Textual Analysis of Virtual Reality Game Reviews

Tibor Guzsvinecz, and Judit Szűcs

Abstract—**Virtual reality systems are complex and made of various parts. Since a person is an integral component of such systems, virtual reality technologies also have a cognitive aspect. As such, these technologies engage with the perceptual, attentional, and decision-making processes of users. Consequently, they can be considered cognitive tools. Thus, it is imperative to understand what people think of such environments. To take a step towards this understanding, textual reviews of virtual reality games made for entertainment were investigated using text mining methods. Thus, 1,635,919 textual reviews were scraped from the Steam digital video game distribution platform in the spring of 2023. The reviews were grouped by whether they were positive or negative. According to the results, the following conclusions can be made regarding virtual reality games: 1) Negative reviews are significantly longer than positive ones. 2) Negative reviews are written significantly earlier than positive ones, although no correlation was found between the review type and the playtime before writing the review. 3) The most frequent words and word correlations are different between review types since negative reviews are more focused on game mechanics and bugs. Due to the results, insights can be provided to virtual reality game developers to help them refine their games.**

Index Terms—**computer games; game review; player experience; Steam; textual analysis**

I. Introduction

IN this digital age, the popularity of virtual reality (VR) applications is unquestionable. As VR is a synthetic reality, it is possible to create virtual environments (VEs) that are either similar to or different from the real world. Depending on the goal of such virtual spaces, they could be created for various purposes [1, 2]. For example, VR technologies play an important role in education [3–6], training [7, 8], healthcare [9, 10], and even entertainment [11, 12].

As can be expected based on these previously mentioned fields, a VR system requires a person to interact with it to work perfectly [13]. This is due to the fact that these systems have cognitive aspects as well [14, 15]. VR can also be considered a cognitive tool [16]. Therefore, when designing such systems, it is important to keep the target groups in mind during the process. Naturally, after a VR system or application is implemented, users can experience it and leave feedback about its strengths and weaknesses. This is also the case with VR applications for research or entertainment purposes. Feedback can also be verbal or textual.

Understanding textual feedback is crucial to know how people reacted to various experiences. This textual feedback can come in the form of a review [17, 18], which allows game developers to learn how to improve their games [19]. Video game reviews can contain several topics such as achievements, accessories, general experience, social interaction, social influence, narrative, visual/value, and information about bugs in the game [20]. Thus, it is possible to know how playable a game is from the reviews [21]. Reviews can also detail several factors that can make a game popular [22]. They can also serve as a product review: they can influence other players whether to buy or not to buy a game [23, 24]. Also, critics tend to highlight different aspects of games than players [25].

As can be seen, reviews contain critical information about the experiences of players. Furthermore, many reviews are written daily, thus it is possible to analyze a large number of data [26]. Due to this data, game developers and researchers can ascertain the strengths and weaknesses of the analyzed games. Naturally, these can improve the quality of future games [27, 28].

Thus, the goal of this paper is to take a step towards understanding VR games and applications made for entertainment using textual analysis methods. For this, the following research questions (RQs) were formed:

- RQ1: How long are the reviews of VR games?
- RQ2: Is there a correlation between playtime and the length of VR game reviews?
- RQ3: What are the most frequent words and their word associations in the reviews?

The first question aims to investigate the length of textual reviews for VR games, comparing word count of positive and negative reviews. The second one seeks to explore whether there is a relationship between playtime and the length of reviews. By examining potential correlations, it is possible to determine if users who spend more time playing VR games are more likely to write longer reviews, and vice versa. Lastly, by answering the third one we can uncover key terms, expressions, or themes that emerge frequently in both positive and negative reviews. Thus, understanding reviews can provide insights into the level of detail and depth of user feedback, which can be valuable for developers and researchers.

Submitted on...
Tibor Guzsvinecz is with the Department of Information Technology and its Applications, Faculty of Information Technology, University of Pannonia, Zalaegerszeg, Hungary (e-mail: guzsvinecz.tibor@zek.uni-pannon.hu). He is the corresponding author.
Judit Szűcs is with the Department of Information Technology and its Applications, Faculty of Information Technology, University of Pannonia, Zalaegerszeg, Hungary (e-mail: szucs.judit@zek.uni-pannon.hu)

DOI: 10.36244/ICJ.2024.5.10

Therefore, this paper is structured as follows. Section 2 details the Steam scraping process and the textual analysis. The results are presented in section 3. In section 4, the results are discussed along with the limitations of the study. Lastly, conclusions are made in section 5.

II. Materials and methods

The reviews on the Steam digital game distribution platform were chosen for the analysis. The platform was chosen because it was the largest digital game distribution platform in 2017 [29]. In 2021, it was still one of the biggest platforms with more than 50,000 video games in its library [30]. Not to mention, due to the Covid-19 pandemic, digital video game distribution platforms gained popularity as well [31].

On Steam, players have the opportunity to write reviews on a game's page, although they have to register a free profile and play the said game beforehand. Naturally, it is free to browse and read reviews on the platform. Valve Corporation – the creator of this platform – has developed an application programming interface (API) to freely access and scrape some of the platform's contents, including video game reviews [32].

Thus, this section presents the following. In the first subsection, the reviews on Steam are defined. Afterward, the scraping process is detailed in the second subsection. Lastly, the textual analysis is shown in the third subsection.

A. Video game reviews on Steam

On the Steam digital video game distribution platform, each game has its own store page. These pages contain the reviews as well. According to the Steam API, each review object has multiple components that can be accessed [33]. The following components were used for this research: the textual part, the language of the review, playtime when writing the review, and whether a review is positive or not. For the latter, it should be mentioned that Steam does not have a numerical rating system. Thus, players can either recommend the game or not. The first represents a positive review, while the latter is a negative one. Naturally, in the previously mentioned textual component, players can write down their experiences with no character limitation.

B. The scraping process

The statistical program package R was used for the scraping process along with its *rvest* and *httr* packages. The Steam API was also used to access content during the process. The scraping process was conducted in the spring of 2023.

First, the list of games and applications was created using the *GetAppList* function that could be found in the Steam API. It returned the list of all application IDs on the platform. Then, the *read_html* function was used on every application ID to load their store's pages which contain tags. Among other things, these tags allow us to see whether a game is a VR application. The IDs of the VR application were saved into a vector.

Then, the actual scraping started. According to the documentation of Steam, the *GET* function was used in R [34]. Due to the large amount of data, only English and the most recent 1,000 reviews were scraped per game. Naturally, if a game did not have at least 1,000 reviews, all were scraped. Overall, 1,635,919 reviews were scraped. Out of them, 79.02% were positive and 20.98% were negative.

C. Data analysis

After the scraping was finished, the data analysis process started. First, the number of words was calculated with the regular expression of '[\\w\']+'. This also required the *stringr* package, and the *str_count* function in it. The number of words was also grouped by review type.

To count the occurrences of each word, the *tm* package was used. First, a corpus was created of the textual parts found in the reviews. Then, the text was manipulated as follows: words were converted to lower cases; English stopwords, punctuation, and numbers were removed; whitespaces were stripped; and lastly, the words were stemmed using Porter's algorithm [35]. Afterward, the word occurrences could be calculated. The *ggplot2* package was used to plot the most frequent words.

When investigating the word correlations with frequent words, the *tidyverse*, *tidytext*, *widyr*, *igraph*, and *ggraph* packages were used. After empirical testing, the following parameters were used. First, the words had to occur at least once in at least 100 reviews per game. Then, by using pairwise correlation, the coefficients were assessed among all possible combinations. For plotting, in the case of positive reviews the correlation coefficient was set to at least 0.7, while in the case of negative reviews, it was set to at least 0.6. Otherwise, the figures would have become unreadable.

Letter-value plots were used to better visualize the distribution of data. These types of plots were designed for large datasets and they allow us to see more reliable estimates beyond the quartiles [36]. After them, the upper and lower eights are shown, then upper and lower sixteenths, and so on until the process reaches a stopping criterion. A 95% confidence interval is determined around each letter-value. If an overlap is found between this confidence interval and the previous letter-value, then the current letter-value and the following values are not plotted anymore. Each interval is shown with darker and smaller boxes. Due to the large number of data, a graphical method was used to check whether each dataset followed Gaussian distribution. Thus, quantile-quantile (Q-Q) plots were used. Due to the results found in the previously mentioned plots, the non-parametric Wilcoxon rank sum test was used when comparing word numbers and playtimes between review types [37]. Similarly, when assessing the correlation between playtime and review length, the Spearman rank correlation method was used [38].

III. Results

This section consists of three subsections. In the first one, the length of reviews is analyzed between review types. In the second one, the playtimes when writing reviews are examined. The correlation between playtimes before reviewing and review type is also investigated in it. Lastly, in the third subsection, the most frequent words and their associations are analyzed.

A. Word numbers between review types

The next step was to compare the reviews grouped by whether they were positive or negative. There were 1,292,758 positive reviews and 343,161 negative ones in the dataset. In both types, there were several reviews that had a length of zero. Still, it can be seen that the negative reviews contained more words than positive ones. The median, mean, and standard deviations of negative reviews were 36; 82.1; and 136.73 words, respectively. On the contrary, their respective words were 18; 53.68; and 107.83 in the case of the positive reviews. The longest negative review was 2,667 words long, while the longest positive one was 2,214 words long. Overall, as can be seen, negative reviews were longer than the positive ones. The distribution of word numbers can be observed in Fig. 1.

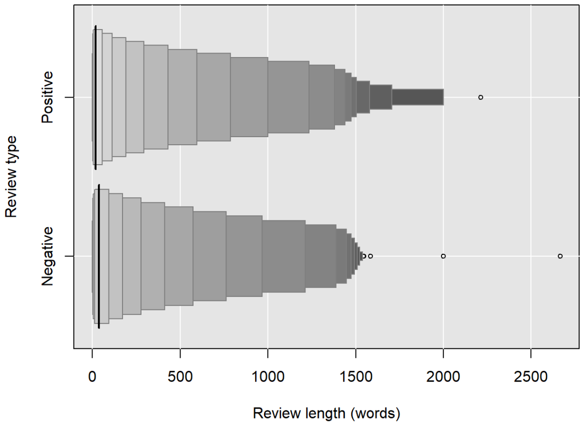

Fig. 1. The distribution of words grouped by review type.

Before using statistical tests to compare the review types to each other, it was also assessed whether word numbers follow Gaussian distribution in the dataset. Due to the large number of data, the previously mentioned Q-Q plots were used for this purpose. As can be seen in Fig. 2, the data did not follow Gaussian distribution.

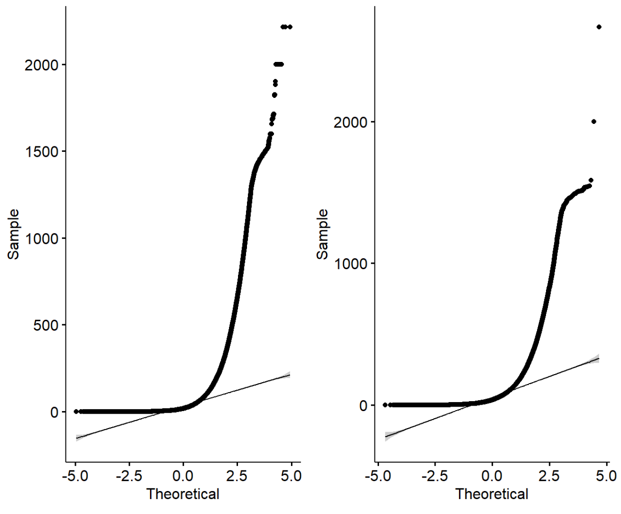

Fig. 2. Q-Q plots of word numbers in positive (left) and negative reviews (right).

Afterward, the Wilcoxon rank sum test was used to see whether the lengths of these review types were significantly different from each other. The results of the test show that the negative ones were significantly longer, $W = 1.6979 \cdot 10^{11}$; $p < 2.2 \cdot 10^{-16}$. It was also assessed with regression analysis methods whether the review type had an effect on review length. The results in Table I show that an effect exists since positive reviews were significantly shorter on average.

TABLE I
RESULTS OF THE REGRESSION ANALYSIS

	Estimate	Standard error	t value	$Pr(>\|t\|)$
Intercept	82.0994	0.1955	419.9	$< 2 \cdot 10^{-16}$
Positive review	-28.4220	0.2200	-129.2	$< 2 \cdot 10^{-16}$

As can be seen in Table I, the average length significantly differs between the two review types. On average, positive reviews contain significantly fewer words than negative ones. The mean difference between the two review types is 28.4220 words.

B. Playtime between review types

Next, the playtime of users between the two review types were investigated. According to the results, players review VR games after playing for an average of 2,172 minutes. The median value is 281 minutes, and the standard deviation is 13,502.37 minutes. Clearly, most players tend to play a VR game for several hours before leaving a review for it. It should be noted that the largest playtime before reviewing was 2,867,784 minutes. That would mean 47,796.4 hours. In the case of positive reviews, the mean, median, and standard deviation values are 2278; 335; and 13,478.66 minutes, respectively. Regarding negative reviews, their respective values are 1,773; 99; 13,584.04 minutes. As can be observed, negative reviews are written much earlier than positive ones. The distribution of playtimes between review types can be seen in Fig. 3.

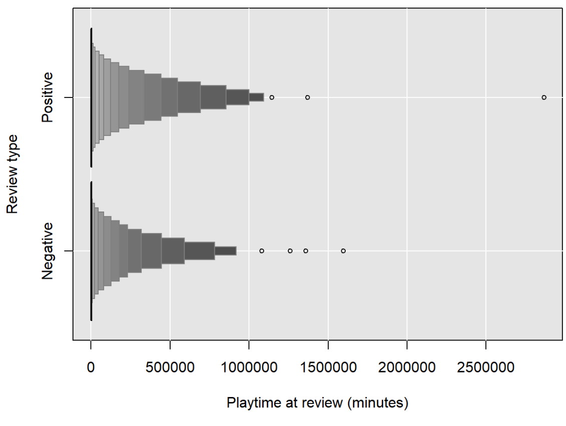

Fig. 3. The distribution of playtime before reviewing grouped by review type.

Similarly, to word numbers, Q-Q plots were used to assess whether playtimes followed Gaussian distribution. These plots can be observed in Fig. 4.

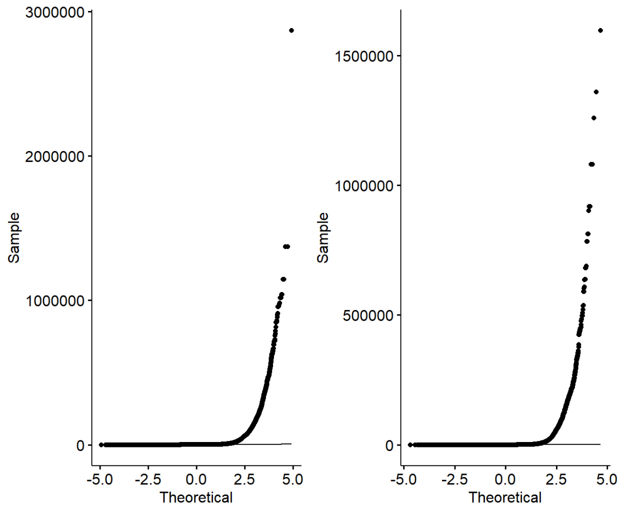

Fig. 4. Q-Q plots of playtimes in positive (left) and negative reviews (right).

As the distribution was non-Gaussian, the Wilcoxon rank sum test was used to compare the playtimes between the two review types. The results show that there is a significant difference between them, $W = 2.8911 \cdot 10^{11}; p < 2.2 \cdot 10^{-16}$. As previously, regression analysis methods were used to see whether review type had a significant effect on playtimes before reviewing. According to the results presented in Table II, a significant effect exists. Positive reviews were written significantly later than negative ones.

TABLE II
RESULTS OF THE REGRESSION ANALYSIS

	Estimate	Standard error	t value	$Pr(>\|t\|)$
Intercept	1,772.74	23.09	76.76	$< 2 \cdot 10^{-16}$
Positive review	505.04	25.98	19.44	$< 2 \cdot 10^{-16}$

It is shown in Table II that level is significance is strong in each case. On average, positive reviews are written significantly later than negative with a difference of 505.04 minutes. This would mean that those who play VR for more hours are more likely to leave a positive review.

However, it is imperative to understand whether a correlation exists between playtime and review length. Therefore, the next step was to assess this. First, this relationship was assessed on the whole dataset. However, no correlation was found, $r_s(1{,}635{,}917) = -0.046;\ p < 2.2 \cdot 10^{-16}$. When only positive reviews were analyzed in this regard, no correlation was found as well, $r_s(1{,}292{,}756) = -0.040;\ p < 2.2 \cdot 10^{-16}$. Then, negative reviews were analyzed, however, they presented a similar relationship between the two variables, $r_s(343{,}159) = 0.106; p < 2.2 \cdot 10^{-16}$. Still, it can be noted that the correlation coefficient was somewhat stronger in this case.

C. The most frequent words and their associations

Next the most frequent words were assessed in both positive and negative reviews. In case of positive ones, they are shown in Figs. 5 and 6.

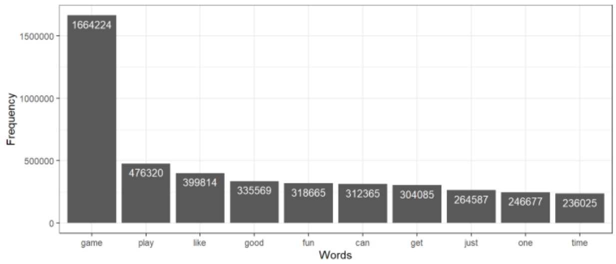

Fig. 5. The most frequent words in positive reviews.

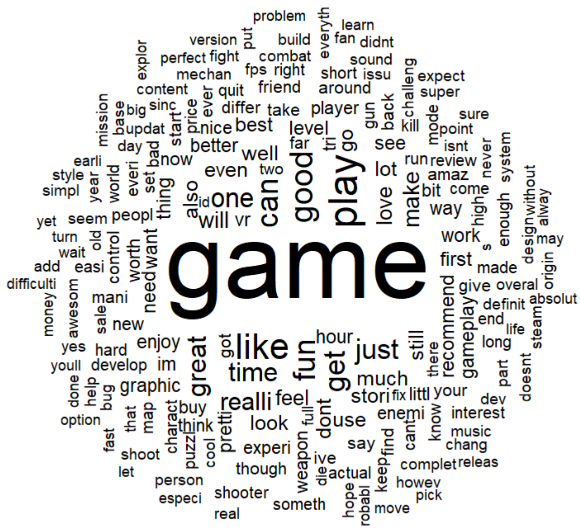

Fig. 6. Word cloud of words in positive reviews.

As can be observed in Figs. 5 and 6, the most frequent word in positive reviews is "game" with 1,664,224 occurrences. The second most frequent was "play" with 476,320 occurrences. Judging from the words, players in positive reviews mention their experiences (e.g. "fun", "love", "good", "great", "awesome", "enjoy"), game difficulty, game mechanics, and that they recommend the game. Interestingly, even within positive reviews, there were mentions of bugs, suggesting that while these issues were acknowledged, they did not detract from the overall positive experiences of players. This indicates that the identified bugs may not have severely impacted the overall enjoyment and satisfaction derived from the games, as evidenced by the overwhelmingly positive sentiments expressed by users.

The most frequent words in negative reviews were examined next. They can be observed in Figs. 7. and 8.

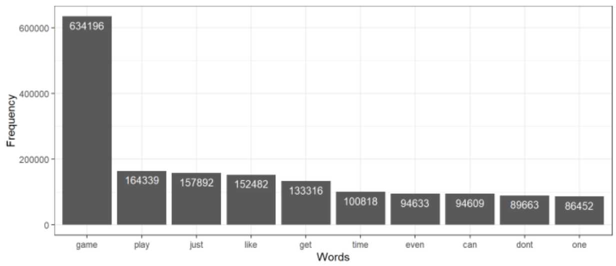

Fig. 7. The most frequent words in negative reviews.

Fig. 8. Word cloud of words in negative reviews.

Similarly to positive reviews, “game” and “play” were the two most frequent words in negative reviews, with 634,196 and 164,339 occurrences, respectively. This highlights the emphasis on gaming experience and active engagement within the VR gaming environment, albeit in a negative context. However, in negative reviews, the word “don’t” emerged as a prominent term, replacing “time” in the top 10 most frequent words, indicating dissatisfaction among users. Correspondingly, the negative sentiment was reflected in the increased frequency of words such as “poor”, “bad”, “bug”, “problem”, and “crash”, signifying a focus on technical problems and performance issues encountered by players. Furthermore, the presence of the word “server” within these reviews suggests that network-related or device-related problems contributed to the negative experiences reported by users. Additionally, the mention of “fix” underscores the imperative for developers to address the identified bugs within the games. Notably, the inclusion of the word “refund” indicates that users expressed a desire for reimbursement due to the unsatisfactory nature of their experiences. Players also showed concerns related to game mechanics, specifically pertaining to combat and weapons, as well as references to gameplay difficulty, as evidenced by the inclusion of the word “hard”. Despite many negative sentiments, a few positive words were also present, albeit less frequently. This indicates a nuanced and varied spectrum of user feedback. Moreover, the words in Fig. 8 revealed the emergence of profanity in the reviews, with the f-word being notably prevalent, showing negative emotions and frustration expressed within the negative reviews.

Naturally, these words alone do not give enough context to understand the strengths and weaknesses of VR games. Thus, as was mentioned in Section II, word associations of commonly occurring words were also examined. The results of this investigation can be observed in Fig. 9 in case of both review types.

When examining positive reviews, the following observations could be made. Among others, the words “voice acting” can be commonly found in these reviews. The cases are similar with the words “single player”, “trial error”, “learning curve”, “motion sickness”, and “paced fast”. Similarly, “extremely”, “absolutely”, “fantastic”, “favorite”, “excellent”, “totally”, “highly” and “recommended” have a strong correlation. Interestingly, profane words are still highly correlated with each other in positive reviews. Even though there were some negative word associations like between “motion” and “sickness”, they were not negative enough to warrant a negative review.

Negative reviews however, present different correlations between words. The correlated word with “money” is “waste”, indicating that players regretted buying the game. Similarly, “alt” correlates with “f4”, suggesting that players frequently quit the games due to anger or frustration. The word

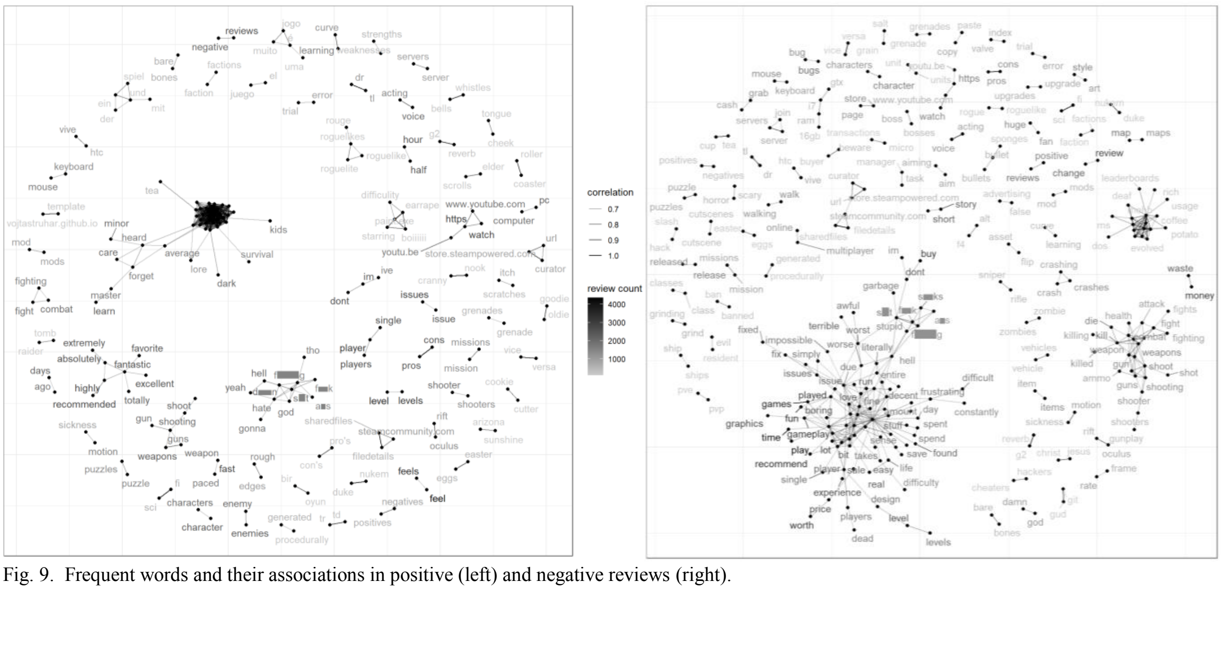

Fig. 9. Frequent words and their associations in positive (left) and negative reviews (right).

"advertising" correlates with "false", showing that even the ads for these games contained false information. "Short" is commonly found associated with "story", indicating that the length of these games was also a problem. Looking at the second largest cluster of word correlations on the right, it can observed that game mechanics regarding shooting with guns, or simply battle mechanics were badly designed, resulting in in-game character death. When examining the largest cluster of word correlations, the following can be stated. Firstly, those words appeared in most negative reviews. Secondly, the cluster of words is full of profanity and negative adjectives. Thirdly, these words can be associated with the game's difficulty or boring gameplay, bad level design, bugs/issues, and not recommending the games. Interestingly, "sale" is also mentioned, indicating that the games should be bought during a sale as they were not worth their full asking price.

IV. Discussion

The research questions were answered by the findings which provided an understanding of VR game reviews. Thus, in this section, the implications of the results are discussed.

The first research question focused on understanding the length of VR game reviews. The results indicate that negative reviews tend to be longer on average compared to positive ones. This suggests that players express their dissatisfaction in greater detail. This is similar to the results presented by Lin et al. [29]. In their study, they compared the length of reviews between various video game genres. Although they did not assess VR games, our results show that a similar phenomenon exists in their case.

The second research question revolved around the relationship between playtime and word numbers in the reviews. While no correlation was found, there was a significant difference in when players wrote the reviews. Positive reviews are written much later than negative ones. This raises interesting questions about player motivations. Negative reviews are written earlier due to frustration or disappointment, while positive ones are written after a more extensive gameplay session that strengthens positive impressions. These results are also similar to the ones concluded by Lin et al. when they examined review times between video game genres [29]. Our results show that VR games show a similar phenomenon in this regard.

The third research question focused on the understanding of word frequencies and their associations in the reviews. The results provided valuable contextual information about player experiences. Positive reviews highlight the players' appreciation for narrative elements, gameplay, and game mechanics. On the contrary, negative reviews often emphasized dissatisfaction with purchasing decisions and they showed the importance of how players evaluate the value of money. Similarly, players were critical of game length and narrative depth. The strong correlations between certain words, particularly profanity and negative adjectives, highlights the emotional and critical nature of negative reviews. These findings show that players use specific language to express their frustrations with game mechanics, and certain design elements.

This study holds significant implications for both VR game developers and researchers. For developers, gaining insights into the correlation between review length and playtime can serve as a valuable foundation for creating new strategies that are aimed at enhancing player engagement and immersion. By addressing the highlighted concerns within negative reviews, such as game mechanics, level design, and fixing the identified bugs, developers can actively contribute to an improved player satisfaction and experience. Moreover, the word associations within the reviews present an opportunity to see the preferences and priorities of players. With this understanding, developers can optimize and refine aspects of their games that resonate positively with players, while simultaneously identifying and solving issues that create negative sentiments. Furthermore, the identification of prevalent terms within positive reviews, a roadmap can be provided for developers. With it, they can reinforce the strengths of their games and bolster player satisfaction as well. Using these results, developers can more effectively tailor their future projects to align more closely with the preferences and expectations of their player base.

Naturally, this study has its limitations. Firstly, only English reviews were scraped, and the limit of reviews was 1,000 per VR game. Secondly, the analysis was restricted to textual content. Thirdly, only Steam reviews were investigated. Future research could expand the analysis by including other digital video game distribution platforms and other sources of feedback, such as forum discussions or social media conversations. Also, sentiment analysis techniques and natural language processing algorithms could be included to provide a deeper understanding of emotions in the reviews.

V. Conclusions

In this study, we analyzed VR game reviews to gain a deeper understanding of player experience. We investigated 1,635,919 textual reviews comprising both positive and negative reviews from the Steam digital video game distribution platform. Our goal was to understand review length, playtime before reviewing, and frequent words as well as their associations regarding VR games.

The results within this study show that negative reviews are written significantly earlier and contain more words than positive ones. This suggests that players tend to write about their dissatisfaction as early as possible and they express their concerns in greater depth. On the contrary, positive reviews contain concise language. These positive reviews also highlight the significance of narrative elements, gameplay, and learning experiences. Negative reviews, on the other hand, range from monetary concerns to gameplay mechanics, and even false advertising. The resulting word correlations provided a glimpse into players' experience.

In conclusion, our results can provide recommendations for developers and researchers alike. By understanding the relationships between review length, playtime, and word frequency as well as their associations, richer player experiences can be created in the realm of VR.

Acknowledgment

This work has been implemented by the TKP2021-NVA-10 project with the support provided by the Ministry of Culture and Innovation of Hungary from the National Research, Development and Innovation Fund, financed under the 2021 Thematic Excellence Programme funding scheme.

References

[1] G. Wersényi, "Musings on the Metaverse and on how the Internet of Digital Reality encompasses future developments of the Internet," *Infocommunications Journal*, vol. 15, no. Special Issue: Internet of Digital & Cognitive realities, pp. 21–28, 2023, DOI: 10.36244/ICJ.2023.SI-IODCR.4.

[2] F. Erdős, R. Németh, and B. Firuza, "Virtual Teamwork in Gamified 3D Environment," *Infocommunications Journal*, vol. 15, no. Special Issue: Internet of Digital & Cognitive realities, pp. 15–20, 2023. DOI: 10.36244/ICJ.2023.SI-IODCR.3.

[3] F. Faiqotuzzulfa and S. A. Putra, "Virtual reality's impacts on learning results in 5.0 education: A meta-analysis," *International Transactions on Education Technology (ITEE)*, vol. 1, no. 1, pp. 10–18, 2023, DOI: 10.33050/itee.v1i1.172.

[4] S. G. Izard, J. A. Juanes Méndez, and P. R. Palomera, "Virtual reality educational tool for human anatomy," *Journal of Medical Systems*, vol. 41, no. 5, 2017, DOI: 10.1007/s10916-017-0723-6.

[5] M. A. Rojas-Sánchez, P. R. Palos-Sánchez, and J. A. Folgado-Fernández, "Systematic literature review and bibliometric analysis on virtual reality and education," *Education and Information Technologies*, vol. 28, no. 1, pp. 155– 192, 2023, DOI: 10.1007/s10639-022-11167-5.

[6] P. Smutny, "Learning with virtual reality: a market analysis of educational and training applications," *Interactive Learning Environments*, pp. 1–14, 2022, DOI: 10.1080/10494820.2022.2028856.

[7] B. Xie, H. Liu, R. Alghofaili, Y. Zhang, Y. Jiang, F. D. Lobo, C. Li, H. Huang, M. Akdere, C. Mousas, and L.-F. Yu "A review on virtual reality skill training applications," *Frontiers in Virtual Reality*, vol. 2, 2021, DOI: 10.3389/frvir.2021.645153.

[8] D. W. Carruth, "Virtual reality for education and workforce training," in *2017 15th International Conference on Emerging eLearning Technologies and Applications (ICETA)*, Stary Smokovec, Slovakia, 2017, pp. 1–6, DOI: 10.1109/ICETA.2017.8102472.

[9] N. Gasteiger, S. N. van der Veer, P. Wilson, and D. Dowding, "How, for whom, and in which contexts or conditions augmented and virtual reality training works in upskilling health care workers: Realist synthesis," *JMIR Serious Games*, vol. 10, no. 1, p. e31644, 2022, DOI: 10.2196/31644.

[10] M. Matsangidou, F. Frangoudes, M. Hadjiaros, E. Schiza, K. C., Neokleous, E. Papayianni, M. Avraamides, and C. S. Pattichis "'Bring me sunshine, bring me (physical) strength': The case of dementia. Designing and implementing a virtual reality system for physical training during the COVID-19 pandemic," *International Journal of Human-Computer Studies*, vol. 165, no. 102840, p. 102840, 2022, DOI: 10.1016/j.ijhcs.2022.102840.

[11] S. Z. A. Ansari, V . K. Shukla, K. Saxena, and B. Filomeno, "Implementing virtual reality in entertainment industry," in *Cyber Intelligence and Information Retrieval*, Singapore: Springer Singapore, 2022, pp. 561–570, DOI: 10.1007/978-981-16-4284-5_49.

[12] F. Rega and D. Saxena, "Free-roam virtual reality: A new avenue for gaming," in *Advances in Augmented Reality and Virtual Reality*, Singapore: Springer Singapore, 2022, pp. 29–34, DOI: 10.1007/978-981-16-7220-0_3.

[13] G. Burdea and P. Coiffet, *Virtual Reality Technology*. Nashville, TN: John Wiley & Sons, 1994.

[14] I. Horváth, Á. B. Csapó, B. Berki, A. Sudár, and P. Baranyi, "Definition, background and research perspectives behind 'Cognitive Aspects of Virtual Reality' (cVR)," *Infocommunications Journal*, vol. 15, Special Issue: Internet of Digital & Cognitive realities, pp. 9–14, 2023, DOI: 10.36244/ICJ.2023.SI-IODCR.2.

[15] C. V ogel and A. Esposito, "Interaction Analysis and Cognitive Infocommunications," *Infocommunications Journal*, vol. 12, no. 1, pp. 2–9, 2020, DOI: 10.36244/ICJ.2020.1.1.

[16] H. Mclellan, "Cognitive issues in virtual reality," *Journal of Visual literacy*, vol. 18, no. 2, pp. 175–199, 1998, DOI: 10.1080/23796529.1998.11674538.

[17] S. Hedegaard and J. G. Simonsen, "Extracting usability and user experience information from online user reviews," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2013, DOI: 10.1145/2470654.2481286.

[18] H.-N. Kang, "A study of analyzing on online game reviews using a data mining approach: STEAM community data," *International Journal of Innovation, Management and Technology*, pp. 90–94, 2017, DOI: 10.18178/ijimt.2017.8.2.709

[19] C. Chambers, W.-C. Feng, S. Sahu, and D. Saha, "Measurement-based characterization of a collection of on-line games," in *Proceedings of the 5th ACM SIGCOMM conference on Internet measurement – IMC '05*, 2005.

[20] I. Busurkina, V. Karpenko, E. Tulubenskaya, and D. Bulygin, "Game experience evaluation. A study of game reviews on the steam platform," in *Communications in Computer and Information Science*, Cham: Springer International Publishing, 2020, pp. 117–127, DOI: 10.1007/978-3-030-65218-0_9.

[21] X. Li, Z. Zhang, and K. Stefanidis, "A data-driven approach for video game playability analysis based on players' reviews," *Information (Basel)*, vol. 12, no. 3, p. 129, 2021, DOI: 10.3390/info12030129.

[22] S. Ahn, J. Kang, and S. Park, "What makes the difference between popular games and unpopular games? analysis of online game reviews from steam platform using word2vec and bass model," *ICIC Express Letters*, vol. 11, pp. 1729–1737, 2017.

[23] K. Wase, P. Ramteke, R. Bandewar, N. Badole, B. Kumar, and M. Bogawar, "Sentiment Analysis of product review," *International Journal of Innovations in Engineering and Science*, vol. 3, pp. 8–13, 2018.

[24] G. Andreev, D. Saxena, and J. K. Verma, "Impact of review sentiment and magnitude on customers' recommendations for video games," in *2021 International Conference on Computational Performance Evaluation (ComPE)*, Shillong, India, 2021, pp. 992–995, DOI: 10.1109/ComPE53109.2021.9752380.

[25] V. de Souza Goncalves and A. A. Macedo, "Similarities and divergences in electronic game review texts," in *2020 19th Brazilian Symposium on Computer Games and Digital Entertainment (SBGames)*, Recife, Brazil, 2020, pp. 145–153, DOI: 10.1109/SBGames51465.2020.00028.

[26] E. Guzman and W. Maalej, "How do users like this feature? A fine grained sentiment analysis of app reviews," in *2014 IEEE 22nd International Requirements Engineering Conference (RE)*, Karlskrona, Sweden, 2014, pp. 153–162, DOI: 10.1109/RE.2014.6912257.

[27] C. Lu, X. Li, T. Nummenmaa, Z. Zhang, and J. Peltonen, "Patches and Player Community Perceptions: Analysis of No Man's Sky Steam Reviews," in *DiGRA'20-Proceedings of the 2020 DiGRA International Conference*, 2020, pp. 1–24.

[28] Y. Yu, B.-H. Nguyen, F. Yu, and V.-N. Huynh, "Esports game updates and player perception: Data analysis of PUBG steam reviews," in *2021 13th International Conference on Knowledge and Systems Engineering (KSE)*, Bangkok, Thailand, 2021, pp. 1–6, DOI: 10.1109/KSE53942.2021.9648670.

[29] D. Lin, C.-P. Bezemer, Y. Zou, and A. E. Hassan, "An empirical study of game reviews on the Steam platform," *Empirical Software Engineering*, vol. 24, no. 1, pp. 170–207, 2019. DOI: 10.1007/s10664-018-9627-4.

[30] B. Dean, "Steam usage and catalog stats for 2023," *Backlinko*, 17-Mar-2023. [Online]. Available: https://backlinko.com/steam-users. [Accessed: 19-Aug-2023].

[31] E. Blancaflor and J. M. G. San Miguel, "Analyzing Digital Game Distribution in Gaming Industry: A Case Study," in *Proceedings of the 2nd Indian International Conference on Industrial Engineering and Operations Management*, 2022, pp. 674–681.

[32] Valve Corporation, “Documentation home page (steamworks documentation),” *Steamgames.com*. [Online]. Available: https://partner.steamgames.com/doc/home. [Accessed: 19-Aug-2023].

[33] Valve Corporation, “User reviews – get list (steamworks documentation),” *Steamgames.com*. [Online]. Available: https://partner.steamgames.com/doc/store/getreviews. [Accessed: 19-Aug- 2023].

[34] Valve Corportation, “ISteamApps interface (steamworks documentation),” *Steamgames.com*. [Online]. Available: https://partner.steamgames.com/doc/webapi/ISteamApps. [Accessed: 19-Aug-2023].

[35] C. J. Van Rijsbergen, S. E. Robertson, and M. F. Porter, “New models in probabilistic information retrieval,” in *British Library. (British Library Research and Development Report*, London, 1980.

[36] H. Hofmann, H. Wickham, and K. Kafadar, “Letter-value plots: Boxplots for large data,” *Journal of Computational and Graphical Statistics*, vol. 26, no. 3, pp. 469–477, 2017, DOI: 10.1080/10618600.2017.1305277.

[37] H. B. Mann and D. R. Whitney, “On a Test of Whether one of Two Random Variables is Stochastically Larger than the Other,” *The annals of mathematical statistics*, vol. 18, no. 1, pp. 50–60, 1947.

[38] C. Spearman, “The proof and measurement of association between two things,” *American Journal of Psychology*, vol. 15, no. 1, p. 72, 1904, DOI: 10.2307/1412159.

Tibor Guzsvinecz is an Assistant Professor at the Faculty of Information Technology of the University of Pannonia, Hungary. He obtained his PhD degree in the field of Information Science in 2021. His research areas are data science, gamification, human- computer interaction, spatial ability, and virtual reality. He authored 69 scientific publications which include 19 journal papers, and 41 studies found in various conference proceedings. At the moment, he is an editor of a book project about gamification. He is an IEEE member since 2023.

Judit Szűcs is an Assistant Professor at the Faculty of Information Technology of the University of Pannonia, Hungary. She received her PhD degree in 2021 in Computer Science at the University of Szeged. Her main interests include binary tomography, image processing, and computer vision. She has 30 scientific publications which include 6 journal papers, and 19 studies found in various conference proceedings. She is an IEEE member since 2023.