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

Charles Nutrokpor[1] [0000- 0002-9155-4556], Akon O. Ekpezu[2] [0000-0002-9502-1052], Abigail Wiafe[3] [0000 -0001-6019-6074], and Isaac Wiafe [2] [0000-0003-1149-3309]

[1]Department of Computer Science, University of Ghana, Accra, Ghana
[2]Faculty of Information Technology and Electrical Engineering, University of Oulu, Finland
[3]School of Computing University of Eastern Finland, Joensuu, Finland
iwiafe@ug.edu.gh

**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

## 1 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.

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.

## 2 Background Literature

### 2.1 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.

### 2.2 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.

### 2.3 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 web-based 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.

## 3 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.

### 3.1 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*.

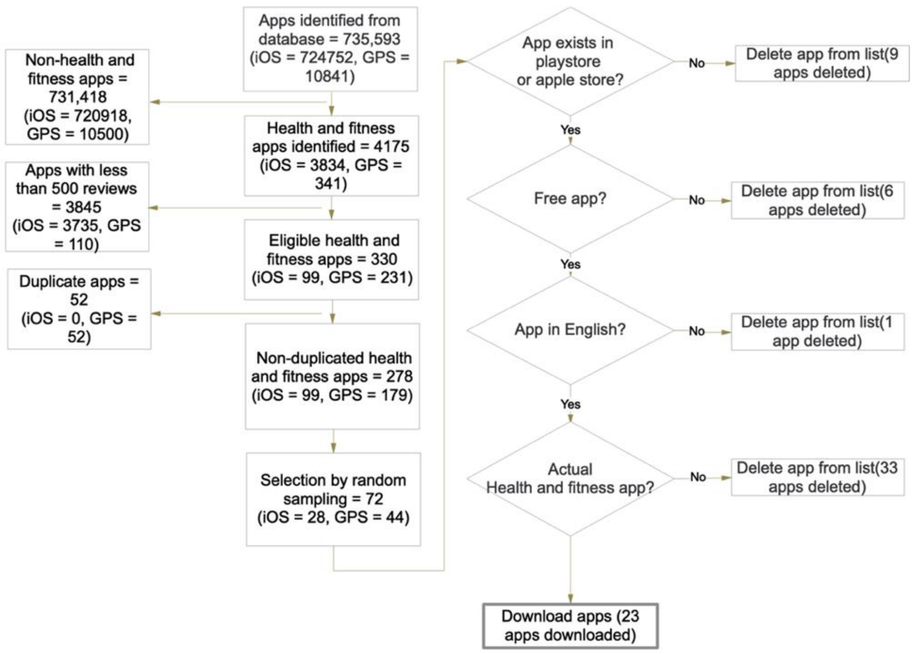


**Fig. 1.** Procedure for selecting apps

### 3.2 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 |
| 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 Reminder | | |

### 3.3 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.

# 4 Findings and Discussion

## 4.1 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].

### 4.2 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.

**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, amus jolly, joviality, delight, enjoyment, glad, gladness, happiness, happy, jubilation, elation, elating, satisfaction, satisfying, satisfied, ecstasy, euphoria, zest, enthusia exhilaration, exhilarating, content, contentment, pleasure, pride, triumph, optimism, optimistic, eager, eagerness, hope, enthrallment, rapture, relief, beautiful, enj |
| 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 |

| | **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 |
| **System Credibility Support** | **Trustworthiness** | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ | | ■ | | ■ | ■ | ■ | ■ | ■ | ■ | 21 |
| | 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 | |

| **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** | | | | |

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).

### 4.3 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 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.

## 5 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.

## References

1. H. Oinas-Kukkonen and M. Harjumaa, “Persuasive systems design: Key issues, process model, and system features,” *Communications of Association of Information Systems*, vol. 24, no. 1, p. 28, 2009.
2. I. Wiafe, F. N. Koranteng, F. A. Kastriku, and G. O. Gyamera, “Assessing the impact of persuasive features on user’s intention to continuous use: the case of academic social networking sites,” *Behaviour and Information Technology*, vol. 0, no. 0, pp. 1–19, 2020, doi: 10.1080/0144929X.2020.1832146.
3. J. Dabi, I. Wiafe, A. Stibe, and J. D. Abdulai, “Can an enterprise system persuade? The role of perceived effectiveness and social influence,” in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 10809 LNCS, 2018, pp. 45–55.
4. T. Lehto and H. Oinas-Kukkonen, “Explaining and predicting perceived effectiveness and use continuance intention of a behaviour change support system for weight loss,” *Behaviour and Information Technology*, vol. 34, no. 2, pp. 176–189, 2015, doi: 10.1080/0144929X.2013.866162.
5. I. Wiafe, M. M. Alhammad, K. Nakata, and S. R. Gulliver, “Analyzing the persuasion context of the persuasive systems design model with the 3D-RAB

model," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2012, vol. 7284 LNCS, pp. 193–202, doi: 10.1007/978-3-642-31037-9_17.
6. I. Wiafe, "The Role of U-FADE in Selecting Persuasive System Features," *Encyclopedia of Information Science and Technology (4th ed.)*. pp. 7785–7795, 2017, doi: 10.4018/978-1-5225-2255-3.ch677.
7. I. Adaji and J. Vassileva, "Perceived effectiveness, credibility and continuance intention in e-commerce: a study of Amazon," in *International Conference on Persuasive Technology*, 2017, pp. 293–306.
8. K. Oyibo, R. Orji, and J. Vassileva, "Investigation of the social predictors of competitive behavior and the moderating effect of culture," *UMAP 2017 - Adjun. Publ. 25th Conf. User Model. Adapt. Pers.*, no. October, pp. 419–424, 2017, doi: 10.1145/3099023.3099113.
9. D. DeSteno, D. T. Wegener, R. E. Petty, D. D. Rucker, and J. Braverman, "Discrete Emotions and Persuasion: The Role of Emotion-Induced Expectancies," *J. Pers. Soc. Psychol.*, vol. 86, no. 1, pp. 43–56, 2004, doi: 10.1037/0022-3514.86.1.43.
10. B. J. Fogg, "A behavior model for persuasive design," *Proc. 4th Int. Conf. Persuas. Technol. - Persuas. '09*, p. 1, 2009, doi: 10.1145/1541948.1541999.
11. S. Langrial, T. Lehto, H. Oinas-Kukkonen, M. Harjumaa, and P. Karppinen, "Native mobile applications for personal wellbeing: A persuasive systems design evaluation," in *Proceedings - Pacific Asia Conference on Information Systems, PACIS 2012*, 2012, no. January.
12. I. Wiafe and K. Nakata, "A Semiotic Analysis of Persuasive Technology: An Application to Obesity Management," 2012.
13. T. Lehto and H. Oinas-Kukkonen, "Examining the Persuasive Potential of Web-based Health Behavior Change Support Systems," *AIS Trans. Human-Computer Interaction.*, vol. 7, no. 3, pp. 126–140, 2015, doi: 10.17705/1thci.00069.
14. T. Lehto, H. Oinas-Kukkonen, and F. Drozd, "Factors Affecting Perceived Persuasiveness of a Behavior Change Support System," in *Proceedings of the International Conference on Information Systems (ICIS)*, 2012, pp. 1–15.
15. R. E. Petty and J. T. Cacioppo, "The elaboration likelihood model of persuasion," *Adv. Exp. Soc. psychology*, vol. 19, pp. 123–205, 1986.
16. G. J. Stigler, "The economics of information," *J. Polit. Econ.*, vol. 69, no. 3, pp. 213–225, 1961, doi: 10.1300/J111v26n01_07.
17. P. Ekman, "Basic emotions. Handbook of cognition and emotion," in *Handbook of Cognition and Emotion*, New York, New York, USA: John Wiley & Sons, Ltd, 1999, pp. 301–320.
18. D. Keltner and J. S. Lerner, "Emotion.," in *Handbook of social psychology, Vol. 1, 5th ed.*, Hoboken, NJ, US: John Wiley & Sons, Inc., 2010, pp. 317–352.
19. J. So, C. Achar, D. H. Han, N. Agrawal, A. Duhachek, and D. Maheswaran, "The psychology of appraisal: Specific emotions and decision-making," *J. Consum. Psychol.*, vol. 25, no. 3, pp. 359–371, 2015, doi: 10.1016/j.jcps.2015.04.003.
20. W. N. W. Ahmad and N. M. Ali, "Engendering trust through emotion in

designing persuasive application," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 8237 LNCS, 2013, pp. 707–717.

21. J. P. Dillard and R. L. Nabi, "The persuasive influence of emotion in cancer prevention and detection messages," *J. Commun.*, vol. 56, no. 2006, pp. 123–139, 2006, doi: 10.1111/j.1460-2466.2006.00286.x.
22. R. L. Nabi, "Emotional Flow in Persuasive Health Messages," *Health Commun.*, vol. 30, no. 2, pp. 114–124, 2015, doi: 10.1080/10410236.2014.974129.
23. W. N. W. Ahmad and N. M. Ali, "Trust perceptions in using persuasive technologies," in *3rd International Conference on Computer and Information Sciences, ICCOINS 2016 - Proceedings*, 2016, pp. 49–53, doi: 10.1109/ICCOINS.2016.7783187.
24. K. Halttu and H. Oinas-Kukkonen, "Persuading to Reflect: Role of Reflection and Insight in Persuasive Systems Design for Physical Health," *Human-Computer Interact.*, vol. 32, no. 5–6, pp. 381–412, 2017, doi: 10.1080/07370024.2017.1283227.
25. W. N. W. Ahmad and N. M. Ali, "A Study on Persuasive Technologies: The Relationship between User Emotions, Trust and Persuasion," *Int. J. Interact. Multimed. Artif. Intell.*, vol. 5, no. 1, pp. 57–61, 2018, doi: 10.9781/ijimai.2018.02.010.
26. P. Indraratna *et al.*, "Mobile phone technologies in the management of ischemic heart disease, heart failure, and hypertension: systematic review and meta-analysis," *JMIR mHealth uHealth*, vol. 8, no. 7, 2020, doi: 10.2196/16695.
27. K. T. Win, M. R. H. Roberts, and H. Oinas-Kukkonen, "Persuasive system features in computer-mediated lifestyle modification interventions for physical activity," *Informatics Heal. Soc. Care*, vol. 44, no. 4, pp. 376–404, 2019, doi: 10.1080/17538157.2018.1511565.
28. M. M. Alhammad and S. R. Gulliver, "Persuasive technology and users' acceptance of e-commerce: users' perceptions of website persuasiveness," *J. Electron. Commer. Organ.*, vol. 12, no. 2, pp. 1–13, 2014.