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Haptic technology in society: A sentiment analysis of public engagement

Abstract

With the rapid rise of metaverse spaces, the integration of haptic technology has become an integral part of users' immersion and engagement in different domains. This study shades the light on public engagement with haptic technology applications in various contexts. The YouTube Application Programming Interface was used to extract data about haptic technology within a specific time period. Public engagement was estimated based on users' cognitive and behavioral engagement with haptic-video materials. A topic modeling approach was used to extract the main topics associated with haptic technology. The main types of users' emotions and their word association were extracted using the association rules mining technique. The results showed that public engagement with haptic technology was mostly observed in few categories (e.g., gaming). Joy and positive sentiments were strongly associated with the extracted topics. The findings offer new insights into the tendency of utilizing haptic technology across communities. The outcomes can help industries and decision makers understand ways to improve the integration of haptic technology in according to the needs of specific domains.

Keywords: *haptic technology; haptics; technology and society; sentiment analysis*

1. Introduction

The recent innovations in haptic technology have opened new ways for people to immerse and engage in virtual environments. Haptic technology is defined as the technology of applying touch sensation while interacting with a physical or virtual environment (Sreelakshmi & Subash, 2017). Other haptic-related terminologies (e.g., haptic interfaces, feedback, display, devices, etc.) have been widely used by many scholars to describe the role of technology in context specific situations.

Industries, organizations, and individuals have been engaging in the development, design, and utilization of haptic technology in an attempt to compensate for the lack of human contact in the virtual world. To this end, there is limited knowledge of how the technology is perceived by people in different contexts and situations (Bermejo & Hui, 2021). In addition, assessing certain cognitive and emotional aspects in relation to individuals' use of technology or service is critical for future utilization and development (Makransky & Petersen, 2021). Traditionally, individual cognitive and emotional attributes are commonly collected and analyzed by neuropsychologists through different means (e.g., facial expressions, eye-movements, brain activation, and questionnaire). While these measures are valuable in characterizing the fundamental mechanisms of individuals' experience, they pose some challenges of limited sample sizes and relatively high cost of experiment (Huang et al., 2017). Yet, with the rapid development of microblogs, it is possible now to assess people's thoughts and feelings about a specific type of technology.

Social media generates large volumes of real-time social signals which can offer new insight on human behavior and emotions (Sarsam & Al-Samarraie, 2022; Sarsam et al., 2022). People all over the world are constantly engaging (e.g., cognitively and emotionally) with social media. People's engagement with social media has always been viewed as one source that can help policy makers, businesses, and organizations understand how effectively a technology or service can be integrated or used. With that said, this study explored public's engagement with haptic technology from cognitive and behavioral perspectives. The study also looked at the different types of emotions associated with public haptic engagement. This study is the first of its kind to investigate public haptic engagement using a sentiment analysis approach. Outcomes from this study are sought to provide an early indication of public engagement with haptic technology. Furthermore, understanding people engagement with haptic inclusion can help businesses and organizations to recognize key areas and topics that feed into current policy agendas.

2. Literature review

Extended reality, in the form of virtual and augmented reality (VR/AR), is sought to provide an immersive experience for users through seamless interaction with visual and auditory cues. With the aid of haptic technology, the VR/AR industry has grown rapidly over the past decades to various domains such as tele-manipulation, medical/military training, and gaming entertainment (Yang et al., 2021). In addition, it has become an adynamic emerging technology supported by the recent advances in computer graphics, sensors/tracking technologies, and integrated circuit manufacturing techniques. People now connect and meet others virtually in an immersive environment to communicate more effectively.

Considering the continually evolving cutting-edge VR technologies, haptics plays a significant role in providing multisensory feedback to enhance user experience. Instead of using massive equipment to provide kinesthetic feedback, vibrotactile based haptic actuators such as the eccentric rotating mass (ERM), linear resonant actuator (LRA) and piezoceramic actuators, are widely commercialized (Dementyev et al., 2020; Martínez et al., 2020). To provide portability and degree-of-freedom in users' interaction with virtual environments, people demand more compact with high-resolution haptic feedback. Haptic technology refers to the use of machines to replace human touch through telerobotic or haptic interfaces (Srinivasan, 1995). Most haptic technology relay on detecting and monitoring positions or contact forces from certain parts of the body. This includes predicting and visualizing haptic information based on the position and forces taken from users. Haptic technologies based on certain tactile sensations have become prominent over the last couple of years. Some scholars reported that the main advantage of haptic technology is in the creation and rendering of sense of touch and feel of virtual objects (Biswas & Visell, 2021; Yang et al., 2021). This can be achieved by using various prediction algorithms and software architectures. In addition, most haptic devices available in the market uses force feedback and vibrotactile feedback to stimulate sense of touch via joysticks, robotic arms, and actuation systems (Wee et al., 2021). As such, the technology has been perceived differently in various communities. Furthermore, understanding public engagement with haptic technologies is critical to ensuring their effectiveness in a specific domain (Webb et al., 2022). Previous research on the use of haptic technology focused mainly on the development and use of the technology in a discipline specific context. For example, Brewster (2017) reported some of the possibilities of haptic technology and its use in cultural applications. The study was limited to exploring how the visual displays of haptic technology can be extended to make them realistic, useful and engaging for museum visitors. Meanwhile, other previous studies (e.g., Breitschaft et al., 2019; Fallows et al., 2022; Goldsworthy et al., 2020; Kirginas, 2022; Ustunel & Keles, 2019) looked at the potential of haptic technology in various disciplines such as medical, education, automotive, entertainment, and safety. These studies were only looking at how the technology can be used to facilitate individuals' interaction with the task.

The literature also revealed a notable lack in understanding emotions a user may experience when using haptic technology. Such understanding has been viewed by many scholars (e.g., Bielozorov et al., 2019; Dzedzickis et al., 2020; Lu et al., 2019) as an important aspect for the development of human interaction with the virtual world. In contrast, identifying the social functions of emotions in haptic-related contexts can provide designers and developers of the technology with the necessary clues to design effective sensational experience that promote both users' immersion and engagement in the virtual world (Jewitt et al., 2022). Based on these, it can be concluded that exploring public engagement with haptic technology can open new avenues in the design and development of the technology. Previous studies have mainly looked at aspects related to 1) the application of technology in different contexts, 2) development of haptic systems, and 3) assessment of haptic interaction. Based on these, this study aims to answer the following key questions: 1) 'What are public cognitive and behavioral engagement with haptic technologies?', 2) 'What are the main topics associated with haptic technology?', and 'What are the embedded sentiments in haptic technology-related topics?'. To achieve this, social media sites, such as YouTube, was used to characterize how users perceive the technology through understanding their reactions to haptic-related video materials. It is anticipated that outcomes from this work can pave the way for high-tech businesses to effectively customize future haptic systems.

3. Method

A combination of sentiment analysis and topic modeling approaches were considered in this study to reveal recent haptic trends on YouTube. The reason for choosing YouTube as the main data collection platform in this study back to its capability in categorizing videos by topics. This allowed us to link certain sentiments / topic to a specific category (e.g., science, gaming, etc.). The implemented process consists of data collection, video categorization, data pre-processing, estimation of behavioral engagement, estimation of cognitive engagement, topic modeling, emotion extraction, part-of-speech tagging, and association rules mining (see Figure 1).

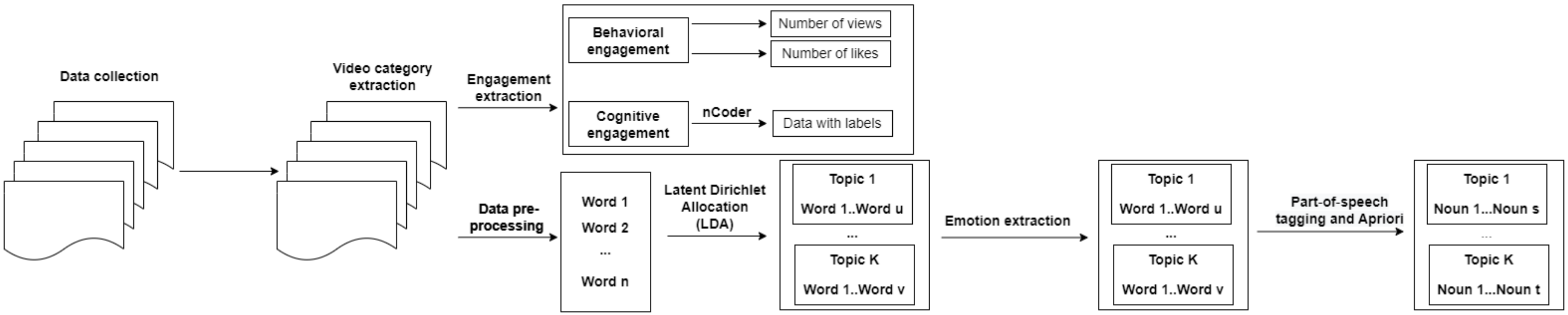


Figure 1: The conducted research process

3.1 Data collection and video categorization

We collected a total of 510 videos within a time span of 10 years (Jan 1st, 2012, till 30th September 2022) using YouTube Data Application Programming Interface (API). In this sense, several keywords were used to collect the desired videos: ‘haptic technology’, ‘haptics’, haptic devices’, ‘haptic / tactical sensation’, ‘haptic feedback’, ‘haptic systems’, ‘haptic interface’, and ‘force feedback’. We then extracted video category and video ID from each video. This information was obtained from the YouTube Data API category list which consists of 29 categories. In addition, users’ comments on each video along with the number of likes and view counts. The extracted comments from each video were prepared via several text preparation techniques to build a high-quality corpus (see Section 3.2). Figure 2 shows the category distribution of the haptic-related videos within ten years. From this figure, it can be observed that the ‘Gaming’ category was the dominant (popular) category, followed by ‘People & Blogs’, ‘Science & Technology’, and ‘Education’. In order to answer the above research questions, we used these categories and associated data for 2022.

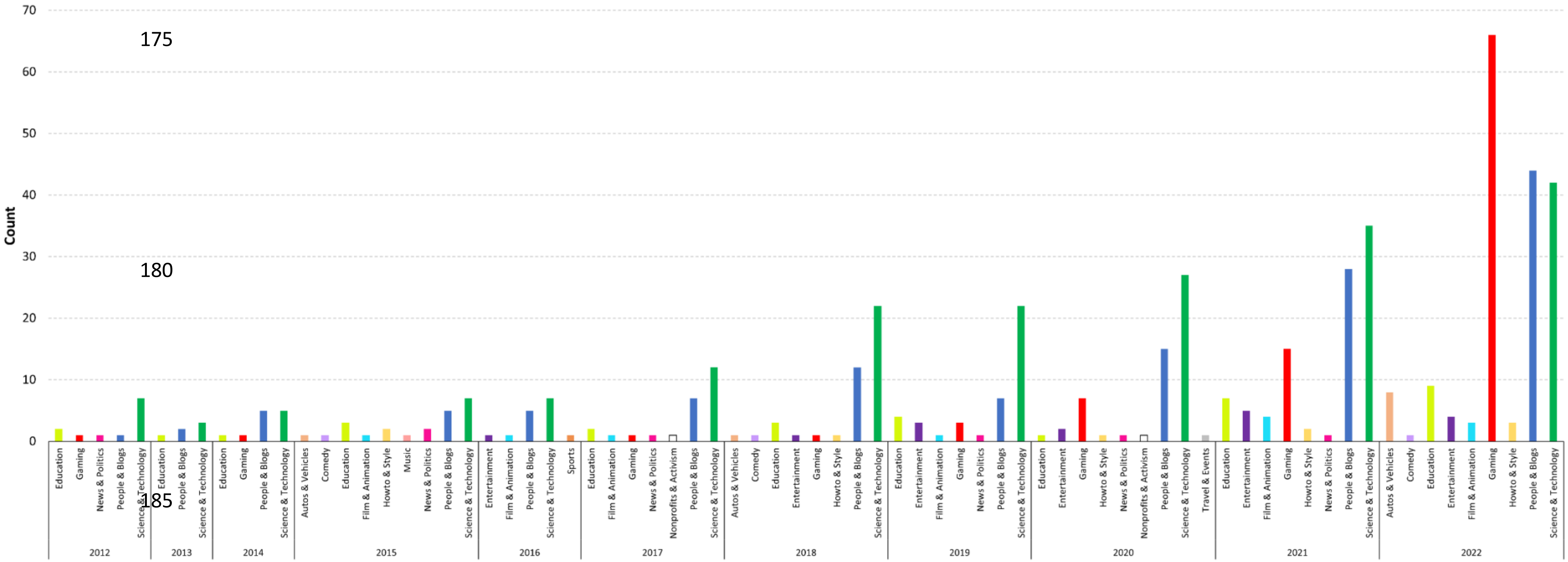


Figure 2: Number of videos per category

3.2 Estimation of behavioral engagement

To assess the level of behavioral engagement with haptic technology-video contents, we counted the number of views in an attempt to estimate users' involvement with the technology. We also used the number of likes as an estimation of users' intimacy with the technology. The overall behavioral engagement was accomplished by summing the averages of number of views and likes of each video. Additionally, to understand the quality of interaction in the observed categories (Gaming, People & Blogs, Science & Technology, and 'Education'), we computed the correlation between the number of likes and views for the four categories. We also examined users' engagement with each topic in order to understand their estimate their engagement behavior with haptic technology. The process for estimating users' behavioral engagement in this study was based on previous recommendations (e.g., Dubovi & Tabak, 2021; Shen et al., 2022).

3.3 Estimation of cognitive engagement

To identify users' cognitive engagement, we developed an automated coding approach of linguistic argumentation elementary units (e.g., agree/disagree, reason, and fact). After that, we used nCoder tool (Arastoopour Irgens et al., 2020) to automatically apply the coding model to the examined comments where the interrater reliability between raters (authors of this study) and the automated algorithm achieved a high Cohen's kappa value of 0.95. Section 4.1 demonstrates the result for both behavioral and cognitive engagement of users with haptic videos.

3.4 Data pre-processing

This stage consists of data filtering and cleansing processes. Data filtering was achieved by reducing the raw sentence found in the comments of each video. Data cleansing was also carried out to remove links and unwanted symbols from the filtered comments. The cleansed data were further processed by using the "Tokenization" technique. This technique was used to extract important and relevant video features and establish the overall dictionary for this study. The resulting words were then converted into a lowercase form. This is followed by using the Stopwords list technique to delete some of the less important words in our corpus. Finally, all the remaining textual comments were normalized (the length of the sentence) via the L2 norm (Sarsam et al., 2020).

3.5 Topic modeling

Latent Dirichlet Allocation (LDA) algorithm was implemented on the processed data to obtain the hidden topics in each video. LDA is an unsupervised generative probabilistic method that models group of textual data (comments in the case of this study). These comments were characterized as random mixtures over hidden topics, where a topic was explained by a distribution over words. LDA model has several K topics φ_k, $k \in \{1, ..., K\}$, the pseudo code for the LDA algorithm (Foulds et al., 2013) is as follows:

Pseudo code for the LDA algorithm
Generate each topic $\varphi_k \sim$ Dirichlet (η), $k \in \{1, ..., K\}$
For each document j

Generate a distribution over topics $\theta_j \sim$ Dirichlet (α)
For each word i in document j
Sample a topic $z_{ij} \sim$ Discrete (θ_j)
Sample the word $w_{ij} \sim$ Discrete (φz_{ij}).

Where φ_k refers to the distribution of words for each topic k, θ_j indicates the distribution of topics for each document j, and z_{ij} indicates the topic for i and j—the i word of the j document.

To get an overview of the general distribution of the discussed topics, we extended the LDA results by highlighting the most important topic-related components with the help of heatmap using a density-based method. In this case, the intensity of colors was distributed based on the number of items in the neighboring textual content and its importance. In the produced heatmap, the color of a point was identified based on the item density of the point. The larger the number of neighboring items, the smaller the distances between these items and the point of interest, and thus the higher the density level. Besides, the content with high density is associated with the weights of the neighboring items. In this context, the $\bar{d}$ denote the average distance between two items (Van Eck & Waltman, 2010):

$$\bar{d} = \frac{2}{n(n-1)} \sum_{i<j} \|x_i - x_j\|$$

The item density $D(\mathrm{x})$ of a point $\mathrm{x} = (x_1, x_2)$ is expressed as follows:

$$D(\mathrm{x}) = \sum_{i=1}^{n} w_i K\left(\|\mathrm{x} - \mathrm{x}_i\| / \bar{d}h\right)$$

where $K: [0, \infty) \rightarrow [0, \infty)$ refers to a kernel function, $h > 0$ refers to the kernel width, and w_i refers to the weight of item i (the total number of occurrences/co-occurrences of item i). The implemented density was based on the following Gaussian kernel function:

$$K(t) = \exp(-t^2)$$

In order to facilitate the labeling of the generated items, we invited three experts in the kinaesthetic communication field to assess the content of the resulting topics and provide proper labels for them. Then, we measured the agreement between them using kappa statistics (see Section 4.2).

3.6 Emotion extraction

We extracted the sentiment from users' comments using NRC Affect Intensity Lexicon and SentiStrength (Mohammad, 2017). The NRC Affect Intensity Lexicon consists of a list of English words and their associations. We used these associations to represent four emotions: anger, fear, sadness, and joy (Sarsam et al., 2022). Here we gave a score ranges between 0-1 for a particular word and emotion X. A score of 1 indicates a high emotional level, while a score of 0 indicates a low emotional level. We then compared the emotion for each comment by adding the relevant associations of the words for a particular lexicon. On the other hand, to extract the polarity from the tweets, 'SentiStrength' approach was used. SentiStrength assigns values ranging from '+1' for 'not positive' to '+5' for 'extremely positive' and '-1' for 'not negative' to '-5' for 'extremely negative'. Based on these values, the authors labeled the tweets with +5 as 'Positive' tweets and -5 as 'Negative' tweets.

3.7 Part-of-speech tagging

Part-of-speech tagging is an important method for extracting various parts of speech from a textual data by assigning a unique tag that can be used to extract relevant terms. Here we applied POS via the Penn State Treebank tokenizer in conjunction with the Document Pre-processor approach. After that, the Penn State Treebank tokenizer was performed to form a list of relevant words before performing the Probabilistic context-free grammar parser. By doing so, we were able to extract 'noun' words from the sentences in an attempt to build associations with the help of association rules mining approach. This process is discussed in the following section.

3.8 Association rules mining

To predict the terms that are highly linked to a particular topic of interest, the association rules mining technique was implemented using the Apriori algorithm. Here we set the delta value to 0.05 in order to reduce the support value until reaching the minimum value. Besides, the minimum metric score of the Apriori algorithm was set to 0.9, while 1.0 was set to represent the value of both upper and lower bounds of the support. The following Apriori algorithm working steps were used according to Agrawal and Srikant (1994):

1. L_1 = {large 1-itemsets};

2. for (k = 2; $L_{k-1} \neq \emptyset$; k++) do begin

3. C_k = apriori-gen(L_{k-1}); // New candidates

4. for all transactions $t \in D$ do begin

5. C_t = subset (C_k, t) // Candidates contained in t

6. for all candidates $c \in C_t$ do

7. c.count ++;

8. end

9. $L_k = \{c \in C_k \mid c.\text{count} \geq \text{minsup}\}$

10. end

11. Answer = $\bigcup_k L_k$;

Where L_k refers to the set of large k-itemsets (minimum support) whereas each member of this set consists of itemsets and support count. C_k indicates the candidate k-itemsets (large itemsets) where $c[1] . c[2] . \ldots . c[k]$ represents a k-itemsets c. The Apriori algorithm operates by applying the procedure of counting item occurrence necessary for choosing the large 1-itemset. In this sense, the subsequent pass (e.g., k) involves two phases. The first phase is designed to locate the large itemsets L_{k-1} that are existed in the (k-1)th pass. This step is necessary for generating the candidate C_k. The second phase involves scanning the data and counting the support of essential candidates in C_k where these candidates can be found in each t transaction.

4. Results

4.1 Cognitive and behavioral engagement results

To understand the current trend in haptic technology, we examined the strength of engagement by means of average behavioral engagement and cognitive engagement. Four main categories were used for data interpretation in this study. Our results illustrated that the 'Gaming' category had the highest Pearson correlation coefficient value (r = 1.00), followed by 'Science & Technology' (r = 0.82), 'Education' (r = 0.82), and People & Blogs' (r = 0.86), respectively.

The temporal engagement changes from January to September 2022 were measured to further assess the quality of engagement among the examined categories. The percentage of comments in each video categories and their cognitive and behavioral engagement are presented in Figure 3. Figure 3a shows that users were highly engaging (average behavioral engagement) with videos that demonstrated the use of haptic technology in gaming-related experiences. In addition, Figures 3b shows how users' cognitive engagement was highly associated with videos from the same category. Users' heavy engagement with haptic technology for gaming can be attributed to its potential in facilitating their sense of immersion and engagement in a game environment. The results also showed that users' cognitive and behavioral engagement with haptic technology were found in videos for 'Science & Technology' and 'Education'. Videos categorized under 'People & Blogs' were found to receive the least average score of users' behavioral and cognitive engagement with haptic technology. This result can be due to that haptic technology might be less circulated or applied by people for the purpose of advancing lifestyle and health, as well as other similar topic in the form of success stories and news about people experience with the technology. It is also interesting to mention that both cognitive and behavioral engagement of users for all categories were close to each other.

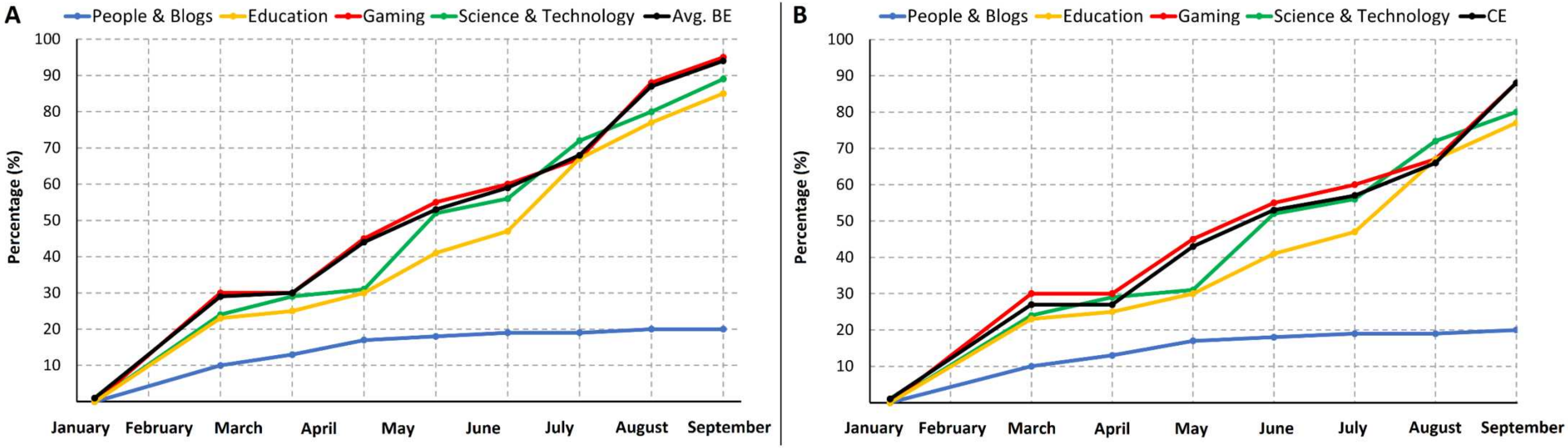


Figure 3: Behavioral and cognitive engagement of users with haptic technology

4.2 Topic modeling results

The LDA method was configured by performing several experiments. We identified the number of topics based on the trade-off between information loss and information overload. After conducting several experiments on the comments found in the four categories, we were able to estimate the number of topics for each category in this study. The resulted topics from using the LDA technique are shown in Figure 4a where each circle corresponds to a specific topic found in the comments in the videos. In addition, the size of a circle indicates the frequency of a topic repeated in that category whereas the distance between circles shows the similarity between topics. The LDA heatmap results (see Figure 4b) shows some insights about the density of the extracted topics. In this sense, the color of a point depends on the number of items in the neighborhood of the point and on the importance of the neighboring items. Important areas are very dense and frequently repeated in the comments. To form a complete understanding of the LDA results, we invited three experts in the kinaesthetic communication field who evaluated the content of the topics/themes and provided appropriate labels for them. Then, we measured the agreement between the suggested labels via kappa statistic which indicated an agreement value of 0.94. The experts highlighted four main themes that were labeled as “Haptic sensation”, “Haptic technology and virtual reality”, “Video game consoles and tools”, and “Smart phones”.

In the first theme (Haptic sensation), our results showed that YouTube comments were mostly related to users’ positive experiences with haptic devices in terms of providing precision force feedback and enhancing simulations. Some comments reported the effectiveness of using haptic suit in facilitating individual immersion and engagement with the VR world. In the second theme (Haptic technology and virtual reality), it was found that most of the comments focused on the link between haptic technology and virtual reality in promoting individuals to feel virtual spaces. The comments indicated that haptic technology may still in its fancy stage to offer a varied level of roughness, which may directly influence user experience. Furthermore, some comments suggested the use of haptic gloves in simulator-based training to allow the user to better control a process inside the VR environment.

Our review of users' comments related to the third theme (Video game consoles and tools) showed a high tendency among users to spend more time learning about various video games consoles and their associated tools for entertainment purposes. For instance, several comments reported that the use of haptic technology in game consoles allowed them to fully engage in the game activity, as well as enabling them to reflect and identify actions that were required to improve and develop their gaming experience. Also, other comments mentioned the potential of Duelsense haptic feedback and the adaptive triggers in facilitating their control of the avatar and game objects.

In the fourth theme (Smart phones) users were generally concerned about the quality of the implemented haptic technology in mobile touchscreen devices. For instance, the comments highlighted how haptic touchscreen provided users with the feeling of traditional analog camera, especially when zooming in and out, tapping the shutter button, and changing modes. Such experience enabled users to perceive UI as the main source for both visual and tactile sensations. In addition, some comments discussed how changes in users’ decisions to purchase mobile devices can be triggered by the quality of its haptic feature. For instance, users were found to prefer Google's Pixel phones due to its multiple haptic features that allowed them to feel in control when typing and navigating. It is also worth mentioning that most of the comments that we retrieved from YouTube were mainly driven by users’ desire to explore and share their experiences regarding the feasibility and benefits of using haptic technology in a specific context.

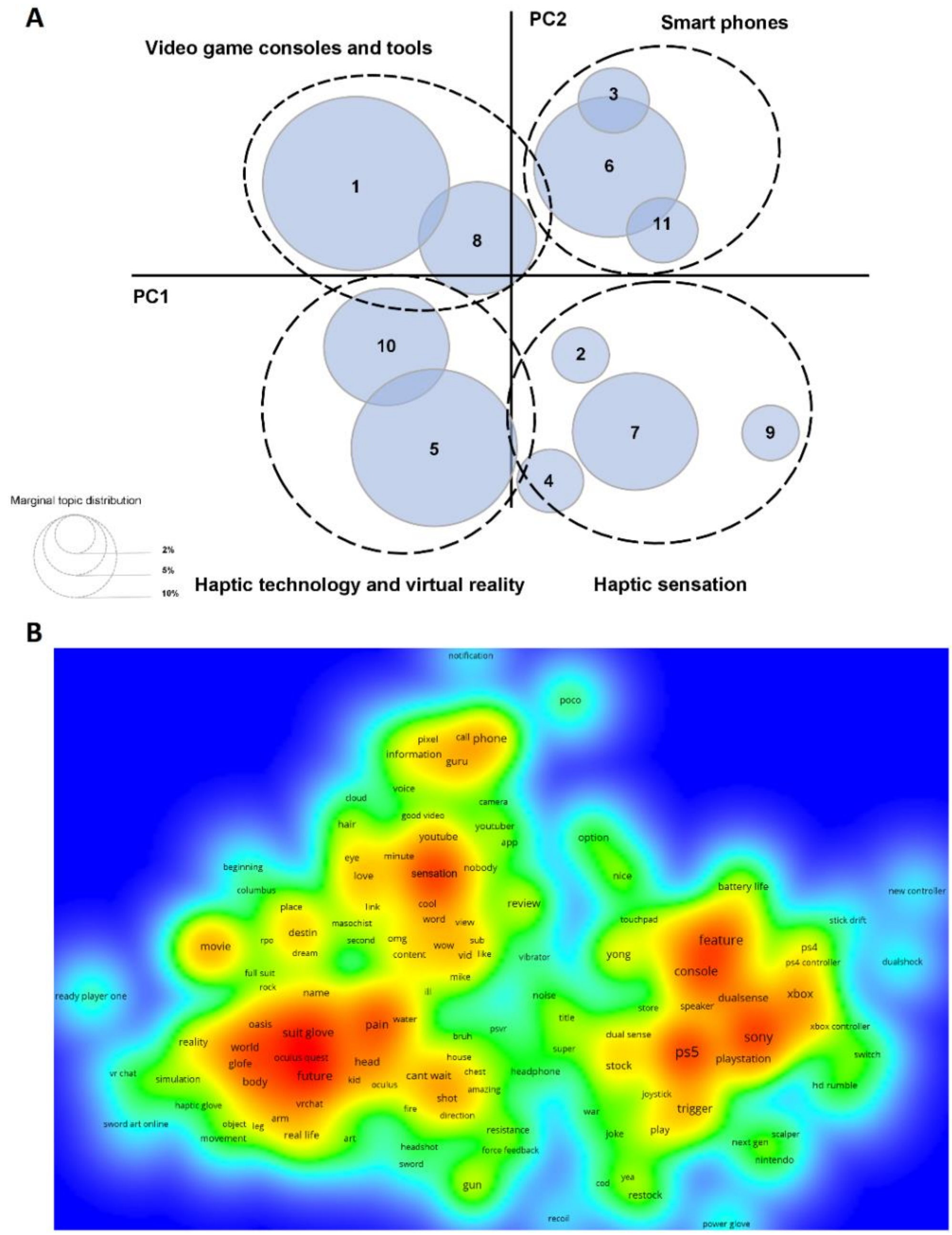
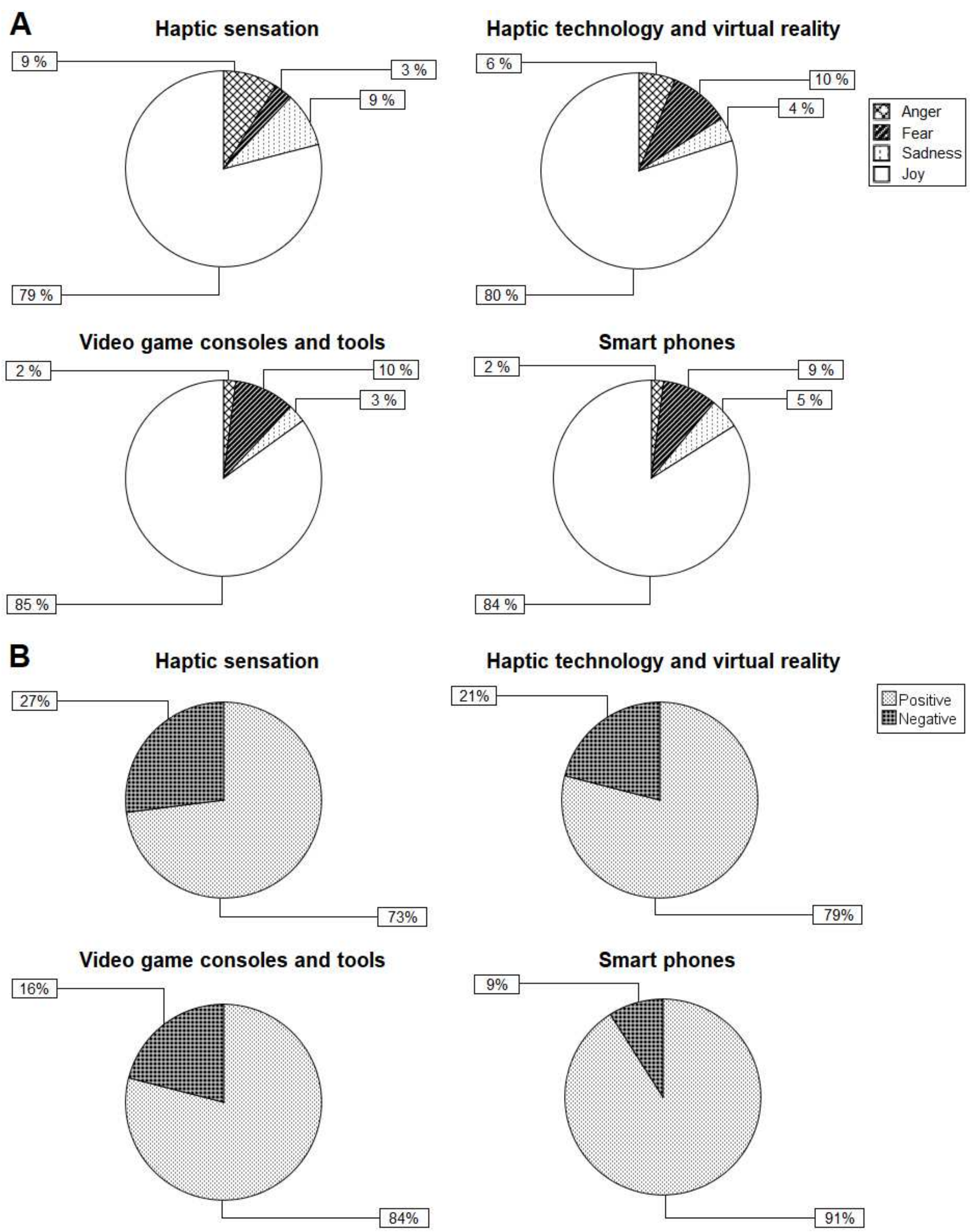


Figure 4: LDA results. A: the general topics and themes; B: the LDA heatmap

4.3 Sentiment analysis and association rules results

The sentiment analysis results of the four types of emotions (anger, fear, sadness, and joy) are summarized in Figure 5a. From this figure, it can be observed that the first theme (Haptic sensation) consists of several emotional types such as joy (79%), followed by anger/sadness (9%) and fear (3%) emotions, respectively. Also, comments contained joy emotions were highly observed (80%) in the second theme (Haptic technology and virtual reality), compared with fear (10%), anger (6%), and sadness (4%), respectively. A similar pattern of emotions was observed in the third theme (Video game consoles and tools)– joy (85%), followed by fear (10%), sadness (3%), and anger (2%) emotions, respectively. Finally, in the fourth theme (Smart phones), comments contained low value of anger emotion (2%), followed by sadness (5%), fear (9%), and joy (84%), respectively. Figure 5b illustrates the polarity results extracted from tweets. From the figure, it can be observed that positive sentiment was dominant among the four themes. Precisely, the theme associated with Smart phones had the highest percentage of positivity (91%), followed by Video game consoles and tools (84%), Haptic technology and virtual reality (79%), and Haptic sensation (73%). Based on these, it can be said that most of the comments related to haptic technology in the four themes had a high level of joy and positive sentiments.



A
Haptic sensation
9 %
3 %
9 %
79 %
Haptic technology and virtual reality
6 %
10 %
4 %
80 %
Anger
Fear
Sadness
Joy
Video game consoles and tools
2 %
10 %
3 %
85 %
Smart phones
2 %
9 %
5 %
84 %
B
Haptic sensation
27%
73%
Haptic technology and virtual reality
21%
79%
Positive
Negative
Video game consoles and tools
16%
84%
Smart phones
9%
91%

Figure 5: Sentiment analysis results for each LDA topic. A: topic sentiment; B: sentiment polarity

The Apriori results are summarized in Figure 6. From the figure, terms like vibration, feelings, glove, tactile, and comfort were found to be highly associated "Haptic sensation" theme with confidence values of 98%, 93%, 88%, 85%, and 81%, respectively. Also, we found that augment, interface, brilliant, interaction, and physical terms were highly associated with the "Haptic technology and virtual reality" theme (confidence value: 94%, 88%, 82%, 74%, and 73%, respectively). In addition, the Apriori method demonstrated that words like controller (confidence: 97%), fun (confidence: 93%), racing (confidence: 87%), trigger (confidence: 82%), and environment (confidence: 75%) were mainly associated with the "Video game consoles and tools" theme. Finally, words such as touch (confidence: 99%), screens (confidence: 95%), play (confidence: 93% confidence), controller (confidence: 91%), and VR (confidence: 81% confidence) were highly associated with the "Smart phones" theme.

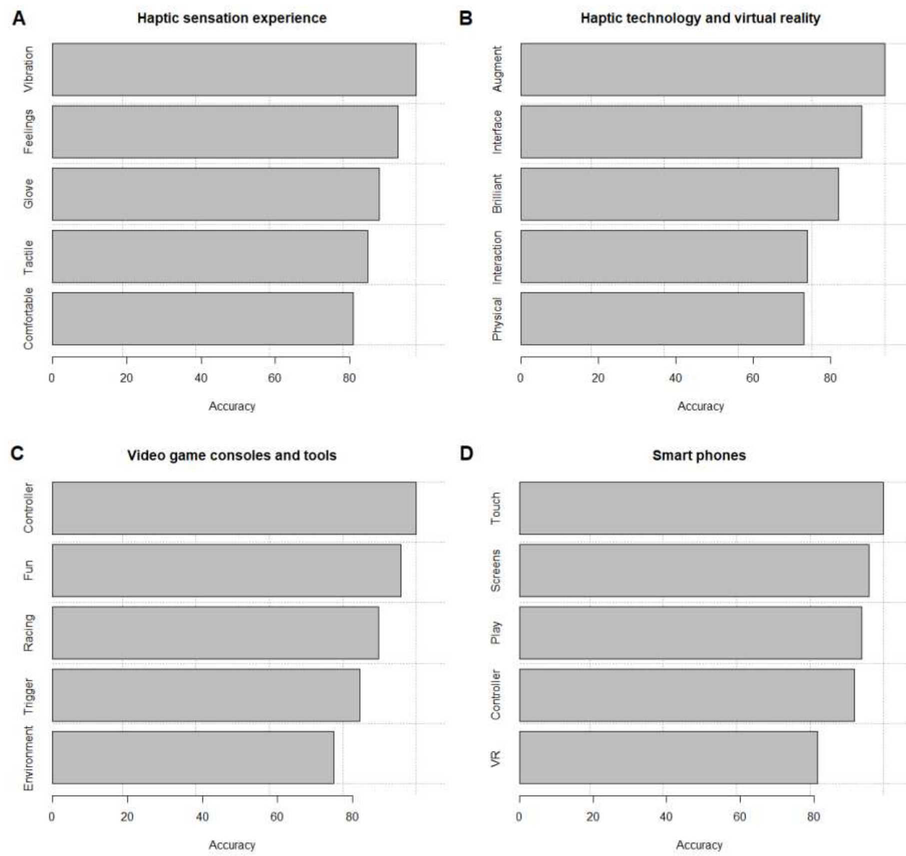


Figure 6: Top words for each theme

5. Discussion

Understanding people's views and perceptions about haptic technology is a very important area of research for building an effective immersive experience. People's use and awareness of this technology can be shaped based on their reaction to haptic-related contents available on microblogs. The YouTube API was the main source of data and information to construct an understanding of people's association with haptic technology. This study used sentiment analysis to explore the current trends in haptic technology over a ten-year span. Our search showed that the use of haptic technology was mostly concentrated in four categories: 'Gaming', 'People & Blogs', 'Science & Technology', and 'Education'. We further inspected people's engagement with these categories by analyzing their cognitive and behavioral engagement patterns. The results showed that people's behavioral and cognitive engagement with haptic was higher in 'Gaming', followed by 'People & Blogs', 'Education', and 'Science & Technology'.

Videos from the identified categories were found to reflect different levels of users' cognitive and behavioral engagement (involvement and intimacy). This could be reasonable as many users with experience using haptic technology in various disciplines tend to share their experience with others, as well as answering questions, responding to comments, or suggesting solutions. People's cognitive and behavioral engagement with haptic-related topics was found to be higher in 'Gaming', 'Science & Technology', and 'Education'. This can be reasoned to the direct application of haptic technology in wearable contexts, such as entertainment, simulation, and learning, which facilitated players' control and sense of presence (Chapman, 2019).

The topic modeling and sentiment analysis results provided an in-depth understanding of the discussed related topics and emotions associated with haptic technology. We found four themes in the retrieved video comments: “Haptic sensation”, “Haptic technology and virtual reality”, “Video game consoles and tools”, and “Smart phones”. Most of the topics found in the comments consisted of joy emotion. This can be due to the potential of haptic technology in facilitating users’ immersion and engagement with the activity. For example, Schrader and Nett (2018) reported that individuals with high and moderate control of the activity are likely to experience a higher level of enjoyment and lower frustration and anger. However, such experience is likely to change based on the needs of players / users. Our review of the topics supports the finding of Vasara and Surakka (2021) who addressed the role of haptic technology in evoking emotions that can help enhance people’s interaction and communication in the virtual space. It is believed that tactile sensation through vibration is likely to stimulate individual’s feelings of joy. This is supported by Lohre et al. (2022) who reported a relationship between individuals’ sense of control through vibration and their emotional response to experience. The results also showed that haptic augmentation-based experience can facilitate users’ haptic sensations in real-time. It is assumed that users tend to get more exhilarating experiences when touching the surrounding objects, and recognition of haptic properties became easier (Maeda et al., 2016). The functions associated with the use of controller were found to stimulate sense of fun in racing-related environments. It is understood that augmenting a controller functionality in the virtual world with force feedback and actuated movement can help users experience force and tactile renderings for the most commonly expected hand interactions: grasping, touching, and triggering (Choi et al., 2018). The associated implications from exploring the main topics, terms, and emotions of haptic technology within different video categories are discussed in the next section.

6. Implications

Outcomes from this study can advance the current understanding about public engagement with haptic technology. The use of sentiment analysis to characterize the main topics related to haptic technology can offer essential guidelines for technology developers and researchers to effectively respond to the various needs of today's haptic users' interaction. In addition, identifying users' emotions associated with the use of haptic technology can pave the way for designing emotionally responsive technology that feeds on the emotions and vital signs when user progress in the virtual world. This includes the possibility of customizing haptic experience to fit users' specific emotional characteristics. The study also addresses the current gap in knowledge about the cognitive and emotional engagement of users with the technology in specific domains. Such knowledge can help future researchers, practitioners, and designers to understand what is currently perceived by public to be important when it comes to the use and adaption of haptic technology.

7. Limitations and future works

This study was limited to the use of sentiment analysis to understand people's use of haptic technology. The study relied mainly on YouTube API as the main source for characterizing public's engagement with haptic technology. The focus on cognitive and emotional engagement with haptic technology can be attributed to the limited nature of data generated from YouTube (e.g., number of likes and comments). In addition, this study focused on certain domains with the highest public engagement (e.g., gaming, science, etc.). Based on these, future studies may consider looking at other API sources, such as Twitter, to perform a wider sentiment analysis task. Future studies may also consider other features than a view count, likes, and comments to characterize public engagement with haptic technology. This includes the development of prediction models of public's engagement with the technology based on certain emotional data or profile.

8. Conclusion

This study extends the current understanding of people's engagement and perceptions of haptic technology by performing a sentiment analysis of their reactions to videos on YouTube. The results revealed four main categories of videos with high users' behavioral and cognitive engagement (e.g., gaming, people & blogs, education, and science & technology). The main themes and topics associated with haptic technology were attributed to "Haptic sensation", "Haptic technology and virtual reality", "Video game consoles and tools", and "Smart phones". Across all themes, several emotions were reported. However, both joy and positive sentiments resulting from users' engagement with haptic technology were mainly identified in all themes. This can be attributed to the functionality of the technology and its role in stimulating users' control of the activity. Findings from this study can help practitioners, policy makers, and researchers to better understand how haptic technology is perceived by the public. This research can also offer additional insights guiding haptic developers as well as researchers to the main emotions resulting from using haptic technology.

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