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A Mapping Approach to Identify Player Types for Game Recommendations

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Received: 23 October 2019; Accepted: 28 November 2019; Published: 2 December 2019

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Abstract: As the size of the domestic and international gaming industry gradually grows, various games are undergoing rapid development cycles to compete in the current market. However, selecting and recommending suitable games for users continues to be a challenging problem. Although game recommendation systems based on the prior gaming experience of users exist, they are limited owing to the cold start problem. Unlike existing approaches, the current study addressed existing problems by identifying the personality of the user through a personality diagnostic test and mapping the personality to the player type. In addition, an Android app-based prototype was developed that recommends games by mapping tag information about the user's personality and the game. A set of user experiments were conducted to verify the feasibility of the proposed mapping model and the recommendation prototype.

Keywords: game; recommendation system; personality diagnosis; types of gamers

1. Introduction

In modern society, gaming has become a part of popular culture that everyone enjoys regardless of gender or age. With the advent of various gaming platforms, such as mobile, high-end PC, and console games, users can enjoy playing games as per convenience; thus, their needs (or wishes) regarding games have diversified. Recently, a new genre that combines several existing game genres has been researched and developed to meet the needs of users. Owing to such efforts, the gaming industry has grown and will continue to expand steadily. It has been analyzed that the total size of the gaming industry will grow to approximately $196 billion by 2022, if the mobile and online markets are combined [1].

Owing to the rapid growth of the gaming industry, a large number of games are being released in an increasingly short period of time and game development has become faster. Indeed, statistics from a platform called Steam, which is one of the leading overseas online game platforms, show that a total of 9050 games have been released in the year 2018. This shows a 28% increase over the year 2017 [2]. Thus, many games have been released in a short period of time, making it difficult for people to find the games they want. To address such difficulties, game recommendation systems and services have emerged.

Game recommendation systems in the past tended to focus on the classification of games rather than on recommendation. An example is Naver's "Game Smart Finder," which does not exist anymore. In this system, it was possible to search without specifying a keyword, and detailed results were provided according to category. However, detailed analysis and information about the game were insufficient, and the absence of self-assessment and review and recommendation systems resulted in a failure to meet the needs of users.

In addition, existing game recommendation systems were developed for gamers who played a variety of games. In this case, to analyze a player's propensity to play, the system used "collaborative filtering", a recommendation system based on the gaming experience of the user [3]. In this process, additional reviews were utilized to encourage users to review and evaluate games based on additional criteria. However, with such recommendation systems, effective recommendations were only available to users who had sufficient gaming experience. For users having little or no knowledge or experience of games, appropriate game recommendation was almost impossible. There are also recommendation systems using word embeddings (e.g., word2Vec and Glove) [4,5]. However, the word embeddings method is not suitable for our settings. The used words that describe games are quite diverse and it is very hard to prepare the training corpus for word embeddings in the game domain; to get meaningful word embeddings, the training corpus should cover various genres and the overall game titles. However, such kind of a corpus that satisfies all conditions is not available.

In the present study, a method is introduced to use personality tests to determine the game player category of users and thereby recommend relevant games according to the identified player type. In personality tests, the user's personality is analyzed according to five indicators, utilizing the "big five personality traits" (as termed hereinafter, the OCEAN model) model, which is commonly used in psychology [6,7]. Specifically, a new mapping approach is proposed between the OCEAN model and 10 different player types in various aspects of game play. The mapping table classifies characteristics of players into 60 types at a finer level.

The key enabler of game recommendations are the tags. By analyzing the tag field in the game information extracted from the Steam website, about 351 game tags that are used for game representation were identified. Subsequently, unnecessary tags for game recommendation were filtered out to finally obtain 119 tags. In particular, the weight of each tag was calculated using cosine similarity between two different vectors: One vector was used to represent the relation between player type and tag, and the other vector represented that between game title and player type. Results using Google search engine were used to construct the vectors [8,9]. Each tag was assigned a weight between 1 and 5 after scaling. As a result, weight values for meaningful tags for about 26,000 games were assigned in advance for each of the 10 player types.

To perform a set of user experiments, an Android app-based prototype system was built which includes a user survey and game recommendations. Once users complete the survey through the user interface, a player type is assigned to them from among 10 different types. Based on the player type information, 25 games are recommended to users. In an experiment involving 10 college students who enjoy playing games frequently, the player type analysis result is promising, but the results of game recommendations have confirmed that there is still much room for improvement.

The remainder of the paper is organized as follows. Section 2 describes how the game information has been constructed and summarizes their statistics. Section 3 introduces the proposed OCEAN player type mapping table based on psychological basis and gamers' characteristics. In Section 4, the working of the game recommendation system is explained, and this includes the Android app-based user interface and data flow between the server environment and the user environment. Section 5 analyzes the results of user experiments on 10 testers, and Section 6 discusses existing limitations of the proposed approach. Subsequently, conclusions and directions for future research are presented.

2. Preparation of Game Data

In order to construct sufficient amount of game information, several game portals that are updated actively on the Web were investigated. Among them, the Steam site was selected because it is a large gaming site with 33 million users per day according to an announcement made in 2017 by Valve Corp., which operates Steam [10]. In addition to Steam, Metacritic (www.metacritic.com) and Opencritic (https://opencritic.com/) are the main game review sites. Metacritic is a site that deals with various reviews, including those of games and movies. However, the site also provides information about games that are not on sale. We excluded it because we really wanted to use only games that are available for purchase. Opencritic was excluded because it only provides information on games after 2013. To generate effective game recommendations, overall game information (e.g., game title, description, release date, tags.) was extracted from existing games. Additionally, it was confirmed that 351 tags are used for representing about 26,000 games.

2.1. Game Data Collection

To complete the game information table, a total of five categories of information were collected as shown in Table 1. The 'Text' field is a description of the game displayed by the seller for sale on the webpage. In the case of 'Tags' field, the top 20 tags among various types have been chosen that have been annotated by multiple users. If a game has less than 20 tags, all the tags assigned to the game have been collected. The 'Image URL' field represents the Uniform Resource Locator (URL) location where the game picture is located.

Table 1. Selected samples of the game information table.

Name (Game Title)	Text (Detailed Description of the Game)	Date (Release Date)	Tags (Features of the Game/Genre)	Image URL (Game Title Image URL)
PLAYER UNKNOWN'S BATTLEGROUNDS	PLAYERUNKNOWN'S BATTLEGROUNDS is a battle royale shooter that pits 100 players against each other in a struggle for survival. Gather supplies and outwit your opponents to become the last person standing.	Dec 21, 2017	/Survival/Shooter/Multiplayer/ PvP/Third-PersonShooter/FPS/ Action/OnlineCo-Op/ BattleRoyale/FPS/ Tactical/Co-op/First-Person/EarlyAccess/ Strategy/Competitive/ ThirdPerson/Team-Based/ Difficult/ Simulation/Stealth	https://steamcdn-a.akamaihd.net/steam/apps/578080/header.jpg?t=1544485873
MONSTER HUNTER: WORLD	Welcome to a new world! In Monster Hunter: World, the latest installment in the series, you can enjoy the ultimate hunting experience, using everything at your disposal to hunt monsters in a new world teeming with surprises and excitement.	Aug 9, 2018	/Action/Hunting/Co-op/Multiplayer/ OpenWorld/ThirdPerson/RPG/ Adventure/Fantasy/ CharacterCustomization/Difficult/ Singleplayer/ActionRPG/Exploration/ GreatSoundtrack/ReplayValue/ Atmospheric/HackandSlash/JRPG/ Souls-like	https://steamcdn-a.akamaihd.net/steam/apps/582010/header.jpg?t=1544082685

As a result, a total of 55,825 URLs were collected, and the unique number of games amounted to 26,411. The difference between the actual number of collected URLs and the unique number of games is attributed to the following two reasons in general: (1) Websites requiring age authentication were excluded because the collecting program failed to access their content, (2) if the game's downloadable content (DLC) existed, it was connected to the same link as the original game, and hence duplicate games were excluded.

2.2. Game Tag Information

To get tags statistics of games, the tags field from the game information table presented in Section 2.1 was used. The tags were basically tokenized on a '/' basis to separate each. Table 2 shows the game tag data statistics based on their occurrence.

Table 2. Statistics of game tags.

Total Number of Unique Tags	Maximum Frequency of Occurrence	Minimum Frequency of Occurrence	Average Frequency of Occurrence
351	6754	1	233.79

It was confirmed that a total of 351 game tags were used and the average frequency of occurrence was approximately 234. For example, publicly known tags, such as, Action, Adventure, Strategy, and RPG have shown up more than 2000 times, meanwhile individual tags of games such as Battle Royale have shown low frequencies.

3. The Proposed Model for Mapping

3.1. Personality Diagnosis

In this study, the Big Five Personality Traits (hereinafter, the OCEAN model) model was used to gauge the user's personality, and each of them represented the attributes of nervousness, extroversion, affinity, sincerity, and openness [6]. Among the personality traits, the two most suitable and the most inappropriate one were selected. As a result, 60 types of combinations were created and mapped to the type of player. The most inappropriate personality trait was selected to account for somewhat transient characteristics of gamers. In this process, 50 sample questions from the International Personality Item Pool (IPIP) were utilized that examined the type of individual OCEAN from the OCEAN test. Points were allocated based on the responses and these helped to determine the personality type [11,12].

3.2. Player Type

The player type was initially set based on an interest graph consisting of the x- and y-axes [13]. "The x-axis goes from an emphasis on players (left) to an emphasis on the environment (right); the y-axis goes from acting with (bottom) to acting on (top)". The models were designed in the form of Multi-User Dungeons (MUDs), a game genre which is currently hard to find and is not suitable for modern games [14]. In modern games, thus, new hexagonal, octagonal, and 12-sided polygon models for have been presented. However, the new models are not feasible for recommending games because they were developed from the perspective of game developers' views rather than from the gamers' views [15]. Therefore, the current model has been devised by referring to more detailed models of hexagonal, octagonal, and 12-sided polygon. The proposed model, consisting of 10 types in total, can be divided into six types based on defined criteria, and four types derived from the basic interest graph. The type names and detailed descriptions are presented in Table 3 as follows.

For models of hexagonal or higher, the model was newly set to 10 types based on the four basic interest graphs which evaluated whether the player type was suitable. Based on the new settings, the 60 combinations discussed in Section 3.1 were first compared to the four types of basic interest graph models, and then the combination of OCEAN personality types were identified in cases that did not correspond to any of the existing ones. Subsequently, they were newly set to fit that type.

Table 3. Detailed descriptions of 10 different player types.

Type	Detailed Description
Interest type	The type that seeks attention and wants to help people. There are times when people help or bully for attention. Corresponds to the philanthropist of the existing quadrilateral model.
Honor type	A type that focuses on performance and achieving a high position within a game. Examples include users who try to complete the game's achievements and those who aim to rank high in competitions. Applicable to the achiever of the existing quadrilateral model.
Freedom type	A type that values free play within a game. This type can be divided into creators and explorers. Creators prefer to create new things and decorate avatars, and explorers tend to explore every corner of the game. Applicable to the free spirit of the existing quadrilateral model.
SNS type (Social Network Services)	The type that values interaction between users. Importance is given to chatting and interacting with other users in many ways. Corresponds to the socializer of the existing quadrilateral model.
Arcade type	A type that cannot play a game for a long time. They prefer games that end quickly or are simple to play, otherwise they quit. This type has been newly added to this study.
Good loner type	They like to help others but are not interested in doing so if other users do not ask for help first. The type has been newly added from this study.
Classic type	A type that likes classical games or old-style games. They like the graphics or the conservative style of gameplay. The type has been newly added from this study.
Solo type	A type that likes to play alone. A typical example is a user who enjoys playing a story-oriented game by themselves. The type has been newly added from this study.
Criticism type	A type that likes to make an assessment regarding a game. Most of them complain excessively about inconveniences. The type has been newly added from this study.
Stubborn type	A type that plays without regard for other users. They usually play single-player games, but they also play multi-player games without hesitation. An example is the so-called 'troll' who willfully acts against the team. The type has been newly added from this study.

3.3. OCEAN Personality Analysis and Player Type Mapping

To build an OCEAN player type mapping table, manual mapping has been performed by utilizing the personality and characteristics that are readily apparent in the case of high individual tendencies, and the results are shown in Table 4.

Table 4. OCEAN player type mapping table.

BEST	SECOND	WORST	TYPE
O	C	E	Freedom type
		A	Freedom, SNS type
		N	Freedom, SNS type
	A	E	Freedom, Solo type
		C	Arcade, Interest type
		N	Freedom, SNS type
	E	N	Freedom, SNS type
		C	Arcade type
		A	SNS type
	N	A	Freedom type
		E	Freedom type
		C	Arcade type
C	O	E	Honor, Freedom type
		A	SNS type
		N	SNS type
	A	E	Good loner type
		O	Honor, Interest type
		N	SNS, Interest type
	E	N	SNS type
		O	Honor, Interest type
		A	SNS type
	N	A	Honor type
		E	Honor type
		O	Honor type
A	C	E	Good loner type
		O	Interest, Honor type
		N	Interest type
	O	E	Freedom, Solo type
		C	Arcade, Interest type
		N	Interest, Freedom, SNS type
	E	N	Interest type
		C	SNS, Arcade, Interest type
		O	Interest type
	N	O	Interest, Classic type
		E	Honor, Good loner type
		C	Arcade, Interest type

Table 4. *Cont.*

BEST	SECOND	WORST	TYPE
E	C	O	Interest type
		A	SNS, Stubborn type
		N	SNS type
	A	O	Interest, Honor type
		C	SNS type
		N	SNS type
	O	N	SNS type, Freedom type
		C	SNS, Arcade, Interest type
		A	Freedom, SNS type
	N	A	Freedom, SNS, Honor type
		O	Interest Classic type
		C	SNS, Criticism type
N	C	E	Honor type
		A	Honor type
		O	Classic, Honor, Interest type
	A	E	Honor, Freedom, Solo type
		C	Criticism, Arcade, Interest type
		O	Classic, Interest type
	E	O	Classic, Interest type
		C	SNS type
		A	Honor, SNS, Stubborn type
	O	A	Honor, Freedom, SNS type
		E	Honor, Freedom, Solo type
		C	Arcade, Interest type

- "O" has the characteristics of being imaginative and like new things. Therefore, it means high exploration.
- "C" is sincere, empowers, and enjoys achieving goals. So, they try to achieve their achievements in the game. It also means working toward your goals.
- "E" is sociable and confident. That is why they like cooperation with people.
- "A" is considerate with altruism. Because of this, they enjoy helping the players around them.
- "N" often feels anxious and hostile. It is also stressful. As a result, they often act negatively or critically.

3.4. Mapping between Game Tags and Player Types

As mentioned above, 351 game tags were initially identified. Tags are created by the user in general. Those tags are evaluated by other users. If one user agrees with the tag for the given game page, the tag's popularity is increased by pressing the "+" button. In this paper, we adopted only the top 20 tags from each game page in the Steam site. However, all the 351 tags were not used. A few tags could be merged into one because their meanings are almost identical although tag representations reside sometimes in high-level or sub-level concept. However, these different representations were maintained to allow diversity of tags simply by allocating the same weight. After additionally excluding non-related tags that could not be assigned to the OCEAN model, the actual number of tags were substantially reduced from 351 to 119. In the process of reduction, we assumed that some game tags can be grouped to their own higher-concept tags as in Figure 1. In other words, we considered game tags taxonomy in the reduction, only Is-A relationship. In this way, the weights of the lower-concept tags were set as same as that of the upper-concept tag and reduced to 119 tags in total.

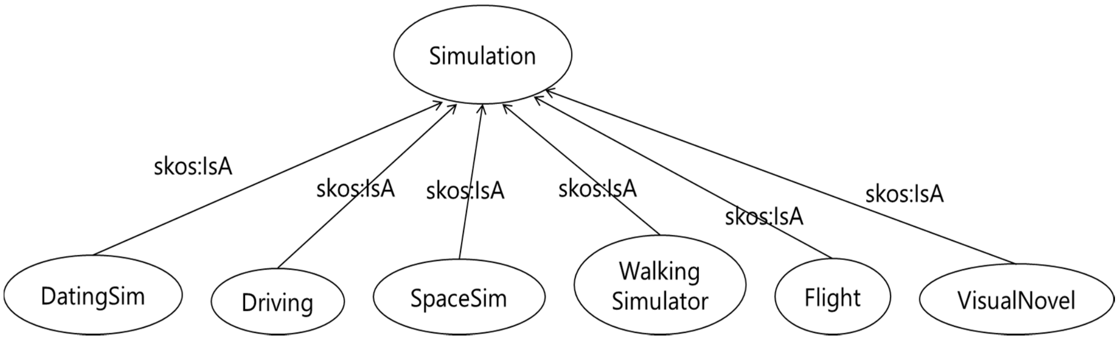
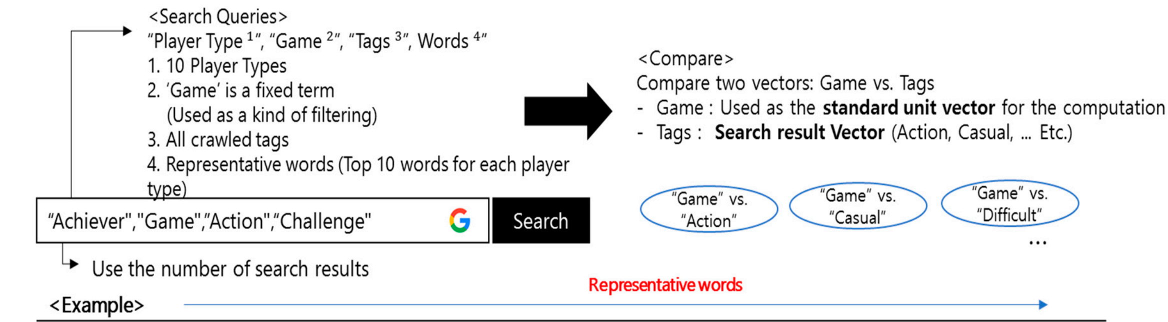


Figure 1. Example of game tag taxonomy.

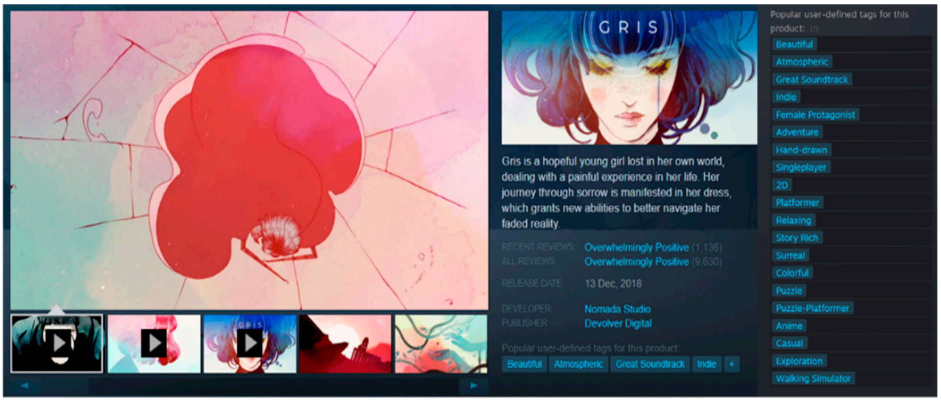
The concept of cosine similarity computation was used to assign weights [16]. The configuration of vectors to obtain similarity leveraged the number of search results from Google search engine [8,9]. For example, as in Figure 2, 10 words representing each player type are the most frequent 10 words obtained from Top-100 Google search results for the given player type. Our search queries including each of the 119 selected tags and the representative words were constructed. The number of search results signified the relation between the given player type and the tag name. Based on a number of search results, the values of the vectors were specified. Subsequently, new vectors were constructed based on the number of results that contained a player type, a tag, and representative words. Each tag was assigned a weight between 1 and 5 based on the cosine similarity between them.



	Challenge	Trophy	master	complete	platinum	Ranker	winning streak	Achievement	pro gamer	Expert
Game	800,000	427,000	782,000	1,030,000	356,000	8,350	37,100	356,000	3,370	537,000
Action	551,000	357,000	646,000	648,000	355,000	7,710	30,800	296,000	2,300	48,000
Casual	205,000	77,100	201,000	221,000	83,400	5,100	18,300	110,000	1,610	149,000
Difficult	354,000	107,000	375,000	383,000	82,700	5,400	21,100	220,000	1,130	292,000

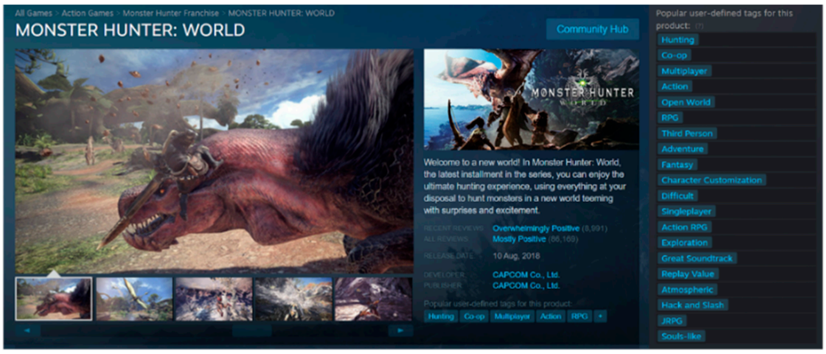
Figure 2. Details of search query and example vector.

As a result, a weight table of 119 tags was created for each type and utilized in the mapping process. Figure 3a shows a real example which is mapped to a game 'GRIS' that is on sale on Steam. Although there were various tags in the game, only nine tags were used for real mapping by following the method as described above. Figure 3b is another example of mapping. The difference from Figure 3a was that a total of 13 tags were used. It should be noted that the sum of weights and the number of tags that were used could be changed depending on the game.



Game Tag	Interest	Honor	Freedom	SNS	Arcade	Good loner	Classic	Solo	Criticism	Stubborn
Atmospheric	1	2	4	5	3	4	2	4	2	3
Adventure	2	5	5	1	1	3	1	5	2	4
Singleplayer	1	4	4	1	3	4	3	5	3	5
Relaxing	2	2	4	2	1	2	1	2	5	2
Story Rich	1	4	3	1	1	4	2	5	3	3
Puzzle	1	5	3	3	2	4	3	2	2	2
Puzzle-Platformer	1	5	3	3	2	4	3	2	2	2
Casual	4	2	1	3	4	3	1	2	2	2
Exploration	2	5	4	3	1	3	1	5	2	3
Sum	**15**	**34**	**31**	**22**	**18**	**31**	**17**	**32**	**23**	**26**

(**a**) Game tag-player type mapping table of the game 'GRIS'



Game Tag	Interest	Honor	Freedom	SNS	Arcade	Good loner	Classic	Solo	Criticism	Stubborn
Co-op	4	2	4	5	1	4	3	1	1	1
Multiplayer	4	3	1	5	1	3	1	1	1	1
Action	3	3	4	1	3	2	1	5	3	4
OpenWorld	1	3	5	3	1	4	1	5	3	2
RPG	3	5	4	2	1	5	3	3	3	4
Adventure	2	5	5	1	1	3	1	5	2	4
Fantasy	4	4	4	4	3	4	1	3	3	3
Difficult	4	5	3	2	1	4	1	4	2	4
Singleplayer	1	4	4	1	3	4	3	5	3	5
ActionRPG	3	5	4	2	1	5	3	3	3	4
Exploration	2	5	4	3	1	3	1	5	2	3
Atmospheric	1	2	4	5	3	4	2	4	2	3
JRPG	2	5	2	2	1	1	1	3	1	1
Sum	**34**	**51**	**48**	**36**	**21**	**46**	**22**	**47**	**29**	**39**

(**b**) Game tag-player type mapping table of the game 'MONSTER HUNTER: WORLD'

Figure 3. Examples of actual mapping table: (**a**) GRIS and (**b**) MONSTER HUNTER: WORLD.

Hereby, a total sum of different weights was calculated for each game, and relevant games could be recommended to users based on the total value of the weights. For example, if one of the games in Figure 3 is to be recommended to a user of Honor type, this is done by comparing the sum of the

'Honor Type' weights between 'GRIS' and 'MONSTER HUNTER: WORLD'. Because the latter game has a higher total value, it is recommended.

4. Overview of Game Recommendation System

The overall architecture of the game recommendation system is largely divided into the user environment and the server environment, as shown in Figure 4. The overall data flow consists of the communication between the user environment and the server environment and the database access within the server environment.

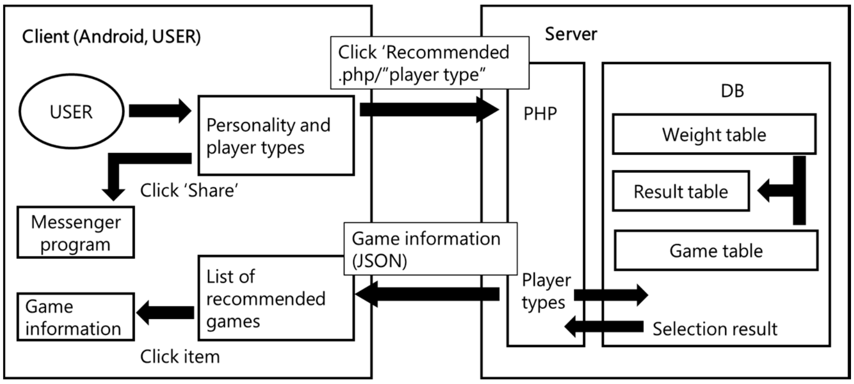


Figure 4. Overall data flow of the game recommendation system.

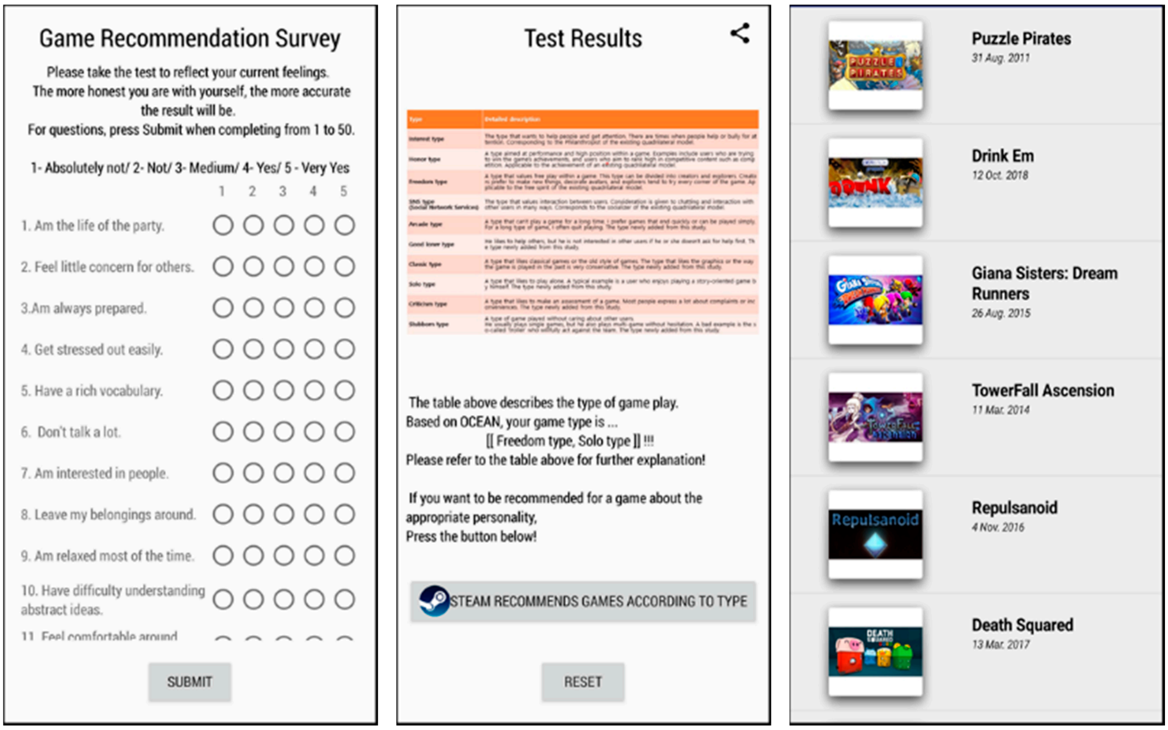
The user environment has been developed as an Android app and consists of two parts: (1) responsible for calculating the output of surveys and (2) player type analyses. The server environment has a database containing information related to the recommendation, and this information can be transferred to the user environment in JSON (JavaScript Object Notation) format.

4.1. User Interfaces in Android App

As shown in Figure 5, the Android app has three different interfaces which show the user survey, survey results, and game recommendations based on the results.

The International Personality Item Pool (IPIP) that examines an individual's OCEAN type through a psychological test is implemented by referring to the existing GitHub code [17], but details have been translated into Korean language and configured in the same way as in Section 3.1. In the original program, a scale of 1 to 5 was assigned to options to produce results for OCEAN entities. In the present study, the variation in the respective increase/decrease was so significant that the O and C of the five entities in the OCEAN was always high and, hence, the accuracy of the resulting values was supplemented by adjusting via the method of −2, −1, 0, 1, and 2.

On the result screen, based on the results obtained from the previous survey, the 10 types of players in Section 3.2 were mapped. On clicking the "Recommend Game" button in the results pane, the underlying software module accessed the server-side database to organize a list of games, using PHP's MySQL improved (i.e., MySQLi) Extension [18].



(**a**) User survey (**b**) Personality test result (**c**) Recommendation results

Figure 5. Three main user interfaces (UIs) for user-side Android app.

4.2. Server-Side Data Flow

For the server environment, MySQL database was used for data storage and management. In addition, most of the data access functions were developed with PHP's MySQLi Extension which enabled MySQL Query to perform the subordinating operations. The overall data flow for game recommendations is described in Figure 6.

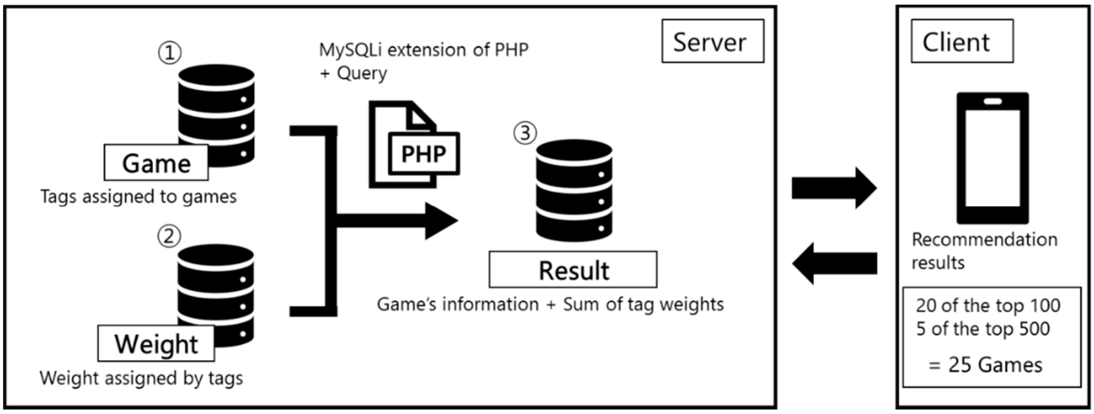


Figure 6. Server-side data flows.

The game database (DB) table (①) in Figure 6 (i.e., 'Game' table) has full meta-information of all the games, which amount to 2300, and the weight DB table (②) has weight value data for each tag. The result DB table (③), created using data from the game and weight DB tables, is a table that stores the sum of the tags assigned to each game based on tag information for each of the 10 player types.

Overall data flow in server-side is operated by the MySQLi Extension of PHP. First, it reads game data from the game DB table, and tokenizes their tag. Then, it uses the tokenized tags and the weight

DB table to generate the sum of weights. Finally, it saves the sum of weights to the result DB table along with the game data obtained from the game DB table.

When a request is received from the user's environment (i.e., user interface in Android app) through PHP, the corresponding player type of the user is passed as a parameter to compute the result DB table according to the given player type. If the computation is completed, the weighting result is delivered to the user environment in a descending order. Subsequently, in the user environment, 25 games in total (20 of the top 100 and 5 of the top 500 randomly selected within scope) are recommended to the user.

4.3. Comparison with Other Recommendation Systems

Most existing recommendation systems in the game domains are based on experience-based collaborative filtering, as mentioned above. Outside of the game domains, various recommendation systems have been suggested. Among these systems, the state-of-the-art recommendation system includes collaborative filtering and content-based filtering [19–21]. However, cold-start problems are problematic in recommendation systems [22,23]. To solve the problem, hybrid recommender systems have been proposed [24]. Similarly, our proposed approach tackles the cold-start problem of game recommendations by suggesting a mapping approach to identify a game player type based on the OCEAN model borrowed from psychological area. Compared with other recommendation systems, our game recommendation prototype is quite straight-forward—after the player type identification, 25 games are recommended in an ad hoc manner.

5. Experimental Results

5.1. Player Type Analysis

The user tests were conducted on ten randomly selected university students in their 20's. The students were investigated for player type matching by conducting personality tests using the Android app developed as shown in Figure 5.

Figure 7 summarizes the results of the player type tests. Ten users participated in the test, and only three, or 30%, were assessed to be completely inconsistent. Five of the remaining seven said that the player type was perfectly consistent with their propensity, while two said that there were additional results that matched them, or which should be excluded.

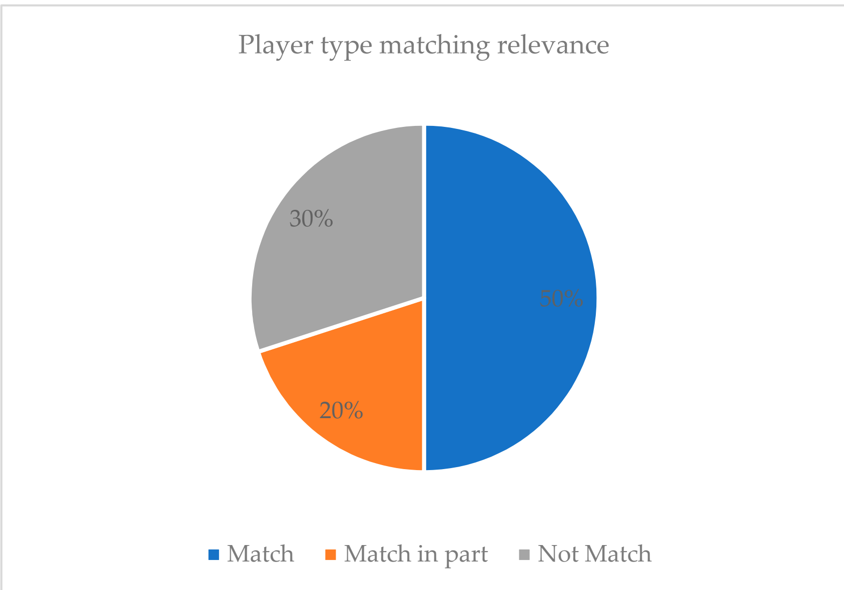


Figure 7. Results of player type tests.

5.2. Game Recommendation Based on the Identified Player Type

The survey was conducted on the same users as in Section 5.1. Figure 8 shows the results of the game recommendations. Unlike the results of Section 5.1, users stated negative opinions about the recommendation results. Only two out of 10 users were satisfied with the recommendations, and the rest were not.

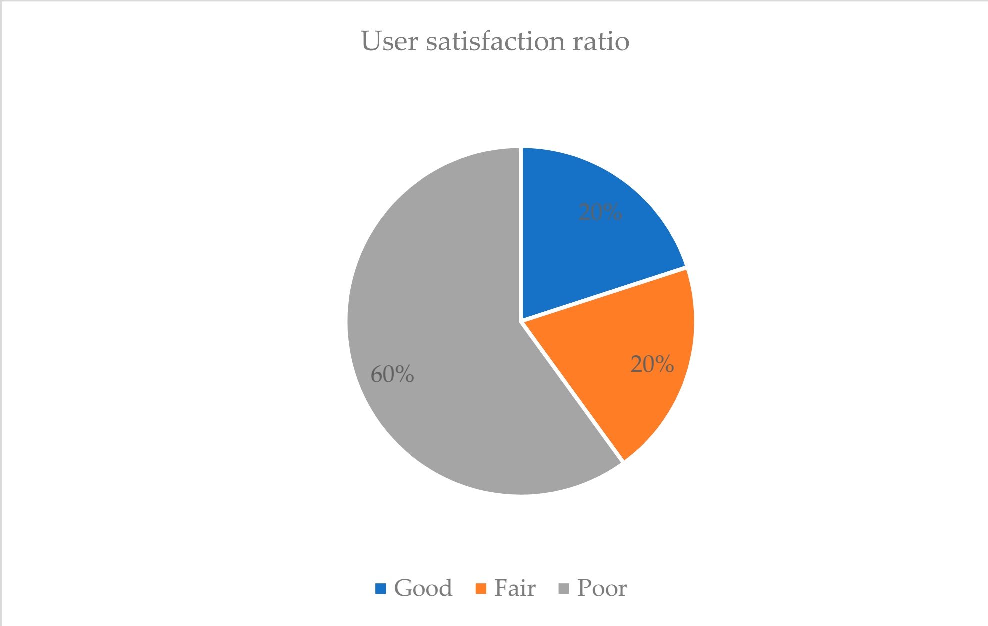


Figure 8. Results of game recommendations.

Most of the users who played several kinds of games were satisfied, the reason being that a few recommended games were unknown or not seen often. The analysis results of unsatisfactory users can be summarized as follows: (1) Many unfamiliar games were recommended, and (2) a few of them had negative reviews on the Steam website.

6. Discussion

Analysis on user experiment results has led to the following inferences regarding the developed player types and recommendation of games based on player type.

For player type analysis, the accuracy is about 70%, and hence not perfect. The reason is that the mapping method between OCEAN and the player type is a method that simply considers the main character of the player. It is assumed that the accuracy would improve if these parts were to be arranged by automation or modalities.

Regarding game recommendations, only 30% of test users have been satisfied. A few factors are inferred to be incorrect in the recommended algorithm and in the tag weighting settings. For the recommended algorithm, only the sum of the weights has been considered, but the type of game is identical at the time of the actual satisfaction survey, and hence the game recommendation itself is not satisfactory. In order to solve this problem, it is expected that game evaluation criteria such as sales volume can be adopted to prioritize high-quality games in addition to weighting, thus increasing satisfaction level.

For tag weighting, the accuracy was reduced because it was not modifiable in the same way as the aforementioned player type analysis. Additionally, it would be difficult to reflect the graphical representation of the player's preferences other than the player's propensity, the timing of the play, and the background story of the game, since the current character and type of player have been weighted only with related tags. Hence there is room for improvement by adding questionnaires to determine the preferences of players other than OCEAN items.

7. Conclusions and Future Work

In order to overcome the problem of cold start, which is a disadvantage in existing game recommendation systems, the present study has proposed an OCEAN player type mapping by employing the OCEAN model that is frequently used in the field of psychology. Android app-based user tests involving 10 randomly selected college students have been performed to demonstrate the feasibility of the proposed model.

In particular, information regarding approximately 26,000 games has been collected from Steam, which is one of the biggest online gaming websites. A total of 351 tags have been compiled and these were used to describe/represent the games. Additionally, 119 key game tags have been derived after filtering out unnecessary tags while mapping OCEAN-based player types to each game. The proposed model has been tested from user testing through the Android app, which recommends top-k games to users through tag weight mapping based on the derived player type.

In the case of game recommendation, user satisfaction is generally low as of now. Further research is required on upgrading the game mapping algorithm, deriving new evaluation factors to improve user satisfaction, and improvement of the OCEAN model to improve quality of game recommendations in future. To enhance user satisfaction, deep-learning-based recommendations and ranking techniques using TensorFlow have been planned to be implemented which can introduce personalized session-based recommendations [25,26].

To sum up, most of the existing recommendation systems are based on experience-based collaborative filtering. However, aggregating large-scale user experiences is cumbersome, and the cold-start problem is usually encountered. Our proposed approaches alleviate the cold-start problem in game recommendation by mapping a psychological model and user-generated game tags. Although the user satisfaction of our preliminary game recommendation is lower than expected, our proposed OCEAN player type mapping is quite successful in identifying gamers' player type. We have a firm belief that the OCEAN player type mapping can be developed further and used effectively for more advanced game recommendation system.

Author Contributions: Conceptualization, Y.L. & Y.J.; Data curation, Y.L.; Writing—original draft preparation, Y.L.; Writing—review and editing, Y.J.; Visualization, Y.L.; supervision.

Funding: This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korean government (Ministry of Science and ICT (MSIT)) (no. 2018R1C1B5031408).

Conflicts of Interest: The authors declare no conflict of interest.

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