UNIVERSITY OF GHANA

COLLEGE OF BASIC AND APPLIED SCIENCE

EXPLORING THE PERSUASIVE SYSTEM FEATURES AND SENTIMENTS ON MOBILE HEALTH APPLICATIONS AND TRAVELING APPLICATIONS

BY  
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A THESIS SUBMITTED TO THE SCHOOL OF UNGRATUATE STUDIES IN PARTIAL FULFILMENT OF THE AWARD OF DEGREE OF GRADUATE OF SCIENCE IN COMPUTER SCIENCE.

DEPARTMENT OF COMPUTER SCIENCE

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## **Declaration**

I, hereby declare that, this project work, apart from the references provided has been my own contribution to the field of persuasive technology literature. This work is in combination with a research paper that I, including other researchers have published and given consent to use it in this project.

Nutrokpor Charles (Student) Dr Isaac Wiafe (Supervisor)

\_\_\_\_\_\_\_\_\_\_\_Date: \_\_\_\_\_\_\_\_ \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_Date: \_\_\_\_\_\_\_\_\_\_

## **Related Publication**

Sections of this work have already been published and presented to an international body. The published portion of this work is known as “Exploring the Impact of Persuasive System Features on User Sentiments in Health and Fitness Apps”.

Full documentation can be seen in Appendix A.

## **Abstract**

Although persuasive technologies have proven to be effective in changing user behavior, the need to design effective persuasive systems that optimize the persuasive experience of users, continue to remain a challenge. This seeks to contribute to existing literature that aims at addressing this challenge. Through a stratified random sample, 23 health and fitness apps along with 35 traveling mobile apps were selected. The reviews of each app were downloaded and compared with the corresponding persuasive systems features present in each app using cluster analysis. The findings demonstrated that the provision of more system features does not guarantee higher positive sentiment. It was also observed that apps with more social support features were associated with higher frequencies of fear, sadness and anger related sentiments.

**Keywords:** persuasive systems design, HBCSS, sentiment analysis, system features, health and fitness apps, traveling mobile applications.

## **Dedication**

This project is dedicated to my supervisor, Dr. Isaac Wiafe, for all his massive input and guidance alongside my mother and brothers for their encouragement.

GOD, bless all of you greatly.

## **Acknowledgement**

My first and foremost gratitude goes to The Almighty God for his protection, guidance, love and supervision in my life. He has graced me with wonderful parents and family members, lecturers and friends that have all one way or another, through His will, seen me this far. He has been there in my lowest of lows and highest heights and in my upcoming adventures, His grace and mercy shall keep hovering.

Secondly, I give acknowledgement to my mother and brothers for their financial support in pursuing a BSc. Course in computer science at the University of Ghana. I would like to express my deepest sentiment of love for how graciously they have been with me.

To Dr. Isaac Wiafe of the Computer Science Department of the University of Ghana, Legon. He has been a counsellor and mentor to me. His doors have always been open and his teachings both academically and of life’s principles have been very impactful in my life. For that I say, thank you sir.   
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**CHAPTER ONE**

## **INTRODUCTION**

## **Research Background**

The concept of using social cues and messages within a context to change the behavior or reasoning of an individual to accomplish a target by the use of a computerized system illustrates the functionality of a persuasive technology. To enhance the purpose of change in behavior, the term, Persuasive System Design framework was established. Functions of the framework involved using design features which comprises of persuasive messages or software requirement techniques to gradually allow users of the application to change their behavior.

There are 28 major persuasive system techniques based on the PSD framework that are classified into four main task support features. Namely; Primary Task Support, Dialogue Support, System Credibility Support and Social Support(Oinas-kukkonen & Harjumaa, 2009) . To the understanding of most, the persuasive technology features are adopted in computer applications (i.e., websites, mobile apps, expert systems, etc.) to influence a behavioral change in individuals (T. Lehto & Oinas-Kukkonen, 2015a).

The above features are defined as the fundamental system requirements needed in identifying a design, model or research as persuasive (Oinas-kukkonen & Harjumaa, 2009). Though not all the features need to be involved in making a persuasive design, there is the necessity to introduce those features of which an application is persuasive. The question then becomes, what features are necessary to be used for a given design or application? This then rises a key challenge - determining how to select the most relevant persuasive system features to increase the persuasiveness of a user (Wiafe et al., 2020). It is important to note that, studies have engaged in producing frameworks and procedures to enhance the selection process of persuasive system features to heighten the persuasive experience of users. Nevertheless, these studies are fixated on definite situations. They do not efficiently bring out information needed to go about the selection process of the persuasive features. In other words, no generalized guidelines to enhance selecting persuasive system features in order to optimize user persuasiveness. For such reasons, this study aims to contribute by redirecting perspectives to persuasive system features and how it triggers opinion and emotional sentiments in users. Approaching a path of persuasive features such that, information is gathered on the relationships discovered between users’ sentimental take on applications and the persuasive features used in those applications.

## **Research Problem & Relevance**

Studies have shown that, sentiments (emotional or opinion) influence the behavior of humans (Dillard & Nabi, 2006) and impinge on persuasion (DeSteno et al., 2004). Therefore, investigating the discoveries of patterns that maybe exposed based on persuasive system features and the emotions or sentiments that turn to arise from users, would provide tangible information that may assist in the selection process of effective and essential persuasive features.

Emphatically, there have been studies with the objective of evaluating persuasive system features and their impact on users (Adaji & Vassileva, 2016; Dabi et al., 2018; T. Lehto & Oinas-Kukkonen, 2011, 2015a; Oyibo et al., 2017; Wiafe et al., 2020). That said, upon recollection, none of these studies’ evaluations focused on investigating and accessing correlations on persuasive system features and sentiments of users.

Eventually, the study also seeks to find comparative analysis that may exist between the persuasive features of health and fitness mobile applications as well as the traveling mobile applications. The aim of this approach, based on a sequel attempt at finding relationships between the persuasive systems features and associated sentiments on different mobile application domains; is to expand the contribution of providing information in selecting relevant persuasive system features. Such that, a general knowledge can be obtained on which persuasive system features are relevant for which mobile application domain.

## **Aims & Objectives**

The study seeks to find relationships that may exist between persuasive system features and user sentiments. Exploring the patterns that may be found in such an environment. Thus, this research will:

1. Find correlations that exist between persuasive system design features and sentiments from mobile applications (health & fitness mobile applications and traveling mobile applications).
2. Serve as a contributing factor in curbing the challenge on how to optimize persuasiveness using persuasive system design framework.
3. Provide designers and developers of health and traveling mobile apps what to look out for when meeting the sentiments of users.
4. Identify which PSD framework techniques are mostly being recognized by users in the domain of health and traveling mobile applications and any correlations within the PSD features.
5. Contribute to the data acquisition aimed at developing a machine learning model that can predict sentiments based on persuasive system features.

## **Expected contributions**

## **Theoretical contribution**

This research provides another perspective to the study and investigation of persuasive system design based on the PSD framework and its alternate impact on user persuasion. This is through emphasizing on exploring how various persuasive system features trigger specific sentiments (opinion and emotions) based on user reviews. Finding comparative analysis that may exist between the persuasive features of health and fitness mobile applications as well as the traveling mobile applications. The research further extends on the sequel attempts at finding relationships between the persuasive systems features and associated sentiments on different mobile application domains, thus expanding the contribution of providing information in selecting relevant persuasive system features. Such that, a general knowledge can be obtained on which persuasive system features are relevant for which mobile application domain.

## **Practical Contribution**

The finality of the study shall contribute to the development of a machine learning model or artificial intelligence application, that predict sentiments based on persuasive system features. This is to give analysis on what developers have to look into if the mobile application to be developed would give positive reviews and be objectively essential.

## **Project Chapters Review**

The documentation to this research has been broken down into five chapters. A brief description of what each section contributes to, and the structure of the project documentation is as follows:

**Chapter One:** This chapter represents the beginning of the research documentation. It provides a background to studies on persuasive technology and overview of the persuasive system design (PSD) framework, a relatable challenge in the PSD framework and how the effort of this project can help contribute a new perspective in addressing the problem. The project chapters review provides a summary of what to expect in each chapter.

**Chapter Two:** This chapter contains sections that illustrates the number of mobile applications that were involved in the study and a quick depiction of what these applications were used for. It further gives a thorough background on related studies in PSD, sentiments, mobile health applications and traveling applications. Within these explanations, we discover how and why fitness and health mobile apps along with traveling mobile applications were used.

**Chapter Three**: This presents the step-by-step procedures of natural language processing (NLP) and clustering that were adopted to achieve the objectives of the project work. The Data collection and sampling section have been broken down into two bullets. The first bulletin describing the end result of sampling the health and fitness applications. The second bulletin giving its own account of the end result of the sampled traveling mobile applications. An intuitive approach to the code base on the NLP has been described in this section alongside the extraction of the persuasive features and clustering technique.

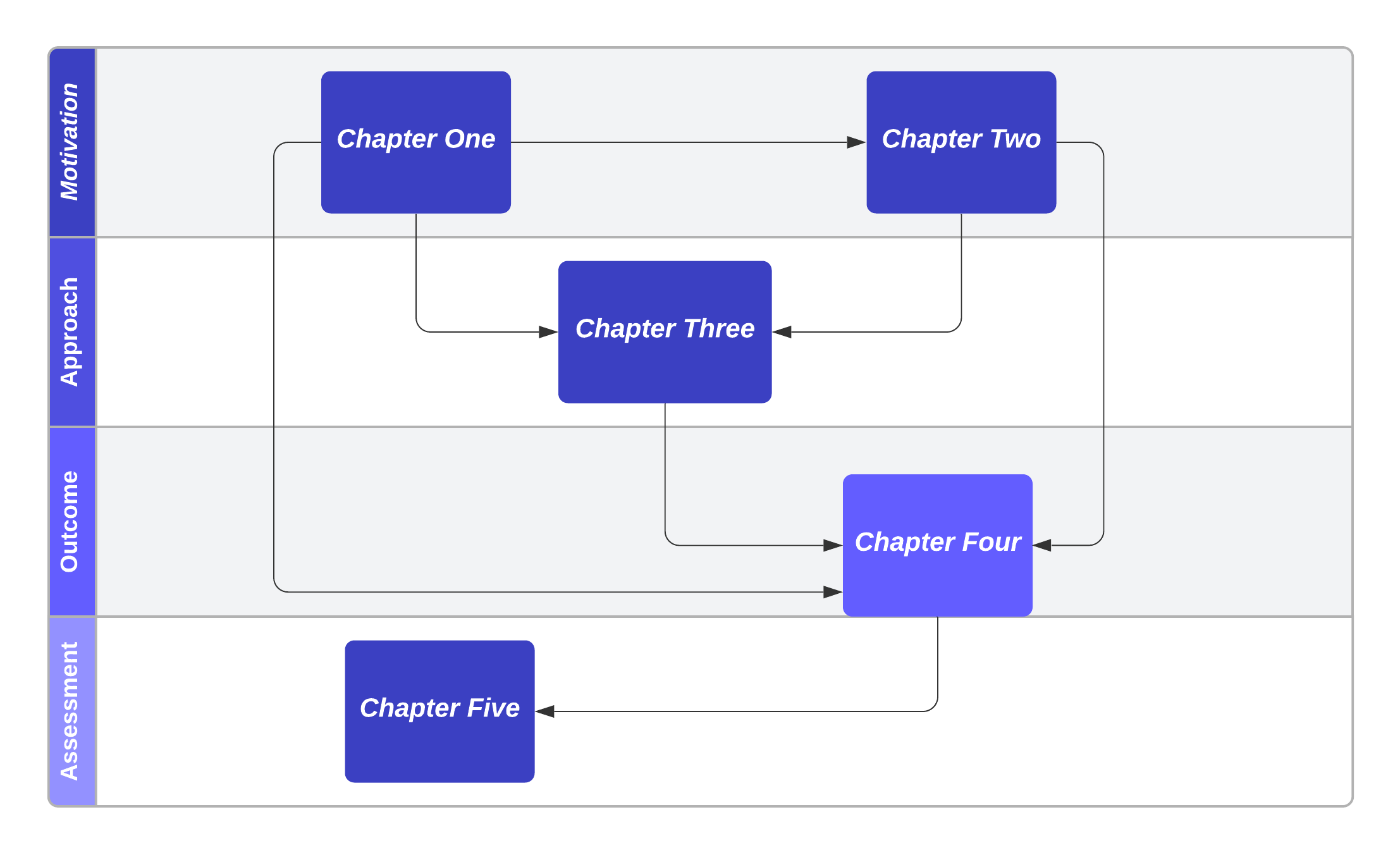
**Chapter Four**: This evaluates the aftermath of chapter three. It looks into the observations that can be made from the two sets of clusters (health & fitness and traveling apps) and the connections observed between the sentiments and the persuasive features of the applications. It continues to provide the implications that could be deduced from the health & fitness mobile applications and traveling mobile applications as well as the difference between the two application domains.   


Figure 1-1: Documentation Structure

The figure above is termed as the documentation structure of the project. There are five chapters in all. These are categorized into four main types. Chapter 1 and 2 presents the motivation, background and overview for the study. Chapter 3 illustrates the methodology on how the objectives intended in Chapter 1 was executed. Chapter 4 depicts what was observed and implications made. Chapter 5 gives an assessment of the study.

**Chapter Five**: This chapter presents the conclusion of the research study. It provides confirmation to the research and evaluating the research objectives and contributions. A section on future work is provided in this chapter as well.

# **CHAPTER TWO**

## **RELATED RESEARCH**

## **Chapter Overview**

This chapter gives details into related works and research that have been tackled in the field of persuasive technology system design features. These include challenges faced in the areas of optimizing persuasive system design frameworks, alternative approach into using sentiment or emotions in evaluating the impact of the PSD framework on mobile health and fitness applications as well as traveling mobile applications. Within this chapter, discussions on the persuasive systems design & related studies, sentiments and persuasion, persuasion and mobile health apps and persuasion and traveling mobile apps are looked into.

## **Persuasive Systems Design & Related Studies**

The intention to change ones behavior using technology depends on three major factors, the designer, the distributer and the users (Fogg, 2009). Considering that the main prerogative of persuasive systems is to alter behavior, it is incumbent for designers to ensure that they employ techniques that facilitate persuasion by optimizing the use of persuasive features. Yet, studies have shown that persuasive software features are not mostly considered by designers during the design stage (Langrial et al., 2012) and also most persuasive designers employ ad hoc design methods (Wiafe & Nakata, 2012). Persuasive systems design features provide a means for designers to enhance the content and or functionalities of persuasive software. The 28 PSD features are: primary task support (reduction, tunneling, tailoring, personalization, self-monitoring, simulation, and rehearsal), dialogue support (praise, rewards, reminders, suggestion, similarity, liking, and social role), system credibility support (trustworthiness, expertise, surface credibility, real-world feel, authority, third-part endorsements, and verifiability), and social support (social learning, social comparison, normative influence, social facilitation, cooperation, competition, and recognition) (Oinas-Kukkonen & Harjumaa, 2009). It has been argued that a good understanding of these features and their impact on specific persuasive activities provide the needed information that facilitates the design of effective persuasive systems (Karppinen et al., 2016). Nevertheless, it is a challenge to identify specific and exact features that enhances persuasion. This challenge is a result of the complex nature of human attitude and behavior, and it was inherited from traditional methods for changing human behavior.

That notwithstanding, several studies have attempted to understand the relationship between persuasive system features as proposed by (Oinas-Kukkonen & Harjumaa, 2009) and the possible impacts it has on persuasion (T. Lehto & Oinas-Kukkonen, 2015a), (T. T. Lehto et al., 2012), usability, credibility and continuous usage (Adaji & Vassileva, 2017; Wiafe et al., 2020). These studies have however produced relatively conflicting results. For instance, it has been argued that the presence of persuasive system features in Health Behavior Change Support System (HBCSS) does not necessitate the sufficiency and or efficiency of the system, rather more attention should be given to designing and implementing systems that are captivating and attractive to users (T. Lehto & Oinas-Kukkonen, 2015a). Others, have argued that perceived effectiveness, availability, and credibility (trust, reliability, etc.) of a system has direct impact on user intention to continuous use of systems (T. T. Lehto et al., 2012), (T. Lehto & Oinas-Kukkonen, 2015b). Accordingly, there is the need for further investigations on how these features impact persuasion design from a different perspective.

## **Sentiments and Persuasion**

Opinion mining has been an exploding requirement in decision making of companies when it comes to their products, services or applications. Internet reviews, comments and feedbacks acquired from consumers provide the key for various companies to analyze what general perception their products are having on users. This strategy allows the companies to either change or maintain their manufacturing or development process towards their products. In return, the users find themselves not getting enough of the product or service. The extraction of sentiments from sentiment analysis, an application of opinion mining, helps to achieve most of these decisions. The reviews or feedback obtained from users are basically elaborative forms of how they actually feel or respond to the application or service after using it. These sorts of data are more effective to investigate perceptions since they do away with complexities and limitations that may arise when the users are interviewed or provided with questionnaires. One reason will have to do with the free-range environment encountered as users have the liberty to extensively write in the comment section their entire experience with the product rather than being restricted by a set of selected questions. These elaborative forms of user feelings can then be reduced to collective sentiment (emotion) representing the entirety of what they were expressing or classification feedback of positive or negative intensities. Information from the sentiments throws light on whether consumer gratification is being met. This information also ends to what the different levels of user emotions on the product were.

Hence, due to complexities in understanding human attitude, behavior and the limitations of using questionnaires to collect and investigate perceptions, it is more appropriate to adopt other self-reporting methods that do not involve questionnaires to study human behavior. So, some recent studies have adopted sentiment analysis for investigating human emotions and behavior. Sentiment analysis provides a better option for investigating user perceptions because it analyses feedback of application users. Mostly these users express their opinions on applications or products to demonstrate their level of satisfaction. In recent times, the web has become a viable space where individuals express their opinions. Internet reviews have become a relevant part of decision making for individuals and industries. Particularly, user feedback is a fundamental variable for purchase decision, and it provides relevant information for determining satisfaction levels and emotions of customers.

With regard to persuasive systems design, existing evidence confirms that there is a relationship between sentiments and persuasion (Petty & Cacioppo, 1986). Persuasion is a communication activity which present arguments to motivate or change the cognitive state of the listener (Stigler, 1961). Thus, persuasion techniques exert influences on the thought and behavior of individuals, and this induce sentiments. A change in an individual’s sentiment may affect behavior and this has been demonstrated in how sentiments expedite decision making (Ekman, 2005; Keltner & Lerner, 2010; So et al., 2015). Individuals rely on their emotions to make economic, political, social and personal decisions. It is, however, evident that the extent of decision making based on emotions can be bias: whether deducted from persuasive messages or incidental contextual factors. This notion has been confirmed by Petty & Cacioppo (Petty & Cacioppo, 1986) in the Elaboration Likelihood Model (ELM) that explains the effect of emotions on attitude and judgement.

In persuasive systems design, emotions play a crucial role in translating the effects of feeling from computers (application) to humans (Ahmad & Ali, 2013). Hence, emotions can influence a user’s acceptance of a persuasive system. Incorporating emotional strategies into persuasive messages might motivate a user towards achieving persuasive goals: for example, evoking fear can be a good means of alerting an individual of the risks of heart disease due to smoking (Dillard & Nabi, 2006). Yet, a critical observation of persuasive systems design literature demonstrates inadequate investigations on the relationship between sentiments and persuasive features. Studies have mainly focused on individual emotions such as fear (Nabi, 2015), trust (Ahmad & Ali, 2016), and self-reflection (Halttu & Oinas-Kukkonen, 2017). It has been argued that positive emotions increase trust while negative emotions decreases it (Ahmad & Ali, 2018). Nonetheless, in persuasive systems, cognitive trust has a higher impact on credibility and continuance of use compared to affective trust (Ahmad & Ali, 2016), a decrease in cognitive trust is directly proportional to a decrease in affective trust (Nooraishya & Ahmad, 2018). As argued earlier, considering implications of current literature, it is relevant to investigate or explore the relationship between sentiments and persuasive features. Accordingly, this study sought to explore this relationship in health and fitness mobile applications as well as traveling mobile applications.

## **Persuasion and Mobile Health Apps**

Health and fitness application was adopted because it has become popular in recent times. It has been demonstrated to be effective in addressing a number of health-related issues. Consequently, research on the use of persuasive features in health-related apps have gained more attention (Wiafe & Nakata, 2012). Some researchers have argued that mobile health applications present a better opportunity for addressing barriers to patient education (Indraratna et al., 2020) and disease prevention (Halttu & Oinas-Kukkonen, 2017; Langrial et al., 2012). Mobile health apps are ubiquitous and pervasive, thus, more accessible when compared to traditional systems. More specifically, running health apps on mobile phones and smart devices have addressed the problem of infrequent use of web-based health intervention; smart phone users are more responsive to behavior change strategies available in mobile health and fitness apps (Win et al., 2019). Although there has been no significant difference in mortality rates between mobile phone interventions users and non-users, the use of mobile applications has reduced the rate of hospital admissions and significantly improved health outcomes such as lower systolic blood pressure and medication compliance (Indraratna et al., 2020).

However, although health applications seek to promote healthier habits, they are more technology and consumer driven without much attention on the persuasive design principles (Langrial et al., 2012). Yet, these applications can be further improved if they leverage on effective system features to provide effective communication. Considering this backdrop and the widespread use of mobile health apps, this study adopted it as one of the domains of investigation.

## **Persuasion and Traveling Mobile Apps**

Traveling applications gradually have become one of the popular domains of mobile application services in these times. The likes of booking plane tickets and seats online, ordering a car ride, car rentals, navigating to unknown locations, among other traveling services and miscellaneous have become necessary and easier by taps on one’s mobile screen. The importance of traveling mobile applications have reached areas of tourism in ways such that, relationship between online travel agents of tourism chain and tourist are being investigated in order to increase purchase intentions of travel mobile applications (Yip, 2020).

Consumers have expressed expectation of easiness, security and simplicity when using mobile travel applications (Parro, 2013) whilst PEOU and trust concept do not hold strong positive significance that affect the purchase intentions of traveling mobile applications (Yip, 2020). The use of the PSD framework can help elaborate if these downsides to traveling mobile applications still exist by looking at the features of Credibility Support of the traveling applications.

Considering that these applications are serviced-based platforms and are initiated when a user finds himself or herself wanting to apply for one traveling service or another, the section of persuasion to be applied here will have to do with what keeps an individual from coming back to use the application and not on any form of cognitive attempt at behavior change. More so, the application of traveling mobile apps with the persuasive framework is to determine how effective designers consider the PSD framework in their development of these applications. This is alongside building comparative studies between this domain and the health and fitness mobile domain in regards to the PSD framework.

Moreover, using the PSD framework to help figure out how likely certain persuasive features are acceptable in traveling applications based on user sentiments and how designers can use PSD to take advantage of such information when developing traveling applications will be subtly recognized in the study.

## **Chapter Summary**

This chapter begun by giving a brief introduction on the health & fitness mobile applications and traveling mobile applications that were sampled and clustered to find patterns between their user sentiments and identified PSD features. The chapter continued to show how health & fitness application can be improved by leveraging on the power of persuasive system features and the reasons why it was adopted as one of the domains of interest. The section on persuasion and traveling mobile application informs on the massive use of traveling mobile applications used in aiding tourism in certain countries and what users have expected from the application over the years.

# **CHAPTER THREE**

## **METHODOLOGY**

## **Chapter Overview**

A two-fold methodology approach was used within this chapter. Illustratively, the same Data Collection & Sampling Approach, Review Extraction, Sentimental Retrieval Approach, Intuitive Approach, PSD Features Extraction and Clustering activities were repeatedly followed for both the health & fitness mobile applications and traveling mobile applications.

To ensure a compressive and rigorous review of sentiments and persuasive system design features of mobile health apps and traveling mobile apps, the study was conducted as follows: firstly, a sample of both mobile apps and traveling mobile apps categorized as “health and fitness” and “travel” respectively, were selected from the Android and iOS stores. Each app was assessed based on an approved selection criterion. The persuasive features and the associated sentiments of the selected apps were extracted. The patterns in app design features and related sentiments were explored to draw conclusions. The following sections give a detail discussion on how each stage of the investigation was conducted.

## **Data Collection & Sampling**

## **Health & Fitness Mobile Application Sampling**

The dataset on the health & fitness mobile apps was acquired from the two main mobile app stores (iOS and Android). The Kaggle datasets for Google Play store apps (https://www.kaggle.com/gauthamp10/google-playstore-apps) and Apple iOS app store (https://www.kaggle.com/cmqub19/763k-ios-app-info) were downloaded (on September 14, 2020). The dataset consisted of 735,593 applications and 4,175 applications are classified as health and fitness. The dataset was preprocessed and fields or data that were considered to be irrelevant for the study were excluded. Further, apps that had less than 500 reviews were excluded. This was to ensure that all apps used in the study have received adequate number of reviews and ratings. Duplicate apps including those that were present in both iOS and Android were removed. This reduced the number of apps to 278 (i.e., 99 apps for iOS and 179 for android).

For a population of 278 applications, a sample of 72 is needed to ensure a 10% margin of error at 95% confidence level. A stratified sampling approach resulted in 28 samples for iOS and 44 for Android. Our motivation to use a stratified random sample approach was to reduce biases and ensure that the findings of this study can be generalized. Each application was downloaded and installed. After installation, applications that were not in English, those that were for sale, no longer available or did not demonstrate an intention of changing the user behavior were omitted. This resulted to 23 applications for the study. Figure 3-1 is a diagrammatic representation of the stages involved in the selection process and Table 3-3 is a list of the selected apps used for the study.

## **Traveling Mobile Application Sampling**

The gathering of the mobile applications for the study were sourced from two main markets. The google play store (<https://www.kaggle.com/gauthamp10/google-playstore-apps>) and iOS (<https://www.kaggle.como/cmqubl9/763k-ios-apps-info>). The combination of both datasets showed one million plus applications out of which 23983 were traveling apps.

These traveling applications after undergoing a series of selection criteria such as apps with less than 1000 reviews eliminated and the elimination of duplicated apps existing in both the apple and google play store reduced the selected apps to 700. The reviews selection criterion was adopted to ensure the study received a commendable number of reviews and ratings as well as to make sure the applications were in present day of use. A 15% margin of error at 95% confidence level along with application’s geographical compatibility and current availability on the two platforms coupled with a stratified sampling approach resulted on a total of 65 traveling applications. Stratified random sampling approach was to reduce biases and ensure that the finding of this study can be generalized. 35 out of the 65 applications where eligible for the study based on limitations such as OS compatibility and reviews extractions. The 35 traveling applications were downloaded and installed. Figure 3-2 gives a diagrammatic illustration of certain criteria processes that took place and Table 3-2 shows the list of the selected traveling apps used.

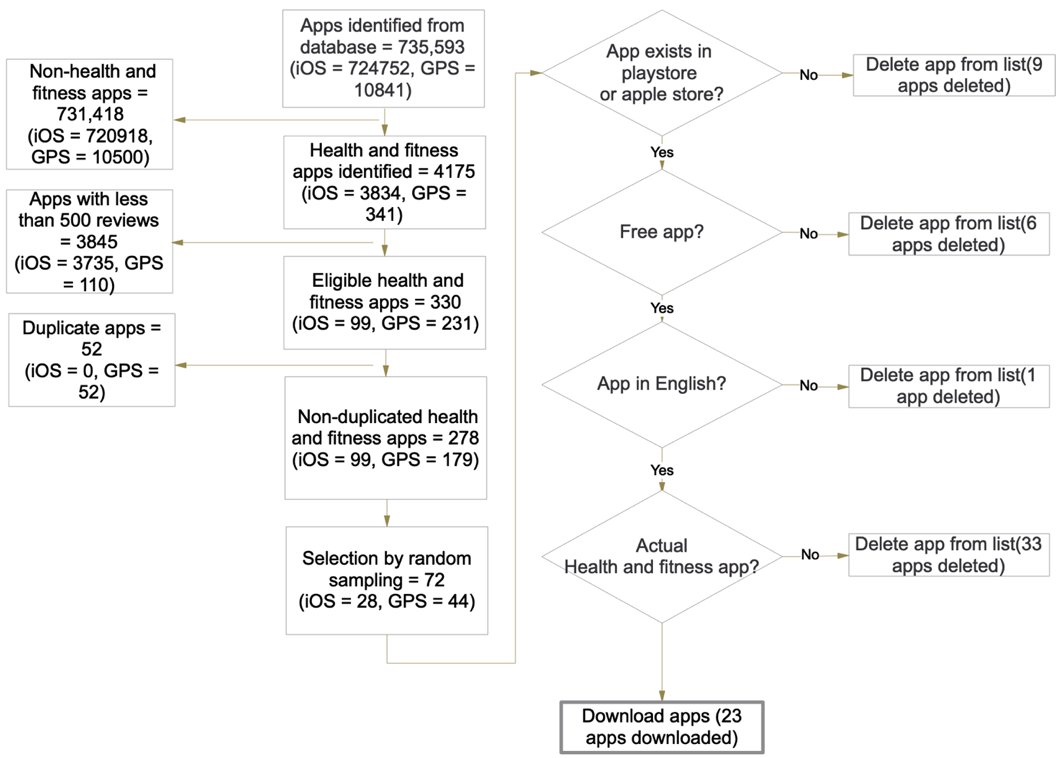


Figure 3‑1: Health & Fitness Apps Sampling Process

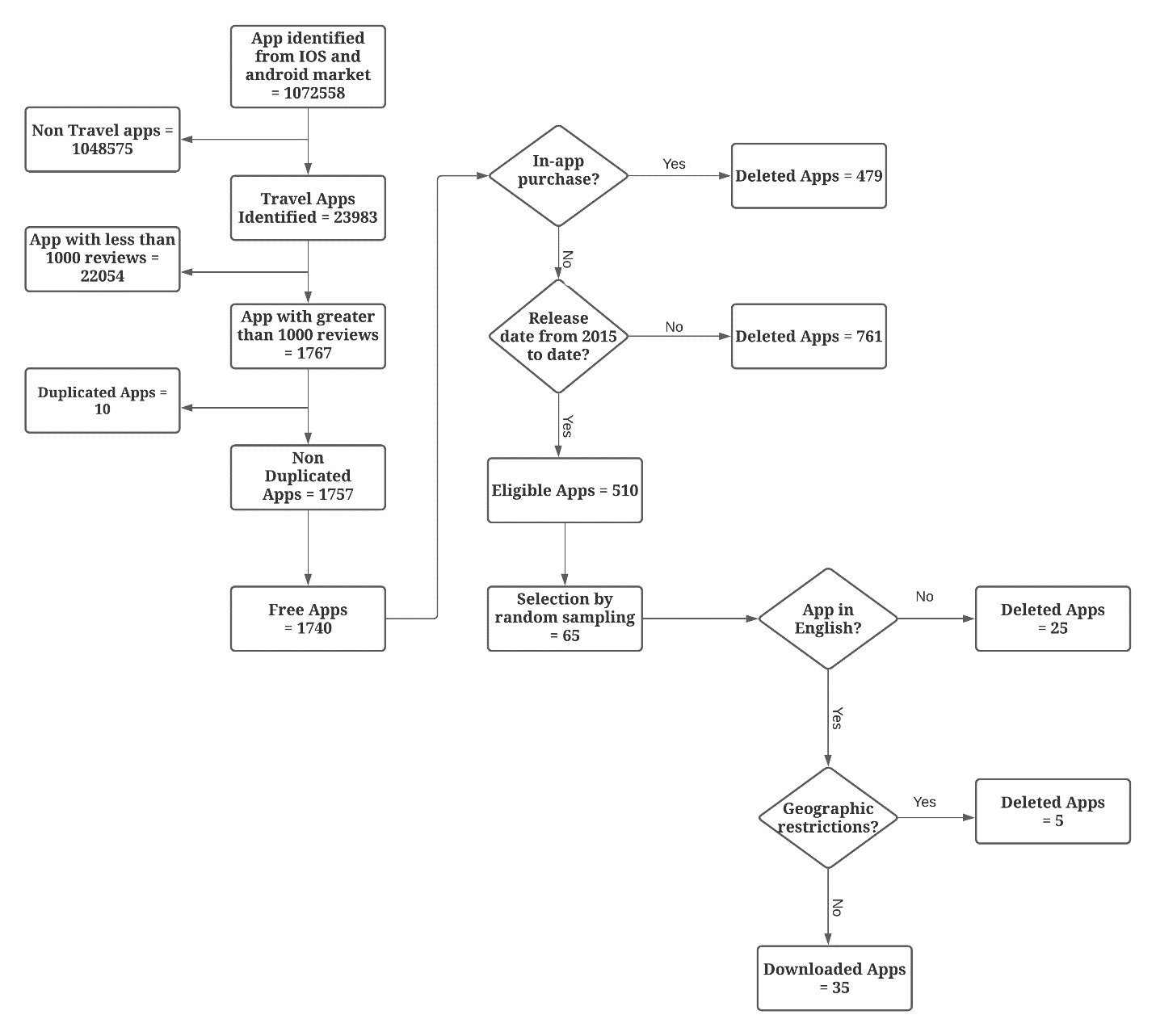
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Figure 3‑2: Traveling Mobile Apps Sampling Process

## **Review Extraction**

The user sentiments that were obtained were sourced through the scraping of user reviews from the respective digital stores.

The reviews and ratings for these applications (health & fitness and traveling) were extracted using Python libraries including beautifulsoup, selenium and JSON. Downloaded reviews for individual apps ranged from 202 to 123,719. Each review consists of ratings, categorical\_url, company\_name, date, developerResponse, reviews/content, title, and isEdited as attributes in each applications’ review dataset.

## **Sentimental Retrieval Approach**

Fundamental data preprocessing corresponding to how natural language processing analysis is undertaken were applied to the various set of reviews extracted. The main goal of the sentiment extraction was to obtain sentimental words from the reviews; hence each row of reviews was scrapped of numbers, special characters, punctuations and filtered to allow only alphabets. Words less than four characters long were also removed. Tokenization and Lemmatization of individual words in each row of the reviews were not considered for reason such as preserving the uniqueness of the words without any root factor, counting the frequency of words which tokenization might have interrupted the accuracy of such principle. The final attachment to this section was the application of eliminating stopwords (i.e., words such as who, whose, whom, why, is, that, there, etc..) by the help of the wordcloud library to each set of reviews.

The total number of positive and negative words were accounted for from the cleaned reviews as well as classifying these positive and negative words into general sentiments of liking, trust, anger, sadness and fear. This stage can be implemented in a number of ways especially whilst a programming language such as python is involved. Nevertheless, for accuracy and effective ideological reasoning into the accumulation of the sentimental words, an intuitive implementation was designed for the study. This implementation is shown in Figure 3-3.

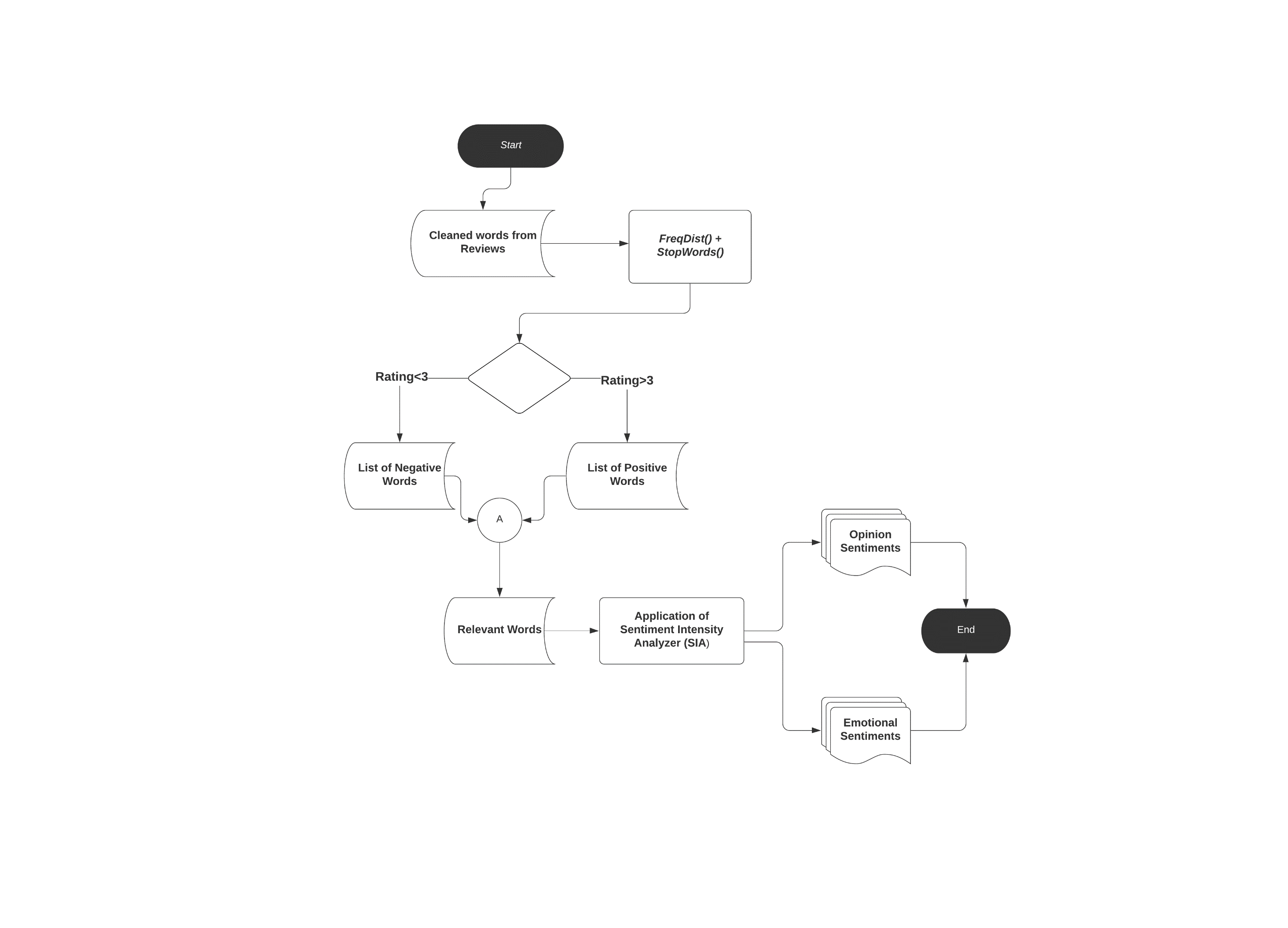
****

Figure 3‑3: Sentiment Extraction Flowchart

## **Intuitive Approach**

1. **Classification of Reviews:**

The cleaned reviews (i.e., the final outcome of the data preprocessing stage) based on their corresponding ratings or stars were grouped into positive and negative words. Using a simple word extraction function, each row of the cleaned reviews was evaluated to determine whether or not their ratings fell above or below three (3). A list of positive words (ratings above 3) and negative words (ratings below 3) were formed from the entire cleaned reviews of each individual app.

1. **Frequency of Words**

Using the nltk library, words from both the positive and negative lists were combined and the FreqDist function was applied on the lists to output a dictionary of all the frequency words within the list. This approach was initiated to obtain relevant words from the total column of reviews in each application. Each word and their corresponding frequency distributions were placed into a python dataframe.

1. **Extracting Sentimental Words**

The establishment of the Valence Aware Dictionary for Sentiment Reasoning (VADER) model was used as a sentiment analyzer. In effect, targeting polarity of each word greater than 0.5 or less than -0.5 on the dataframe of relevant words created, resulted in the extraction of the sentimental words. This was done by grouping words that can be termed as having positive sentimental intensity (i.e., greater than or equal to 0.5) and negative sentimental intensity (i.e., less than or equal to -0.5) as one whole list of sentimental words from each set of the 35 traveling mobile applications and the 23 health & fitness mobile applications. In terms of finding the total number of positive and negative sentiments per each mobile application, the combined words were further split into their respective positive and negative sentiments and calculated.

1. **Emotional Sentiment Extraction**

The combined list of sentiments was looped through and categorized under either Liking, Trust, Anger, Sadness and Fear. The categorization was maneuvered by considering a list of related words associated with liking, trust, anger, sadness and fear (represented in Table 3-1) and using the wordnet library in finding all other synonyms pertaining to each word in these stated emotional sentiments. Subsequently, cross checking if words from the list of sentimental words fall within any of the emotional sentiments and their featured synonyms. Percentages of the emotional sentiments were calculated and reported.

## **PSD Features Extraction**

Two members of the research team were tasked to extract the various persuasive system design features of the selected apps. They used each app for a period of one month simultaneously to assess the apps and identify the various persuasive features employed in each app. To reduce biasness, reports from the two assessors were combined and disparities were addressed. Similar to studies conducted by (T. Lehto & Oinas-Kukkonen, 2015a) features including liking and similarity were not assessed. This is because they are relatively subjective, ambiguous and dependent on the user. Although, it is challenging to assess surface credibility and trustworthiness, in this study surface credibility was evaluated using claims by (Langrial et al., 2012). Thus, the absence or minimal use of adverts and unnecessary pop-ups was used to assess surface credibility whereas trustworthiness was evaluated by the ability of the application to provide users with control of security/privacy setting.

Table 3‑1: Classification of Emotional Words used for the emotional sentiments

|  |  |
| --- | --- |
| Sentiments | Synonyms & related Words |
| Liking | affection, adoration, fondness, fond, liking, like, attraction, attracted, attract, caring, care, tenderness, tender, compassion, sentimentality, sentiment, lust, sexual, desire, passion, infatuation, infatuated, infatuate, longing, lovely, excellent, good, loved, adore, best, perfect, magnificence, magnificent, yummy, love, wonderful, cheerfulness, cheerful, cheer, amusement, amuse, amused, amusing, bliss, blissful, gaiety, glee, woohoo, jolliness, jolly, joviality, delight, enjoyment, glad, gladness, happiness, happy, jubilation, elation, elating, satisfaction, satisfying, satisfied, ecstasy, euphoria, zest, enthusiasm, enthusiastic, zeal, excitement, exciting, thrill, thrilling, exhilaration, exhilarating, content, contentment, pleasure, pride, triumph, optimism, optimistic, eager, eagerness, hope, enthrallment, rapture, relief, beautiful, enjoy, super, fantastic, superb, free, brilliant, success, |
| Trust | trust, comfort, comfortable, encourage, encouraging, marvelous, marvel, kudos, thankful, perfect, perfection, friendly, friend, friendliest, ideal, flawless |
| Anger | Irritability, irritating, irritated, irritation, aggravation, agitation, agitated, annoyed, annoyance, annoying, grumpy, crosspatch, exasperation, frustration, rage, raging, annoy, anger, outrage, outraged, fury, wrath, hostility, hostile, ferocity, bitter, bitterness, hate, hatred, scorn, spite, vengeful, dislike, disliking, disliked, resent, resenting, resentment, disgusting, disgust, revulsion, contempt, loathing, loathe, envy, jealous, jealousy, torment, tormenting, idiot, suck, sucker, loser, |
| Sadness | Sad, suffer, suffering, pain, painful |
| Fear | Horror, alarm, alarming, shocking, shock, fear, fearful, terror, panic, hysteria, mortification, nervous, nervousness, anxious, anxiety, suspense, uneasy, uneasiness, suspenseful, apprehension, apprehend, worry, worrying, distress, distressful, dread, dreadful, danger, dangerous, fraud, hell, scam, stress, stressing, stressful |

Table 3‑2: List of Selected Traveling Mobile Apps

|  |  |  |  |
| --- | --- | --- | --- |
| **App ID** | **Name of Application** | **App ID** | **Name of Application** |
| 1 | Indian Railway Train Status: Where is my Train | 20 | Spin - Electric Scooters |
| 2 | Visa Travel Tools | 21 | Turkish Airlines - Flight ticket |
| 3 | Pune (Data) m-Indicator | 22 | TIER e-scooter sharing & more |
| 4 | Grabaseat | 23 | VOI Scooters: Get Magic Wheels |
| 5 | eZhire - Rental Car, Delivered #on-demand | 24 | TUI Holidays & Travel App: Hotels, Flights, Cruise |
| 6 | Universal HollywoodTM App | 25 | WeShare: Share WiFi Worldwide freely |
| 7 | TT RideShare | 26 | Live Train & Indian Rail Status - Locate My Train |
| 8 | Live Train & Station Status, Confirm Train Seat | 27 | SAUDIA |
| 9 | Your Parking Space - Parking App | 28 | KKday: Adventure Like a Local |
| 10 | GPS Maps, Voice Navigation & Live Street Direction | 29 | 2GIS beta |
| 11 | Cheap Hotels | 30 | Polarsteps - Travel Planner & Tracker |
| 12 | Celebrity Cruises | 31 | Pakistan Railways Official |
| 13 | Earth Live Cam & Public CCTV | 32 | Greyhound (US) |
| 14 | Taxi 838 | 33 | Justfly.com Book Cheap Flights |
| 15 | FabHotels: Safe Rooms on Best Hotel Booking App | 34 | Southwest Airlines |
| 16 | Compass | 35 | Royal Caribbean International |
| 17 | OBHAI |  |  |
| 18 | Etihad Airways |  |  |
| 19 | Govinda - Tirumala Tirupati Devasthanams |  |  |

Table 3‑3: List of selected health & fitness mobile apps

|  |  |  |  |
| --- | --- | --- | --- |
| **App ID** | **Name of Application** | **App ID** | **Name of Application** |
| 1 | Ideal Weight | 13 | Step Counter - Calorie Counter |
| 2 | WalkingApp | 14 | Weight Loss Running by Verv |
| 3 | Step Counter | 15 | Abs Workout |
| 4 | Walking for Weight Loss | 16 | Pocket Yoga |
| 5 | Headspace | 17 | Dr.Greger's Daily Dozen |
| 6 | Calorie Counter by FatSecret | 18 | HidrateSpark Smart Bottle |
| 7 | Cycling - Bike Tracker | 19 | Jillian Michaels Fitness App |
| 8 | Running Distance Tracker + | 20 | PlayFitt |
| 9 | Daily Yoga - Yoga Fitness Plans | 21 | WaterLama Water Tracker |
| 10 | Pregnancy & BabyTracker | 22 | Six Pack in 30 Days |
| 11 | Workout Tracker & Gym Trainer | 23 | Plant Nanny |
| 12 | Water Drink Remainder |  |  |

## **Clustering**

A tabulated data was created for both sets of the health & fitness mobile applications and traveling mobile applications respectively. For the purpose of finding patterns, the k-means clustering approach was used. Hence, the tabulated data was organized in such a way that, it had recorded values of all sentiment (emotional and opinion) intensities from the selected mobile applications from the two separate mobile domains under study and their corresponding persuasive system design features extracted.

## **Health & Fitness Mobile Applications Clustering**

K-Means clustering approach was used to assess the relationship between persuasive systems features and their respective sentiments. The Elbow method for selecting the optimal k clusters produced 6 clusters as the optimal number of clusters. The health & fitness dataset after undergoing feature scaling was fitted to a K-Means function, where n\_clusters = 6 and random\_state = 42. The predicted outcome of the computation was retrieved and analyzed.

## **Traveling Mobile Applications Clustering**

Feature scaling of standardization was applied to the percentage values of the emotional and opinion sentiments of the mobile apps and their corresponding persuasive features. Using k-means algorithm, a k-value of seven (7) was chosen using the elbow method. The elbow method was used to determine the manner of estimating the best possible number of clusters for the traveling mobile application dataset. The scaled dataset was fitted to a k-means function from sklearn with a random\_state of 42. The predicted outcome of the computation was also retrieved and analyzed.

## **Chapter Summary**

The reviews and ratings for each selected app was extracted and preprocessed. Data preprocessing is an essential part of Natural Language Processing (NLP). It enables stemming and elimination of redundant data such as stop words and noise. Hence, stop words including prepositions, pronouns, special characters, punctuation marks and numbers were eliminated from the dataset.

A sentiment intensity calculation was performed. The total number of opinions and emotional sentiments were analyzed. The reviews and their corresponding ratings were grouped into positive and negative words. Using a word extraction function, each app review was evaluated to determine whether or not their ratings fell above or below three (3). Further, the use of the VADER model, gave precise sentimental categorization of words that fall under positive and negative.

K-Means clustering approach was used to assess the relationship between persuasive systems features and their respective sentiments. The end results of the clustering shows that, the health & fitness mobile applications were grouped into six (6) clusters whilst the traveling mobile applications were grouped into seven (7) clusters.

**CHAPTER FOUR**

## **FINDINGS & DISCUSSION**

## **Chapter Overview**

This section describes the observations and findings that were discovered after the methodology. It outlines in details what findings existed between the two-separate set of clusters, the connections that were developed between the sentiments and persuasive system features in both the fitness & health mobile apps and the traveling mobile apps. This section finishes it off with the implications based on the findings in the health and fitness mobile apps. It further makes a comparative analysis between the findings of the health & fitness mobile apps and the traveling mobile apps.

## **Descriptions & Characteristics**

## **Health & Fitness Mobile Applications**

The findings from the persuasive feature extraction demonstrated that no application used all the 28 persuasive systems features. However, primary task support was dominant in health and fitness applications. With regard to Dialogue support features, 18 out of the 23 applications used Reminders and 20 used Suggestion. These were the two most used Dialogue support feature. In most cases, applications that used reminders also used suggestions. Praise (11), rewards (10) and social role (12) were averagely used. A notable observation in the evaluation of Credibility support features was that there was a relationship between the presence of Trustworthiness and Surface credibility. Trustworthiness was present in 22 out of the 23 applications evaluated whereas surface credibility was present in 21. Third party endorsement (6) and authority (4) were sparingly used. Generally, social support features were the least adopted features. Social learning was observed in 16 applications and 10 used social facilitation. Normative influence (9), cooperation (6), social comparison (5), recognition (4), and competition (2) were barely used. Refer to table 3 for a complete list of persuasive systems features identified in the 23 mobile health apps evaluated.

This findings reveal that Primary Task support features are dominant in mobile health apps and this confirms current knowledge (T. T. Lehto et al., 2012), (Alhammad & Gulliver, 2014). Also, social support features are sparingly used. Similar claims have been made on a study that investigated persuasive features of e-commerce platforms (Alhammad & Gulliver, 2014). Findings also contradicts existing that argue that Dialogue support features are the most (Alhammad & Gulliver, 2014).

|  | **Features/App ID** | 2 | 3 | 5 | 6 | 8 | 9 | 10 | 18 | 19 | 22 | 23 | 4 | 11 | 15 | 16 | 20 | 17 | 21 | 1 | 7 | 12 | 13 | 14 |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Primary Task**  **Support** | Reduction |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Tunneling |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Tailoring |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Personalization |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Self-monitoring |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Simulation |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Rehearsal |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| **Dialogue Support** | Praise |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Rewards |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Reminders |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Suggestion |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Social role |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| **System Credibility Support** | **Trustworthiness** |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Expertise |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Surface credibility |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Real-world feel |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Authority |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 3rd party endorsement |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Verifiability |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| **Social Support** | Social learning |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Social comparison |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Normative influence |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Social facilitation |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Cooperation |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Competition |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Recognition |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  | **C1** | | | | | | | | | | | **C2** | | | **C3** | **C4** | **C5** | | **C6** | | | | | |

(Nutrokpor et al., 2021)Figure 4-1: The Intensity of PSD features – health & fitness apps

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **App** | **Liking (%)** | **Trust (%)** | **Anger (%)** | **Sadness (%)** | **Fear (%)** | **Positive (%)** | **Negative (%)** | **No. of features** |
| **C1** | **2** | 19.6 | 5.0 | 10.5 | 4.1 | 2.7 | 61.8 | 38.2 | **22** |
| **3** | 22.9 | 5.7 | 9.9 | 3.1 | 3.7 | 66.7 | 33.3 | **14** |
| **5** | 14.1 | 2.9 | 9.1 | 5.6 | 3.7 | 46.7 | 53.3 | **17** |
| **6** | 21.3 | 5.0 | 8.9 | 4.0 | 3.5 | 60.4 | 39.6 | **18** |
| **8** | 20.6 | 6.7 | 7.2 | 5.0 | 2.2 | 65.6 | 34.6 | **15** |
| **9** | 18.2 | 5.3 | 7.1 | 3.1 | 4.0 | 64.4 | 35.6 | **18** |
| **10** | 23.0 | 6.7 | 7.3 | 2.8 | 2.8 | 65.7 | 34.3 | **13** |
| **18** | 23.9 | 8.0 | 11.4 | 6.8 | 1.1 | 60.2 | 39.8 | **20** |
| **19** | 24.6 | 8.5 | 10.2 | 4.2 | 1.7 | 66.9 | 33.1 | **20** |
| **22** | 17.5 | 4.4 | 8.4 | 4.7 | 4.0 | 59.6 | 40.4 | **11** |
| **23** | 21.6 | 5.4 | 7.0 | 3.2 | 3.8 | 62.7 | 37.3 | **17** |
| **C2** | **4** | 32.8 | 7.5 | 9.0 | 0.0 | 6.0 | 64.2 | 35.8 | **12** |
| **11** | 50.0 | 10.7 | 7.1 | 0.0 | 3.6 | 85.7 | 14.3 | **14** |
| **15** | 29.2 | 8.3 | 8.3 | 1.0 | 5.2 | 75.0 | 25.0 | **13** |
| **C3** | **16** | 56.3 | 3.1 | 3.1 | 0.0 | 3.1 | 90.6 | 9.4 | **1** |
| **C4** | **20** | 42.4 | 3.0 | 3.0 | 0.0 | 6.1 | 72.7 | 27.3 | **22** |
| **C5** | **17** | 36.5 | 6.4 | 4.8 | 3.2 | 0.0 | 79.4 | 20.6 | **18** |
| **21** | 43.6 | 2.6 | 2.6 | 2.6 | 0.0 | 84.6 | 15.4 | **18** |
| **C6** | **1** | 30.6 | 6.7 | 9.3 | 4.0 | 2.7 | 65.3 | 34.7 | **5** |
| **7** | 33.7 | 8.4 | 6.3 | 2.1 | 2.1 | 72.6 | 27.4 | **6** |
| **12** | 20.0 | 4.8 | 8.3 | 3.9 | 3.5 | 60.4 | 39.6 | **10** |
| **13** | 26.5 | 6.8 | 4.8 | 5.4 | 2.0 | 72.1 | 27.9 | **7** |
| **14** | 25.0 | 9.8 | 5.4 | 4.4 | 4.4 | 64.1 | 35.9 | **12** |

(Nutrokpor et al., 2021)Figure 4-2: The Intensity of emotional and opinion sentiments – health& fitness apps

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **Features/App ID** | 9 | 33 | 3 | 4 | 12 | 8 | 10 | 11 | 2 | 5 | 15 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 27 | 31 | 32 | 34 | 35 | 1 | 7 | 14 | 16 | 26 | 28 | 30 | 6 | 13 | 25 | 29 |
| **Primary Task Support** | Reduction |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Tunneling |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Tailoring |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Personalization |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Self-Monitoring |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Simulation |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Rehearsal |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| **Dialogue Support** | Praise |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Rewards |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Reminders |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Suggestions |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Social Role |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| **System Credibility Support** | Trustworthiness |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Expertise |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Surface Credibility |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Real-World Feel |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Authority |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 3rd Party Endorse |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Verifiability |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| **Social Support** | Social Learning |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Social Comparison |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Normative Influence |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Social Facilitation |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Cooperation |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Competition |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Recognition |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  | C1 | | C2 | | | C3 | | | C4 | C5 | | | | | | | | | | | | | | | C6 | | | | | | | C7 | | | |

Figure 4‑3: The Intensity of PSD features – traveling mobile apps

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **App ID** | **Liking (%)** | **Trust (%)** | **Anger (%)** | **Sadness (%)** | **Fear (%)** | **Positive (%)** | **Negative (%)** | **No. of Features** |
| **C1** | **9** | 37.5 | 2.5 | 5 | 7.5 | 7.5 | 57.5 | 42.5 | 12 |
| **33** | 34.04 | 0 | 4.26 | 4.26 | 8.51 | 55.32 | 44.68 | 11 |
| **C2** | **3** | 57.14 | 0 | 14.29 | 0 | 0 | 57.14 | 42.86 | 13 |
| **4** | 46.43 | 0 | 3.57 | 3.57 | 0 | 53.57 | 46.43 | 11 |
| **12** | 44.44 | 0 | 13.89 | 2.77 | 2.77 | 61.11 | 38.89 | 14 |
| **C3** | **8** | 72 | 8 | 4 | 0 | 0 | 88 | 12 | 8 |
| **10** | 62.16 | 5.41 | 0 | 0 | 0 | 97.3 | 2.7 | 9 |
| **11** | 54.55 | 4.55 | 0 | 0 | 2.27 | 90.91 | 9.09 | 9 |
| **C4** | **2** | 54.55 | 0 | 0 | 18.18 | 0 | 72.73 | 27.27 | 9 |
| **C5** | **5** | 35.94 | 7.81 | 7.81 | 0 | 3.13 | 65.63 | 34.38 | 15 |
| **15** | 22.76 | 4.14 | 8.97 | 3.45 | 4.14 | 61.38 | 38.62 | 13 |
| **17** | 24.71 | 3.53 | 12.94 | 4.71 | 4.71 | 49.41 | 50.59 | 7 |
| **18** | 29.27 | 3.66 | 9.76 | 2.44 | 3.66 | 60.98 | 39.02 | 15 |
| **19** | 34.33 | 4.48 | 5.97 | 0 | 5.97 | 65.67 | 34.33 | 14 |
| **20** | 19.38 | 3.75 | 11.25 | 4.38 | 4.38 | 46.88 | 53.13 | 11 |
| **21** | 27.4 | 5.48 | 15.07 | 4.11 | 2.74 | 53.42 | 46.58 | 14 |
| **22** | 29.33 | 4 | 9.34 | 2.67 | 4 | 53.36 | 46.64 | 12 |
| **23** | 25.3 | 4.82 | 8.43 | 3.61 | 6.02 | 54.22 | 45.78 | 15 |
| **24** | 25.22 | 4.35 | 11.3 | 4.35 | 5.22 | 51.3 | 48.7 | 9 |
| **27** | 42.31 | 5.77 | 9.62 | 0 | 3.85 | 69.23 | 30.77 | 15 |
| **31** | 26.92 | 5.77 | 9.62 | 3.85 | 1.92 | 66.35 | 33.65 | 10 |
| **32** | 19.28 | 7.23 | 9.64 | 8.43 | 4.82 | 48.19 | 51.81 | 16 |
| **34** | 17.31 | 4.33 | 7.7 | 5.29 | 5.29 | 60.58 | 39.42 | 14 |
| **35** | 30.34 | 3.37 | 5.62 | 2.25 | 4.49 | 68.54 | 31.46 | 12 |
| **C6** | **1** | 30.38 | 7.59 | 6.33 | 2.53 | 1.27 | 77.22 | 22.78 | 8 |
| **7** | 41.38 | 6.9 | 10.34 | 6.9 | 0 | 75.86 | 24.14 | 14 |
| **14** | 46.15 | 7.69 | 0 | 7.69 | 0 | 76.92 | 23.08 | 8 |
| **16** | 42.86 | 8.16 | 2.04 | 0 | 4.08 | 79.59 | 20.41 | 9 |
| **26** | 36.67 | 8.33 | 8.33 | 1.67 | 5 | 78.33 | 21.67 | 7 |
| **28** | 42.11 | 2.63 | 2.63 | 2.63 | 2.63 | 81.58 | 18.42 | 16 |
| **30** | 31.76 | 8.24 | 7.06 | 2.35 | 1.18 | 76.47 | 23.53 | 14 |
| **C7** | **6** | 63.64 | 0 | 4.55 | 0 | 4.55 | 68.18 | 31.82 | 9 |
| **13** | 61.9 | 0 | 4.76 | 0 | 9.52 | 76.19 | 23.81 | 8 |
| **25** | 50 | 0 | 8.82 | 0 | 5.88 | 64.71 | 35.29 | 9 |
| **29** | 73.33 | 0 | 0 | 0 | 0 | 73.33 | 26.67 | 10 |

Figure 4-4: The Intensity of emotional and opinion sentiments – traveling mobile apps

## **Traveling Mobile Applications:**

Certain primary task support features were mostly adopted in the application of the mobile traveling apps such that Reduction (35) and Tunneling (35) were present in all 35 applications followed by Self-Monitoring (29) and Personalization (21). Tailoring (8), Simulation (0) and Rehearsal (1) were the least used features within the primary task support. Suggestions (31) and Reminders (28) dominated the Dialogue Support features. Within some clusters (C2, C5, C6) there seems to be a correlation between the two features such that, when there are suggestions, remainders followed. Praise (10) and Rewards (13) were notably used with Social Role (2) being less employed across the 38 traveling applications. In examining the System Credibility Support techniques, Trustworthiness (35) and Expertise (35) were present across all the applications with Real-World Feel (34), Surface Credibility (29) and Verifiability (21) following suite. It can be argued that, the dominance of these techniques is due to functionalities of most of the traveling applications. Since most traveling apps depend on using time of arrival, geographical locations, departure times, stations scheduling, information on places of arrival and payment of transportation, hence the need for clear cut descriptions to show all these features to ensure users’ trust. Authority (4) and 3rd Party Endorsement (1) were merely used. Social Support features were also barely used. Social Facilitation (18), Social Learning (2), Social Comparison (2) and Normative Influence (5) were sporadic across the clusters of the traveling application.

Similar claims on the infrequent use of social support features on a study that investigated persuasive features of e-commerce platforms apps (Adaji & Vassileva, 2016). Findings also makes confirmatory analysis to the dominance of primary task support features in mobile applications in general (Adaji & Vassileva, 2016; Langrial et al., 2012). Each cluster (C1 – C7) had most positive sentiments being greater than negative sentiments. Liking being the highest emotional sentiment. Three clusters (C2, C4, C7) showed high frequencies of trustworthiness and expertise but emotional sentiment of trust was absent. Clusters C1, C3, C4, C7 showed other patterns where a combination of different features had different observations from the emotional sentiments.

Generally, the findings inform that, no application used all the 28 persuasive system features present. Below shows a complete list of persuasive system features identified in the 35 mobile traveling applications accessed.

## **Connections Between Sentiments and PSD features**

## **Health & Fitness Mobile Applications**

It was observed that, mobile applications including WalkingApp *(app2)*, Step Counter *(app3)*, Headspace *(app5)*, Calorie Counter by FatSecret *(app6)*, Running Distance Tracker + *(app8)*, Daily Yoga *(app9)*, Pregnancy & Baby Tracker *(app10)*, HidrateSpark Smart Bottle *(app188)*, Jillian Michaels Fitness App *(app19)*, Six Pack in 30 Days *(app22)* and Plant Nanny *(app23)* were in one cluster (i.e., C1). See Figure 4-1 for a list of the various apps and the corresponding clusters labelled as C1 to C6. This cluster set was characterized with a high frequency of Primary Task support features including reduction, tunneling, tailoring, personalization and self-monitoring. Simulation and rehearsals were present, however, they had lower frequencies. With regard to dialogue support features, praise, reminders, suggestion and social role were present with high frequencies whilst rewards had a low frequency. For credibility support, high frequencies were observed for trustworthiness, expertise, surface credibility, real world feel and verifiability whilst authority and third-party endorsement had low frequencies. All seven (7) features within social support were present in this cluster (i.e., C1), however they were marginally represented. Again, in terms of opinion sentiments, this group of mobile applications had higher positive sentiment values with the exception of Headspace *(app5)* that record low positive sentiments.

Walking for Weight Loss *(app4)*, Workout Tracker & Gym Trainer *(app11)*, Abs workout *(app15)* formed a cluster (i.e., C2). This group of apps were characterized with a high frequency of primary support features including reduction, tunneling, tailoring, personalization and self-monitoring. Simulation and rehearsals were however absent within this cluster. Dialogue support features such as reminders and suggestions had the highest frequencies compared to praise, rewards and social role. Trustworthiness was the only feature within credibility support with the highest frequency, followed by expertise and surface credibility. Real world feel had the lowest frequency. Authority, third party endorsement and verifiability were absent within this cluster. For social support features, social learning was the only feature present, and it had a high frequency. In terms of opinion sentiments, this cluster also had a higher positive sentiment value compared to negative sentiment value.

Ideal Weight *(app1)*, Cycling – bike tracker *(app7),* Water Drink Reminder *(app12),* Step Counter – Calorie Counter *(app13)* and Weight Loss Running *(app14)* were found to have higher frequencies of tailoring, personalization and self-monitoring as primary support features. In this cluster (i.e., C6) however, simulation had the lowest frequency and rehearsal was absent. Dialogue support, features including rewards, reminders and suggestions were marginally present with reward having the lowest frequency. Also praise and social role features were absent. With regard to credibility support expertise, real world feel, authority and verifiability were absent while trustworthiness and surface credibility were present with high frequencies. See Figure 4-1 for details of the various clusters and their corresponding sentiments. Clusters are differentiated with different fills and patterns.

## **Traveling Mobile Applications:**

*Pune (Data) m-Indicator*, *Grabaseat* and *Celebrity Cruises* formed a cluster (i.e., C2). This group of apps were characterized with high frequency of primary task support features including reduction, tunneling, personalization and self-monitoring. All dialogue support features were present with remainders and suggestions of the highest frequencies. Trustworthiness, expertise, real world feel and surface credibility had high frequencies with verifiability marginally present. Social Comparison and Social Facilitation appearing in one or two apps in the cluster were the only social support features present. All apps in this cluster exhibited greater value of positive sentiment than negative sentiments. Furthermore, emotional sentiment of liking was greater than anger and fear. Trust was not present within this cluster.

The group of traveling applications: *Live Train & Station Status*, *Confirm Train Seat*, *GPS Maps – Voice Navigation & Live Street Direction and Cheap Hotels* formed a cluster on their own (i.e., C3). Within this cluster, it was observed that, reduction and tunneling had higher frequencies compared to low frequencies of tailoring and self-monitoring. Remainders and Suggestions were the only dialogue support features present with suggestion of a higher frequency. Trustworthiness, expertise and real-world feel were of high frequencies compared to verifiability and surface credibility. Social facilitation was present and of a moderate dominance. Positive opinion sentiment values were greater than the negative opinion sentiments. Liking and Trust were present with the highest frequencies among the emotional sentiments whilst anger and fear had the lowest frequencies. Sadness was not present within their emotional sentiments.

It was observed that, mobile application; *Visa Travel Tools* formed a cluster on its own (i.e., C4). This application, just like other apps in different clusters, had a total of nine (9) persuasive system features present. Namely; reduction, tunneling, self-monitoring, suggestions, trustworthiness, expertise, surface credibility, real world feel and verifiability. Unlike most other apps with their PSD features present, *Visa Travel Tools* had no social support features present. Compared to its presence of system credibility support features, emotional sentiment of trust was absent as well as fear and anger. Positive sentiments outweighed the negative sentiments.

*eZhire – Rental Car, Delivered #no-demand*, *FabHotels: Safe Rooms on Best Hotel Booking App*, *OBHAI*, *Etihad Airways*, *Govinda – Tirumala Tirupati Devasthanams*, *Spin – Electric Scooters*, *Turkish Airlines – Flight ticket, TIER e-scooter sharing & more, VOI Scooters: Get Magic Wheels, TUI Holidays & Travel App: Hotels, Flights, Cruise*, *SAUDIA*, *Pakistan Railways Official*, *Greyhound(US)*, *Southwest Airlines* and *Royal Caribbean International* formed a cluster (i.e., C5). This group of apps were characterized with a dominance of primary support features including reduction, tunneling, personalization, self-monitoring with a sporadic presence of tailoring. Praise, reward, remainders and suggestions were the only dialogue support features present with reminders and suggestions active than the others. Within system credibility support, there was a high magnitude of trustworthiness, expertise, surface credibility and real-world feel. All other credibility support features were present but in very low magnitude. Normative influence and social facilitation were the only two social support features present and of low intensities. All apps in this cluster showed higher positive sentiments than negative sentiments excluding *OBHAI*, *Spin – Electric Scooters* and *Greyhound (US)*.

*Universal HollywoodTM App*, *Earth Live Cam & Public CCTV*, *WeShare: Share WiFi Worldwide freely* and *2GIS beta* were the category of applications that formed the next set of clusters (i.e., C7). Reduction, tunneling, personalization and self-monitoring were the primary support task present. Remainders, suggestion and social role were present among the dialogue support features with remainders of relatively high frequency. Credibility support saw features such as trustworthiness, expertise, surface credibility, real-world feel and verifiability present. No authority nor third-party endorsement. Social facilitation was the only social support present and of the lowest frequency. Positive sentimental value was greater than the negative. Although enough credibility support features were present, this cluster had an absence of the trust emotional sentiment as well as sadness. Liking, fear and anger were present and in that order of magnitude.   
See Figure 4-2 and Figure 4-3 above for a list of the various clusters labelled as C1 to C7 and their corresponding sentiments respectively.

## **Implication of Study 1 (Health & Fitness Mobile Applications)**

Generally, the findings revealed that health and fitness apps are popular since user reviews are mostly positive. Almost all the apps had high positive sentiments. Some applications recorded positive sentiments above 90% and this is promising for HBCSS research and practice. With regard to emotional sentiments (i.e., Liking, Trust, Anger, Sadness and Fear), the findings revealed that most users express some form of likeness for the apps.

Sentiment words that exhibit likeness was observed in most of the reviews. However, an analysis of the various clusters of apps in relation to system features showed that the provision of more persuasive features does not guarantee favorable sentiments from users. This is because it was observed that apps that had more systems features did not record higher emotional sentiments. For instance, Pocket Yoga (*app16*) had only one persuasive feature (i.e., reduction), yet it recorded the highest emotional sentiment intensity. In addition, it had the highest positive sentiment intensity. It recorded lower ratings for Trust, Anger, Fear, and Sadness. This demonstrates that although the absence of credibility support features leads to lack of trust, credibility support has less impact of application acceptance (likeness). Also, the presence of more features does not guarantee specific sentiments (i.e., no clear pattern between system features and sentiments). It can be argued that the presence of more persuasive features rather provides users the opportunity to assess each functionality as compared to fewer features. Hence, applications with more persuasive features appears complex to users and therefore does not attract high sentiments of likeness.

The study also revealed that the presence or absence of credibility support features does not guarantee trust in user sentiments. Credibility support features seek to demonstrate that a system can be trusted, thus this finding is worrying. Observe that apps including WalkingApp *(app2)*, Headspace *(app5)*, and HidrateSpark Smart Bottle *(app18)* had relatively high credibility support features yet recorded less trust sentiments when compare to Cycling - Bike Tracker *(app7)* and Weight Loss Running by Verv *(app14)*. It was also observed that applications that had more social support features had more sentiment words that demonstrates anger, fear and sadness when compared to those with no or less social support features. For instance, apps including WalkingApp *(app2)*, Headspace *(app5)*, HidrateSpark Smart Bottle *(app18)*, and Six Pack in 30 Days *(app22)* had more social support features present and they also recorded higher sentiment words when compared to Cycling - Bike Tracker *(app7)*, Water Drink Remainder *(app12)*, Step Counter - Calorie Counter *(app13)*, and Weight Loss Running by Verv *(app14)* that had less social support features.

## **Implication of Study 2 (Traveling Mobile Applications)**

Based on the above findings, the study revealed that traveling mobile applications are quite likable applications in general since users express high liking intensities and greater positive reviews. This was deduced from the high positive sentiments in comparison to the negative sentiments. Almost all the applications had high positive sentiments. Some applications recorded positive sentiments above 90%. Among the emotional sentiments (i.e., Liking, Trust, Anger, Sadness and Fear), liking recorded the most intensity out of them all and that is for every given application. This also shows the amount of interest users showed in travel apps.

Provision of more or less persuasive features within traveling apps does not guarantee any exact expression from users. It was observed that different apps with more system features did record both low and high opinion sentiments as well as emotional sentiments at different clusters and vice versa. For instance, *Greyhound(US)* from C5 of Figure 4.2 and *KKday: Adventure Like a Local* from C6 of Figure 4-3 both recorded the highest number of persuasive features among all the applications yet *Greyhound(US)* showed lower positive opinion sentiment compared to its negative sentiments and higher intensities of anger, sadness and fear. Whereas *KKday: Adventure Like a Local* recorded a higher positive sentiment and very lower intensities of trust, anger, sadness and fear. Similarly, *Greyhound(US)* had higher liking than *KKday: Adventure Like a Local*. Furthermore, from the same two clusters (C5, C6), *OBHAI* and *Live Train & Indian Rail Status – Locate My Train* respectively recorded the least number of persuasive systems features present. Yet, *OBHAI* had lower positive sentiment whilst *Live Train & Indian Rail Status – Locate My Train* had higher positive sentiment and arbitrary values of anger, sadness and fear coming from *OBHAI*.

The study continued to deduce that the availability of high intensity system credibility support features does not correlate to users exhibiting the expression of trust towards the application. Notably, most clusters (i.e., C7, C5, C4, C2 of Figure 4.2) showed consistent presence of namely: trustworthiness, expertise and real-world feel. Defiantly, their emotional sentiment of trust was either of lower values or absent. It can be argued that, probably users express their sense of trust in words relatable to liking and not necessarily trust or users found features outside of system credibility appealing to them a sense of trust instead of the actual features of credibility which were present.

Social support features with traveling applications generally are of lower importance. This may be due to the design concept of travel apps being service-based apps and not emphatically socially interactive applications. Contrary to the health and fitness implications, there was no clear-cut pattern between social support features, their dominance, and how they influence emotional sentiments of anger, fear and sadness. See how clusters (C6, C5, C2 and C1 of Figure 4.2) which have fairly a presence of social support features and their corresponding emotional intensities do not tell the same stories.

## **Comparison of the Two Studies**

This section seeks to explore the relationships of similarities and differences that are been shared between the two respective mobile application domains. Earlier on, it was mentioned that, the research aims to contribute to finding not only the patterns that maybe discovered between persuasive system design features (PSD) framework and sentiments of application – to help look at a different perspective in approaching PSD optimization - but also find out what changes or PSD features are being observed the most within these different domains, eventually, coupling these findings in building a machine learning model to predict PSD features for mobile application domains based on sentiments to be expressed.

## **Similarities:**

Implication of study 1 and 2 detailed that, the findings into the two separate domains addressed a high affinity of positive sentiments compared to negative sentiments. This could be illustrated within the percentage scores among most of the fitness & health applications and mobile applications selected. Further, emotional intensity of liking was expressed by the two mobile domains. These implied that, both application domains are popular and used among individuals. Some external reasons why health and fitness apps maybe that popular can be derived from the massive development of mHealth applications in the eHealth sectors. This should be no surprise since record shows over 100,000 health apps available tackling physical activities, diet, monitoring exercise, calorie and body-weight (Lean, Michael E J, Charoula, 2017) Also the continuous use of mobile health apps by healthcare professionals in accessing and analyzing clinical information (Lohnari et al., 2016). Among the general usability of traveling mobile application services such as booking and ordering transportation rides and accommodations within localities, (Lee et al., 2017; Yip, 2020) have expressed the essential impact and relationship between tourism within countries and the important need on how traveling mobile application can help achieve adoration towards tourism.

Both domains had similar relationships to the absence and presence of credibility support features. Whilst study 1 (health & fitness apps) exhibited that, the presence or absence of credibility support made subtle effects in the sentiment of trust, study 2 (traveling apps) propelled in somewhat of that same direction. Such that, the presence of credibility support features even though were quite dominant cross the cluster of traveling mobile application did not reflect in guaranteeing high intensity of the trust sentiments.

## **Differences:**

Contrary to the traveling mobile application findings, the health & fitness observations, resulted in an implication, proposing that, the unfavorable sentiments generated by users is due to the high provision of persuasive system features. It was argued that the more clustered the PSD features are within mHealth apps, the more complex the features become for users to show likeness towards the app. The traveling mobile applications analysis across its cluster, illustrated that, high and low provision of PSD features within the applications does not generate any exact sentiments from users. Such that, high provision of PSD features could either generate favorable sentiments from users at one point and unfavorable sentiments and vice versa. Arguable, this development may have more to do with the purpose of the traveling application and less to do with the PSD features being used. Such that, even though the persuasive system design feature were present, the applications did not deliver the on their purpose of use.

Social support features were dominant among health & fitness applications and least present within the traveling applications. Furthermore, there was no correlation between social support features and their impact on the sentimental words expressed by users within the traveling mobile application as there were within the health & fitness mobile applications.

## **Chapter Summary**

This chapter illustrated interesting findings that could be observed from the two-separate set of clusters. It was seen that, there were certain correlations that existed between the sentiments and PSD features in the two domains – health & fitness mobile apps and traveling mobile apps. Nevertheless, even though repeated patterns can be seen occurring within the two mobile domains, some correlations were also very different between the sentiments and the PSD features of the two respected applications.

# **CHAPTER FIVE**

## **CONCLUSIONS**

## **Chapter Overview**

The research objectives from the study are evaluated in this chapter along with the expected contributions from Chapter One. Limitations to the study focusing mostly on the traveling mobile application domain are detailed here as well. Future works that can be adopted given the implications of this study are outlined showing how beneficial this study has would be to the future works.

## **Evaluation of Research Objectives**

The below sections indicate how the stated objectives outlined in Chapter One have been met successfully. Taking the five (5) targeted objectives, discoveries were made showing certain relationship characteristics that existed between the persuasive system design features and sentiments from each mobile application domain. The correlations observed in effect will play as a contributing factor to both the challenge of optimizing persuasiveness in a system as well as providing developers of apps on what PSD features to look out for. Interesting findings as seen in Chapter Five, provides the data on what PSD features are mostly being recognized by users, some features being perceived or actual. In the long run, the accumulation of more data from different mobile application domains will be essential in accomplishing to develop a machine learning model to predict sentiments based on persuasive system features for developers and users like.

## **Health & Fitness Mobile Applications**

This study presents finding of a study that seeks to investigate the relationship between user sentiments and persuasive systems features. It adopted a stratified random sampling technique to select health and fitness apps on the Android and iOS markets. The sentiments of app users were extracted and compared with systems features that are available in each app using clustering techniques. The results demonstrated that the provision of more persuasive features does not guarantee favorable sentiments from users. Particularly, it was observed that apps that used less system features attracted more sentiments relating to likeness. Also, it was observed that social support features most promote negative emotions such as anger, fear and sadness. Perhaps, these findings corroborates with existing knowledge that argues that presence of persuasive system features in Health Behavior Change Support System (HBCSS) does not necessitate the sufficiency or efficiency of the system (T. Lehto & Oinas-Kukkonen, 2015a).

More importantly, there is the need for further investigation to be conducted to explain the causal effects of these phenomenon. Particular attention must be given to the type and structure of messages used in conveying the various persuasive features. This is because although designers’ persuasive applications may convey the intention to change in their messages, the messages may be creating emotional shifts from their intentions.

## **Traveling Mobile Applications**

The aim of the study was to explore any patterns or correlations that may exist between user sentiments extracted from traveling application reviews and their corresponding persuasive system features. 35 traveling applications were sampled using random stratified sampling from both the Android and iOS platforms. These applications’ sentiments from their reviews and associated persuasive system features were recorded and relationships that could be observed were analyzed using a clustering algorithm technique. The results and findings illustrated that the dominance of system credibility support does not guarantee trust. Additionally, the increase or decrease in the number of persuasive systems features in a traveling application does not determine the intensity of emotional and opinion sentiments. Thirdly, there is no attention to social support features with traveling apps. Finally, there is a correlation between the appearance of reduction and tunneling among the primary task support of travelling applications.

## **Research Limitations**

Challenges with geographical restrictions of the traveling application’s functionality resulted in a lower app sample than the initial stratified sampling. Since some of the applications were coming from countries different from Ghana, it rendered the work through of the application useless. This is because, the application was designed for those countries with certain location information associated to the GPS of those countries.

Operating System compatibility with in the IOS platform made it difficult to also use majority of the sampled application. The iPhone used for accessing and extracting the PSD features was that of version 5. Majority of the apple travel apps demanded IOS version “Big Sur” which was not compatible with the iPhone version used for the study. In addition, an update to big spur on the iPhone at hand was not available nor ready.

Thirdly, extracting reviews for the various applications limited the number of sampled applications for the study. The dynamic architecture of the apple preview store and the google play store website made it quite difficult to extract reviews at the exact review selection criteria and beyond. Even though the programming tools and libraries used were quite sophisticated enough for review extraction for dynamic websites, the timeouts criteria security precautions provided by these websites made data extraction cumbersome. Indeed, the use of app reviews subscription services which would allow a huge collection of these reviews was an alternative, nevertheless, this study did not have any financial support.

## **Evaluation of Research Contributions**

Evaluation of research contributions is going to be analyzed based on the listed objectives mentioned within Chapter One. The explanation follows how each of the objectives mentioned has been ascertained by taking each objective against resulting conclusions of the research project.

1. **Find correlations that exist between persuasive system design features and sentiments from mobile applications**:

Within the scope of the two selected domains (health & fitness mobile application and traveling mobile applications) relationships between persuasive system design features and sentiments were established such that, both domains showed a dominant relationship between the primary task support features and the sentiment of liking as seen in the cluster tables.

Secondly, a high frequency of credibility support features exhibited a low percentage on the presence of trust within the applications. Social support features within the mobile health applications exhibited favorable sentiment intensities when those features are few but vice versa when the features are in dominance.

1. **Serve as a contributing factor in curbing the challenge on how to optimize persuasiveness using persuasive system design framework:**

Chapter One’s research problem and relevance established the need to use the PSD framework to optimize persuasiveness as well as identify the essential PSD features for a selected application domain in order to ensure persuasiveness. As stated, studies have investigated the framework and the impact the features have on users. Nevertheless, some of these challenges persists. Different researches have contributed to curbing these challenges in their own approach and understanding, This project, using sentiments from users and comparing those sentiments to PDS features within these mobile applications, technically serves as another perspective into the study.

1. **Provide designers and developers of health and traveling mobile apps what to look out for when meeting the sentiments of users**:

This study has further provided implications into certain correlations that can be observed within the user sentiments and PSD features. Thus, providing a practical contribution into what designers of persuasive models should have in mind. For instance, the findings showed that, Primary task support features such as reduction, tunneling, tailoring and personalization along with suggestions and remainders from Dialogue support features contribute to increasing the sentiment of liking from most users.

1. **Identify which PSD framework techniques are mostly being recognized by users in the domain of health and traveling mobile applications and any correlations within the PSD features:**It was observed that, features within primary task support were dominant across the two mobile domains, as well as dialogue support features. Reduction, tunneling and personalization could be said to be in correlations such that the presence of reduction also indicated the presence of tunneling and personalization. Dialogue support features were seen to be most consistent within the two domains as they showed high frequency of suggestion, praise and rewards. These and other pattern observations could be seen in Chapter Five’s Findings & Discussions.
2. **Contribute to the data acquisition aimed at developing a machine learning model that can predict sentiments based on persuasive system features:**  
   The implications and findings of the study can serve as an informational base that can be used to develop a machine learning model to learn about the complexities of user sentiments and the PSD features in different mobile domains. Thus, another effort of practical contribution to the field of PSD frameworks.

## **Future Work**

Exploration of different mobile domains such as (social, games, e-commerce, education, etc.,) to identify patterns between persuasive system features and the corresponding sentiments of applications in these domains. Reason being, these patterns, whether present or not can give insights into how addressing the key challenge of selecting relevant persuasive features in order to optimize the persuasive experience of users (Wiafe et al., 2020).

Secondly, developing a machine learning model that can predict sentiments based on persuasive system features. This can give analysis on what developers have to look into if the mobile application to be developed would give positive reviews and be objectively essential.

Based on the implication of the study, looking at the dominance of certain system credibility support features and the absence of emotional sentiment of trust within the most of the applications, there is the need to make investigations into defines perceived trust and actual trust in persuasive system development.

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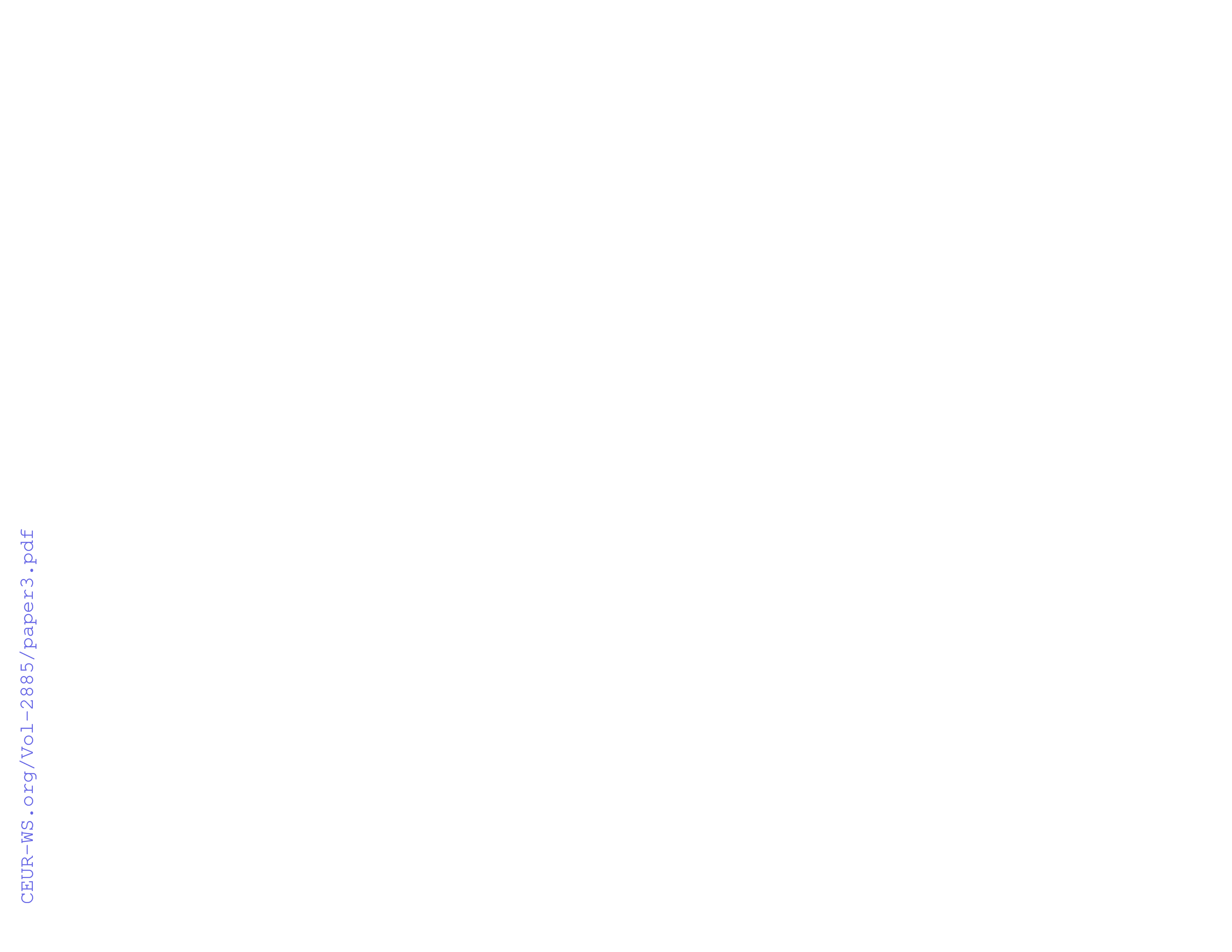
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## **APPENDIX A**

Full documentation of the published paper.

**Exploring the Impact of Persuasive System Features on User Sentiments in Health and Fitness Apps**

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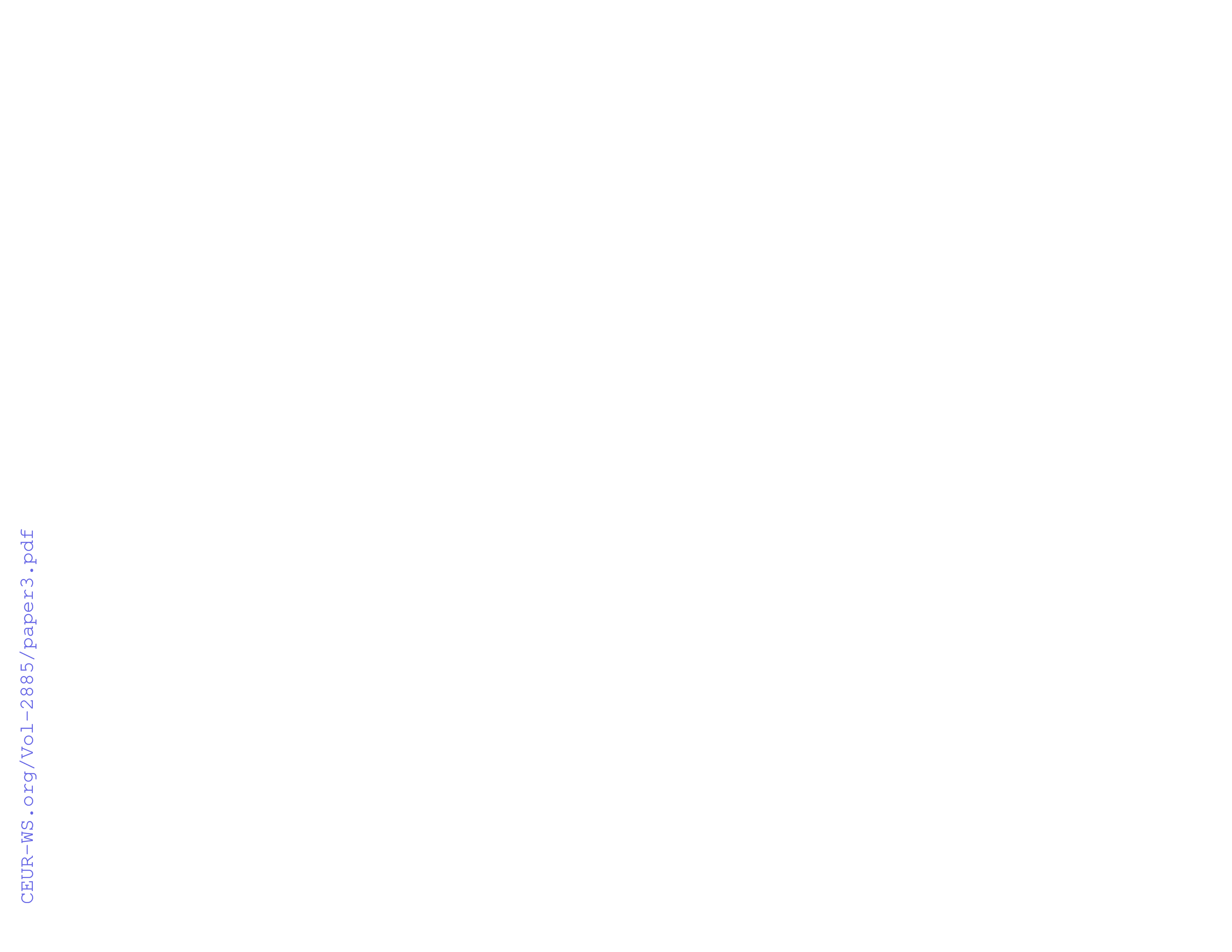
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**Abstract.** Although behavioural change support systems have proven to be effective in changing user’s behaviour, the need to design effective persuasive systems that optimize persuasive experiences of users continue to remain a challenge. This study seeks to contribute to existing literature that aims at addressing this challenge. Using stratified random sampling technique, 23 health and fitness iOS and Android apps were selected. User reviews of each app were downloaded and compared with the corresponding persuasive systems features using cluster analysis. The findings demonstrated that more system features do not produce higher positive sentiment. It was also observed that apps with more social support features were associated with higher frequencies of fear, sadness and anger related sentiments.

**Keywords:** Persuasive and Sentiments, Health Behaviour Change Support System, Sentiment analysis, Mobile Health, Health and fitness apps

# Introduction

Since the introduction of the Persuasive Systems Design (PSD) framework [1] several studies have attempted to investigate the efficacy of the 28 suggested persuasive features in different domains [2]–[4]. The PSD framework proposed system features that are categorized into four main supports (i.e., Primary Task Support, Credibility Support, Dialogue Support, and Social Support) for changing behaviour. These features are the fundamental system requirements of a behaviour change support system (BCSS), and although it is not mandatory for all the features to be present for a system to be considered as a persuasive [1] there is the need for some representation of these features to be present. A key challenge in BCSSs research is to determine how to select the most relevant persuasive features to increase the persuasive experience of users [5]. Accordingly, several studies [5], [6] have proposed methods and frameworks for selecting persuasive systems features to optimize user persuasive experience. Yet, these methods do not adequately provide information on how system features can be selected. To address this challenge, this study seeks to contribute by exploring how various persuasive system features trigger specific sentiments or emotions in users.

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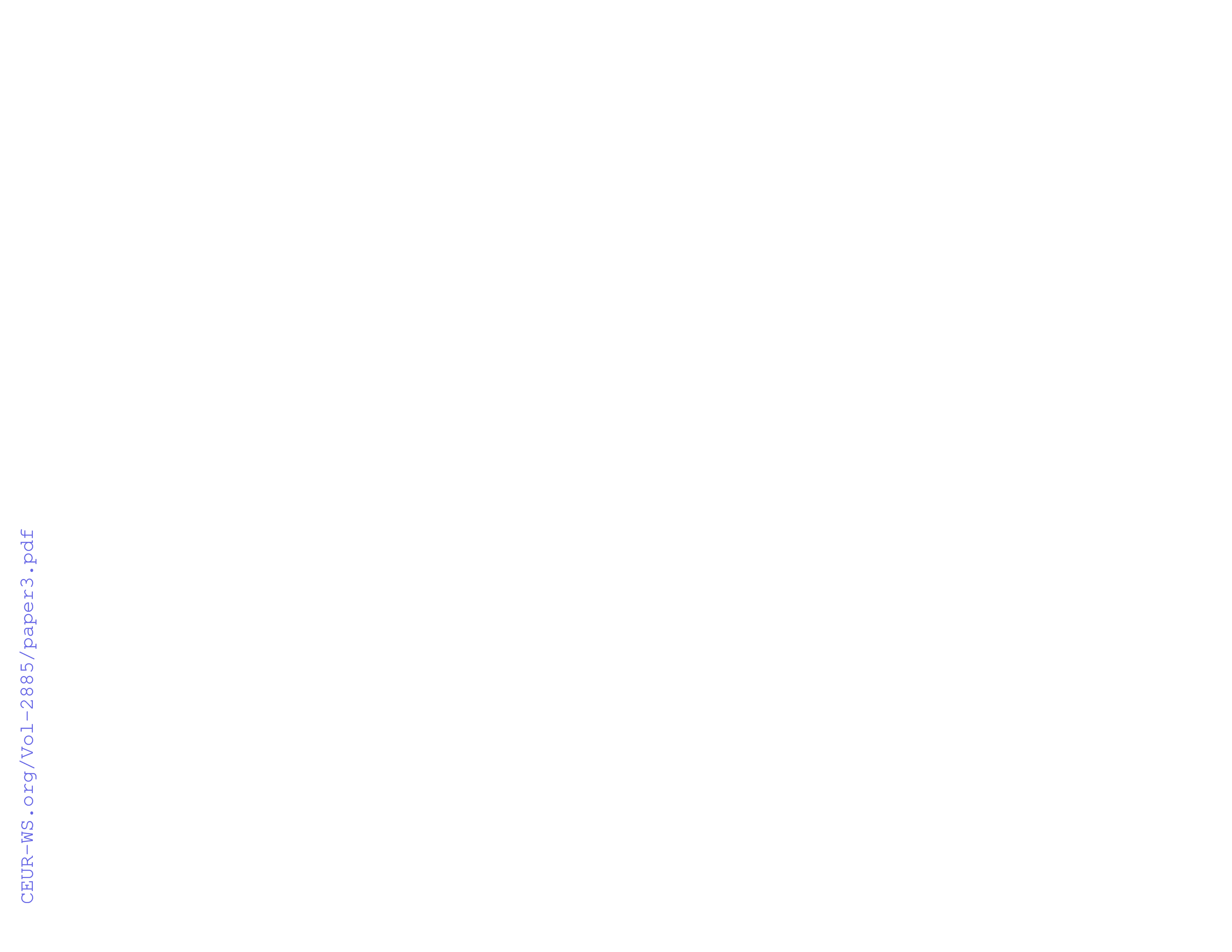
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It is emphasized that, although some studies have attempted to assess or evaluate the relationship between persuasive features and their impacts on users [2], [4], [7], [8], to our knowledge none have investigated the effects of persuasive systems design features on user sentiments. However, understanding how system features trigger specific sentiments provide pertinent information that may aid the selection of effective and efficient persuasive features. This is because there is enough evidence that emotions or sentiments moderate human behaviour and thus impacts persuasion [9].

Specifically, this study assessed 23 selected health and fitness mobile applications in the Android and iOS markets and explored the relationship between users’ sentiments and app features. Next is a discussion on related literature. This is followed by a description of how the study was conducted. The findings and implications of the study are presented before conclusions are drawn.

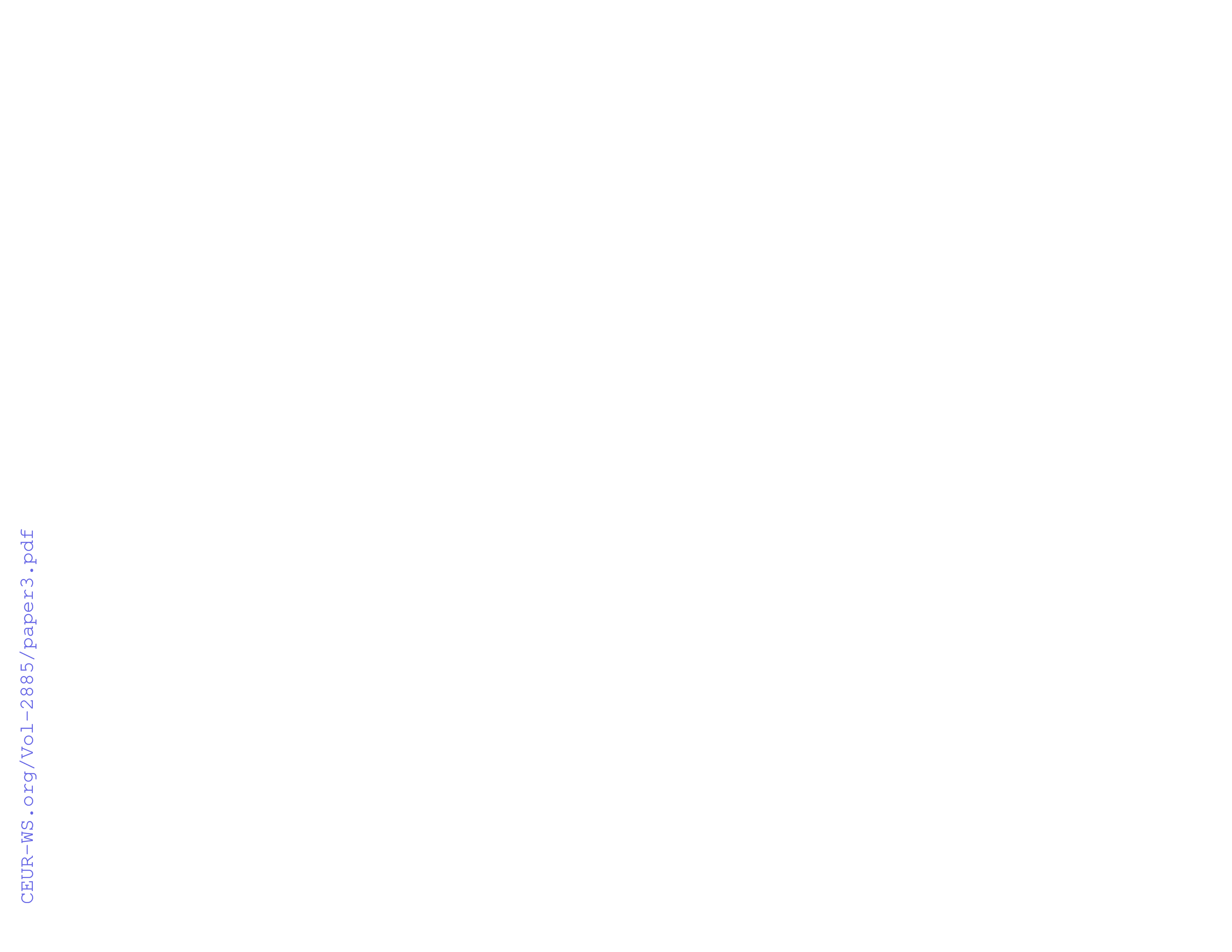
# Background Literature

## Persuasive Systems Design Features and Related Studies

The intention to change one's behaviour using technology depends on three major factors, the designer, the distributor and the user [10]. Considering that the main prerogative of BCSSs is to alter behaviour, it is incumbent for designers to ensure that they employ techniques that facilitate persuasion by optimizing the use of persuasive features. Yet, studies have shown that persuasive software features are not mostly considered by designers during the design stage [11] and also most persuasive designers employ ad hoc design methods [12]. Persuasive systems design features provide a means for designers to enhance the content and or functionalities of persuasive software. The 28 PSD features are primary task support (reduction, tunnelling, tailoring, personalization, self-monitoring, simulation, and rehearsal), dialogue support (praise, rewards, reminders, suggestion, similarity, liking, and social role), system credibility support (trustworthiness, expertise, surface credibility, real-world feel, authority, third-part endorsements, and verifiability), and social support (social learning, social comparison, normative influence, social facilitation, cooperation, competition, and recognition) [1]. It has been argued that a good understanding of these features and their impact on specific persuasive activities provide the needed information that facilitates the design of effective persuasive systems [13]. Nonetheless, it is a challenge to identify specific and exact features that enhances persuasion. This challenge is a result of the complex nature of human attitude and behaviour, and it was inherited from traditional methods for changing human behaviour.

That notwithstanding, several studies have attempted to understand the relationship between persuasive system features as proposed by Oinas-Kukkonen and Harjumaa [1] and the possible impacts it has on persuasion [13], [14], usability, credibility and continuous usage [2], [7]. These studies have however produced relatively conflicting results. For instance, it has been argued that the presence of persuasive system features in Health Behaviour Change Support System (HBCSS) does not necessitate the sufficiency and or efficiency of the system, rather more attention should be given to designing and implementing systems that are captivating and attractive to users [13]. Others have argued that perceived effectiveness, availability, and credibility (trust, reliability, etc.) of a system has a direct impact on user intention to continuous use of BCSS [13], [14]. Accordingly, there is a need for further investigations on how these features impact persuasive design from a different perspective.

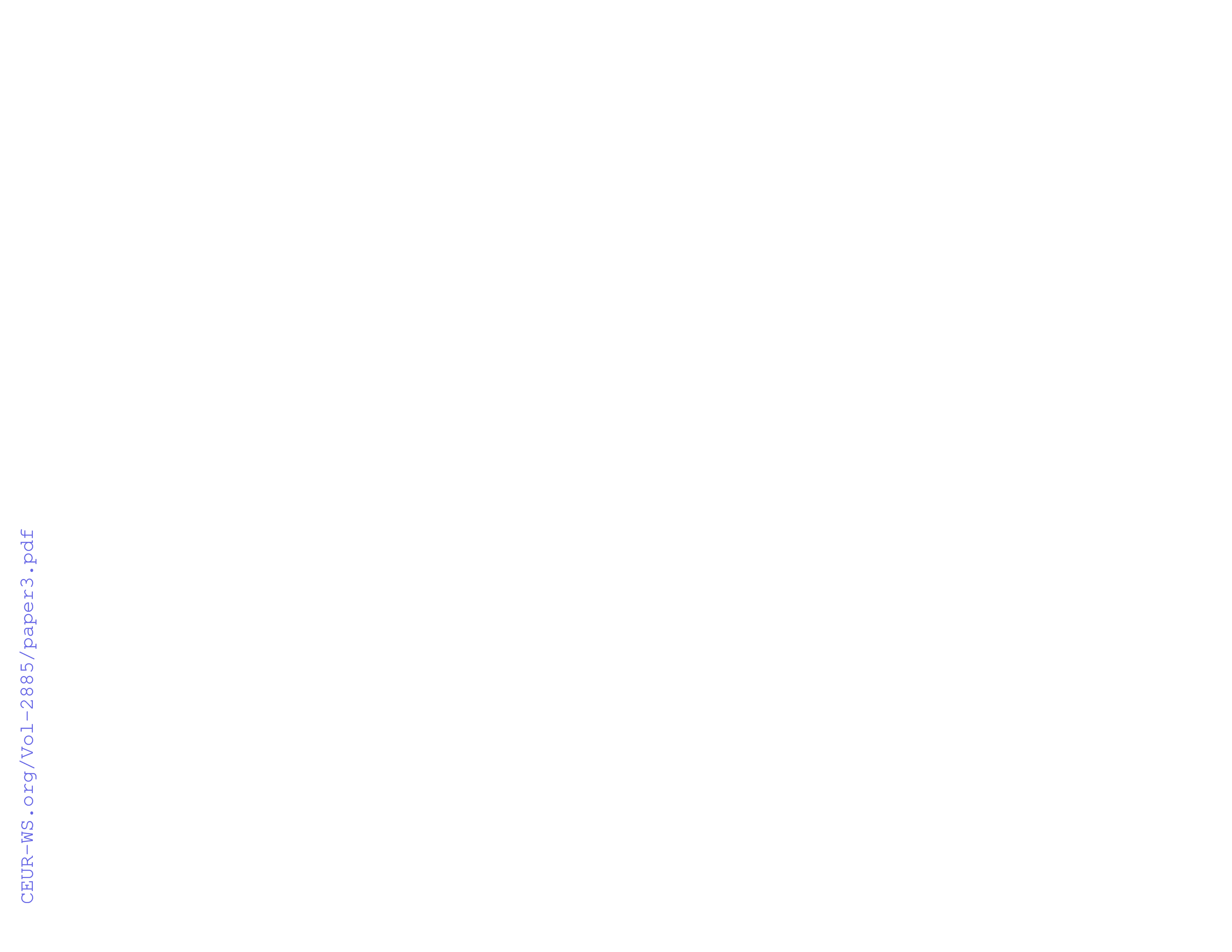
## Sentiment and Persuasion

Due to complexities in understanding human attitude, behaviour and the limitations of using questionnaires to collect and investigate perceptions, it is more appropriate to adopt other self-reporting methods that do not involve questionnaires to study human behaviour. Thus, recent studies have adopted sentiment analysis for investigating human emotions and behaviour. Sentiment analysis provides a better option for studying user perceptions. Mostly, users express their opinions on applications or products to demonstrate their level of satisfaction and these opinions provide rich information for investigations. In recent times, the web has become a viable space where individuals express their opinions. Internet reviews have become a relevant part of decision-making processes for individuals and industries. Particularly, user feedback is a fundamental variable for purchase decisions, and it provides relevant information for determining the satisfaction levels and emotions of customers.

Considering BCSS designs, existing evidence confirms that there is a relationship between sentiments and persuasion [15]. Persuasion is a communication activity which present arguments to motivate or change the cognitive state of the listener [16]. Thus, persuasion techniques exert influences on the thoughts and behaviour of individuals, and this induces sentiments. A change in an individual’s sentiment may affect behaviour and this has been demonstrated in how sentiments expedite decision making [17]– [19]. Individuals rely on their emotions to make economic, political, social and personal decisions. It is, however, evident that the extent of decision making based on emotions can be biased: whether deducted from persuasive messages or incidental contextual factors. This notion has been confirmed by Petty & Cacioppo [15] in the Elaboration Likelihood Model (ELM) that explains the effect of emotions on attitude and judgement.

In BCSS design, emotions play a crucial role in translating the effects of feeling from computers (application) to humans [20]. Hence, emotions can influence a user’s acceptance of a BCSS. Incorporating emotional strategies into persuasive messages might motivate a user towards achieving their persuasive goals. For example, evoking fear can be a good means of alerting an individual of the risks of heart disease due to smoking [21]. Yet, a critical observation of BCSS design literature demonstrates inadequate investigations on the relationship between sentiments and persuasive features. Studies have mainly focused on individual emotions such as fear [22], trust [23] and self-reflection [24]. It has been argued that positive emotions increase trust while negative emotions decrease it [25]. Nonetheless, in BCSS, cognitive trust has a higher impact on credibility and continuous use when compared to affective trust [23]: a decrease in cognitive trust is directly proportional to a decrease in affective trust [25]. As argued earlier, considering the implications of current literature, it is relevant to investigate or explore the relationship between sentiments and persuasive features. Accordingly, this study sought to explore this relationship in health and fitness mobile applications.

## Persuasive Mobile Health

Health and fitness application was adopted because of its popularity in recent times. It has demonstrated to be effective in addressing several health-related issues. Consequently, research on the use of persuasive features in health-related apps has gained more attention [12]. Some researchers have argued that mobile health applications present a better opportunity for addressing barriers to patient education [26] and disease prevention [11], [24]. Mobile health apps are ubiquitous and pervasive, thus, more accessible when compared to traditional systems. More specifically, health apps on mobile phones and smart devices have addressed challenges of infrequent usage of webbased health intervention: smartphone users are more responsive to behaviour change strategies available in mobile health and fitness apps [27]. It has been argued that although there is no significant difference in mortality rates between users and non-users of mobile health apps, mobile apps have reduced hospital admission rates and have also improved health outcomes such as lower systolic blood pressure and medication compliance significantly [26].

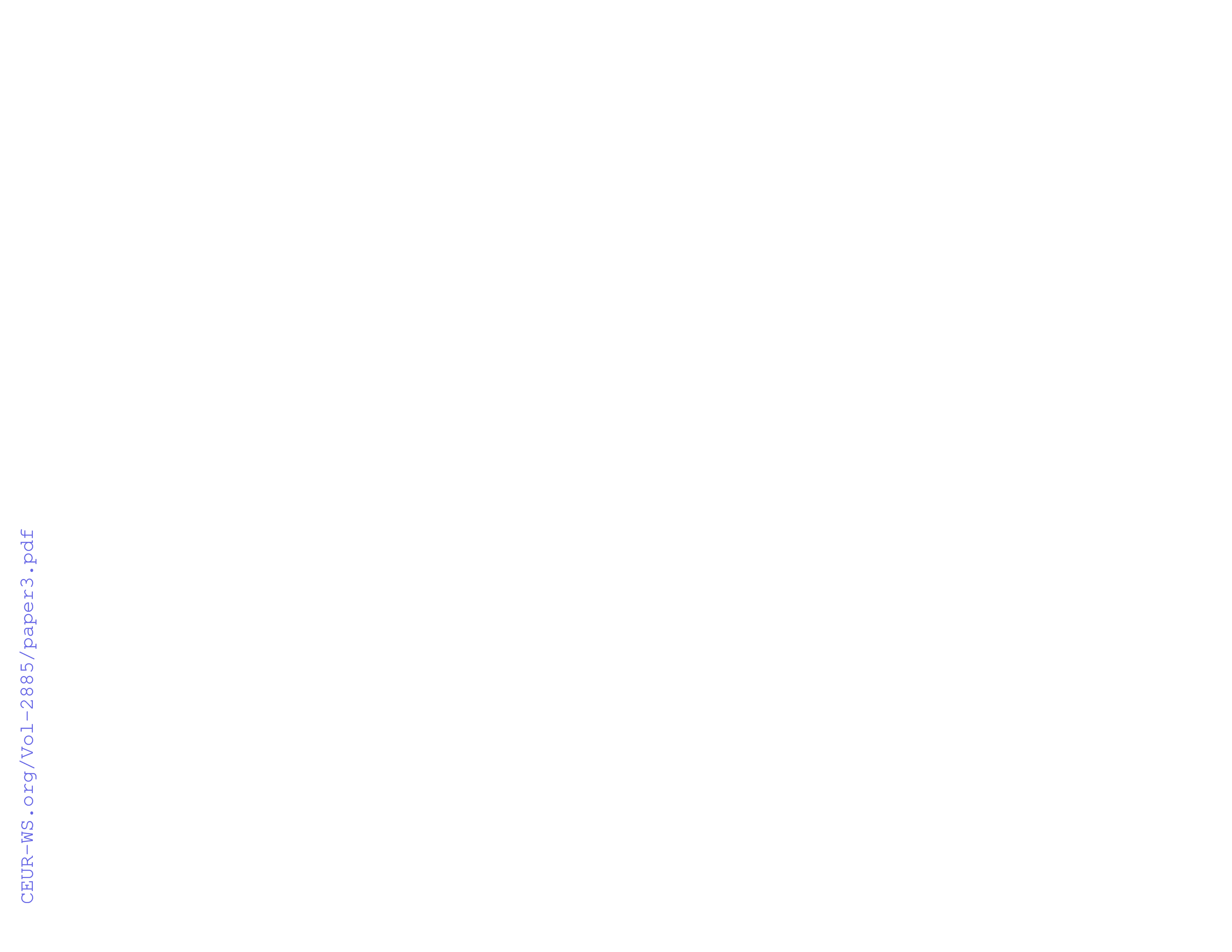
However, existing mobile health applications seek to promote healthier habits by improving its technology [11] rather than paying attention to the fundamental persuasive principles that addresses consumer needs. Specifically, existing applications can be improved by leveraging effective persuasive system features to provide effective communication and persuasion. Considering this backdrop and the widespread use of mobile health apps, this study adopted mobile health application as the domain of investigation.

# Methodology

To ensure a compressive and rigorous review of sentiments and features of mobile health apps, the study was conducted as follows: firstly, a sample of mobile apps categorized as “health and fitness” were selected from the Android and iOS stores. Each app was assessed based on an approved selection criterion. The persuasive features and the associated sentiments of the selected apps were extracted. The patterns in app design features and related sentiments were explored to draw conclusions. Below is a detailed discussion on how each stage of the investigation was conducted.

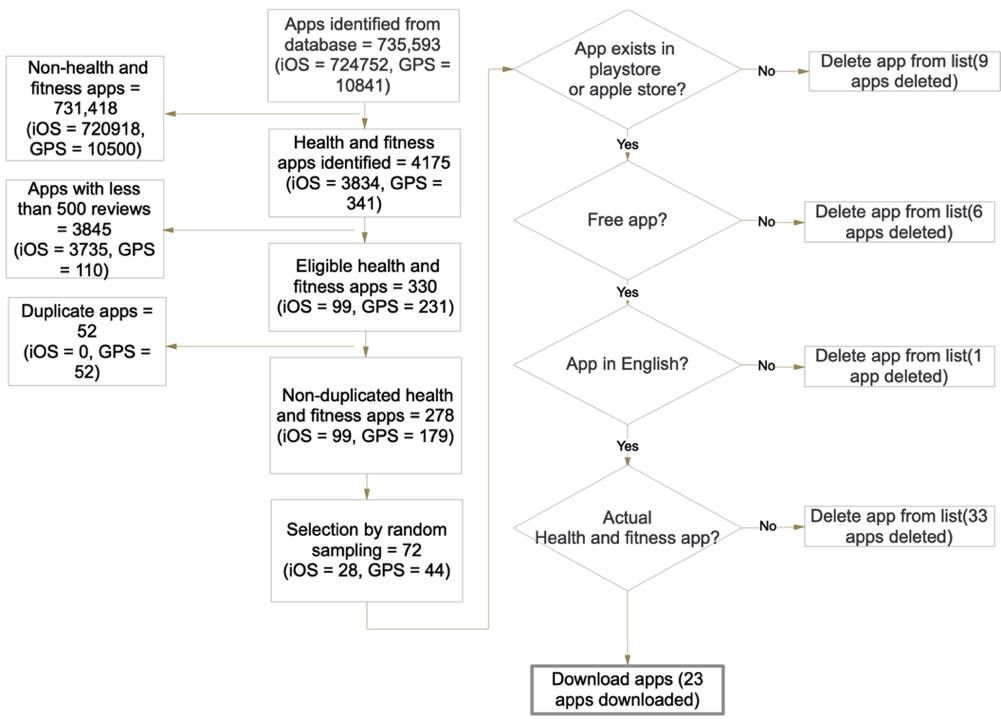
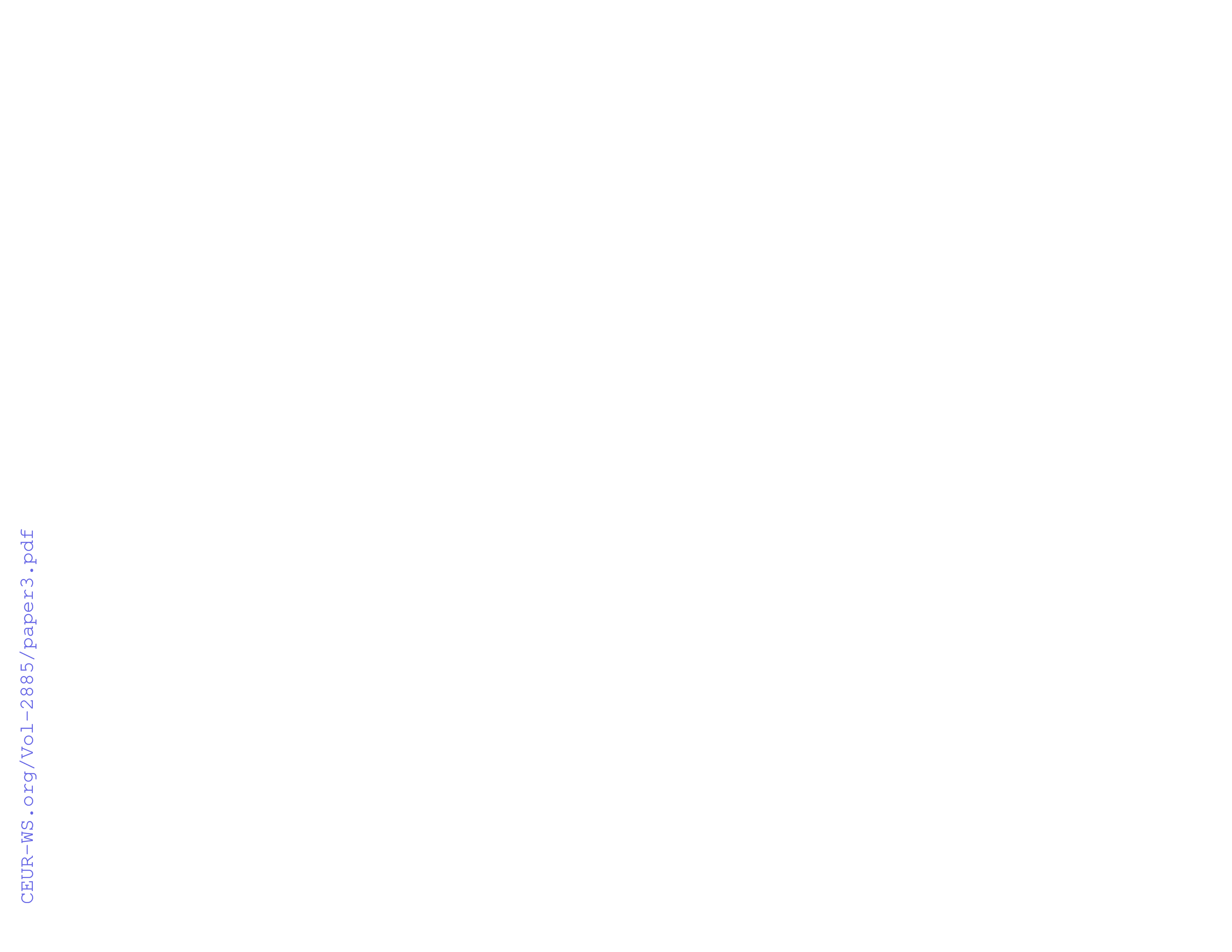
## Datasets

The dataset for the study was acquired from the Kaggle datasets for iOS and Android. The Kaggle datasets for Google Play store apps (https://www.kaggle.com/gauthamp10/google-playstore-apps) and Apple iOS app store

(https://www.kaggle.com/cmqub19/763k-ios-app-info) were downloaded (on September 14, 2020). The database consists of 735,593 and 4,175 applications classified as health and fitness for Android and iOS respectively. The dataset was pre-processed and fields or data that were considered to be irrelevant for the study were excluded. Further, apps that had less than 500 reviews were excluded. This was to ensure that all apps used in the study have received an adequate number of reviews and ratings. Duplicate apps including those that were present in both iOS and Android were removed. This reduced the number of apps to 278. (i.e., 99 apps for iOS and 179 for Android).

For a population of 278 applications, a sample of 72 is needed to ensure a 10% margin of error at a 95% confidence level. A stratified sampling approach resulted in 28 samples for iOS and 44 for Android. Our motivation to use a stratified random sample approach was to reduce biases and ensure that the findings of this study can be generalized. Each application was downloaded and installed. After installation, applications that were not in English, those that were for sale, no longer available or did not demonstrate an intention of changing user behaviour were omitted. This resulted in 23 applications for the study. Figure 1 is a diagrammatic representation of the stages involved in the selection process and Table 1 is a list of the selected apps used for the study.

The reviews and ratings for these applications were extracted using Python libraries (i.e., beautifulsoup, selenium and JSON). Downloaded reviews for individual apps ranged from 202 to 123,719. Each review consists of *ratings, categorical\_url, company\_name, date, developerResponse, reviews/content, title*, and *isEdited*.



**Fig. 1.** Procedure for selecting apps

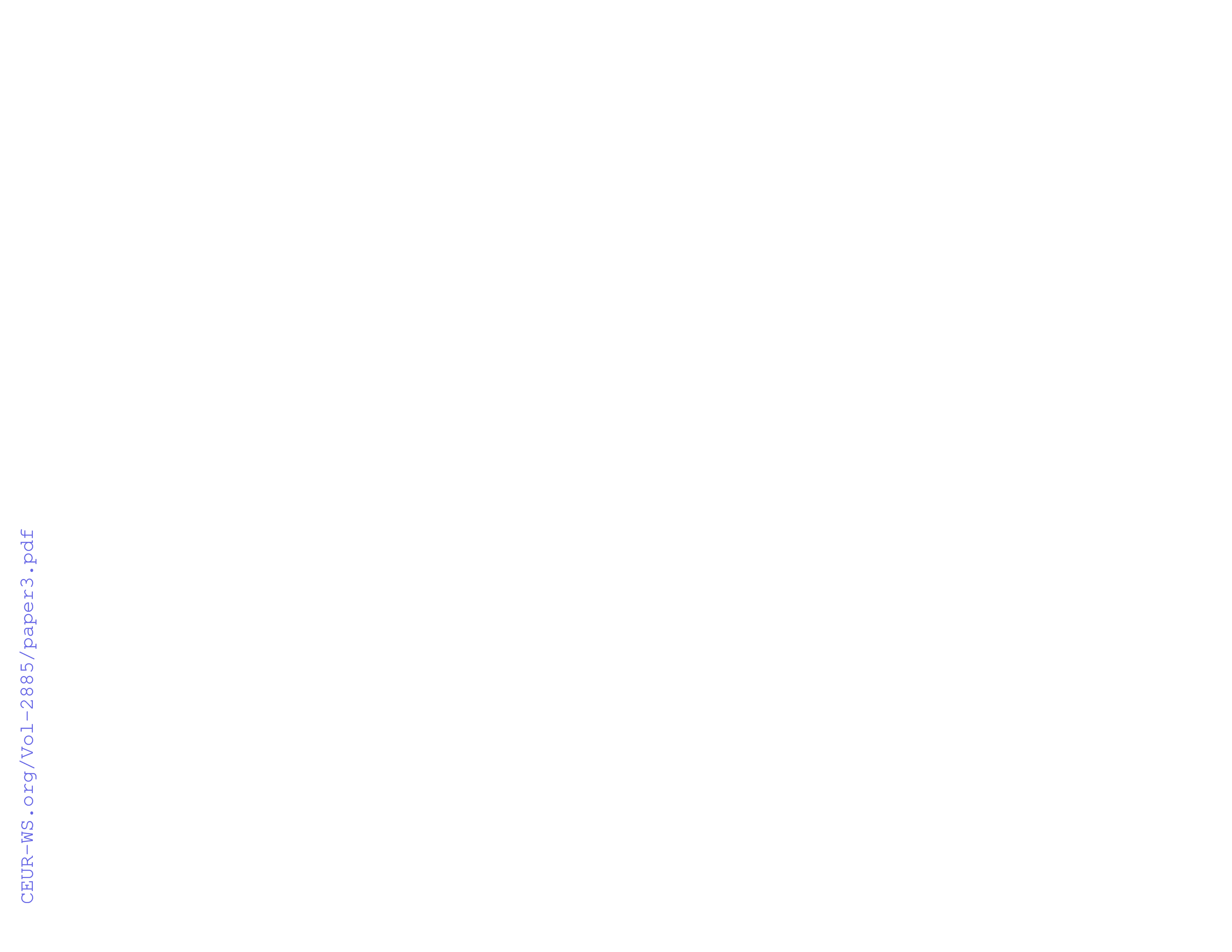
## Persuasive Feature Extraction

Two members of the research team were tasked to extract the various persuasive features of the selected apps. They used each app for one month simultaneously to assess the apps and identify the various persuasive features employed in each app. To reduce bias, reports from the two assessors were combined and disparities were addressed. Similar to studies conducted by Lehto and Oinas-Kukkonen [13], features including liking and similarity were not assessed. This is because they are relatively subjective, ambiguous and dependent on the user. Although, it is challenging to assess surface credibility and trustworthiness, in this study surface credibility was evaluated using claims by [11]. Thus, the absence or minimal use of adverts and unnecessary pop-ups was used to assess surface credibility whereas trustworthiness was evaluated by the ability of the application to provide users with control of security/privacy settings.

**Table 1 List of Applications used for the Study**

**App ID Name of Application App ID Name of Application**

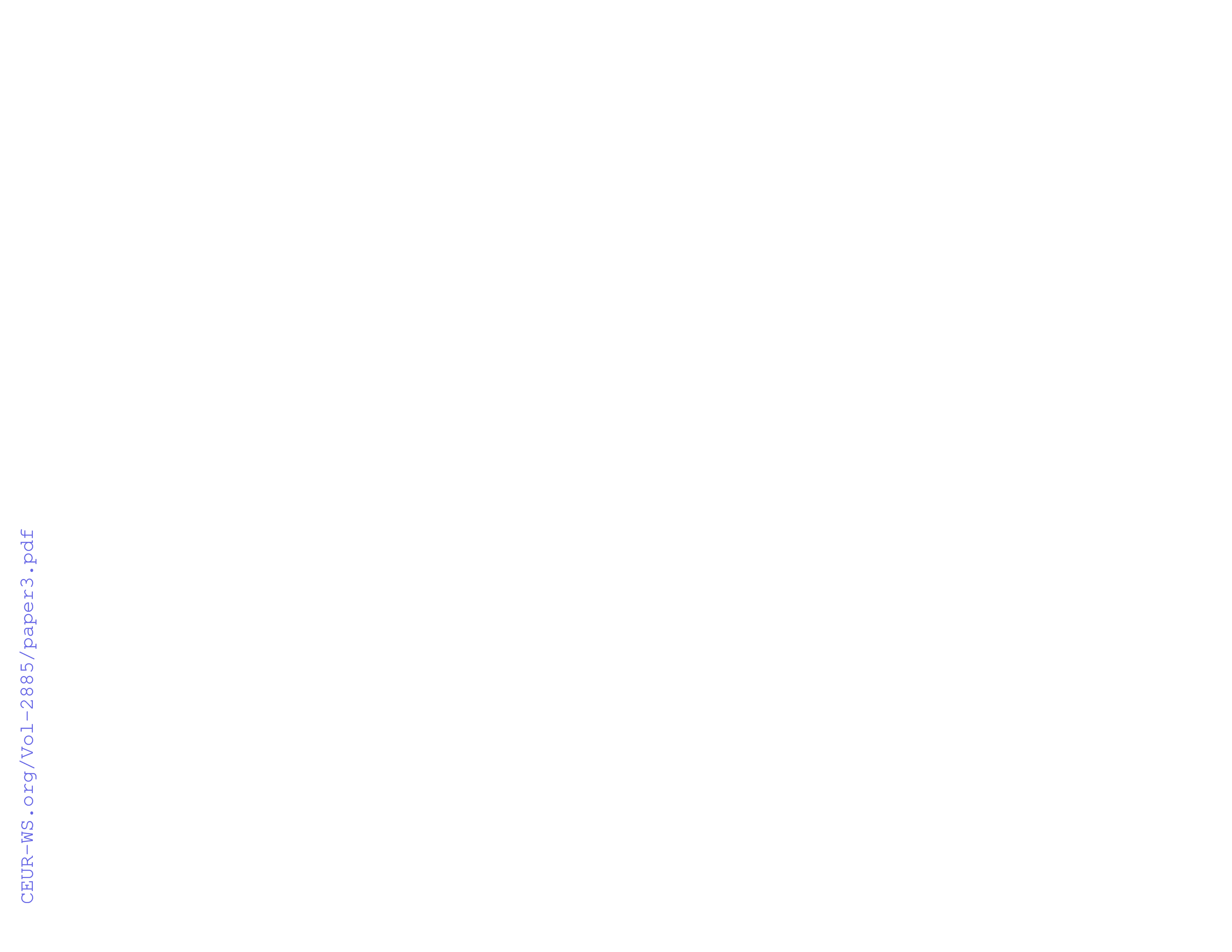
|  |  |
| --- | --- |
| 1 Ideal Weight | 13 Step Counter - Calorie Counter |
| 2 WalkingApp | 14 Weight Loss Running by Verv |
| 3 Step Counter | 15 Abs Workout |
| 4 Walking for Weight Loss | 16 Pocket Yoga |
| 5 Headspace | 17 Dr.Greger's Daily Dozen |
| 6 Calorie Counter by FatSecret | 18 HidrateSpark Smart Bottle |
|  |  |
| 8 Running Distance Tracker + | 20 PlayFitt |
| 9 Daily Yoga - Yoga Fitness Plans | 21 WaterLama Water Tracker |
| 10 Pregnancy & BabyTracker | 22 Six Pack in 30 Days |
| 11 Workout Tracker & Gym Trainer | 23 Plant Nanny |

 12 Water Drink Reminder

## Sentiment Extraction and Analysis

The reviews and ratings for each selected app were extracted and pre-processed. Data pre-processing is an essential part of sentiment analysis (i.e., Natural Language Processing). It enables the stemming and elimination of redundant data such as stop words and noise. Hence, stop words including prepositions, pronouns, special characters, punctuation marks and numbers were eliminated from the dataset. Furthermore, to avoid short words pollution and eliminate words that were not removed during stop words removal, words with three characters and below (e.g., eat, run, got) were removed. Two categories of sentiments were considered: the opinion sentiments consisting of positive or negative and emotional sentiments consisting of five classes of emotions namely liking, trust, anger, sadness and fear. These five classes were identified in an initial exploration of the dataset that identified them as the main classes present in the dataset. The five classes of emotions were categorized by synonyms and related words. Due to mix of words relating to adjectives, nouns, adverbs and verbs that can be found within the list of sentimental words, the wordnet database was used to find other synonyms. See table 2 for the categorization of words for the classes used in this study.

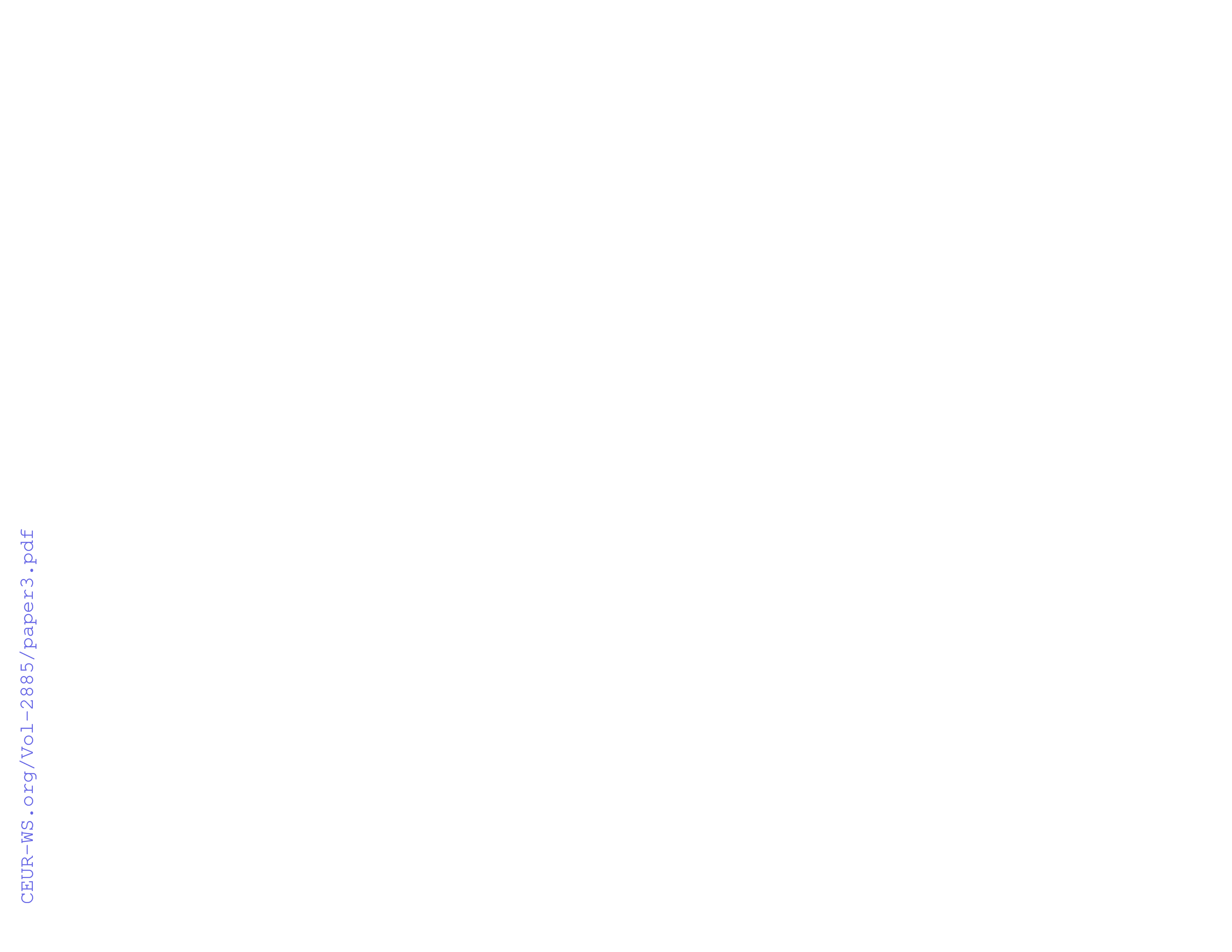
A sentiment intensity calculation was performed, here the total number of opinions and emotional sentiments were analysed. To accumulate the exact sentiments extracted from the reviews, sentiment extraction was conducted in two folds. The first fold used a four-way approach for categorizing emotional sentiments; Classification of Reviews, Frequency of Words, Extracting Sentimental Words and General Sentimental Grouping. The second fold used a three-way approach; calculating the percentage of the opinion sentiments, categorizing the opinion sentiments into the five stated emotional sentiments and calculating the percentage of the total number of positive and negative sentimental words respectively.

The reviews and their corresponding ratings were grouped into positive and negative words. Using a word extraction function, each app review was evaluated to determine whether or not their ratings fell above or below three (3). Additionally, sentiment retrieval was performed using the frequency of words and the extraction of sentimental words. Words from both the positive and negative lists were combined and a Frequency Distribution function was used to output a dictionary of the most frequent words within the list. This facilitated the identification of relevant words for each application. Each word and its corresponding frequency distribution were placed into a data frame. The sentiments were extracted from the data frames and analysed. The Valence Aware Dictionary for Sentiment Reasoning (VADER) model was used as the sentiment analyser. Words with compound exposure of 0.5 or -0.5 based on their polarity property of VADER were combined to form the list of sentimental words with their positive and negative sentimental intensity. The combined words were split into their respective positive and negative sentiments and the polarity of each app was calculated.

*K-Means* clustering approach was used to assess the relationship between persuasive systems features and their respective sentiments. The Elbow method for selecting the optimal *k* clusters produced *6* clusters as the optimal number of clusters. The dataset was fitted on *K-Means* where *n\_clusters = 6* and *random\_state = 42*. The predicted outcome of the computation was retrieved and analysed.

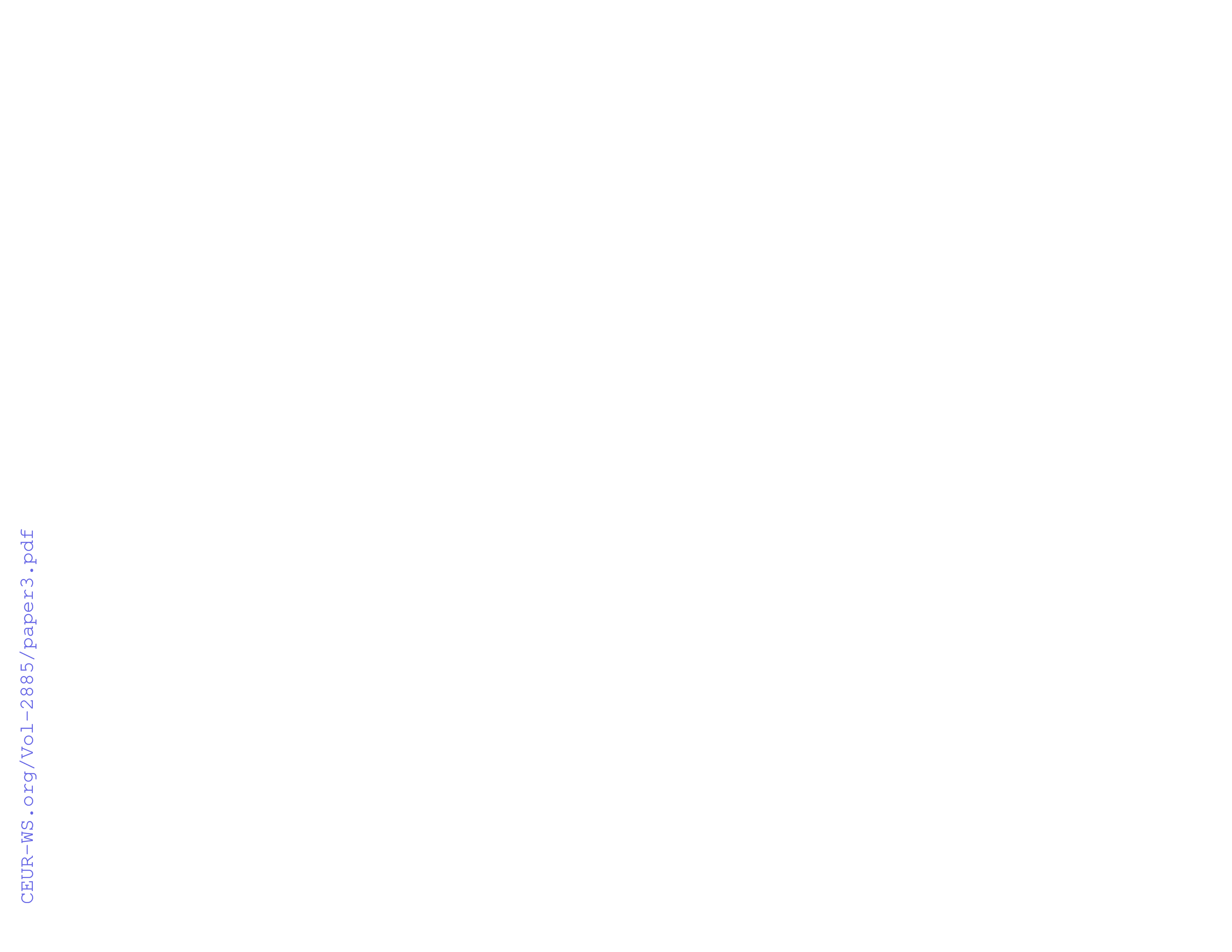
# Findings and Discussion

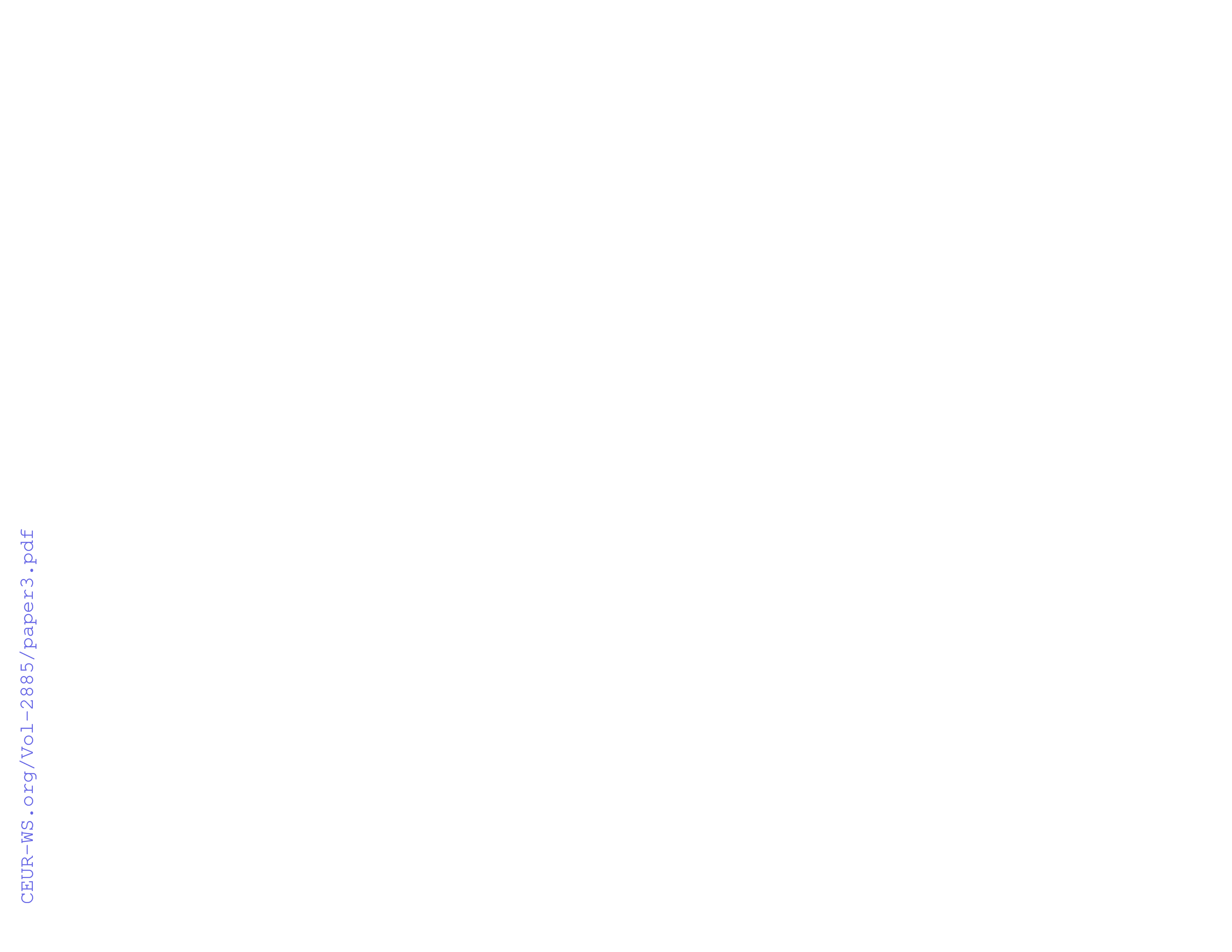
## Characteristics of Selected Apps

Findings from the persuasive feature extraction demonstrated that no application used all the 28 persuasive systems features. However, Primary Task support was dominant in health and fitness applications. With regard to Dialogue support features, 18 out of the 23 applications used Reminders and 20 used Suggestion. These were the two most used Dialogue support feature. In most cases, applications that used reminders also used suggestions. Praise (11), rewards (10) and social role (12) were averagely used. A notable observation in the evaluation of Credibility support features was that there was a relationship between the presence of trustworthiness and surface credibility. Trustworthiness was present in 22 out of the 23 applications evaluated whereas surface credibility was present in 21. Third-party endorsement (6) and authority (4) were sparingly used. Overall, Social support features were the least adopted features. Social learning was observed in 16 applications and 10 used social facilitation. Normative influence (9), cooperation (6), social comparison (5), recognition (4), and competition (2) were barely used. Refer to table 3 for a complete list of persuasive systems features identified in the 23 mobile health and fitness apps evaluated. These findings revealed that Primary Task support features are dominant in mobile health apps and this confirms current knowledge [11], [28]. Also, Social support features are sparingly used. Similar claims have been made on a study that investigated persuasive system features of e-commerce platforms [28].

## Relationship between Sentiments and System Features

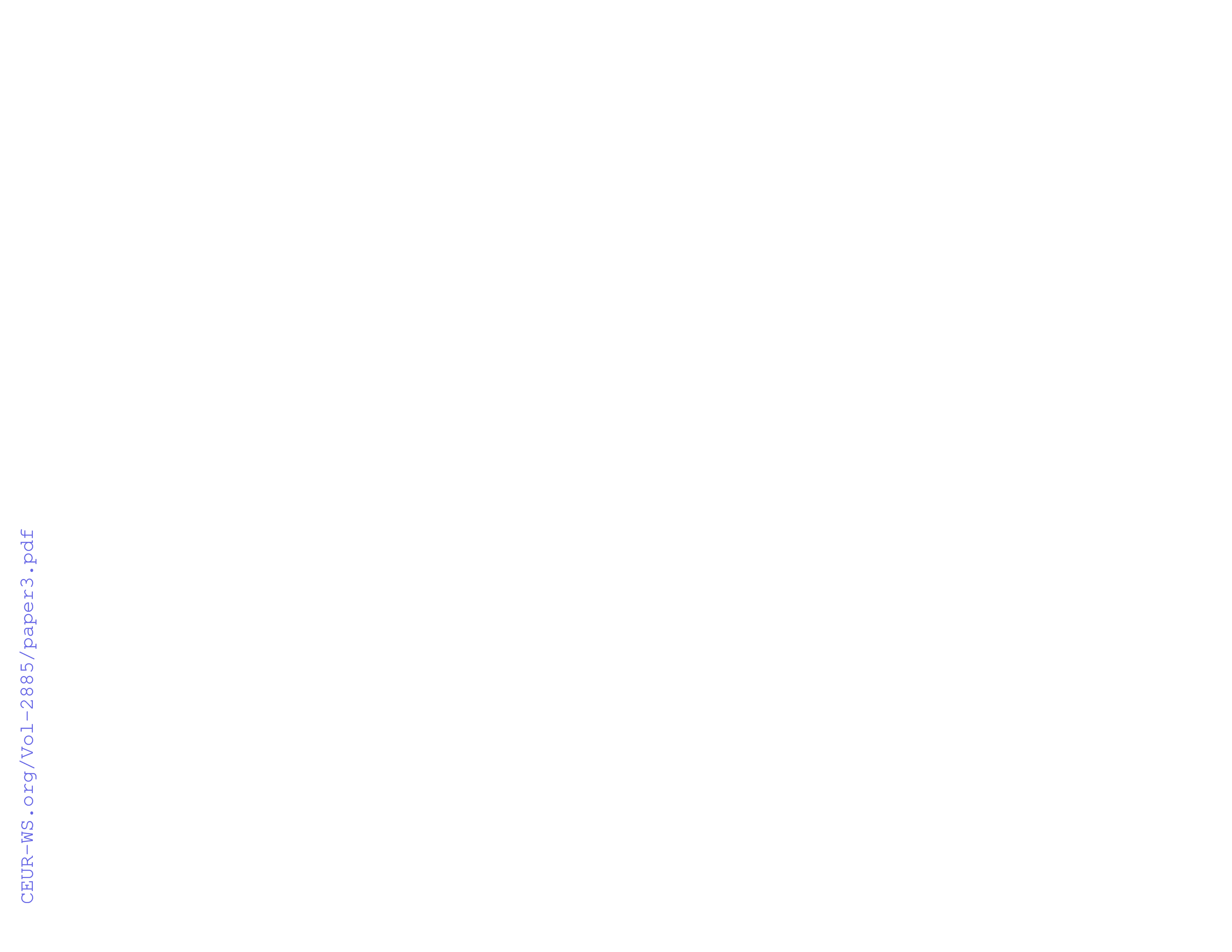
It was observed that applications including WalkingApp *(app2)*, Step Counter *(app3)*, Headspace *(app5)*, Calorie Counter by FatSecret *(app6)*, Running Distance Tracker + *(app8)*, Daily Yoga *(app9)*, Pregnancy & Baby Tracker *(app10)*, HidrateSpark Smart Bottle *(app188)*, Jillian Michaels Fitness App *(app19)*, Six Pack in 30 Days *(app22)* and Plant Nanny *(app23)* were in one cluster (i.e., C1). See table 3 for a list of the various apps and the corresponding clusters labelled as C1 to C6. This cluster set was characterized by a high frequency of Primary task support features including reduction, tunnelling, tailoring, personalization and self-monitoring. Simulation and rehearsals were present, however, they had lower frequencies. With regard to dialogue support features, praise, reminders, suggestion and social role were present with high frequencies whilst rewards had a low frequency. For Credibility support, high frequencies were observed for trustworthiness, expertise, surface credibility, real-world feel and verifiability whilst authority and third-party endorsement had lower frequencies. All seven (7) features within Social support were present in this cluster (i.e., C1), however, they were marginally represented. Again, in terms of opinion sentiments, this group of mobile applications had higher positive sentiment values except for Headspace *(app5)* which record a low positive sentiment.

Walking for Weight Loss *(app4)*, Workout Tracker & Gym Trainer *(app11)*, Abs workout *(app15)* formed a cluster (i.e., C2). This group of apps were characterized by a high frequency of Primary support features including reduction, tunnelling, tailoring, personalization and self-monitoring. Simulation and rehearsals were however absent within this cluster. Dialogue support features such as reminders and suggestions had the highest frequencies compared to praise, rewards and social role. Trustworthiness was the only feature within Credibility support with the highest frequency, followed by expertise and surface credibility. Real-world feel had the lowest frequency. Authority, third party endorsement and verifiability were absent within this cluster. For Social support features, social learning was the only feature present, and it had a high frequency. In terms of opinion sentiments, this cluster also had a higher positive sentiment value compared to negative sentiment value.

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**Table 2** Classification of Emotional Words used for the emotional sentiments

|  |  |
| --- | --- |
|  | Synonyms & relatable words |
| Liking | affection, adoration, fondness, fond, liking, like, attraction, attracted, attract, caring, care, tenderness, tender, compassion, sentimentality, sentiment, lust, sexual lovely, excellent, good, loved, adore, best, perfect, magnificence, magnificent, yummy, love, wonderful, cheerfulness, cheerful, cheer, amusement, amuse, amuse jolly, joviality, delight, enjoyment, glad, gladness, happiness, happy, jubilation, elation, elating, satisfaction, satisfying, satisfied, ecstasy, euphoria, zest, enthusias exhilaration, exhilarating, content, contentment, pleasure, pride, triumph, optimism, optimistic, eager, eagerness, hope, enthrallment, rapture, relief, beautiful, enjo |
| Trust | trust, comfort, comfortable, encourage, encouraging, marvellous, marvel, kudos, thankful, perfect, perfection, friendly, friend, friendliest, ideal, flawless |
| Anger | Irritability, irritating, irritated, irritation, aggravation, agitation, agitated, annoyed, annoyance, annoying, grumpy, crosspatch, exasperation, frustration, rage, raging, annoy, anger, outrage, outraged, fury, wrath, hostility, hostile, ferocity, bitter, bitterness, hate, hatred, scorn, spite, vengeful, dislike, disliking, disliked, resent, resenting, resentment, disgusting, disgust, revulsion, contempt, loathing, loathe, envy, jealous, jealousy, torment, tormenting, idiot, suck, sucker, loser, |
| Sadness | Sad, suffer, suffering, pain, painful |
| Fear | Horror, alarm, alarming, shocking, shock, fear, fearful, terror, panic, hysteria, mortification, nervous, nervousness, anxious, anxiety, suspense, uneasy, uneasiness, suspenseful, apprehension, apprehend, worry, worrying, distress, distressful, dread, dreadful, danger, dangerous, fraud, hell, scam, stress, stressing, stressful |

,

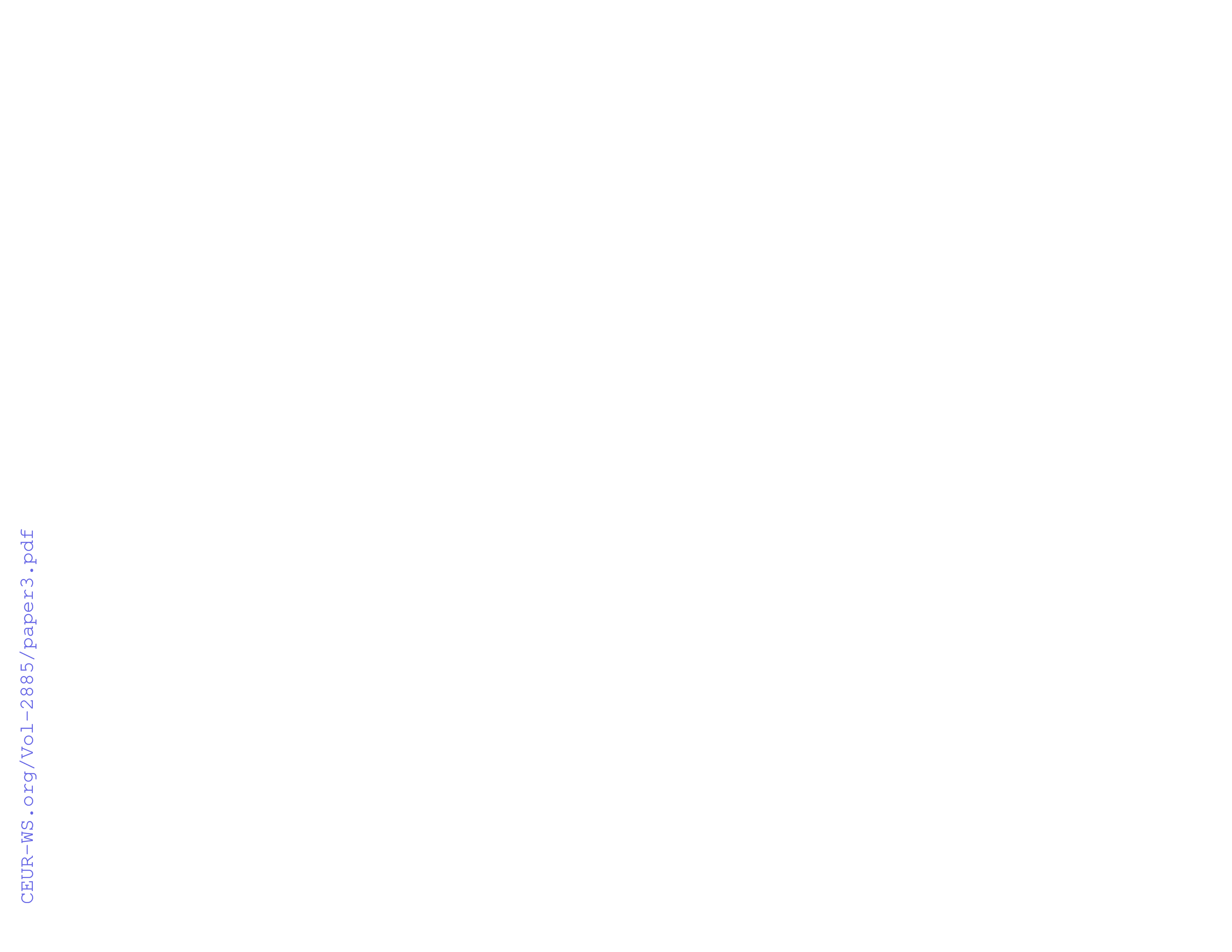
**Table 3:** The Intensity of Emotional and Opinion Sentiments

**Features/App ID** 2 3 5 6 8 9 10 18 19 22 23 4 11 15 16 20 17 21 1 7 12 13 14

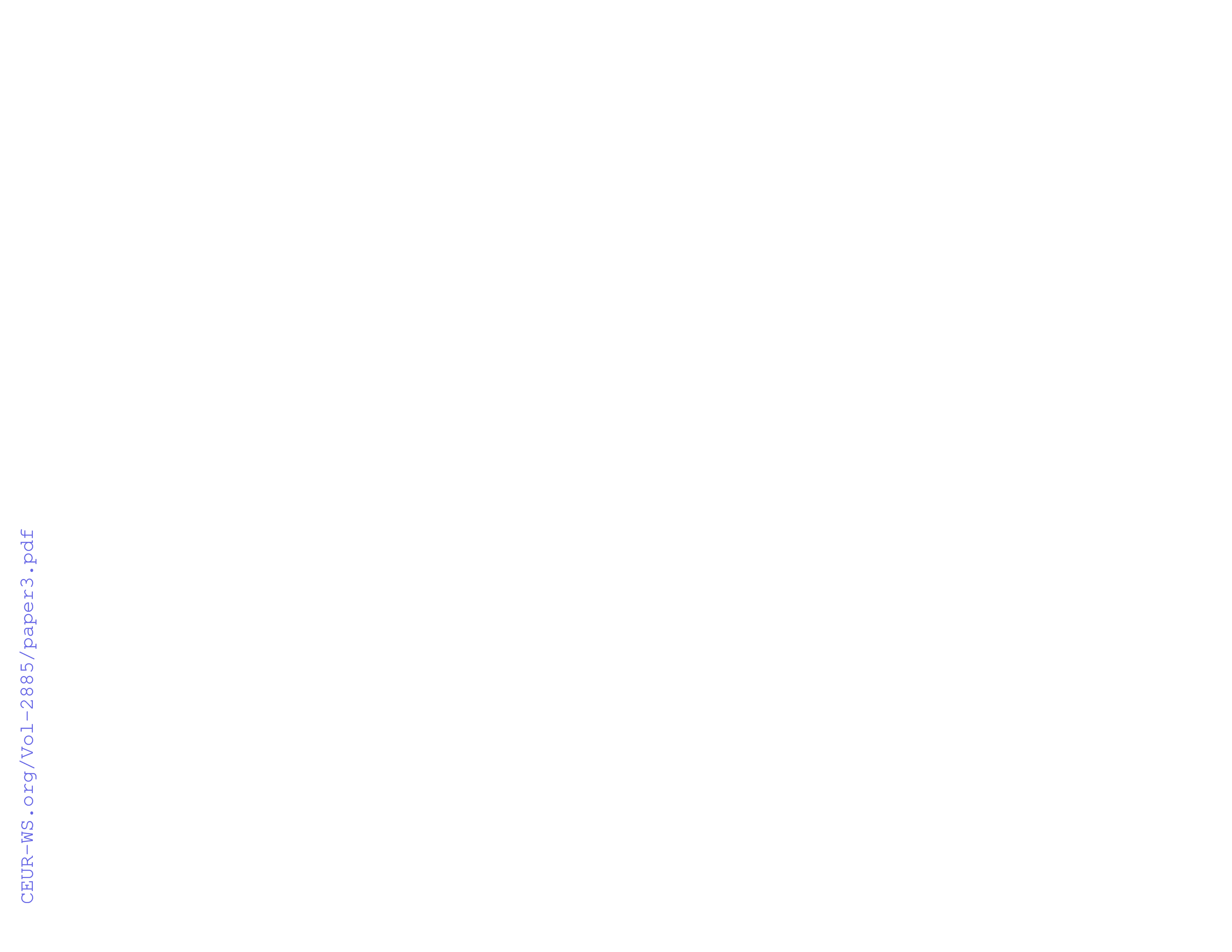
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Primary Task**      **Support** | Reduction |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 21 |
| Tunnelling |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 20 |
| Tailoring |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 21 |
| Personalization |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 21 |
| Self-monitoring |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 19 |
| Simulation |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 4 |
| Rehearsal |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 3 |
| **Di-**  **a-**  **logue** | Praise |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 11 |
| Rewards |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 10 |

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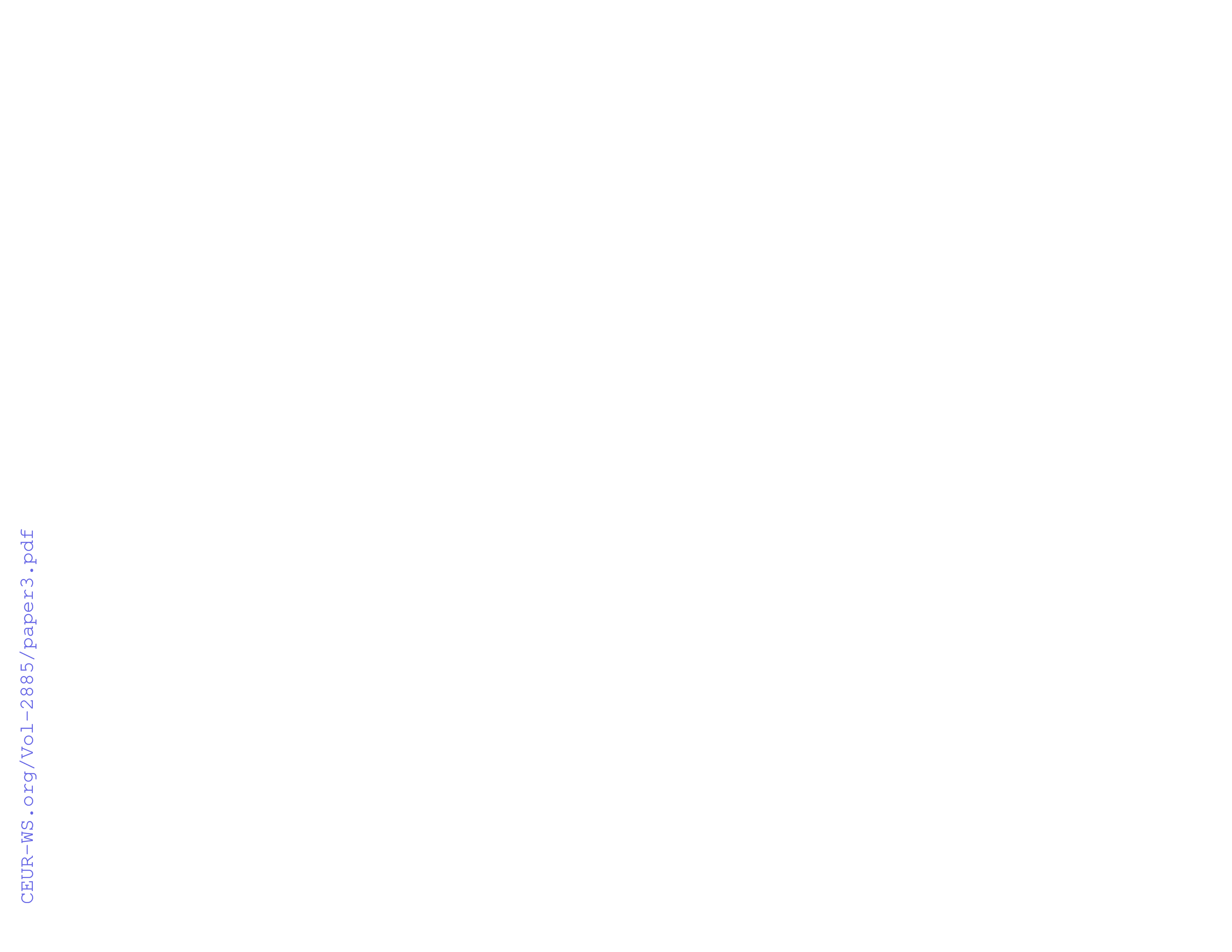
 **Features/App ID** 2 3 5 6 8 9 10 18 19 22 23 4 11 15 16 20 17 21 1 7 12 13 14

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Reminders |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 18 |
| Suggestion |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 19 |
| Social role |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 11 |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Expertise |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 15 |
| Surface credibility |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 21 |
| Real-world feel |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 11 |
| Authority |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 3 |
| 3rd party endorsement |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 5 |
| Verifiability |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 10 |
| **Social Support** | Social learning |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 13 |
| Social comparison |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 5 |
| Normative influence |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 8 |
| Social facilitation |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 9 |
| Cooperation |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 5 |
| Competition |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 2 |
| Recognition |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 3 |
| **Sentiments** | Liking (%) | 19.6 | 22.9 | 14.1 | 21.3 | 20.6 | 18.2 | 23.0 | 23.9 | 24.6 | 17.5 | 21.6 | 32.8 | 50.0 | 29.2 | 56.3 | 42.4 | 36.5 | 43.6 | 30.6 | 33.7 | 20.0 | 26.5 | 25.0 |  |
| Trust (%) | 5.0 | 5.7 | 2.9 | 5.0 | 6.7 | 5.3 | 6.7 | 8.0 | 8.5 | 4.4 | 5.4 | 7.5 | 10.7 | 8.3 | 3.1 | 3.0 | 6.4 | 2.6 | 6.7 | 8.4 | 4.8 | 6.8 | 9.8 |
| Anger (%) | 10.5 | 9.9 | 9.1 | 8.9 | 7.2 | 7.1 | 7.3 | 11.4 | 10.2 | 8.4 | 7.0 | 9.0 | 7.1 | 8.3 | 3.1 | 3.0 | 4.8 | 2.6 | 9.3 | 6.3 | 8.3 | 4.8 | 5.4 |
| Sadness (%) | 4.1 | 3.1 | 5.6 | 4.0 | 5.0 | 3.1 | 2.8 | 6.8 | 4.2 | 4.7 | 3.2 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 3.2 | 2.6 | 4.0 | 2.1 | 3.9 | 5.4 | 4.4 |
| Fear (%) | 2.7 | 3.7 | 3.7 | 3.5 | 2.2 | 4.0 | 2.8 | 1.1 | 1.7 | 4.0 | 3.8 | 6.0 | 3.6 | 5.2 | 3.1 | 6.1 | 0.0 | 0.0 | 2.7 | 2.1 | 3.5 | 2.0 | 4.4 |
| **Positive (%)** | 61.8 | 66.7 | 46.7 | 60.4 | 65.6 | 64.4 | 65.7 | 60.2 | 66.9 | 59.6 | 62.7 | 64.2 | 85.7 | 75.0 | 90.6 | 72.7 | 79.4 | 84.6 | 65.3 | 72.6 | 60.4 | 72.1 | 64.1 |

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**Features/App ID** 2 3 5 6 8 9 10 18 19 22 23 4 11 15 16 20 17 21 1 7 12 13 14

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **Negative (%)** | 38.2 | 33.3 | 53.3 | 39.6 | 34.4 | 35.6 | 34.3 | 39.8 | 33.1 | 40.4 | 37.3 | 35.8 | 14.3 | 25.0 | 9.4 | 27.3 | 20.6 | 15.4 | 34.7 | 27.4 | 39.6 | 27.9 | 35.9 |  |
|  |  | **C1** | | | | | | | | | | | **C2** | | | **C3** | **C4** | **C5** | | **C6** | | | | |

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Ideal Weight *(app1)*, Cycling – bike tracker *(app7),* Water Drink Reminder *(app12),* Step Counter – Calorie Counter *(app13)* and Weight Loss Running *(app14)* were found to have higher frequencies of tailoring, personalization and self-monitoring as primary support features. In this cluster (i.e., C6) however, simulation had the lowest frequency and rehearsal was absent. Dialogue support features including rewards, reminders and suggestions were marginally present with reward having the lowest frequency. Also, praise and social role features were absent. With regard to Credibility support, expertise, real-world feel, authority and verifiability were absent while trustworthiness and surface credibility were present with high frequencies. See table 3 for details of the various clusters and their corresponding sentiments (clusters are differentiated with different fills and patterns).

## Implication of Study

Generally, the findings revealed that health and fitness apps are popular since user reviews are mostly positive. Almost all the apps had high positive sentiments. Some applications recorded positive sentiments above 90% and this is promising for HBCSS research and practice. With regard to emotional sentiments (i.e., Liking, Trust, Anger, Sadness and Fear), the findings revealed that most users expressed some form of likeness for the apps. Sentiment words that exhibit likeness were observed in most of the reviews. However, an analysis of the various clusters of apps in relation to system features showed that the provision of more persuasive features does not guarantee favourable sentiments from users. This is because, apps that had more system features did not record higher emotional sentiments. For instance, Pocket Yoga (*app16*) had only one persuasive feature (i.e., reduction), yet it recorded the highest emotional sentiment intensity. Also, it had the highest positive sentiment intensity. It recorded lower ratings for Trust, Anger, Fear, and Sadness. This demonstrates that although the absence of Credibility support features leads to a lack of trust, credibility support has less impact on application acceptance (likeness). Also, the presence of more features does not guarantee specific sentiments (i.e., no clear pattern between system features and sentiments). It can be argued that the presence of more persuasive features rather provides users with the opportunity to assess each functionality as compared to fewer features. Hence, applications with more persuasive features appear complex to users and therefore do not attract high sentiments of likeness.

The study also revealed that the presence or absence of Credibility support features does not guarantee trust in user sentiments. Considering that Credibility support features seek to promote system trust, this finding is worrying. It was observed that apps including WalkingApp *(app2)*, Headspace *(app5)*, and HidrateSpark Smart Bottle *(app18)* had relatively high Credibility support features, yet they recorded lower trust sentiments when compared to Cycling - Bike Tracker *(app7)* and Weight Loss Running by Verv *(app14)*. It was also observed that applications that had more Social support features had more sentiment words that demonstrate anger, fear and sadness when compared to those with no or less social support features. For instance, apps such as WalkingApp *(app2)*, Headspace *(app5)*, HidrateSpark Smart Bottle *(app18)*, and Six Pack in 30 Days *(app22)* had more social support features present and they also recorded Ninth International Workshop on Behavior Change Support Systems (BCSS 2021): 37 E*xploring the Impact of Persuasive System Features on User Sentiments in Health and Fitness Apps* higher sentiment words when compared to Cycling - Bike Tracker *(app7)*, Water Drink Reminder *(app12)*, Step Counter - Calorie Counter *(app13)*, and Weight Loss Running by Verv *(app14)* that had less Social support features.

# Conclusion

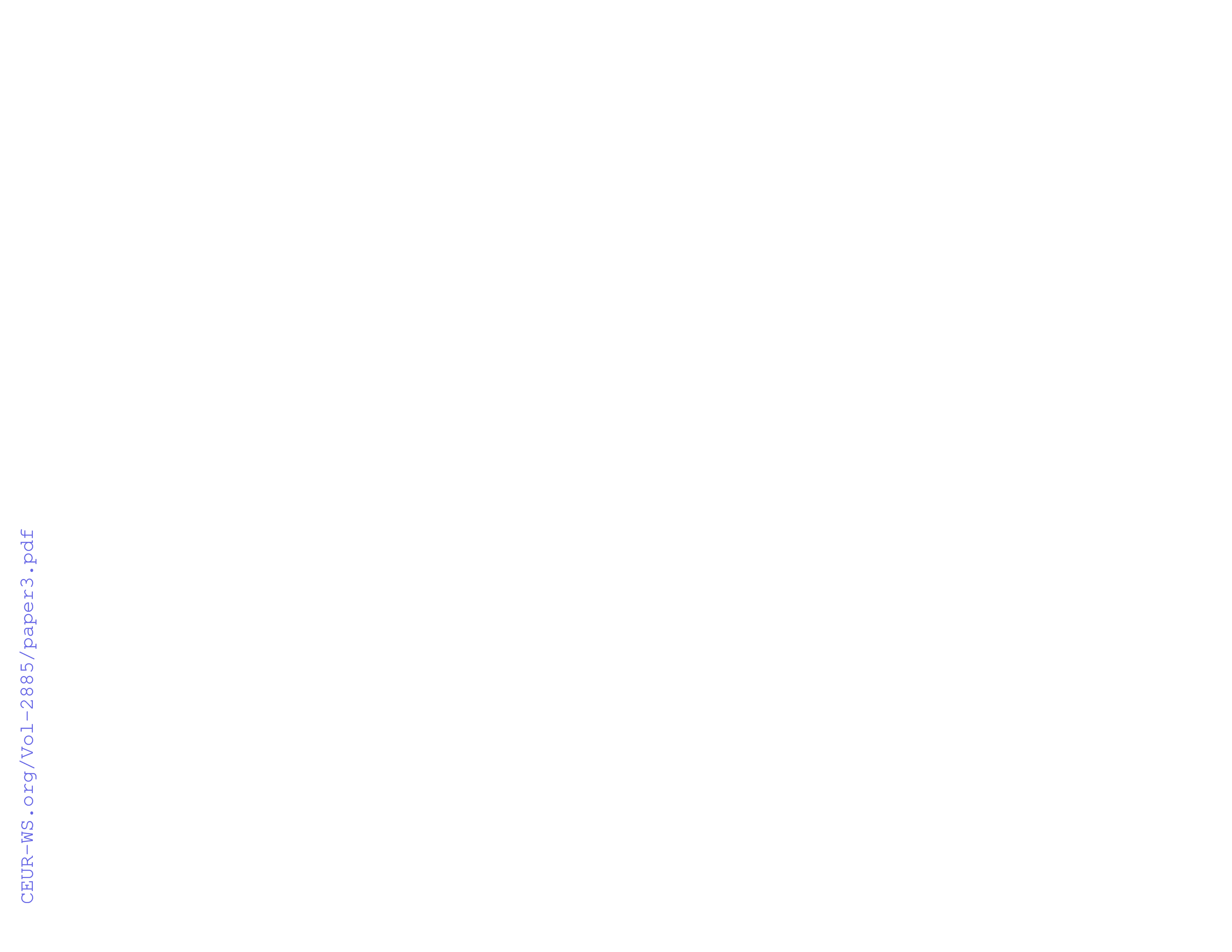
This study presents findings from an investigation of the relationship between user sentiments and persuasive system features. It adopted a stratified random sampling technique to select health and fitness apps on the Android and iOS markets. The sentiments of app users were extracted and compared with systems features that are available in each app using clustering techniques. The results demonstrated that the provision of more persuasive features does not guarantee favourable sentiments from users. Particularly, it was observed that apps with less system features attracted more sentiments relating to likeness. Also, it was observed that Social support features mostly promote negative emotions such as anger, fear and sadness. Perhaps, these findings corroborate with existing knowledge that argues that the presence of persuasive system features in Health Behaviour Change Support Systems (HBCSSs) do not necessitate the sufficiency or efficiency of the system [13]. More importantly, there is a need for further investigation to be conducted to explain the causal effects of this phenomenon. Particular attention must be given to the type and structure of messages used in conveying the various persuasive features. This is because although designers of persuasive applications may convey the intention to change in their messages, the messages may generate an emotional shift from their intentions.

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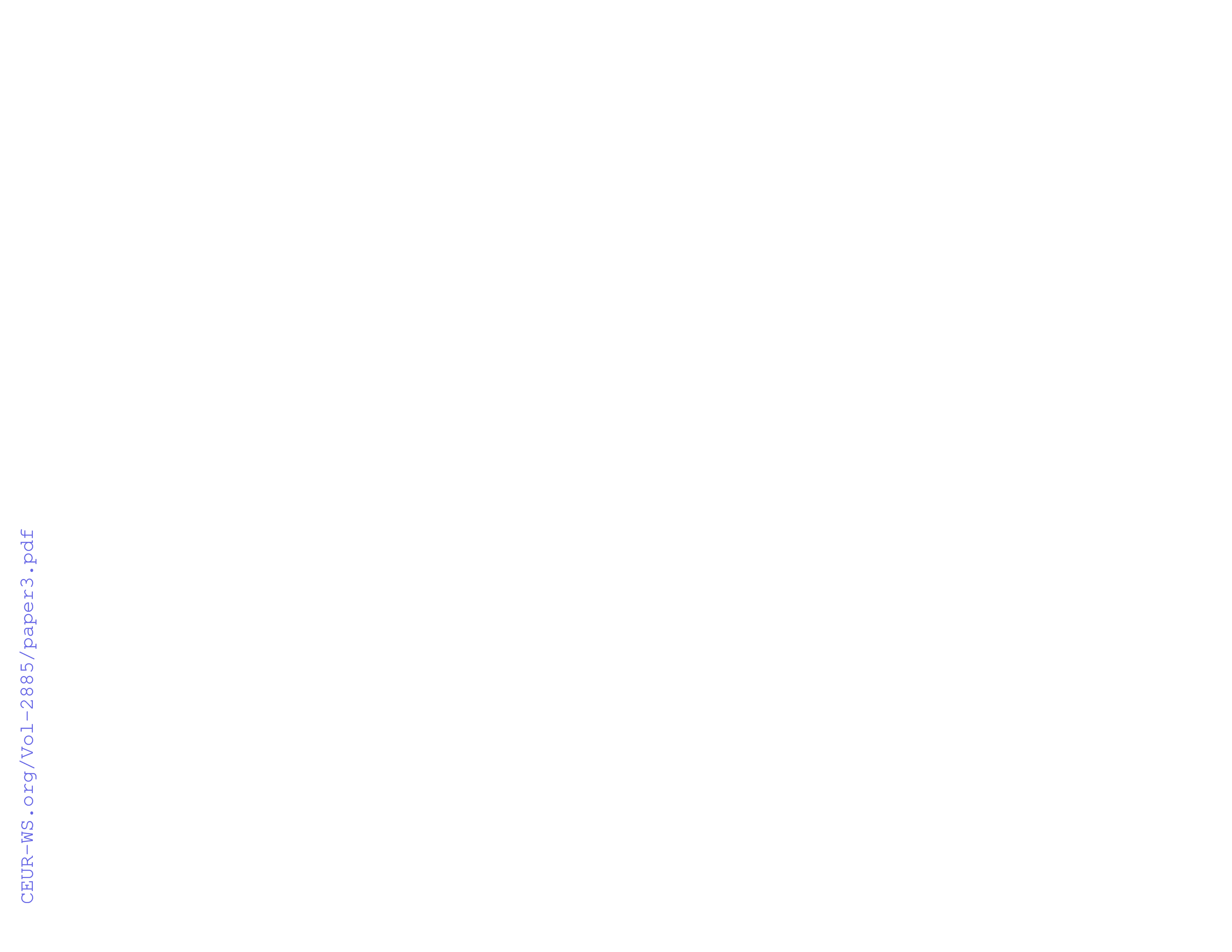
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## **APPENDIX B**

Figure B‑1: Bar Graph Representation of PSD features in selected traveling apps

Figure B‑2: Bar Graph Representation of PSD features in selected health & fitness apps