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Groups of Gamers: Market Segmentation of Brazilian Electronic Gamers

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ABSTRACT

The electronic games industry is a new, dynamic, and fast-growing economic sector. However, organizations in this industry do not know the profile of their consumers. In view of this knowledge gap, the objective of this research paper is to analyze groups of electronic games consumers in the Brazilian market, in terms of their socio-demographic, behavioral, and expenditure characteristics. Using market segmentation literature and motivational variables found in games literature, this paper uses self-organizing maps and analysis of variance to segment 601 Brazilian gamers. The results demonstrate the existence of five different groups of games players and that, in order to reach each group, different strategies need to be used. The first group consists of t players who play all the time. The second has the same features as the first, but they do not have the same amount of time available to play. The third group consists of pro players. The fourth group and fifth group are the new challenge for games companies.

KEYWORDS

Electronic games, market segmentation, consumer behavior, self-organizing maps, Brazil

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1. INTRODUCTION

The electronic games industry is a fast-growing economic sector, one which is larger than the film industry, and represents one of the largest leisure providers in society (Mascena, Pimentel, Fischmann, & Polo, 2012; Baumgarten, 2013; Newzoo, 2019). There are more than 2 billion gamers in the electronic games market, who generate around US$152 billion revenue per year (Newzoo, 2019). Brazil is the fourth biggest electronic gaming market, with 77 million gamers and annual revenue of around US$1.5 billion. This value represents an increase of 25% in two 2 years, which makes the Brazilian electronic games market the thirteenth most profitable in the world (Newzoo, 2019; Istoé, 2017). This is thus an important market that warrants being better understood in order to improve its profitability.

It is not only in Brazil that an expansion of the electronic games market is expected; forecasts estimate that, in 2020, the worldwide profits of this market will be around US$165 billion (Newzoo, 2019). This growth is occurring because there are now diverse ways available to play games. Today, there are still the traditional console or pc games, but it is also possible to play at any time using smartphones, with this being both the most prominent market as well as the hardest to reach (Hsu & Lin, 2015; Kim & Lee, 2017). Furthermore, this growth is not limited only to different platforms on which to play, but also the existence of miscellaneous purposes of games. Electronic games are very diverse, with varying foci – such as, entertainment, casual games, serious games, games for medicine, and even e-sport, where the user is a real professional gamer (pro player). This market thus presents many opportunities to be explored.

Nevertheless, the electronic games market is new and dynamic, and organizations need to recognize their customers' profiles (Jin, 2014; Gedigames, 2014). Furthermore, it is important not only to know the socio-demographic variables of these consumers, but also what the experience of being a player is like, and their motivations to play in a social context (Mosca, 2017). To explore these topics, research was conducted to understand the factors that can influence a person to play and purchase an electronic game and to identify the profiles of different groups of consumers (*e.g.* Hsiao & Chen, 2016; Park & Lee, 2011; Shelton, 2010; Souza & Freitas, 2017). Moreover, Zammitto (2010) suggests that the preference for a game is based on personality, and there are personal traits that influence the types of games that a player may be inclined to purchase. Additionally, Cohen (2014), Engl and Nacke (2013), and Wei and Lu (2014) have studied gamers' behavior, while Sherry, Lucas, Greenberg and Lachlan (2006) and Souza and Freitas (2017) focused on motivational variables that influence play and purchase intention.

Identifying the profiles and desires of gamers is important in order to formulate strategies to reach consumers. However, there is little information about players worldwide, including Brazilian players, and their motivation to play electronic games (Bowman, Oliver, Rogers, Sherrick, Woolley, & Chung, 2016; Arruda Filho & Gammarano, 2018). Such factors create fierce competition between local games providers and better-equipped, larger foreign providers. It is strategically important to understand local markets in terms of consumption and motivation to play electronic games and to identify their particular characteristics when compared to international patterns. In the period from 2015 to 2016 there was an increase of 600% in the number of games organizations in Brazil, but these companies do not know the main reasons that motivate a person to play or purchase a game (Gedigames, 2014; Istoé, 2017).

There is no broadly accepted model which defines the main variables that cause a person to play or purchase a game (Manero, Torrente, Freire, & Fernández-Manjón, 2016). Thus, this research used the motivational factors that influence the intention to play and purchase to segment the Brazilian games market. Segmenting the market into homogenous groups is an efficient strategy to identify and understand the profile of a specific market (Wedel & Kamakura, 2000). This research aims to identify groups of electronic game consumers based on motivational variables that drive them to play and purchase games. Moreover, it uses personal features to describe the groups and formulate a better explanation of how these groups came to be formed.

The electronic games market is very competitive, and it is impossible to satisfy all the desires of different consumers (Cheung, Shen, Lee, & Chan, 2015). This research uses market segmentation strategy to identify the features of the main groups of games consumers. Market segmentation is a method through which the consumer market, with its heterogeneous features, can be divided into homogeneous groups (Smith, 1956). This concept is so important that Brandt (1966) posited that it is impossible for an organization to enter into a competitive market without using this strategy. Market segmentation has become an essential activity for industrialized countries, given that products or services cannot be sold or made without organizations considering consumers' desires (Wedel & Kamakura, 2000).

Nagygyörgy et al. (2013), also using market segmentation strategy with massively multiplayer online (MMO) game players, pointed out that socio-demographic characteristics can influence game choice. Moreover, both game and player characteristics can influence the intention to play and keep playing.

The general objective of this research paper is to analyze groups of electronic games consumers in the Brazilian market and their associated socio-demographic, behavioral, and expenditure characteristics. As a natural outcome of a market segmentation exercise, this research paper can provide profiles for different market groups, making it easier to target them in developing and selling games.

2. THEORETICAL BACKGROUND

This section is divided into two parts. The first section explains the market segmentation concept and the main indispensable criteria that form part of it. The second section shows the motivational variables used to segment gaming consumers.

2.1. Market segmentation

Market segmentation is a very useful strategy for managers. It enables the delineation of strategic market plans that, in operational terms, should obey the following criteria: differential behavior; membership identification; reachability; feasibility; substantiality; responsiveness; stability; profitability; actionability, and projectability (Chart 1) (Desarbo & Desarbo, 2003; Desarbo & Grisafe, 1998; Wedel & Kamakura, 2000).

Furthermore, market grouping should employ segmentation bases, which might be general or product-specific and can be divided into observable and non-observable (Frank, Massey, & Wind, 1972). Chart 2 clarifies that, in line with the product-specific and non-observable nature of this research paper, electronic games are a particular outcome of the leisure industry and, as such, should have product-specific segmentation bases. Consumer groups are based on constructs that are measured in lieu of non-observable behavioral aspects, like motivation, preferences, and intentions.

Chart 1
Market segmentation criteria

Differential Behavior	The members of different market segments should behave differently – either toward the brand or product class or toward the marketing mix activity oriented toward them.
Membership Identification	The marketer should be able to classify each customer in the market place into one or more segments on the basis of obtainable information.
Reachability	The marketer should be able to reach the members of target market segments by means of a distinct marketing mix strategy.
Feasibility	Market segmentation should be a feasible endeavor. Feasibility, here, refers to the formation of market segments that obey or satisfy application-specific technological, environmental, and managerial constraints.
Substantiality	The derived segments must be of different size and magnitude to be taken seriously from a marketing perspective.
Responsiveness	The derived market segments should respond uniquely to the marketing efforts targeted at them.
Stability	Market segments should be stable over time – at least for the period required for identification of members and implementation of associated strategies.
Profitability	Implementing market segmentation must be profitable, yielding increases in expected revenues.
Actionability	The formation of market segments should lead to the specification of associated marketing strategies toward segment targets.
Projectability	The results of a market segmentation study should be projectable to the entire marketplace at hand.

Source: Desarbo and Grisafe (1998), Wedel and Kamakura (2000) and Desarbo e Desarbo (2003).

Chart 2
Classification of Segmentation Bases

	Observable	Non-observable
General	Cultural, geographic, demographic, and socio-economic variables.	Psychographics, values, personality, and lifestyle.
Product-specific	User status, usage frequency, store loyalty, and patronage situations.	Psychographics, benefits, perceptions, elasticities, attributes, preferences, intention.

Source: Frank et al. (1972).

Wedel and Kamakura (2000) present the set of decisions that should be taken before undertaking a segmentation study, creating a four-cell structure using *a priori* and *post hoc* definitions of groups and descriptive and prescriptive segmenting variables. A priori and post hoc refer, respectively, to the initial suggestion of groups or to their unveiling as a result of the segmentation exercise. The latter enables the analysis of the formed market segments as they emerge as a result of qualitative and quantitative data, as this research paper supports.

A predictive approach to researching a phenomenon refers to the use of a dependent variable that is best modeled by different groupings. In the descriptive approach it does not involve envisioning or explaining how a dependent variable will behave. This research used a post hoc descriptive approach that best suits an exploratory study.

According to Goyat (2011), Snellman (2000), and Yankelovich and Meer (2006), behavioral attitudes toward products might be represented by loyalty, preference, motivation, and intention to buy a product or to experience it. Therefore, behavioral segmentation will be based on general characteristics of consumers, considering their attitudes toward playing and buying products, which means that no a priori number of market segments is proposed, nor are variables taken with different weights. After groups are independently proposed, differences in intention to play and in purchase intention for electronic games products are tested.

2.2. Consumer motivation for playing electronic games

Souza and Freitas (2017), in a literature review, found eight motivational variables that have an influence on play and purchase intention. In an empirical analysis, they discovered that only six of these variables have a significant impact: challenge; competition; diversion; fun; fantasy; and social interaction (Souza & Freitas, 2017). These significant variables will be used to segment the games consumer in this research. Furthermore, to give a better description of the groups formed, play intention, purchase intention, time flexibility, arousal, and socio-demographic variables will be used.

Challenge is a fundamental construct in games (Sherry et al., 2006). It is what makes the game flow and what guide the players to take the action that they need to in order to advance in the game (Engl & Nacke, 2013; Grizzard et al., 2015; Reich & Vorderer, 2015; Sherry et al., 2006). How challenging a game must be in order to be considered attractive is also a matter of balance (Hsiao & Chiou, 2012), thus developing efforts are going into offering games that present different challenge levels to players on a unique platform (Murray, 2003).

Another important factor is competition. In the work of Souza and Freitas (2017), this variable had a negative impact; however, it was kept because it had a significant impact and because this variable is extensively discussed in games literature (Sherry et al., 2006). The focus of the competition is to reach a goal in a better way or faster than the other person or group showing who is the most skilled (Cagiltay, Ozcelik, & Ozcelik, 2015; Sherry et al., 2006). Moreover, Chou and Tsai (2007) found that men have a greater preference for competitive games than women. Those reasons make this variable one important factor to describe groups of games consumers.

Games have become an important element in combating stress. It is very common for games to be used to "escape" from the real world and distance oneself from problems (Sherry et al., 2006). Consequently, diversion is a construct found in people that want to escape from daily activities, have fun, and reduce stress (Sherry et al., 2006). Playing games is considered a form of relaxation (Giammarco, Schneider, Carswell, & Knipe, 2015; Jin, 2014; Shelton, 2010; Sherry et al., 2006).

Fun is one of the most important variables in intention to play electronic games (Hsu & Lin, 2015). According to Manero et al. (2016), Hsiao and Chiou (2012), and Souza and Freitas (2017), this is the main motivating variable which makes people play. The fun derived from a game is fundamental to people's desire to continue playing that game rather than change the game or activity (Park & Lee, 2011). However, it should be noted that fun is an individual variable that the motivation varies greatly from each person and it depends how much the player have interest in the game (Bowman et al., 2016; Caroux, Isbister, Le Bigot, & Vibert, 2015).

Fantasy is a very common variable in games; furthermore, it is important because it has the power to stimulate players (Sherry et al., 2006). Factors that stimulate fantasy in games are the possibility to become anyone you want or participate in things that are impossible in the real world. These features are one of the reasons that make fantasy an important construct in play intention. One kind of game that uses this variable extensively is the massively-multiplayer online role-playing game (MMORPGs). In this game, the player assumes a new life, and he needs to improve his character. The more the player identifies his or herself with the character, the more he or she will play, thereby increasing his purchase intention (Park & Lee, 2011; Scriven, 2015; Kim & Lee, 2017).

The ability to interact with any person in any place in the world or just play with a friend to complete a challenge, participate in a competition, or relax has a positive influence on play intention (Souza & Freitas, 2017). Social interaction is one of the most studied variables in games research (Chang, 2013; Cheung et al., 2015; Hsiao & Chiou, 2012; Rogers, 2017). Hamari, Alha, Järvelä, Kivikangas, Koivisto, and Paavilainen (2017) argue that this social interaction is one of the most important factors that motivate a person to play and continue to play. Thus, if one of your friends stops playing a game, you are more likely to stop too. Observing this tendency, it could be said that there is a social contract between the players in a game. For example, when you become part of a clan, this increases the chances that you will continue playing the game (Hsiao & Chiou, 2012; Kim & Lee, 2017). According to Williams (2006), games have become a new way to participate in a social network, and Cheung et al. (2015) observed that people who are more engaged have a greater tendency to purchase more items. Furthermore, in a world like that of an MMO game, this interaction is so important because the way that the player relates to the other can be a way to define the player's behavior in the game (Nagygyörgy et al., 2013; Scriven, 2015).

In addition to the variables discussed, time flexibility, arousal, purchase intention, play intention, and socio-demographic information are all variables used in this study to describe the gaming groups. Time flexibility is a new variable that has arisen from the development of smartphones. This variable is related to the free time that people have and the possibility to play quickly in any place (Wei & Lu, 2014). Arousal is a stimulus given by the game that make a person feel emotions and fixes their attention on the game (Grizzard et al., 2015).

3. METHODOLOGY

3.1. Data collection

The data collection for this research was done in two parts: the first one was collected by a face-to-face in game conventions; the second part was online by Google Docs forms that were shared via a link in groups of players from Facebook.

An online questionnaire, utilizing a Likert scale with 7 points and an accessibility criterion, was applied to a group of 601 games players. Players that were willing to participate were automatically accepted in the data bank, with no scrutiny to relate this sample to the universe of players in the Brazilian scenario. The questionnaire was used during a games event that occurred in the city in December of 2014.

To construct the instrument, previous studies' scales were adapted. The scale was passed by a validation process (Churchill, 1979; Costa, 2011). A pre-test was used and a pilot test as well to do translation validity (content and face validity). The criterion validity and construct validity it was done in statistical ways and those validation scale procedures and results can be found in Souza and Freitas (2017).

The questionnaire was constructed using the following scales and papers: Time Flexibility and Intention to Play from Wei and Lu (2014); Arousal, Challenge, Competition, Diversion, Fantasy, and Social Interaction from Sherry et al. (2006); Challenge and Fun from Jin (2014); and Purchase Intention from Toni and Mazzon (2014), Park and Lee (2011), and Chou and Kinsuwan (2013).

Of the 601 games player, 471 (78.37%) were men and 130 (21.63%) were women. Around 75% were younger than 25 years old. In terms of the frequency with which they play electronic games, 211 (35.11%) play more than once a day, 100 (16.64%) once a day, 114 (18.97%) three or four times a week, 87 (14.48%) once or twice a week, and 89 (14.81%) once or twice a month. Consoles are the device used most often to play, with 188 (31.28%) players using this as their main device. Other devices that players indicated they use as their main device included smartphones (160 players; 26.62%), computers (132 players; 21.96%), and online games (107 players; 17.80%). Additionally, 354 (59.70%) players spend money while playing games. Finally, the majority of players (184; 31.78%) play for a duration of 3 hours – 5 hours and 50 minutes at a time; 166 (28.67%) play for 2 hours – 2 hours and 50 minutes; 116 (20.03%) play for 1 hour – 1 hour and 50 minutes; 85 (14.68%) play for 6 hours or more; and 28 (4.84%) play for 10 minutes – 50 minutes.

To obtain an external validation of the sample. The data collected was compared with the results from Gedigames (2014) and Game Brasil (2016). The comparison showed the sample has some similar features like most of the respondents are under 25 years old, the main devices are smartphones, consoles and computers and most of people play more than once per day.

3.2. Method

According to Bigné et al. (2010), the use of neural networks has become an effective method to perform market segmentation, allowing for a more effective segmentation model. Bloom (2005) points out that neural networks are more robust than traditional clustering techniques, and their performance is not affected by missing values. Moreover, in contrast with some cluster methods, where a priori assumptions are necessary, these assumptions are not required for the use of neural networks. Among neural network techniques, self-organizing maps (SOM) is the most widely used (Hiziroglu, 2013), with the best results in group formations (Arunachalam & Kumar, 2018; Kiang, Hu & Fisher, 2006). Furthermore, SOM is considered one of the most reliable clustering methods (Pastukhov & Prokofiev, 2016; Kohonen, 2001). It is also noteworthy that SOM is less impacted by strange variables (noise or outliers) and present better results for large databases (Bação, Lobo & Painho, 2005), in addition to presenting better comparative results than other grouping techniques (Bação et al., 2005; Arunachalam & Kumar, 2018). Furthermore, the SOM clustering gives a good balance between the nonparametric approach of the K-means, which operates on the vector of means and leaves the shape of the distributions free; and the parametric approach given by mixture models (latent profile analysis), which often present no robust results due to outlier observations (Gallegos & Ritter, 2009).

For the methodology of this study, two-level SOM were used. This method receives as input the mean of the following constructs: challenge; competition; diversion; fun; fantasy; social interaction. SOM were used to build clusters and identify market segmentation (Vesanto & Alhoniemi, 2000). After the groups were formed, an analysis of variance (ANOVA) was performed to determine if the groups were statistically different. In addition to the six variables used in the SOM time flexibility, arousal, intention to play, and purchase intention were also used in the ANOVA.

Market segmentation was done by SOM. This is one type of neural network that is trained using unsupervised learning, in which the main objective is to discover patterns of similarities in the input data. This is done by organizing the sample into groups and assigning one or more neurons to each group found (Kohonen, 2001). Because it is a competitive neural network, there is no output vector a priori, and the objective is not to minimize the mean square error but to understand how the data are organized into groups (Kohonen, 2001).

As SOM is an unsupervised neural network with a focus on grouping, there are no defined outputs, so there is no need to divide the sample into validation and test phases as in classification neural networks (e.g., multilayer perceptron and radial basis function) (Vesanto & Alhoniemi, 2000; Pastukhov & Prokofiev, 2016). Although SOM can also be used as a classification method (Haga, Siekkinen & Sundvik, 2015), this was not done in this study, as it seeks to explore the groups in an exploratory way. According to Kohonen (2001), three steps occur in the construction (training) of the SOM. First, there is a competition between the neurons, which are separated according to their similarities to verify which neuron that has the greatest similarity to the applied data in the input layer.

In the second step, there is cooperation; the winning neuron determines its spatial location, which excites the neighboring neurons to cooperate and participate in their group in their space. In the last step, adaptation occurs. In this step, the winning neuron excited is increasing his values; by this he uses a discriminant function to bring the others neurons to be part of his pattern by means of the appropriate adjustment applied to its synaptic weights.

This study used SOM by the MATLAB v.R2014a toolbox of software. The toolbox already has the default values for learning rates and neighborhood functions (Lee, Suh, Kim and Lee, 2004). For the input, the six constructs that had significant impact on play intention in the research done by Souza and Freitas (2017) were used. Furthermore, the input vector was formed by the arithmetic mean for each construct (Lee et al., 2004).

This research executed a two-level SOM (Vesanto & Alhoniemi, 2000). This methodology goes beyond the traditional SOM because there are two levels of clustering using SOM in two different moments. Two-level SOM is more robust, has lower computational cost, minimizes the error, and is less affected by missing values and outliers. This happens because the algorithm runs twice; the first time, it clusters the sample in small groups of only the homogeneous observations, which makes the second clustering more efficient (García & Gonzáles, 2004; Lee et al., 2004; Vesanto & Alhoniemi, 2000).

In the first clustering, the number of neurons is defined by the following formula: $5\sqrt{N}$, where N is the number of individuals in the sample (García & Gonzáles, 2004; Lee et al., 2004; Vesanto & Alhoniemi, 2000). From this result the firsts groups (protoclusters) are obtained. For the second step, another clustering of the protoclusters is done to find the final clusters (García & Gonzáles, 2004; Lee et al., 2004; Vesanto & Alhoniemi, 2000).

Lee et al. (2004) and García and Gonzáles (2004) advise the use of the Davies–Bouldin (DB) index (Formula 1) to analyze the quality of the results from the second clustering. The DB index is one type of dispersion and similarity measure used to determine the quality of the formed clusters. The lesser value found for this index is the best result for the number of clusters.

$$\frac{1}{C}\sum_{K=1}^{C} \max_{l \neq K} \left\{ \frac{S_c(Q_k) + S_c(Q_l)}{d_{ce}(Q_k, Q_l)} \right\} \quad (1)$$

Where:
C = number of clusters
$S_c(Q_k)$ = internal distance of cluster K
$S_c(Q_l)$ = internal distance of cluster L
$d_{ce}(Q_k, Q_l)$ = distance between cluster K and cluster L

In addition to the DB index, a silhouette coefficient was used to make the results more robust. Silhouette uses the mean intra-cluster distance (a) and mean nearest-cluster distance (b) to calculate the quality of the clusterization.

$$S_i = (b_i - a_i) / \max\{a(i), b(i)\}$$

where *a(i)* is the average distance between all points in the samples and *b(i)* is the minimum average distance between to the points in the other cluster when point *i* is given. The results of silhouette varies from -1 to 1. More closer than 1 shows the clustering is well clustered. Closer to -1 the result of clustering show the sample has been misclassified (Rousseeuw, 1987; Bolshakova & Azuaje, 2003). The methodological steps used in this research have already been used in previous studies that also had the aim of performing a market segmentation exercise (Lee et al., 2004).

4. RESULTS

For the input vector, the arithmetic mean of the following constructs was used: challenge; competition; diversion; fun; fantasy; and social interaction. The mean was used because this research aims to segment the individual by construct and not by variable (Lee et al., 2004). Furthermore, Lee et al. (2004) emphasize that the correct value for input is the linear combination of other measures, and this action does not cause any loss to the model or to the neural network.

The sample was composed of 601 people; thus, the number of protoclusters was 122,57 ($5\sqrt{N}$). For analysis, the layer of the neural network was composed of a matrix of 11x11, thus creating 121 protoclusters. The outcome of this step was that each protocluster received some weight, which symbolizes the value each group received to differentiate itself in relation to the input variables and maintain their similarities. These weights were the new input vector for the second clustering. For the second clustering, the DB index was implemented to determine the ideal number of clusters. This is a common and robust index used for this type of operation (García & Gonzáles, 2004; Lee et al., 2004; Vesanto & Alhoniemi, 2000). García and Gonzáles (2004) compared this index with others (e.g., Silhouette, Dunn, and the modified Hubert statistic), and the DB index produced the best results. The DB index test was used for three, four, five, and six clusters and the results were, respectively, 1,4558; 1,3850; 1,3242; and 1,4711.

Additionally, a silhouette coefficient was used to give greater strength to the DB index results. The silhouette coefficient was used for three, four, five, and six clusters, and the results were, respectively, 0.2823; 0.3188; 0.3283; and 0.3013. Consequently, the best result was for five clusters. In addition, K-means on the same basis were used in conjunction with the silhouette coefficient, and the results for three, four, five, and six clusters were the following, respectively: 0.2967; 0.3185; 03258; and 0.2923. According to Isoni (2016), values above 0.35 for the silhouette indicate that the grouping was well performed, and, given that the values found in this research was close to that, we determined that the grouping was acceptable. This result shows that, for both cases, the best choice was five groups. In addition, SOM performed better than K-means, showing a slight superiority.

For SOM there is no output vector – that is, the outputs are not defined at the beginning and, therefore, it cannot be proved whether the network is right. Thus, it is not necessary to divide the sample into learning, validation, and testing. However, to confirm that the network grouped correctly, the silhouette coefficient was used as a measure of quality. Thus, the sample was divided into 90% training and 10% testing (Zhang & Hu, 1998). The silhouette results for five clusters were, respectively, 0.3283 and 0.3231. Thus, it can be seen that in all stages, the grouping presented similar results for the similarity measures.

The initial 121 protoclusters were grouped into five clusters. Table 1 shows the number of people in each group. Group 1 was the biggest and constituted 30% of the sample; the second group constituted 19.8%; the third group 15% (i.e., it was the smallest group); the fourth group 16%; and the fifth group 19.3%.

Table 1
Number of people in each group

Group	People	Percentage
1,00	180	30,0
2,00	119	19,8
3,00	90	15,0
4,00	96	16,0
5,00	116	19,3
Total	601	100,0

Source: Author's own elaboration.

Groups of survey participants that could not yet be designated as market segments were suggested through the use of SOM, as no tests were implicitly performed in SOM to evaluate statistical differences among groups. The ANOVA was the final step, but it still did not indicate a relational causality among variables inside market segments. The ANOVA just demonstrated that the groups were different – both for the six behavioral variables that remained as causal variables for the dependent variables (challenge, competition, diversion, fun, fantasy, and social interaction) and for the remaining variables (time flexibility, arousal, intention to play, and purchase intention (Table 2).

Table 2
ANOVA for clusters

Cluster	1	2	3	4	5	Total	F
Nº	180	119	90	96	116	601	
Challenge	5.93	5.37	5.76	4.87	4.20	5.29	60.49***
Competition	4.38	3.14	4.68	2.53	2.46	3.51	84.36***
Diversion	5.08	2.00	3.95	4.72	1.80	3.61	246.2***
Fun	6.84	6.34	6.42	6.20	5.39	6.19	27.06***
Fantasy	5.67	4.88	2.66	2.98	2.04	3.93	255.25***
Social interaction	4.85	3.86	3.84	2.72	1.80	3.58	104.37***
Time flexibility	5.15	5.32	5.14	5.20	5.66	5.29	2.37^{ns}
Arousal	5.32	4.71	4.74	3.98	3.21	4.49	59.991***
Intention to play	6.17	5.56	5.40	5.07	3.78	5.29	72.832***
Purchase intention	5.32	4.60	4.15	3.65	2.68	4.23	46.35***

Note: ^{ns} non-significant; ***p < 0,001
Source: Author's own elaboration.

Table 3 shows the position of each group in relation to the constructs – not only in terms of the input, but also in terms of the other groups. Group 1 occupied the first position for all the constructs except competition and time flexibility. Most of Group 2's results were in the second and third position; only for diversion was there a decrease to fourth position. Group 3 had a variety of different results – it was first for competition, second for three constructs, third for four constructs, and was in fourth and fifth position for the other two constructs. Group 4 was located in the fourth position with most of its results, but for diversion it was second. Finally, Group 5 was in the last position for all constructs except time flexibility, for which it was first.

Table 3
Group positions in relation to each construct

Construct	Group 1	Group 2	Group 3	Group 4	Group 5
Challenge	1º	3º	2º	4º	5º
Competition	2º	3º	1º	4º	5º
Diversion	1º	4º	3º	2º	5º
Fun	1º	3º	2º	4º	5º
Fantasy	1º	2º	4º	3º	5º
Social interaction	1º	2º	3º	4º	5º
Time flexibility	4º	2º	5º	3º	1º
Arousal	1º	3º	2º	4º	5º
Intention to play	1º	2º	3º	4º	5º
Purchase intention	1º	2º	3º	4º	5º

Source: Author's own elaboration.

5. DISCUSSION

In this section, the groups of games consumers are first defined. Thereafter, the results are analyzed based on the criteria that must be observed for effective market segmentation. Finally, the implications of this study for academics and managers, the limitations of the research, and future research possibilities are discussed.

5.1. Group definitions

Group 1**: **Hard players. This is the largest group, with 180 survey participants out of a total sample of 601. A set of attitudinal, socio-demographic, and economic variables were also collected during this research and used here. These variables highlighted the following regarding hard players: that these participants play more than once every day, with each session being more than 2 hours in duration, throughout the whole week; computers and video games were their favorite electronic devices on which to play games; the majority (85%) were male; and 75% of them reported expenses related to game playing and paid for associated items.

These hard players scored high on their intention to play and average on their purchase intention. While they seem to be bonded to game producers and sellers, continuous playing might be guaranteed by reinforcing game characteristics such as fun, challenge, fantasy, and even arousal (these are the motivation factors most often mentioned associated with intention to play). An important feature of this group is that time flexibility did not have a high effect; this means that hard players play even when they do not have free time.

Group 2: Busy hard players. The second group is similar to the first, except for the fact that their other activities hamper their ability to play as much as the previous group. Motivational variables for this group were connected to the overarching fun and challenge characteristics of playing games present in all five groups. Busy hard players also ranked time flexibility as a driver to play games; thus, although they did not divert from their ongoing activities, they did play games.

Group 2 survey participants usually played on weekends using videogames. Each session lasted at least 1 hour, with a maximum duration of 6 hours. The majority of these players were men (85%), and they reported expenses associated with games. They scored high on their intention to play and average on their purchase intention, but achieved lower scores than their counterparts in Group 1 on both these measures. The implications of these results for game producers and sellers is that, firstly, the elements of fun and challenge, and secondly, the element of fantasy should be maintained as game characteristics. However, a major proposal based on this research is that producers and sellers must provide games that can be played by busy persons – intermittently every weekends and during sessions with average to long durations.

Group 3: Pro players. The third group was the smallest and ranked high on competition as a motivator to play games. Arousal also ranked high when compared to the other groups, except for the members of Group 1. Pro players appreciated the usual fun and challenge components of playing games but ranked low on social interaction and fantasy. Looking at time flexibility, it was observed that pro players played all the time and needed to do so because they are professional players. In addition, their purchase intention was smaller than for Groups 1 and 2. This trend is to be expected, as they spend time and money playing only one type of game, because they need to be a "pro" in that game. Consequently, they spend less money than the other groups.

The majority of Group 3 survey participants play every day of the week and preferred using video games; however, they also made use of online computer games and smartphones. Men represented the majority (84%) of this group, and most of them reported expenses associated with games; notwithstanding, there was great diversity in the amounts spent on this activity.

For game producers and sellers, the pro players group might be the most difficult to reach. This group consists of a select number of players that play a few games and spend money only on those games, so it is important to make these games arouse stimulate the competition, fun, challenge, and arousal aspects. Furthermore, the producers can encourage participation through a tournament that offers prizes for the winners; this would stimulate the players in this group to continue playing the game. Based on Newzoo's (2019) work, the number of people wanting to be pros and watch games matches are increasing, so this group deserves more studies to understand what motivates players to choose a game.

Group 4: Bored players. The fourth group associated games with fun, but displayed weaker links to challenge, arousal, fantasy, social interaction, and competition. Its central motivational behavior was diversion from other activities, but this did not lead to higher scores for intention to play or purchase intention.

Group 4 survey participants play more than once every day, throughout the week. They used smartphones as the major electronic device for playing games but also employed videogames and online computers. The majority reported expenses in connection with games. Their game sessions were well distributed in the range of 1 to 6 hours per session. This group was mainly composed by men (75%).

Game developers and sellers need to ask themselves how their products might enable this fourth group to achieve satisfaction of their needs apart from fun and diversion – two of the motivational behaviors that are catered to. This group plays only when they are bored and looking for something to do, so they spend little money. Enterprises can earn money by advertising within the game, because these players want quick matches could thus see advertisements to earn coins or to play one match.

Group 5: Casual players. These players constituted the third biggest group. They relied on fun and challenge as motivational drivers for playing games, with the lowest scores of the five groups. Their intentions to play and purchase were also the lowest among the five groups.

The vast majority played once or twice a month, with more frequent weekend engagement. Playing sessions took 1 to 2 hours, but this group had the largest proportion of short-session players (10 to 50 minutes). Almost half of this group (40.5%) was comprised of women, and 65% of casual players did not report expenses associated with games. They play mostly on smartphones, and a significant proportion used video gamers. They had the highest score for the association between playing games and time flexibility.

Game developers and sellers should take into account time flexibility as an opportunity to introduce fun in relation to electronic propositions, along with other activities these group members might pursue while conducting their lives with a casual focus on games. There is a slight hope that such electronic games will attract any sort of direct payment. However, given how little time this group spends playing games, encouraging spending can be achieved by following certain strategies. According to Johnson (2019), there are six traits in casual game design that can motivate a person to play, besides time flexibility the author emphasize the ease of learning; fast rewards; appealing themes; minimal required expertise; ease of access. Games enterprises must thus focus on these features and on time flexibility. The other seven variables are not important for these players.

The results of this research showed five different groups of gamers. As this study is an exploratory research project, it is not possible to talk about extrapolation of data to the universe of Brazilian consumers of online games. However, the groups formed are aligned with classifications reported in previous studies that show player profiles. A study by Nagygyörgy et al. (2013), which deals with hard players, highlighted characteristics similar to the members of Group 1, while the work of Juul (2010) identified gamers with characteristics similar to busy hard players and casual players. In addition, studies by Adamus (2012) and Ma, Wu, and Wu (2013) discuss pro players, and a study by Bae, Kim, Kim, and Koo (2019) examined bored players.

5.2. Evaluation of the results based on market segmentation assumptions

This study used a market segmentation strategy based on a specific product and utilized a non-observable, descriptive, post hoc methodology and behavioral segmentation as typology. Using these features, the results meet eight established criteria from market segmentation. The following criteria were achieved:

- **Differential Behavior:** The groups identified show different behaviors, as described in the previous section.
- **Membership Identification:** The groups were classified according to their characteristics.
- **Reachability:** The results of this research have demonstrated ways to reach certain group. It should be through the motivational characteristics or devices of use.
- **Feasibility:** Based on the groups identified, companies can know which groups are feasible for them to target and how to tailor their strategies to acquire this type of client.
- **Substantiality:** The groups identified were substantial, which demonstrates that each type of group exists on the market and is not difficult to find.

- **Responsiveness:** It was shown that each group has its own characteristics. Thus, to serve those different groups, individual actions are required for each group.
- **Profitability:** Through analyzing the purchase intention and determining the types of expenses and the amounts spent, it is possible to identify which groups have the highest expenses and which can be the most profitable group for each company.
- **Actionability:** The identifying characteristics of the groups show companies how to reach them and what actions should be taken to attract them.

5.3. Implications for researchers

This research provides an academic contribution using SOM. Furthermore, the segmentation follows the steps needed for effective market segmentation and for trying to meet the maximum number of possible criteria. In this way, it is possible to identify each group of games consumers.

In terms of usefulness to the games market, this research highlights the existence of five different groups of gamers based on motivational variables. The results show that each group has specific motivational and socio-demographic features. Accordingly, future research must take different gamer profiles into consideration and not approach all gamers as though they have the same features and the results can be generalized.

5.4. Implications for practice

Using this research, organizations can identify their target consumers and determine which main characteristics these consumers would prefer in a game. Recognizing the growth of competition in this market, it has become imperative for organizations to know who their clients are – their profiles and their preferences (Cheung et al., 2015).

Groups 1 and 2 are the average players that want to play and spend money on games. Players in Group 1 play constantly, so companies need to find a way to attract the attention of these players, but it is necessary attention to these players because they could develop problematic gaming behavior (Nagygyörgy et al., 2013). Players in Group 2 are similar to players from Group 1, but they do not have as much free time, so they play a few games at a time. A way to make these players purchase is to offer a discount on the sale, because they will play, so they buy. Group 3 consists of pro players, which means they are loyal to one game. Hence, it is important to offer tournaments and prizes to this type player to make them more loyal. This approach also makes the game continually more competitive, fun, and challenging, thereby increasing feelings of arousal.

Another important factor is related to the profiles of Groups 4 and 5. These groups have a greater tendency to play electronic games on smartphones, and they are the groups that show the greatest increase in number of people (Kim & Lee, 2017). However, these players also have the least value as games consumers. The fact that these groups of consumers display low levels of consumption has already been explored in other studies, and this can still be observed as a big problem that games organizations need to overcome (Hamari et al., 2017; Kim & Lee, 2017; Park & Lee, 2011). This research proposes a solution of using advertisements in games and following Johnson's (2019) strategies to make these players more interested in the game.

This study shows the profiles of these players and demonstrates that diversion, time flexibility, and fantasy are the main motivational variables to Group 4. This means that, for this group, games do not need to be realistic, but they must be easily accessible to be played at any time and are used as an escape mechanism from the real world. Moreover, the game must not cause stress to the player, because their intention is the opposite – to alleviate stress. One solution is the freemium strategy (*i.e.* the player can play the game freely, but he needs to pay to obtain some premium features) which is confirmed by the results of this study, the research done by Souza and Freitas (2017), and the work of Milošević, Živić, and Andjelković (2017). This strategy is achieving good results and advertise that offer benefits to player that see.

For Group 5, time flexibility is the main important variable. This is the most challenging group for games organizations to reach. This is the third biggest group, and it is the group that has the biggest number of women. This group is formed by people who know the games world through smartphones. They are new players; consequently, they need more attention. These players could become a very lucrative segment because they are an unexplored market, but it is imperative to respect their main reason to play: time flexibility. We suggest following Johnson's (2019) strategies to reach this group.

5.5. Limitations and future research

This research was conducted in Brazil, which is the fourth biggest games market in the world. Although Brazilian players have similar features to players in other countries, the results of this research cannot be generalized to the entire world. Consequently, it is suggested that market segmentation be performed in other countries or that cross-cultural research is conducted to explore the real similarities between gamers across the globe.

REFERENCES

Adamus, T. (2012). Playing computer games as electronic sport: In search of a theoretical framework for a new research field. In *Computer games and new media cultures* (pp. 477-490). Springer, Dordrecht.

Arruda Filho, E. J. M., & Gammarano, I. D. J. L. P. (2018). For every "game over" there is a "play again": Analysis of user preferences regarding 7th-and 8th-generation video games consoles. *The Journal of High Technology Management Research, 29*(1), 46-56.

Arunachalam, D., & Kumar, N. (2018). Benefit-based consumer segmentation and performance evaluation of clustering approaches: An evidence of data-driven decision-making. *Expert Systems with Applications*, *111*, 11-34.

Bação, F., Lobo, V., & Painho, M. (2005, May). Self-organizing maps as substitutes for k-means clustering. In *International Conference on Computational Science* (pp. 476-483). Springer, Berlin, Heidelberg.

Bae, J., Kim, S. J., Kim, K. H., & Koo, D. M. (2019). Affective value of game items: a mood management and selective exposure approach. *Internet Research, 29*(2), 315-328.

Baumgarten, M. Z. (2013). *Uma análise do mercado internacional de jogos eletrônicos sob a ótica de Fligstein*. In: Encontro Nacional da Associação Nacional dos Programas de Pós-Graduação em Administração: Rio de Janeiro.

Bolshakova, N., & Azuaje, F. (2003). Cluster validation techniques for genome expression data. *Signal processing*, *83*(4), 825-833.

Bowman, N. D., Oliver, M. B., Rogers, R., Sherrick, B., Woolley, J., & Chung, M. Y. (2016). In control or in their shoes? How character attachment differentially influences video game enjoyment and appreciation. *Journal of Gaming & Virtual Worlds*, *8*(1), 83-99.

Brandt, S. C. (1966). Dissecting the segmentation syndrome. *The Journal of Marketing*, *30*(4), 22-27.

Cagiltay, N. E., Ozcelik, E., & Ozcelik, N. S. (2015). The effect of competition on learning in games. *Computers & Education*, *87*, 35-41.

Caroux, L., Isbister, K., Le Bigot, L., & Vibert, N. (2015). Player–video game interaction: A systematic review of current concepts. *Computers in Human Behavior*, *48*, 366-381.

Chang, C. C. (2013). Examining users′ intention to continue using social network games: A flow experience perspective. *Telematics and Informatics*, *30*(4), 311-321.

Cheung, C. M., Shen, X. L., Lee, Z. W., & Chan, T. K. (2015). Promoting sales of online games through customer engagement. *Electronic Commerce Research and Applications*, *14*(4), 241-250.

Chou, C. M., & Kimsuwan, A. (2013). Factors Affecting Purchase Intention of Online Game Prepayment Card–Evidence from Thailand. *Journal of Internet Banking and Commerce*, *18*(3), 1-13.

Chou, C., & Tsai, M. J. (2007). Gender differences in Taiwan high school students' computer game playing. *Computers in Human Behavior*, *23*(1), 812-824.

Churchill, G. A., Jr. (1979). A paradigm for developing better measures of marketing constructs. *Journal of Marketing Research, 16*(1), 64–73.

Cohen, E. L. (2014). What makes good games go viral? The role of technology use, efficacy, emotion and enjoyment in players' decision to share a prosocial digital game. *Computers in Human Behavior*, *33*, 321-329.

Costa, F. D. (2011). *Mensuração e desenvolvimento de escalas: Aplicações em Administração*. Rio de Janeiro: Ciência Moderna.

DeSarbo, W. S., & DeSarbo, C. F. (2003). A generalized normative segmentation methodology employing conjoint analysis. In Gustafsson, A., Herrmann, A. & Huber, F. (Ed.) *Conjoint Measurement* (pp. 473-504). Springer Berlin Heidelberg.

DeSarbo, W. S., & Grisaffe, D. (1998). Combinatorial optimization approaches to constrained market segmentation: An application to industrial market segmentation. *Marketing Letters*, *9*(2), 115-134.

Engl, S., & Nacke, L. E. (2013). Contextual influences on mobile player experience–A game user experience model. *Entertainment Computing*, *4*(1), 83-91.

Frank, R. E., Massey, W. F., & Wind, Y. (1972). *Market segmentation*. Prentice Hall.

Gallegos, M. T., G. Ritter (2009). Trimming algorithms for clustering contaminated grouped data and their robustness. *Advances in Data Analysis and Classification, 3*(2), 135-167.

GameIndustry. (2017). *Mobile games booming as global games market hits $108.9B in 2017*. http://www.gamesindustry.biz/articles/2017-04-20-mobile-games-booming-as-global-games-market-hits-usd108-9b-in-2017-newzoo. Accessed: 10/10/2017.

García, H. L., & González, I. M. (2004). Self-organizing map and clustering for wastewater treatment monitoring. *Engineering Applications of Artificial Intelligence*, *17*(3), 215-225.

Gedigames, Grupo de Estudos e Desenvolvimento de Indústria de *Games*. (2014) *Relatório Final*: mapeamento da indústria brasileira e global de jogos digitais. São Paulo: USP, 2014.

Giammarco, E. A., Schneider, T. J., Carswell, J. J., & Knipe, W. S. (2015). Video game preferences and their relation to career interests. *Personality and Individual Differences*, *73*, 98-104.

Goyat, S. (2011). The basis of market segmentation: a critical review of literature. *European Journal of Business and Management*, *3*(9), 45-54.

Grizzard, M., Tamborini, R., Sherry, J. L., Weber, R., Prabhu, S., Hahn, L., & Idzik, P. (2015). The thrill is gone, but you might not know: habituation and generalization of biophysiological and self-reported arousal responses to video games. *Communication Monographs*, *82*(1), 64-87.

Haga, J., Siekkinen, J., & Sundvik, D. (2015). Initial stage clustering when estimating accounting quality measures with self-organizing maps. *Expert Systems with Applications*, *42*(21), 8327-8336.

Hamari, J., Alha, K., Järvelä, S., Kivikangas, J. M., Koivisto, J., & Paavilainen, J. (2017). Why do players buy in-game content? An empirical study on concrete purchase motivations. *Computers in Human Behavior*, *68*, 538-546.

Hsiao, C. C., & Chiou, J. S. (2012). The effects of a player's network centrality on resource accessibility, game enjoyment, and continuance intention: A study on online gaming communities. *Electronic Commerce Research and Applications*, *11*(1), 75-84.

Hsiao, K. L., & Chen, C. C. (2016). What drives in-app purchase intention for mobile games? An examination of perceived values and loyalty. *Electronic Commerce Research and Applications*, *16*, 18-29.

Hsu, C. L., & Lin, J. C. C. (2015). What drives purchase intention for paid mobile apps?–An expectation confirmation model with perceived value. *Electronic Commerce Research and Applications*, *14*(1), 46-57.

Isoni, A. (2016). *Machine Learning for the Web*. Packt Publishing Ltd.

Istoé. (2017). Infográfico: o mercado de games no Brasil. https://istoe.com.br/infografico-mercado-games-brasil/. Accessed: 10/10/2017.

Jin, C. H. (2014). The role of users' motivations in generating social capital building and subjective well-being: The case of social network games. *Computers in Human Behavior*, *39*, 29-38.

Johnson, M. R. (2019). Casual Games Before Casual Games: Historicizing Paper Puzzle Games in an Era of Digital Play. *Games and Culture, 14*(2), 119-138.

Juul, J. (2010). *A casual revolution: Reinventing video games and their players*. MIT press.

Kiang, M. Y., Hu, M. Y., & Fisher, D. M. (2006). An extended self-organizing map network for market segmentation—a telecommunication example. *Decision Support Systems*, *42*(1), 36-47.

Kim, Y. B., & Lee, S. H. (2017). Mobile gamer's epistemic curiosity affecting continuous play intention. Focused on players' switching costs and epistemic curiosity. *Computers in Human Behavior*, *77*, 32-46.

Kohonen, T. (2001). *Self-Organizing Maps*. Springer, New York.

Lee, S. C., Suh, Y. H., Kim, J. K., & Lee, K. J. (2004). A cross-national market segmentation of online game industry using SOM. *Expert systems with applications*, *27*(4), 559-570.

Ma, H., Wu, Y., & Wu, X. (2013). Research on essential difference of e-sport and online game. In *Informatics and management science V* (pp. 615-621). Springer, London.

Manero, B., Torrente, J., Freire, M., & Fernández-Manjón, B. (2016). An instrument to build a gamer clustering framework according to gaming preferences and habits. *Computers in Human Behavior*, *62*, 353-363.

Mascena, K. M. C., Pimentel, M. C. P., Fischmann, A. A. & Polo, E. F. (2012) *Videogames e Estratégia: O Posicionamento Estratégico de Empresas Brasileiras de Software de Jogos Digitais*. In: Encontro Nacional da Associação Nacional dos Programas de Pós-Graduação em Administração: Rio de Janeiro.

Milošević, M., Živić, N., & Andjelković, I. (2017). Early churn prediction with personalized targeting in mobile social games. *Expert Systems with Applications*, *83*, 326-332.

Mosca, I. (2017). What Is It Like to Be a Player? The Qualia Revolution in Game Studies. *Games and Culture, 12*(6), 585-604.

Murray, J. H. (2003). *Hamlet no holodeck o futuro da narrativa no ciberspaço*. Unesp, São Paulo.

Nagygyörgy, K., Urbán, R., Farkas, J., Griffiths, M. D., Zilahy, D., Kökönyei, G., Mervó, B. Reindl, A, Ágoston C., Kertész, A, Harmath, E. Oláh, A. & Demetrovics, Z. (2013). Typology and sociodemographic characteristics of massively multiplayer online game players. *International Journal of Human-Computer Interaction, 29*(3), 192-200.

NewZoo. (2019). *Latest market estimates: Key numbers*. https://platform.newzoo.com/key-numbers/. Accessed: 10/10/2017.

Park, B. W., & Lee, K. C. (2011). Exploring the value of purchasing online game items. *Computers in Human Behavior*, *27*(6), 2178-2185.

Pastukhov, A. A., & Prokofiev, A. A. (2016). Kohonen self-organizing map application to representative sample formation in the training of the multilayer perceptron. *St. Petersburg Polytechnical University Journal: Physics and Mathematics*, *2*(2), 134-143.

Reich, S., & Vorderer, P. (2015). Online Games, Player Experiences in. *The International Encyclopedia of Digital Communication and Society*.

Rogers, R. (2017). The motivational pull of video game feedback, rules, and social interaction: Another self-determination theory approach. *Computers in Human Behavior*, *73*, 446-450.

Rousseeuw, P. J. (1987). Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. *Journal of computational and applied mathematics*, *20*, 53-65.

Scriven, P. (2015). The phenomenology of the "other" in computer game worlds. *Games and Culture, 13*(2), 193-210.

Shelton, A. K. (2010). Defining the lines between virtual and real world purchases: Second Life sells, but who's buying?. *Computers in Human Behavior*, *26*(6), 1223-1227.

Sherry, J. L., Lucas, K., Greenberg, B. S., & Lachlan, K. (2006). Video game uses and gratifications as predictors of use and game preference. *Playing video games: Motives, responses, and consequences*, 213-224.

Smith, W. R. (1956). Product differentiation and market segmentation as alternative marketing strategies. *The Journal of Marketing*, *21*(1), 3-8.

Snellman, K. (2000). *From One Segment to a Segment of One-The Evolution of Market Segmentation Theory*. Working paper.

Souza, L. L. F., & Freitas, A. A. F. (2017). Consumer behavior of electronic games' players: a study on the intentions to play and to pay. *Revista de Administração*, *52*(4), 419-430.

Toni, D., & Mazzon, J. A. (2014). Teste de um modelo teórico sobre o valor percebido do preço de um produto. *Revista de Administração-RAUSP*, *49*(3).

Vesanto, J., & Alhoniemi, E. (2000). Clustering of the self-organizing map. *Neural Networks, IEEE Transactions.11*(3), 586-600.

Wedel, M. & Kamakura, W. (2000). *Market segmentation: conceptual and methodological foundations*. Springer.

Wei, P. S., & Lu, H. P. (2014). Why do people play mobile social games? An examination of network externalities and of uses and gratifications. *Internet Research*, *24*(3), 313-331.

Williams, D. (2006). Why game studies now? Gamers don't bowl alone. *Games and Culture*, *1*(1), 13-16.

Yankelovich, D., & Meer, D. (2006). Rediscovering market segmentation. *Harvard business review*, *84*(2), 122.

Zammitto, V. L. (2010). *Gamers' personality and their gaming preferences* (Doctoral dissertation, Communication, Art & Technology: School of Interactive Arts and Technology).

Zhang, G., Patuwo, B. E., & Hu, M. Y. (1998). Forecasting with artificial neural networks: The state of the art. *International journal of forecasting*, *14*(1), 35-62.

AUTHOR'S CONTRIBUTION

LS: Conceptualization; Data curation; Formal analysis; Investigation; Writing-original draft; AAF: Project Administration; Supervision; Validation; Writing-review & editing; LFH: Validation; Visualization; Writing-review & editing; JLW: Methodology; Software.

CONFLICTS OF INTEREST

There are no conflicts of interests.