and they found LambdaMART as the best prediction model for top mobile games.

Table 1

Set of criteria for GameFlow elements (Adapted from the work of Sweetser and Wyeth [5])

Element	Criteria
Concentration	games should offer a lot of motivation from diverse sources
	games must offer contents to stimulate attention
	games should catch the attention of the player and the same is maintained during the course of the game
	the games shouldn't provide unrelated tasks
	games should have adequate workload, suitable for player's limitations in terms of perception, cognition and memory
	players should not be sidetracked from tasks which demand concentration
Challenge	games should offer adequate challenges neither too difficult nor too easy
	different players should be offered different levels of challenge in games
	the intensity of challenge should rise as the player advances towards completion of the game andimproves skills
	games should offer fresh challenges with suitable pace
Player Skills	games should be playable without going through the manual
	player should learn games as part of fun
	games should contain online help in order to avoid exiting the game
	players should be trained by means of tutorials or early stages so that players get the same feeling as obtained while playing the game
	games should enhance player skills according to the progress in the game
	games should offer suitable rewards to the players for development of their struggle and skill
	game should provide interfaces and procedures which are easy to learn and use
Control	players should be capable of controlling characters in the game, their activities and contacts in the game world
	games should allow players to enjoy sense of control over the interface of the game
	players should enjoy the feelings of control in starting, stopping, saving the game
	players should be capable of avoiding unfavorable errors and player should be helped in recovering from errors
	games should provide a sense of control and influence onto the game world
	games should offer players control in taking actions and using plans
Clear goals	goals which are overriding should be precise and provided soon
	intermediary goals should be precise and provided at when necessary
Feedback	challenges in games must tie with the skills of players and games should providefeedback to players about their progress towards achievement of goals.
	games should provide immediate feedback to the players regarding their actions

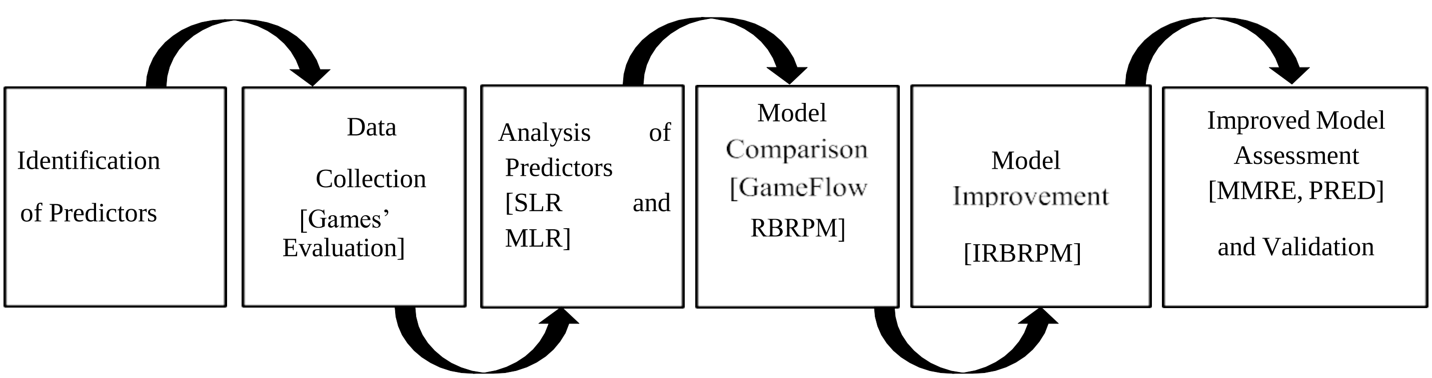

Fig. 1. Research Methodology

Even though researchers have tried to predict the most downloaded games, to the best of our knowledge, the literature does not provide any approach for predicting the rating of mobile games using the elements of the GameFlow model.

4. Research Methodology

Figure 1 presents our research methodology comprising of core steps for derivation and validation of our rating prediction model. These steps are explained in subsequent sub-sections.

4.1 Identification of Predictors

The very first step in our research was the identification of games' rating predictors. To start, we used the 8 elements of the GameFlow model [5] as our predictors. Each element consists of a set of criteria, which can be used for designing and evaluating games for maximizing enjoyment of a player.

4.2 Data Collection

As shown in Table 2, 80 Android-based puzzle games were evaluated by one of the authors using the elements of the model GameFlow. These games were downloaded from the well- known site Google Play Store. The selected games were also downloaded from Apple Store. However, for the purpose of this research work, evaluation results of games downloaded from Google Play Store only were considered because actual ratings on the basis of players' reviews were available for all the selected games on Google Play Store while the same were not available on Apple Store for all the games.

4.3 Analysis of Predictors

First, the predictive strength of each of the eight individual elements/predictors of the GameFlow model was checked through SLR [12]. Later, we used the FS MLR technique [31] to build a rating prediction model for Android-based puzzle games. Both of these regression analyses were performed using IBM SPSS Statistics 22 software [32].

4.3.1 Analysis of predictors using SLR

Table 3 provides SLR results in descending order of predictive strength. FEED turns out to be the strongest individual predictor of actual ratings while IMER appears to be the strongest individual predictor of actual ratings while IMER appears to be the weakest individual predictor. The second most influential predictor is PSKL.

4.3.2 Analysis of predictors using MLR

We made an effort to identify outliers in the dataset using Cook's distance [33].

We observed that no point was more than ((4/n)*3), where n denotes the total number of Android-based puzzle games i.e. 80 in our case. Data comprising of 80 games was used to build our prediction model. FS MLR was applied to identify the best predictors which have the strongest relationship with the dependent variable (i.e. game rating). This approach constructs the model by introducing one independent variable (having maximum association with the dependent variable) at a time. The aim is to figure out the statistically significant predictors which best explain the variation in games' real rating.

The coefficient of determination (R2) [34] is calculated at every stage in order to ensure that the variable added last increases R2. We considered only those combinations/mixtures of predictors wherein all predictors are observed to be statistically significant at α- value of 0.05. Moreover, in order to find the existence of multi-collinearity among the predictors in MLR models, we used Variance Inflation Factor (VIF) [35]. All predictors in obtained MLR models possess VIF Values close to 1. A summary of results obtained by using FS MLR is provided in Table 4.

The final model observed using FS MLR uses five predictors – CONC, PSKL, CLGL, FEED, and SINT – and has R2 value of 0.749. In subsequent discussions, this model is referred to as Regression Based Rating Prediction Model (RBRPM).

Table 3

SLR Results

S. No.	Predictor	Code	R2 Value
1	Feedback	FEED	0.427
2	Players Skills	PSKL	0.398
3	Concentration	CONC	0.324
4	Clear Goals	CLGL	0.319
5	Social Interaction	SINT	0.313
6	Control	CONT	0.214
7	Challenge	CHLN	0.088
8	Immersion	IMER	0.055

4.4 Model Comparison (GameFlow vs. RBRPM)

Figure 2(a) displays the relationship between real ratings and GameFlow model ratings while Figure 2(b) displays the relationship between real ratings and predicted ratings achieved using RBRPM. RBRPM performs better in predicting Android-based puzzle games' rating as is evident from the value of coefficient of determination (R2). Our proposed model accounted for about 75% of the variation in the ratings of Android-based puzzle games (R2 = 0.749) as compared to about 66% variation in case of the general-purpose GameFlow model (R2 = 0.658).

Table 2

List of selected puzzle games

S. No.	Game Name	S. No.	Game Name	S. No.	Game Name	S. No.	Game Name
1	Word Search	21	Cut the Rope	41	Splashy Dots	61	Pet Rescue Saga
2	Roll the Ball	22	Mouse Maze	42	Jump Ball	62	Bubble Mania
3	Toy Blast	24	Piano Tiles	43	Unblock Me	63	Cookie Jam
4	Block Hexa	24	Tic Tac Toe	44	Brain Dots	64	101-in-1 games
5	Jigsaw	25	Brain Balance	45	Cube Critters	65	Garden Scapes
6	Word Cokies	26	Bubble Witch 3	46	Best Fiends	66	Puzzledom
7	Number Knot	27	Marble Temple	47	Infinity Loop	67	Panda Pop
8	Mazez and More	28	Physics Drop	48	Blossom Blast Saga	68	Focus
9	One Touch Drawing	29	Where is my water?	49	The Rings Lord 2	69	Doraemon Gadget Rush
10	Top Gear Racing	30	Balling	50	Jelly Splash	70	Secret Passages
11	Fishdom	31	Cross Stitch	51	Christmas Sweeper 3	71	Diggy's Adventure
12	Flow Free	32	1010! Puzzle	52	Cat vs Block	72	4 Pics 1 Word Puzzle
13	Ice Cream Palor	33	2048 Puzzle	53	Faraway 2	73	Fruit Bump
14	Bad Piggies	34	Wedding Day	54	Car Unblock	74	Word Bubbles
15	Simon's Cat Crunch Time	35	Angry Bird Blast	55	Clever Driver	75	360 Degree
16	Bubble Shooter	36	Magic Cube Puzzle 3D	56	Nut Crunch	76	Six!
17	Block Puzzle	37	Bubble Bust	57	Empires and Puzzles	77	Cradle of Empires
18	Dots and Boxes	38	Match Sticks	58	Snakebird	78	Bubble Struggle
19	Magnetic Ball	39	Interlocked	59	Lolipop	79	Bunny Pop
20	Scale Puzzle	40	Bridge Construction	60	Find the Differences	80	Treasure Hunt

Table 4

FS MLR Results

S. No.	No. of Variables	Predictors	Model Equation ($\hat{Y}$ represents predicted rating)	R^2 Value	Significance	VIF
1	2	FEED	$\hat{Y} = 1.875 + 0.384 * FEED$	0.600	0.000	1.060
		SINT	$+ 0.177 * SINT$		0.000	1.060
2	3	CONC	$\hat{Y} = 1.470 + 0.184 * CONC$	0.676	0.000	1.205
		FEED	$+ 0.319 * FEED +$		0.000	1.177
		SINT	$0.152 * SINT$		0.000	1.111
3	4	CONC	$\hat{Y} = 1.236 + 0.177 * CONC$	0.738	0.000	1.207
		CLGL	$+ 0.157 * CLGL +$		0.000	1.346
		FEED	$0.221 * FEED + 0.150 * SINT$		0.000	1.495
		SINT			0.000	1.111
4	5	CONC	$\hat{Y} = 1.236 + 0.141 * CONC +$	0.749	0.001	1.459
		PSKL	$0.112 * PSKL + 0.146 * CLGL$		0.048	1.752
		CLGL	$+ 0.196 * FEED + 0.137 * SINT$		0.000	1.372
		FEED			0.000	1.586
		SINT			0.000	1.178

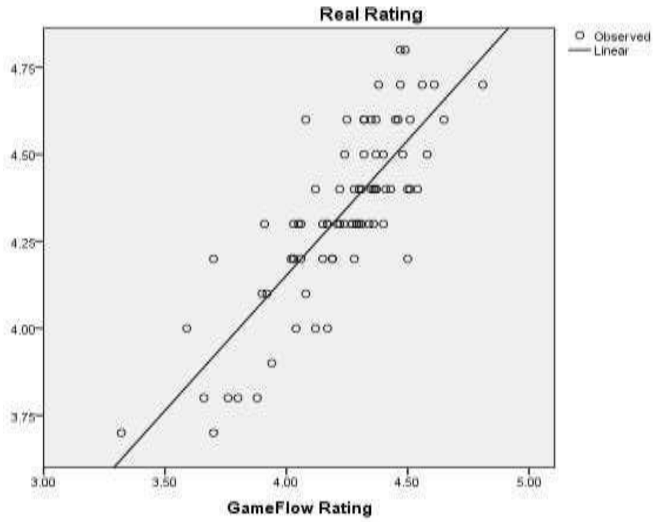

Fig. 2. (a) GameFlow model prediction

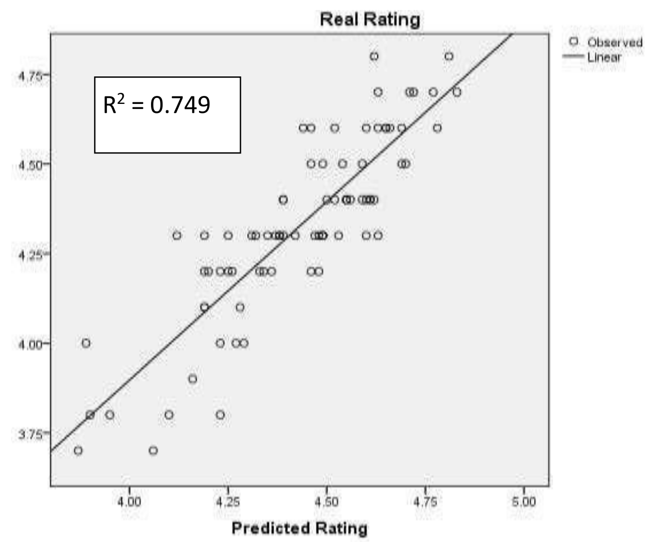

Fig. 2. (b) RBRPM prediction

4.5 Model Improvement (IRBRPM)

Upon further investigation of the literature, we found some new elements (predictors) relevant to player's enjoyment. In particular, three new elements, namely fantasy, mystery, and thrill were found with significant results. Moreover, new criteria related to our initial predictors were also found from the existing literature. Table 5 shows new criteria for existing predictors which were included in our Improved Regression-based Rating Prediction model (IRBRPM). Subsequent sub- sections provide a short description of the three new predictors along with a set of criteria (refer to Table 6).

4.5.1 Fantasy

Fantasy is the ability to perform tasks provided in a game that people are incapable to perform in real life such as flying, driving race cars etc. [36-39]. It is one of the key dimensions of game's characterization and one of the main motivation factors for any activity. The activity in a game does not match any activity outside the game i.e. in real life.

4.5.2 Mystery

Mystery is related to providing a fresh experience for players. It includes curiosity and exploration [40]. Curiosity is the extent of new experience which is provided to players. In games which lack or offer less innovation, players get tired quickly due to the lack of mystery factor.

4.5.3 Thrill

Experience of thrill is derived from an actual or perceived danger [41]. The sense of high speed, for instance is considered as a major source of thrill in some games.

Table 5

New (additional) criteria for existing predictors

Predictor	Code	New Criteria
Player Skills	PSKL	Games should provide intervention/action to improve performance of the players
Clear goals	CLGL	Storyline should be linear, clear and interesting

4.6 IRBRPM

Table 7 provides SLR results with respect to each predictor of IRBRPM. Unlike RBRPM, FANT is the strongest individual predictor while MYST is the weakest individual predictor of games rating. After using FS MLR, the final model obtained consists of 8 predictors and has an R2 value of 0.860. The equation of IRBRPM is given as under.

Predicted Rating = – 0.043 + 0.320 * FANT + 0.106 * SINT + 0.127 * FEED + 0.154 * CONC + 0.134 * MYST + 0.159 * CLGL – 0.112 * THRL + 0.107 * PSKL

4.7 Improved Model Assessment and Validation

4.7.1 Improved model assessment

Prediction accuracy of our proposed IRBRPM can be judged by using Mean Magnitude of Relative Error (MMRE) [42] and PRED(x) [43-44]. These two metrics are the most commonly used de-facto standard metrics for checking prediction accuracy and both are based on MRE.

MMRE comes out to be 0.01739 which is less than the proposed threshold value of 0.25 while PRED (25) = 1which is greater than the proposed threshold value of 0.75 (refer to Table 8).

Table 6

New predictors with their criteria

Predictor	Code	Criteria
Fantasy	FANT	Games should provide association between games' elements and environmental stimuli in the real world
		games should provide fast actions and high quality graphics to increase arousal/excitement
		Games should support the use of words and expressions from the game into real-life conversations
		Games should support sounds and music that activate lively memories about games (clap etc.)
Mystery	MYST	Games should evoke curiosity, e.g. through mysteries [36-37]
		Fame has some surprises [40]
		Players should know more about the follow-game content before ending the game [40]
		Games should allow player to experience of discovering a new solution, place or property [41]
Thrill	THRL	Players should reach desired outcome by experiencing pressure during game play [41]
		Games should allow player to perceive danger or risk [41]

Table 7

SLR results of IRBRPM (Modified predictors italicized and new predictors underlined)

S. No.	Predictors	Code	R2 Value
1	<u>Fantasy</u>	FANT	0.511
2	Feedback	FEED	0.427
3	*Clear Goals*	CLGL	0.341
4	Concentration	CONC	0.324
5	Social Interaction	SINT	0.313
6	*Players Skills*	PSKL	0.290
7	<u>Thrill</u>	THRL	0.085
8	<u>Mystery</u>	MYST	0.076

Table 8

Accuracy metrics

S. No.	Metric	Value
1	MMRE	0.01739
2	PRED(25)	1

4.7.2 Improved model validation

To validate IRBRPM, we used K-fold cross-validation [45]. The dataset comprising of 80 games was distributed into 8 folds (i.e. K = 8) with each fold consisting of 10 games. Randomization was used for distribution of games to folds. In each iteration, 7 folds were used for model calibration while the remaining one fold was used for model validation.

Table 9 summarizes the results of our cross-validation exercise. It shows the rating prediction model obtained in each iteration along with its R2 value. This table also presents the values of accuracy metrics in each iteration. The results of K-fold cross-validation appear to be very encouraging. In all 8 iterations, MMRE is (25) is greater than the threshold value (i.e. 0.75). Moreover, average values of these metrics are also within acceptable thresholds.

This improved model was assessed for accuracy using MMRE and PRED (25) and validated using K-fold cross validation. IRBRPM had even better R2 than RBRPM and provided encouraging results during assessment and validation. This research can be extended in a number of dimensions. Firstly, iOS based puzzle games can also be considered for rating prediction as the present work is limited to Android-based puzzle games. Secondly, other game types such as sports games and action games (instead of just puzzle games) can be evaluated. Last, but not the least, different models other than GameFlow can be explored and used for providing the foundation for the prediction model.

5. Conclusions

This research work has described the derivation of a regression-based model for predicting the rating of Android-based puzzle games. The model was derived by applying FS MLR on a dataset of 80 puzzle games. The dataset of selected games was compiled by using the GameFlow model as a base. The ratings predicted by our proposed model (RBRPM) were better than the ratings provided by the general-purpose GameFlow model.

The initial proposed model consisted of 5 predictors which significantly contribute towards the prediction of ratings. Later on, some new criteria were included in the already identified predictors. Moreover, new elements (predictors) were also found and evaluated. As a result, an improved model (IRBRPM) for predicting the rating of Android-based puzzle games was proposed which relied on eight predictors. This improved model was assessed for accuracy using MMRE and PRED (25) and validated using K-fold cross validation. IRBRPM had even better R2 than RBRPM and provided encouraging results during assessment and validation.

Table 9

K-fold cross-validation results

Iteration	Validation Data Points	Rating Prediction Model ($\hat{Y}$ represents predicted rating)	R2	MMRE	PRED (25)
1	15,19,20,30, 34,55,60,69, 73,76	$\hat{Y}$ = -0.170 + (0.311*FANT) + (0.107*SINT) + (0.137*FEED) + (0.135*CONC) + (0.157*MYST) + (0.167* CLGL) - (0.111* THRL) + (0.124*PSKL)	0.858	0.01789	1
2	3,10,13,31, 49,53,63,70, 71,74	$\hat{Y}$ = 0.205 + (0.279*FANT) + (0.105*SINT) + (0.131*FEED) + (0.150*CONC) + (0.109*MYST) + (0.174* CLGL) - (0.108* THRL) + (0.100*PSKL)	0.845	0.01936	1
3	4,7,12,24, 27,33,57,65, 66,79	$\hat{Y}$ = -0.044 + (0.293*FANT) + (0.108*SINT) + (0.128*FEED) + (0.171*CONC) + (0.137*MYST) + (0.172* CLGL) - (0.100* THRL) + (0.087*PSKL)	0.852	0.01472	1
4	6,8,23,32, 37,48,61,62, 75,80	$\hat{Y}$ =-0.153 + (0.393*FANT) + (0.096*SINT) + (0.142*FEED) + (0.141*CONC) + (0.135*MYST) + (0.146* CLGL) - (0.130* THRL) + (0.101*PSKL)	0.890	0.02811	1
5	2,14,16,29, 40,43,50, 51,54,64	$\hat{Y}$ =-0.030 + (0.323*FANT) + (0.114*SINT) + (0.137*FEED) + (0.163*CONC)+ (0.129*MYST) + (0.157* CLGL)- (0.125* THRL) + (0.096*PSKL)	0.866	0.01509	1
6	5,28,35,36, 45,46,56,67, 68,77	$\hat{Y}$ = -0.23 + (0.310*FANT) + (0.102*SINT) + (0.134*FEED) + (0.154*CONC) + (0.139*MYST) + (0.153* CLGL) - (0.105* THRL) + (0.106*PSKL)	0.837	0.01802	1
7	9,17,22,25,39 ,41,44,47, 59,72	$\hat{Y}$ = -0.070 + (0.373*FANT) + (0.093*SINT) + (0.090*FEED) + (0.152*CONC) + (0.106*MYST) + (0.125* CLGL) - (0.081* THRL) + (0.150 * PSKL)	0.875	0.02654	1
8	1,11,18,21, 26,38,42,52 ,58,78	$\hat{Y}$ = -0.004 + (0.296*FANT) + (0.104*SINT) + (0.103*FEED) + (0.172*CONC) + (0.163*MYST) + (0.177* CLGL) - (0.131* THRL) + (0.102 * PSKL)	0.872	0.02195	1
		Average	0.862	0.02021	1

6. Future Work

This research can be extended in a number of dimensions. Firstly, iOS based puzzle games can also be considered for rating prediction as the present work is limited to Android-based puzzle games. Secondly, other game types such as sports games and action games (instead of just puzzle games) can be evaluated. Last, but not the least, different models other than GameFlow can be explored and used for providing the foundation for the prediction model.

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