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Analyzing User Reviews on Digital Detox Apps: A Text Mining and Sentiment Analysis Approach

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ABSTRACT

Due to the growing concerns around problematic smartphone use and its negative impact, there is a rising interest in digital detox. While many digital detox apps have been developed in recent years, there is still limited understanding of the long-term effectiveness of digital detox applications and the attitude of people towards these apps. This study fills this gap by identifying the topics that people post in their reviews on the Google Play Store about digital detox apps and the emotion-based sentiment of those reviews. A total of 3500 reviews of 25 digital detox apps were collected from the Google Play Store using a scraping tool called "Parsehub." Data was analyzed using R studio. Sentiment analysis results suggest that positive sentiments dominated the data frame. "Trust" and "anticipation" were the two most expressed emotions in the reviews. Regression analysis confirmed that sentiment scores could explain the ratings of the apps. Through LDA topic modeling four major topics of the reviews were identified and are discussed in detail in the later section of the research paper. The findings of this study may help app developers and marketers improve digital detox apps so that people can learn and practice mindful smartphone use with the help of these apps. This study fills a gap in digital detox research by adopting a new methodological approach and procedure since it combines text mining, sentiment analysis (NRC Lexicon using Syuzhet package), regression analysis, and LDA topic modeling. To the best of our knowledge, this is the first study which uses this research approach in the context of digital detox apps.

1 | Introduction

Smartphones have become an integral part of our daily lives since the emergence of the mobile internet era. There has been a progressive shift in the primary uses of mobile phones from phone calls and text messaging to smartphone apps (Fu et al. 2020). In just 5 years, smartphone connections have doubled globally. As of January 2023, there were 229 commercial 5G networks around the world and over 700 5G smartphone models have been launched. By 2030, it is projected that there will be 9 billion smartphone connections, representing 92% of total connections (GSMA 2023). Despite the many benefits smartphones provides, they also come with serious problems that can have a negative effect on a person's mental, physical, and social health (Khan and Khan 2022; Al-Amri et al. 2023; Ge et al. 2023). The rapid increase in global smartphone usage has led to widespread smartphone addiction, identified as an *epidemic* around the world and a rising public health issue requiring special attention (Sullivan and Reiner 2021; Olson et al. 2022).

As smartphones become more integrated into our daily lives, there is a rising interest in digital detox for smartphone users (Nguyen, Büchi, and Geber 2024). Digital detox is a form of therapy that forbids the use of digital devices for a fixed amount of time (Dutt 2023). Various other terms such as "digital diet," "media diet," and "digital wellbeing" have been used to describe the same phenomenon (Nguyen, Büchi, and Geber 2024). However, "digital detox" has gained popularity and is widely used term in this context (Wilcockson, Osborne, and Ellis 2019; Abeele, Halfmann, and Lee 2022). Digital wellbeing or digital detox promotes the development of tools and strategies to help individuals establish a healthy relationship with technology (Alhassan and Adam 2021). Positive technology, also known as positive computing, serves as a kind of "digital coaching," assisting individuals in achieving their objectives and improving their personal and professional behavior (Ross et al. 2024). Creating such technology requires understanding design, psychology, and human-computer interaction. Since these solutions aim to improve wellbeing, they should be prioritized and considered a quality metric when developing digital media and technology (Diefenbach 2018).

Past studies have focused on interventions that encourage people not to use smartphones, such as raising the cost of interactions to deter people from using smartphone (Kim et al. 2019). Additional instances of interventions to discourage smartphone usage include the utilization of digital detox applications. These apps alerts users with information regarding their recorded usage data, prompting them to contemplate their usage patterns, particularly those that are problematic (Almoallim and Sas 2022; Vialle, Machin, and Abel 2023). Research in other fields has shown that self-monitoring smartphone applications have been found to be successful in reducing addiction to smoking (Garrison et al. 2020) and helps in maintaining a healthy diet and lifestyle (König et al. 2022; Semper, Povey, and Clark-Carter 2016). Technology as a behavior therapy tool has shown potential in addressing IT addiction (Schmuck 2020). Thus, if properly designed, IT-enabled behavioral interventions could effectively mitigate smartphone addiction (Lan et al. 2018; Santiago Walser et al. 2022). Despite growing academic interest in digital detox, research on its specific mechanisms and outcomes in improving individual and organizational success remains limited (Sharma and Sharma 2024). Most existing studies have analyzed the technical features of digital detox apps without examining user perceptions and the factors influencing attitudes toward these apps (Radtke et al. 2022). The perception of users regarding these applications and their impact on digital habits and behavior still remain unclear (Roffarello and De Russis 2023). Understanding consumer attitude towards available digital detox apps is crucial for developing effective digital detoxification tools. A significant gap exists in the literature regarding evaluating digital detox apps from the perspective of user sentiment and behavioral outcomes (Schmuck 2020). This gap underscores the need for a comprehensive analysis of user attitudes and the effectiveness of digital detox apps in promoting healthier smartphone usage habit. This study's novelty lies in its approach, which combines text mining, sentiment analysis, and Latent Dirichlet Allocation (LDA) topic modeling to evaluate user reviews of digital detox apps. This methodology allows a deeper understanding of users' emotional and cognitive responses to these apps, providing insights beyond traditional usability studies. By focusing on user-generated content from platforms like the Google Play Store, this research captures real-world perceptions and experiences, offering a nuanced view of the effectiveness of digital detox apps.

In tune with the above discussion, the present study specifically attempts to address the following research questions:

RQ1. What is the attitude of people towards digital detox apps?

RQ2. What emotions are commonly expressed in the reviews of digital detox apps?

RQ3. Can the sentiments expressed in reviews explain the ratings of digital detox apps?

RQ4. What are the most frequently mentioned topics in the reviews of digital detox apps?

RQ5. What areas need focus to improve digital detox apps?

RQ6. What factors determine the success and failure of digital detox apps?

By addressing these research questions, we intend to significantly contribute to the existing literature on digital detox. The anticipated contributions include an in-depth analysis of user attitudes toward digital detox apps and the identification of shared emotions and sentiments expressed in user reviews. Additionally, this research explores the relationship between user sentiments and app ratings, providing insights into how emotional responses shape perceptions of app effectiveness. This study will guide the development of more effective digital detox tools by identifying key topics and recurring themes in user reviews. Furthermore, it will highlight factors that contribute to both the success and failure of digital detox apps, presenting actionable recommendations for developers and policymakers. The insights gained from this research will assist businesses and policymakers in creating and promoting digital detox solutions that foster societal well-being and encourage balanced technology use.

The rest of this paper is structured as follows: Section 2 presents the background literature, followed by Section 3, which details the data collection and analysis methodology. Section 4 discusses the study's findings, and Section 5 offers a comprehensive discussion of the implications of the results. Finally, Section 6 concludes the paper with limitations of the study and future research directions.

2 | Literature Review

2.1 | Digital Detox

Problematic smartphone use can be characterized as the inability to control smartphone usage, resulting in detrimental effects on everyday life (Zhou et al. 2024). The ease of constant connectivity and the variety of applications offered by a smartphone causes addiction to smartphones when used in an unproductive manner (Ge et al. 2023). Although the specific problems related with the overuse of Internet and smartphone are not fully understood, but include: (a) psychological issues like procrastination, sleep disturbance, anxiety, poor memory, and lack of concentration; (b) social issues like relationship malfunction, and (c) physical issues like harm from accidents, and bad posture (Tian et al. 2021; Wacks and Weinstein 2021). In addition, a preponderance of research findings demonstrates that overuse of smartphone was associated with poor academic performance and lower work productivity (Amez and Baert 2020; Sunday, Adesope, and Maarhuis 2021).

There have been a number of technical and non-technical strategies for dealing with problematic smartphone use that are similar to those for limiting dietary or alcoholic intake. For instance, digital diets, in which individuals go a few days without their phone, are a common short-term strategy for breaking the habit of excessive smartphone use (Agha and Obinna 2023).

A digital detox is a deliberate break from smartphone usage for a predetermined amount of time that can be set by the individual. Digital detox applications may reduce the detrimental effects of social networking sites usage since they enable users to track and limit their smartphone usage and perform behavior modification interventions (Mirbabaie, Stieglitz, and Marx 2022).

Taking a break from technology can benefit one's total health, including spiritual, physical, mental, social, and environmental wellbeing. Additionally, it aids in fostering better connections with people (Vialle, Machin, and Abel 2023). There are many different motivations and inspirations that impact digital detox (Abeele, Halfmann, and Lee 2022). The idea of self-optimization is one of the reasons for engaging in digital detox. By doing so, people use software and technologies more effectively, thereby minimizing digital distractions. Other motivations include the concept of balance and awareness. The purpose of digital detox is to minimize distractions produced by constant connectivity to the digital world and to prevent stress caused by excessive use of technology (Burrill 2024). Nassen et al. (2023) stated that performance improvement, self-control, and well-being are the motivating factors behind engagement in digital detoxification.

2.2 | Text Mining

Text mining is an emerging technique that seeks to extract meaningful insights from unstructured textual data. It focuses on discovering models, trends, patterns, and rules from unstructured textual data (Antons et al. 2020; Barbierato, Bernetti, and Capecchi 2021; Hassan, Hudaefi, and Caraka 2021). It is claimed that text mining can produce fascinating results when applied to textual data, such as messages posted on social media sites like blogs and online forums (Liu et al. 2021). Abdous and He (2011) analyzed students' online queries using text mining techniques, and various technology-related difficulties and learning patterns were identified. Percha, Garten, and Altman (2012) employed text mining to extract the semantics of specific gene-drug relationships and to identify new drug–drug interactions. A framework was proposed for extracting business intelligence from blogs and Apple's iPod music player blog content was evaluated using text mining and content analysis (Chau and Xu 2012).

Link analysis, information extraction (text summarization) (Hassan, Hudaefi, and Caraka 2021; Trivedi and Singh 2021), and clustering (Sadeghi Moghadam et al. 2019) are some of the key uses of text mining. The SPSS Modeler, R software, Leximancer, SAS Enterprise Miner, and NVivo are just a few of the many tools available today for text mining and analysis. Opinions and sentiments voiced in blogs, web forums, and online stories were evaluated using text mining techniques (Feizollah et al. 2021).

2.3 | Sentiment Analysis

Sentiment analysis is a kind of contextual text mining technique that extracts information from internet sources to ascertain people's attitudes and opinions regarding business, people, or events (Birjali, Kasri, and Beni-Hssane 2021). It is a machine learning approach that employs NLP (Natural Language Processing) to determine the emotions represented by the writers of a particular text through their words (Barbierato, Bernetti, and Capecchi 2021). Sentiment analysis enables businesses in assessing the effectiveness of their marketing campaigns, quality of their goods and services, and in resolving problems before they become liabilities to the company. In other words, it can assist businesses in leveraging and gaining an appropriate competitive advantage over competitors (Trivedi and Singh 2021).

People frequently express their opinions online through reviews of various goods and services, voting opinions, writings in microblogs, providing feedback, and so forth. As there are abundant online resources available, information technology can be utilized to understand the perspectives of people (Li et al. 2020). Sentiment analysis offers the advantage of being more time and money effective when compared to more conventional market research techniques. Additionally, it is a non-intrusive technique for extracting real-time customer sentiments and opinions (Wankhade, Rao, and Kulkarni 2022).

In many classification techniques, the use of a lexicon has shown to be a constant. Originally studied in computer science, it is now employed in management information systems and business since it greatly aids businesses in making decisions based on how people perceive things (Al-Natour and Turetken 2020; Feizollah et al. 2021). Extant literature has shown that various domains, such as Amazon reviews and Twitter, have undergone sentiment analysis to evaluate customer sentiment. However, a comprehensive study of customer sentiments on reviews from other platforms such as Google Play store is still limited.

3 | Methodology

This section describes the data collection and data analysis approach used in the present study. Figure 1 depicts the methodological architecture of the study.

3.1 | Data Collection

We searched for digital detox apps on the Google Play Store, which is one of the most popular platforms for downloading apps for smartphones and other mobile devices. Google Play Store was chosen as a search medium due to its size and data accessibility compared to other app stores. Apps were searched using the terms “digital detox” and “digital wellbeing.” Further, the apps were selected after going through their descriptions to ensure that they focused on reducing smartphone usage and addiction. Only those apps were selected which aimed at addiction-related behavioral modifications. A total of 3500 reviews of digital detox/wellbeing apps were extracted from the Google Play Store using a scraping tool called “Pareshub.”

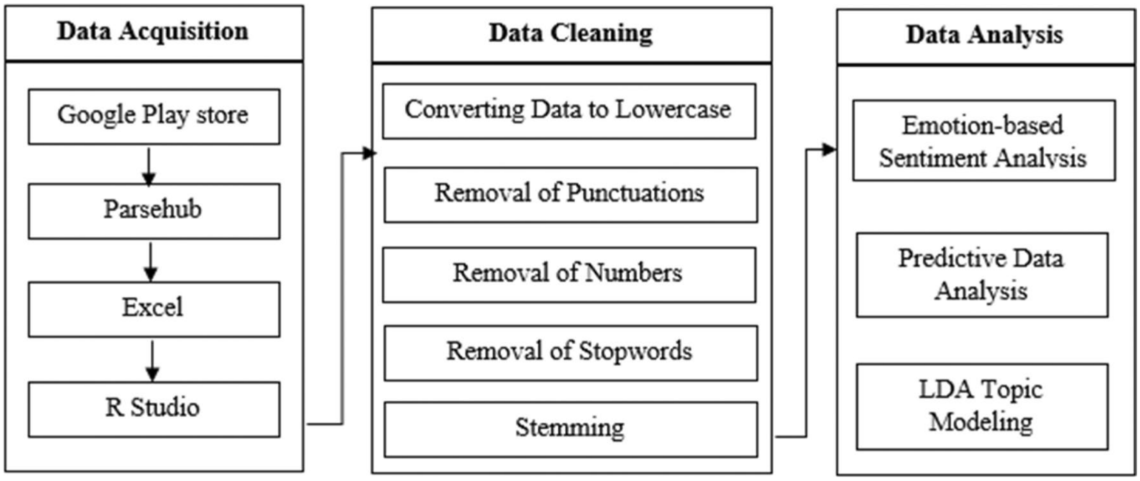

FIGURE 1 | Data collection and analysis process. *Source:* Prepared by researchers.

Parsehub can extract any piece of information, whether text or image. The output can be saved in either JSON or CSV format. We saved the data for this study in CSV format.

3.2 | Text Mining and Data Analysis

3.2.1 | Data Analysis via R-Studio

The analysis of the data started with data collection, pre-processing, cleaning, and visualization. After that, the two main sentiments, that is, positive and negative, along with their eight emotions, that is, anger, anticipation, disgust, fear, joy, sadness, surprise, and trust were assessed using the sentiment lexicon analysis. The results have been illustrated using a variety of data visualization techniques such as bar plot, word cloud and box plot.

3.2.2 | Data Pre-Processing

Before analyzing the data, pre-processing was done on the text using the "tm" library along with library "strinr" and "gsub" (Pahwa, Taruna, and Kasliwal 2018; Sreeja, Sunny, and Jatian 2020). In R studio, a corpus was created which contained the dataset. The data was then converted to lowercase. Punctuations, numbers, and stop words were removed. After that, "stemming" and "sparsity removal" were used to limit the words to only informative ones from the pool of words in the reviews.

3.2.3 | Lexicon Based Sentiment Analysis

"Syuzhet" package of R software was used for sentiment analysis. The NRC dictionary developed by Mohammad and Turney (2010) of syuzhet package was used to classify the text into eight types of emotions, that is, anger, anticipation, disgust, fear, joy, sadness, surprise, and trust and two main sentiments, that is, positive and negative. Further, all the reviews underwent sentiment score calculation by matching them against the words in the lexicon dictionary and the sentiment score of the reviews of each app was calculated (Table 1). A comparison wordcloud (Figure 4) of each emotion was created, reflecting the major words used in those emotions. On the basis of the analysis and classification of the reviews into different categories of emotions mentioned above, conclusion and recommendations have been drawn.

3.2.4 | Predictive Data Analysis

Simple linear regression analysis was used to test the hypothesis. The regression model attempts to analyze whether a linear relationship exists between the app's rating and the sentiment score of the app. In this case, sentiment score of the app is the independent variable and rating of the app is the dependent variable (Figure 2). The objective was to investigate whether a linear change in sentiment score of the app leads to a linear change in rating of the app. Ratings of the apps were retrieved from the Google Play Store and the sentiment score of the reviews of each app was calculated using NRC lexicon sentiment analysis technique.

Hypothesis 1. *Sentiment score has a positive effect on app rating.*

3.2.5 | Latent Dirichlet Allocation Topic Modeling

The previous part of the study aimed at understanding the attitude of people towards the use of digital detox apps. However, a sentimental analysis study will not reveal the key elements that influence the users' evaluation of digital detox apps. In the next part of the study, we did Latent Dirichlet Allocation (LDA) topic modeling to analyze the important topics voiced out by app users that shaped their attitude towards digital detox apps Topic modeling is a process that summarizes a vast archive of texts by discovering the topics and themes hidden in a corpus of text (Negara and Triadi 2021). Latent Dirichlet Allocation follows the "Bag of words" assumption, which characterizes a document as a collection of latent topics, where each topic is a multinomial distribution over words. It operates on the premise that certain groups of terms are more likely than others to

TABLE 1 | Sentiment scores.

S. no.	App Name	Emotions and Sentiments										Score	Ratings
		Anger	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	Trust	Negative	Positive		
1	Digital Detox: Focus and Live	26	56	17	37	52	38	21	75	84	132	48	4.5
2	AppDetox—App Blocker for Digital Detox	20	26	7	19	28	25	13	49	50	70	20	3.5
3	Off the Grid—Digital Detox	20	32	15	17	20	21	11	39	52	64	12	3.8
4	Detox: Procrastination Blocker	17	27	7	16	19	15	10	29	35	50	15	3.8
5	BlackOut: Stay Focused/ Beat Phone Addiction	8	19	3	7	19	16	5	20	24	39	15	3.7
6	Block Apps—Productivity and Digital Wellbeing	8	25	9	11	19	12	8	30	35	54	19	4.4
7	Stay Focused: Block Site and App	18	26	11	27	25	22	13	43	44	73	29	4.4
8	Block Site—Avoid Distractions	119	142	77	140	115	139	73	193	316	366	50	4.2
9	Digitox: Screen Time	13	25	10	13	20	11	9	33	30	52	22	4.5
10	StayOff—Screen Time Tracker + Phone Usage Limit	7	20	7	16	14	13	4	22	26	43	17	4.5
11	My Phone Time—App usage tracking—Focus enabler	12	21	9	16	16	14	5	35	35	65	30	4.2
12	App Usage—Manage/ Track Usage	15	19	15	17	26	18	11	45	40	70	30	4.4
13	Lock My Phone for Study (ZEN MODE/ device lock)	26	53	21	36	49	36	21	69	68	121	53	4.2

(Continues)

TABLE 1 | (Continued)

S. no.	App Name	Emotions and Sentiments										Score	Ratings
		Anger	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	Trust	Negative	Positive		
14	SocialX—Screen Time Tracker	3	6	2	10	7	8	4	20	18	30	12	4.6
15	Lock Me Out: App Blocker	50	57	27	55	55	54	22	93	127	165	38	4.4
16	App Block—Block Apps and Sites	31	46	19	37	38	34	26	63	81	116	35	4.5
17	Stay Free—Stay Focused	24	43	18	29	36	28	18	60	69	108	39	4.5
18	YourHour—Phone Addiction Tracker and Controller	36	70	28	54	59	47	34	82	102	145	43	4.4
19	Action Dash: Screen Time Helper	18	29	8	14	20	18	11	33	38	59	21	4.5
20	AntiSocial: phone addiction	10	21	6	14	15	13	8	28	28	45	17	4
21	Quality Time: Phone Addiction	10	24	8	11	15	16	7	26	39	49	10	3.6
22	Menthal	4	9	2	4	4	5	2	6	10	8	-2	3.8
23	My Addictometer—Mobile addiction tracker	3	9	4	3	6	4	3	7	13	16	3	3.6
24	Stay Away (Phone Lock): Keep Me Out from phone addiction	7	21	1	12	18	11	7	25	24	43	19	4.5
25	SPACE: Break phone addiction, stay focused	14	22	10	16	20	19	6	29	43	58	15	4

Source: Prepared by researchers.

FIGURE 2 | Conceptual model. *Source:* Prepared by researchers.

become linked with particular topics. It is possible to uncover latent topics from extensive unstructured data by using the LDA technique (Buenano-Fernandez et al. 2020). We used the "topicmodels" package of R studio to identify the major topics expressed by the people in their reviews. Through topic modeling, four major topics were formed; the result of topic modeling is presented in Table 4.

4 | Findings

4.1 | Sentiment Analysis

To answer RQ1 and RQ2, sentiment analysis was conducted. It was found that positive sentiments dominated the data frame. As it is clear from Table 1 the sentiment score of all the apps was positive, except for one app. According to the sentiment score of each review, out of the total 3500 reviews, 57% reviews were positive, 19% were negative, and 24% were neutral. Positive sentiments were expressed mainly through the "anticipation" and "trust" emotions as indicated in Figure 3. Comparison word cloud (Figure 4) of the emotions indicated that words like help, recommend, simple, manage, and effect shows the "trust" of people in digital detox apps. Likewise, words such as hope, wonderful, sudden, and option are associated with the "surprise" emotion in the reviews. Users expressed the emotion "joy" for the apps with words like thank, perfect, love, free, and so on. Words like track, usage, better, spend, and amount reflected the emotion, "anticipation." On the other hand, a small proportion of people had negative sentiments. "Anger" was indicated by the words like, annoy, complaint, force, drain, purchase, challenging. "Disgust" was represented by disappointed, struggle, cheat, bug, subscription. "Fear" comprised words like, avoid, unlock, delete, uninstall. "Sadness" was described by restrict, error, lockout, lost, restart. The sentiment analysis results are also graphically represented by a boxplot. It is clear that reviews were more on the positive side, and there is one extreme outlier with positive sentiment being +8, which is the review with the highest positive sentiment score. As can be seen from the boxplot (Figure 5), the median is +1.05, meaning a larger number of reviews tend to be positive. Table 2 provides the box plot summary.

4.2 | Regression Analysis

The hypothesis tests if user review sentiments explain ratings of the apps. Table 3 shows the result of regression analysis. The result indicates that the linear relationship between sentiment score and app rating is well established by the regression model. $F(1, 23) = 8.174$, $p < 0.05$, shows that review sentiments play a significant role in assigning app rating. Moreover, the coefficient of determination or R square has a value of 0.26. So, 26% of the variation in the app ratings is explained by the

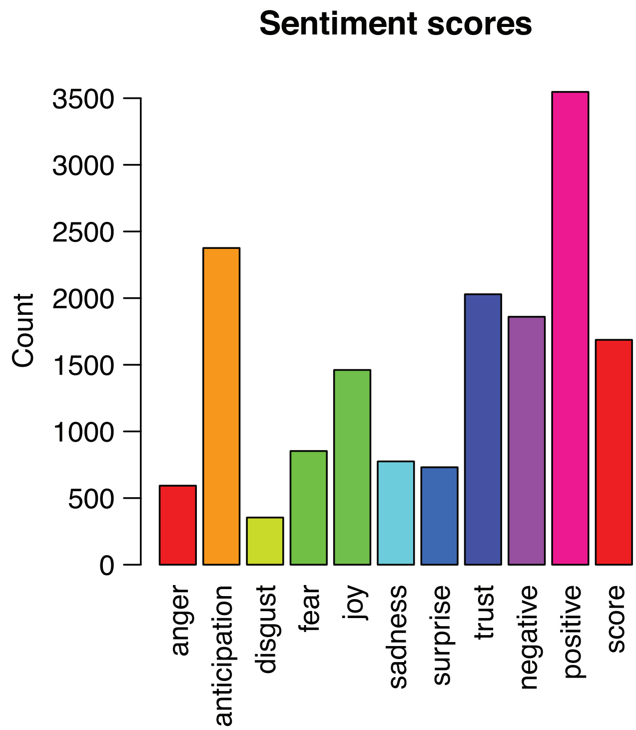

FIGURE 3 | Public sentiments towards digital detox apps. *Source:* Prepared by researchers.

sentiment score. Thus we find support for the linear relationship between sentiment score and rating of the app and it answers our RQ3 users review sentiments explain the ratings of the apps.

4.3 | Topic Modeling

Though sentiment analysis provided an insight into the users' attitude towards digital detox apps and their effectiveness, it did not assist us in understanding the major factors that influence this attitude. Sentiment analysis has shown that reviews were more on the positive side as compared to the negative. Hence, we conducted LDA topic modeling to answer our RQ4, RQ5, and RQ6. Four major topics were formed through LDA topic modeling, which were frequently expressed by reviewers (Table 4). People in their reviews have largely talked about *features* of digital detox apps (Topic 1). The majority of the reviews about features of these apps were positive. Flexibility of customization, simple user interface, strict lockout, accurate usage stats, usage warnings, screen timer, detailed usage report, blocking by location, bedtime limit, motivational challenges, quick customer service, and performance appreciation feedback were the key features praised by the users. There were some negative reviews as well pertaining to features. Users disliked the apps that drain the phone's battery, ask for complete control of the phone, have ads, and block calling functions during the detox period. *Impact* of digital detox apps was Topic 2 wherein users revealed the effectiveness of such apps in their positive reviews. People acknowledged that these apps helped them in (1) avoiding distractions, (2) cutting time on social media, (3) increasing productivity, (4) focusing and concentrating on work and study, (5) improving sleep routine, health (both physical and mental)

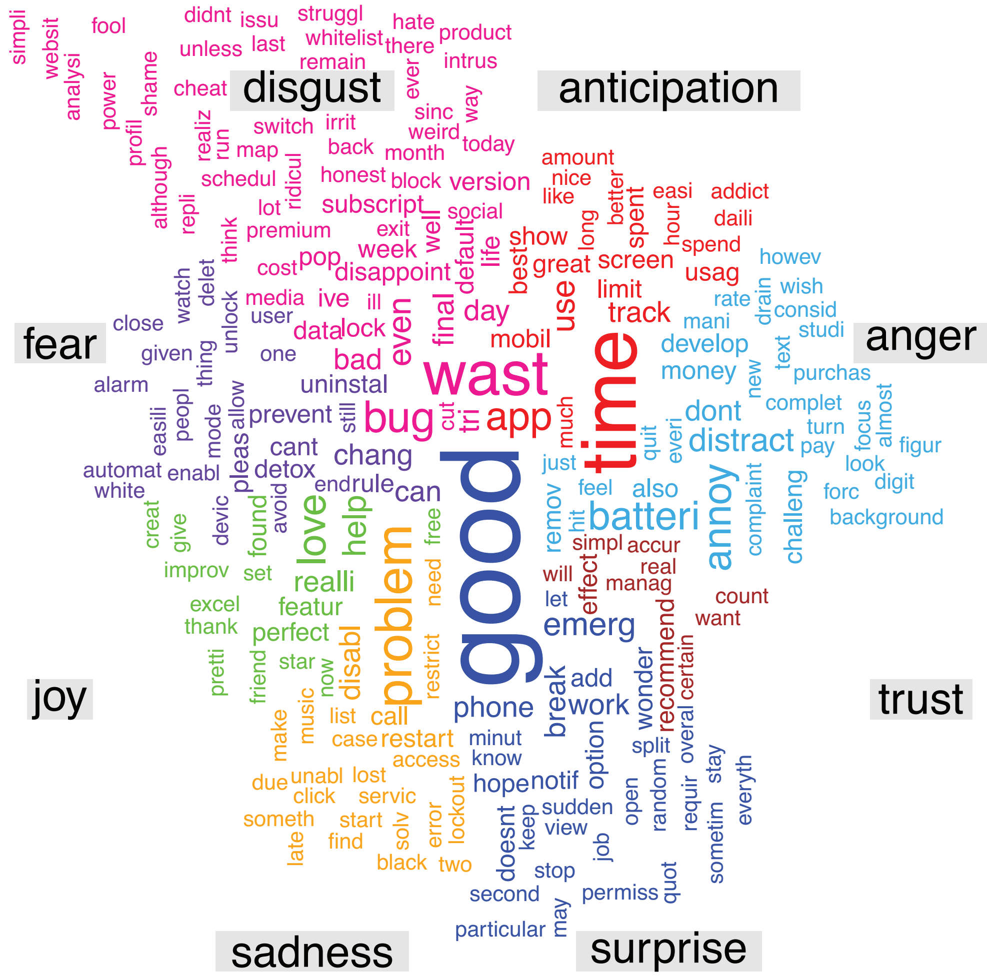

FIGURE 4 | Comparison Word Cloud.

and interpersonal relationships, (6) providing ideas on how to spend free time without the use of smartphone, (7) practicing self-control, (8) reducing procrastination, (9) overcoming smartphone addiction, and (10) assisting with anxiety and ADHD issues.

In Topic 3, users shared the *long-term performance* of the apps and the experience they have had in the long run. Users appreciated the consistent performance of the apps with the terms like good, satisfied, and great. Digital detox apps received acceptance from people because most of them were free of cost and provided all the necessary functions.

Topic 4 comprised *recommendations* given in reviews by app users: (1) password protection, (2) flexibility of setting individual time limits, (3) availability of detailed usage data report, (4) backup and export of usage report, (5) applicability of such apps for websites and desktop, (6) comparison of their usage report, and (7) whitelisting of apps.

5 | Discussion

This study provides assessment of smartphone users' attitudes and perceptions of digital detox apps by doing sentiment analysis, predictive data analysis (regression analysis) and LDA topic modeling of the reviews posted on Google Play Store. Overall, we found that smartphone users displayed positive sentiments towards digital detox apps and were mostly expressing emotions such as "anticipation" and "trust," with only a small occurrence of reviews with negative sentiments. This may be indicative of the fact that people use digital detox apps for their problematic smartphone use. "Anticipation" and "trust," the two highly expressed emotions reflect that users were happy with the apps and trusted them in regulating their smartphone use. It also shows that users expected some improvements in digital detox apps for which they have provided various recommendations. This finding indicates that people are becoming aware that they need some external regulation on their uncontrollable smartphone use to protect themselves from the adverse impact of smartphone addiction.

The findings of regression analysis confirm that sentiment scores explain the ratings of the apps. Hence, it can be said that ratings of the apps are true reflection of the users' reviews. Through ratings of the apps, people will be able to understand which apps are most liked by the users; this will help them in choosing the right digital detox app for themselves.

LDA topic modeling revealed four major topics expressed by the users in the reviews. Topic 1 showed that users largely appreciated the features of the digital detox apps. Features such as ease of customization, simple user interface, strict lockout, usage warnings, screen timer, detailed and accurate usage report, bedtime limit, motivational challenges, and performance appreciation feedback were praised by the users. Friendly and quick support service from developers was a key highlight of the positive reviews. These findings are in line with the findings of Alrobai et al. (2019), a simple and intuitive design is crucial for enhancing users' ability and motivation when using persuasive technologies.

However, a small proportion of people had negative sentiments about the features. Users disliked the apps that drain phone's battery, ask for complete control of the phone, have ads, and block calling functions during the detox period (Kloker, Riegel, and Weinhardt 2020). The result highlights a significant drawback of the digital detox apps, that is, their narrow view of usage restrictions. This ignores the more general objectives of technology use as well as the various avoidance or approach motivations of users. Highlighting the productive use of technology may be a more effective strategy to prevent aimless or habitual technology use (Almoallim and Sas 2022). The finding indicates that the features of the digital detox apps were designed with the primary objective of making people aware of their smartphone usage. Usage tracking, reminders, motivations, and feedback resulted in increased self-awareness and behavioral changes in users. The ease of personal customization, usage warnings, assessment of usage report increases self-efficacy and ensure sustained motivation which in turn influence the attitude and behavior of people (Hsu and Chen 2021). Users did not like giving complete control of the smartphone to the digital detox apps; they also did not like the idea of complete lockout from their phone. They want a category of whitelisting where they can put some apps or functions they don't want to block even after exceeding the smartphone usage limit. Because there may be some functions or apps which are important to them like calls and work-related emails which they don't want to miss. The present study revealed that the reviewed apps implemented the nudge theory through the provisions of user-controlled options and motivations (Roffarello and De Russis 2019; Almourad et al. 2021). This notion corroborates with the findings of research in other domains, one such example is the study conducted by Swendeman et al. (2015) in the health domain. Their study found that smartphone apps improved self-monitoring functionalities in assisting people living with HIV.

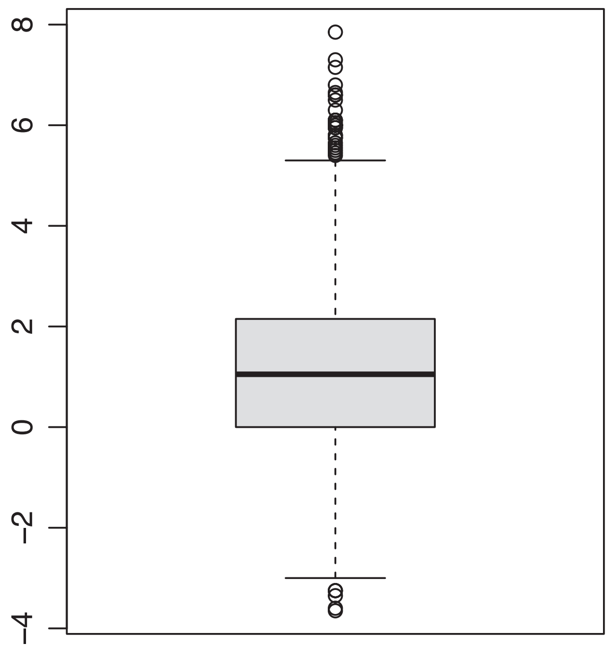

FIGURE 5 | Boxplot.

The second topic identified from LDA topic modeling was the *impact of digital detox apps*. The analysis of the reviews revealed that users experienced positive impact of digital detox apps. Users found these apps to be effective in improving their productivity by helping them in avoiding distractions, reducing procrastination and improving focus and concentration. Detox apps also provide support to users in managing their time by restricting use of social media, and by suggesting ideas on how to spend free time without using smartphone. These apps also assisted users in dealing with ADHD and anxiety issues and in improving the mental and physical health of the people (Schmuck 2020). Overall, detox apps were found to guide people in behavior modification by enhancing self-regulation and overcoming smartphone addiction. However, the positive change observed in behavior was temporary, habit formation process is completely absent from digital detox apps. Digital interventions are designed to break old habits but they are not successful in developing new habits (Roffarello and De Russis 2019). When users are satisfied with the apps, they feel motivated to use it but unfortunately the motivation decreases when behavior becomes routine (Radtke et al. 2022). Third topic talks about the long-term performance of digital detox apps. Most of the apps gave consistent performance and delivered what they claimed. Digital detox apps received acceptance from people because most them were free of cost and provided all the necessary functions. Users were also ready to pay for the premium version of the apps because of their

TABLE 2 | Box plot summary.

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
−3.6500	0.0125	1.0500	1.2104	2.1500	7.8500

Source: Prepared by researchers.

TABLE 3 | Regression output.

Hypothesis	R square	Standard error	*F*	*p*	Hypothesis supported
H1	0.262	0.31	8.174	0.009	Yes

Source: Prepared by researchers.

TABLE 4 | Latent dirichlet allocation topic modeling.

S. no.	Topics	Top terms
1	Features	Warn, limit, set, stats, track, lock, aware, accuracy, easy, service, and free
2	Impact	Best, help, cut, time, health, focus, and avoid
3	Long-term performance	Great, want, like, work, good, satisfied, and consistent
4	Recommendations	Protection, report, block, and bypass

Source: Prepared by researchers.

impressive long-term performance. Although users were overall satisfied with the digital detox apps; however, they wanted some improvements for which they provided *recommendations* (fourth topic). Users wanted strict password protection so that they or their kids don't bypass the lockout period. Even though detox apps provide customization of app-wise locking; however, users expect more personalization and functional control like flexibility of setting individual time limits for blocking day-wise (weekend/weekdays), time-wise, location-wise, and category-wise. The freedom to personalize the intervention contributes to a favorable perception of an application and will consequently enhance the intention of utilizing it. Absence of personalization may result in disinterest and an inability to alter the user's behavior and perspective regarding the application (Almourad et al. 2021). However, achieving a balance between providing users with options and ensuring the efficacy of interventions facilitated by these applications poses a difficulty (Alrobai et al. 2016).

Users not only wanted reminders and locking functions but they also wanted detailed usage data report along with visualization through pie charts, bar charts, and graphs. Visualization may facilitate better understanding of the usage data and in assessing the goals (Almoallim and Sas 2022). Combining an informational health message with visualization led to a higher and stronger intention to modify the behavior (Rennie, Harris, and Webb 2014). Additionally, findings revealed that users demanded social support feature where they can form groups and compare their usage data with others and track their progress. Though prior research has indicated that social support can enhance self-regulation in smartphone usage (Ko et al. 2016; Almoallim and Sas 2022), it appears that the majority of digital detox applications do not focus on promoting self-regulation through social support. Although digital detox apps have the potential to help users with uncontrollable smartphone use, most of them lack a scientific foundation and evidence base (Almoallim and Sas 2022). Hence, we advocate for further developing digital detox apps based on research and evidence.

6 | Implications

6.1 | Theoretical Implications

Our research makes several contributions to the body of literature by providing a broader and richer understanding of public perspective on digital detox apps. First, the study explored public attitude on digital detox apps and identified underlying emotions as opposed to just positive or negative sentiments. Second, this study fills a gap in digital detox studies by adopting a new methodological approach and procedure since it combines text mining, sentiment analysis, and topic modeling. The approach is different from prior studies that have examined these strategies individually. Third, although big data analytics has been heralded as a new research paradigm in many fields, the digital industry has seen very few applications that fully explore its potential. The uniqueness of the present research lies in the use of large data and delineation of user experience drivers on a scale that was not available in traditional survey studies in this area. Despite the fact that this is a preliminary attempt in big data analytics, we have obtained great insights into some of the important concepts related to the role of digital detox apps in controlling excessive smartphone use. As a result, it is envisaged that this study will serve as a model for the incorporation of business analytics in analyzing the growing issue of addiction to technology, especially to smartphones. Fourth, based on the users' experience and perception of digital detox apps, the present study also identifies potential research areas that, if investigated further, might lead to a consensus among scholars about the optimal design of digital detox apps and related tools.

6.2 | Practical Implications

The findings of sentiment analysis and topic modeling will provide better understanding of users' attitude towards digital detox apps and the major factors associated with the experience of the users. This may give a better knowledge of what emotions and factors have the greatest impact on shaping users' perception of digital detox apps. The predominance of positive sentiments in the findings of the present study may indicate the future growth opportunity in adoption of digital control interventions. The feedback of the users will help the developers to update and improve their apps to make them user-centric and provide satisfaction to the users. The present research found that reverting to offline activities and disconnecting leads to a change in consumer behavior, significantly impacting future marketing and branding tactics. Marketing managers can capitalize on a first mover advantage by addressing the evolving issue of their target audience. Considering the emergence of digital detox as a new lifestyle, it is recommended to analyze appropriate advertisement strategies to raise awareness about the benefit of these apps. Furthermore, it is essential to modify not just the marketing strategies but also the existing product range. For example, minor adjustments that enable the utilizations of offline functionalities on digital devices could potentially satisfy the users. Moreover, these business prospects might vary from introducing new offline features to applications or even creating entirely offline alternatives to minimize the unnecessary use of digital technology. An offline mode for emergency texts could be a potential new feature. Users can remain offline while still receiving emergency notifications.

7 | Limitations and Future Research Directions

Future research based on surveys, user interviews, and observations may use the current research findings as a foundation. These may offer a more thorough understanding of users' perceptions. There is further scope in sentiment analysis of digital detox apps. Studies can conduct a comparative sentiment analysis of top-rated apps, free and paid apps, and can use different Lexicon-based sentiment classification methods. The Google Play store is the only data source for this study. However, reviews from the Apple Store and social media platforms could also be incorporated. Sentiment analysis can also be done on articles published on smartphone addiction and digital detox measures. There is also a need for a scale to assess the effectiveness of digital detox apps. Both quantitative and qualitative studies can be taken up in the future to study the role of digital detox apps in controlling smartphone addiction. Another factor is date and time, which may be addressed in future studies. It can provide a more thorough examination, and suggestions may be refined more precisely. Demographic information is generally unavailable in the reviews on the Google Play Store. It limits the demographic segmentation of digital detox app users based on age, gender, and location. Future studies may consider employing triangulation techniques on data from many sources to evaluate the semantic structure of the user experience and create a more thorough understanding of user satisfaction through big data analytics. Researchers should also take into account the role of digital detoxification in different digital gadgets and platforms, such as laptops, desktops, tablets, video games, and websites.

Data Availability Statement

Data was obtained from Google Play Store.

References

Abdous, M. H., and W. He. 2011. "Using Text Mining to Uncover students' Technology-Related Problems in Live Video Streaming." *British Journal of Educational Technology* 42, no. 1: 40–49.

Abeele, M. M. V., A. Halfmann, and E. W. Lee. 2022. "Drug, Demon, or Donut? Theorizing the Relationship Between Social Media Use, Digital Well-Being and Digital Disconnection." *Current Opinion in Psychology* 45: 101295.

Agha, C. J., and A. H. Obinna. 2023. "Tech-Free Zones Establishment and Dumb-Phone Utilization as Digital Detoxification Predictors of students' Academic Improvements in Universities in Rivers State." *EPRA International Journal of Multidisciplinary Research* 9, no. 2: 149–155.

Al-Amri, A., S. Bashir, M. Ahsan, and T. Abualait. 2023. "Effects of Smartphone Addiction on Cognitive Function and Physical Activity in Middle-School Children: A Cross-Sectional Study." *Frontiers in Psychology* 14: 1182749.

Alhassan, M. D., and I. O. Adam. 2021. "The Effects of Digital Inclusion and ICT Access on the Quality of Life: A Global Perspective." *Technology in Society* 64: 101511.

Almoallim, S., and C. Sas. 2022. "Toward Research-Informed Design Implications for Interventions Limiting Smartphone Use: Functionalities Review of Digital Well-Being Apps." *JMIR Formative Research* 6, no. 4: e31730.

Almourad, M. B., A. Alrobai, T. Skinner, M. Hussain, and R. Ali. 2021. "Digital Wellbeing Tools Through Users Lens." *Technology in Society* 67: 101778.

Al-Natour, S., and O. Turetken. 2020. "A Comparative Assessment of Sentiment Analysis and Star Ratings for Consumer Reviews." *International Journal of Information Management* 54: 102132.

Alrobai, A., J. McAlaney, H. Dogan, K. Phalp, and R. Ali. 2016. "Exploring the Requirements and Design of Persuasive Intervention Technology to Combat Digital Addiction." In *Human-Centered and Error-Resilient Systems Development: IFIP WG 13.2/13.5 Joint Working Conference, 6th International Conference on Human-Centered Software Engineering, HCSE 2016, and 8th International Conference on Human Error, Safety, and System Development, HESSD 2016, Stockholm, Sweden, August 29–31, 2016, Proceedings 8*, 130–150. Stockholm, Sweden: Springer International Publishing.

Alrobai, A., J. McAlaney, K. Phalp, and R. Ali. 2019. "Exploring the Risk Factors of Interactive e-Health Interventions for Digital Addiction." In *Substance Abuse and Addiction: Breakthroughs in Research and Practice*, 375–390. Hershey, PA: IGI Global.

Amez, S., and S. Baert. 2020. "Smartphone Use and Academic Performance: A Literature Review." *International Journal of Educational Research* 103: 101618.

Antons, D., E. Grünwald, P. Cichy, and T. O. Salge. 2020. "The Application of Text Mining Methods in Innovation Research: Current State, Evolution Patterns, and Development Priorities." *R&D Management* 50, no. 3: 329–351.

Barbierato, E., I. Bernetti, and I. Capecchi. 2021. "Analyzing TripAdvisor Reviews of Wine Tours: An Approach Based on Text Mining and Sentiment Analysis." *International Journal of Wine Business Research* 34, no. 2: 212–236.

Birjali, M., M. Kasri, and A. Beni-Hssane. 2021. "A Comprehensive Survey on Sentiment Analysis: Approaches, Challenges and Trends." *Knowledge-Based Systems* 226: 107134.

Buenano-Fernandez, D., M. Gonzalez, D. Gil, and S. Luján-Mora. 2020. "Text Mining of Open-Ended Questions in Self-Assessment of University Teachers: An LDA Topic Modeling Approach." *IEEE Access* 8: 35318–35330.

Burrill, S. 2024. "The (Dis) Advantages of Device Free Time: A Mixed-Methods Digital Detox Study."

Chau, M., and J. Xu. 2012. "Business Intelligence in Blogs: Understanding Consumer Interactions and Communities." *MIS Quarterly* 36, no. 4: 1189–1216.

Diefenbach, S. 2018. "The Potential and Challenges of Digital Well-Being Interventions: Positive Technology Research and Design in Light of the Bitter-Sweet Ambivalence of Change." *Frontiers in Psychology* 9: 331.

Dutt, B. 2023. "Wellbeing Amid Digital Risks: Implications of Digital Risks, Threats, and Scams on users' Wellbeing." *Media and Communication* 11, no. 2: 355–366.

Feizollah, A., M. M. Mostafa, A. Sulaiman, Z. Zakaria, and A. Firdaus. 2021. "Exploring Halal Tourism Tweets on Social Media." *Journal of Big Data* 8, no. 1: 72.

Fu, L., P. Wang, M. Zhao, et al. 2020. "Can Emotion Regulation Difficulty Lead to Adolescent Problematic Smartphone Use? A Moderated Mediation Model of Depression and Perceived Social Support." *Children and Youth Services Review* 108: 104660.

Garrison, K. A., P. Pal, S. S. O'Malley, et al. 2020. "Craving to Quit: A Randomized Controlled Trial of Smartphone App–Based Mindfulness Training for Smoking Cessation." *Nicotine and Tobacco Research* 22, no. 3: 324–331.

Ge, J., Y. Liu, W. Cao, and S. Zhou. 2023. "The Relationship Between Anxiety and Depression With Smartphone Addiction Among College Students: The Mediating Effect of Executive Dysfunction." *Frontiers in Psychology* 13: 1033304.

GSMA. 2023. "The Mobile Economy 2023." GSMA. https://www.gsma.com/solutions-and-impact/connectivity-for-good/mobile-economy/.

Hassan, M. K., F. A. Hudaefi, and R. E. Caraka. 2021. "Mining Netizen's Opinion on Cryptocurrency: Sentiment Analysis of Twitter Data." *Studies in Economics and Finance* 39, no. 3: 365–385.

Hsu, C. L., and M. C. Chen. 2021. "Advocating Recycling and Encouraging Environmentally Friendly Habits Through Gamification: An Empirical Investigation." *Technology in Society* 66: 101621.

Khan, N. F., and M. N. Khan. 2022. "A Bibliometric Analysis of Peer-Reviewed Literature on Smartphone Addiction and Future Research Agenda." *Asia-Pacific Journal of Business Administration* 14, no. 2: 199–222.

Kim, J., J. Park, H. Lee, M. Ko, and U. Lee. 2019. "LocknType: Lockout Task Intervention for Discouraging Smartphone App Use." In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–12.

Kloker, S., M. L. Riegel, and C. Weinhardt. 2020. "Sensible or Too Sensitive? Do Privacy Concerns Hinder the Acceptance of Digital Solutions to Treat Smartphone Addiction?" In *2020 IEEE 22nd Conference on Business Informatics* (*CBI*), vol. 2, 10–19. IEEE.

Ko, M., S. Choi, K. Yatani, and U. Lee. 2016. "Lock N'LoL: Group-Based Limiting Assistance App to Mitigate Smartphone Distractions in Group Activities." In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, 998–1010.

König, L. M., M. Van Emmenis, J. Nurmi, A. Kassavou, and S. Sutton. 2022. "Characteristics of Smartphone-Based Dietary Assessment Tools: A Systematic Review." *Health Psychology Review* 16, no. 4: 526–550.

Lan, Y., J. E. Ding, W. Li, et al. 2018. "A Pilot Study of a Group Mindfulness-Based Cognitive-Behavioral Intervention for Smartphone Addiction Among University Students." *Journal of Behavioral Addictions* 7, no. 4: 1171–1176.

Li, Z., Z. G. Tian, J. W. Wang, and W. M. Wang. 2020. "Extraction of Affective Responses From Customer Reviews: An Opinion Mining and Machine Learning Approach." *International Journal of Computer Integrated Manufacturing* 33, no. 7: 670–685.

Liu, M. T., Y. Liu, Z. Mo, and K. L. Ng. 2021. "Using Text Mining to Track Changes in Travel Destination Image: The Case of Macau." *Asia Pacific Journal of Marketing and Logistics* 33, no. 2: 371–393.

Mirbabaie, M., S. Stieglitz, and J. Marx. 2022. "Digital detox." *Business and Information Systems Engineering* 64, no. 2: 239–246.

Mohammad, S., and P. Turney. 2010, June. "Emotions Evoked by Common Words and Phrases: Using Mechanical Turk to Create an Emotion Lexicon." In *Proceedings of the NAACL HLT 2010 Workshop on Computational Approaches to Analysis and Generation of Emotion in Text*, 26–34.

Nassen, L. M., H. Vandebosch, K. Poels, and K. Karsay. 2023. "Opt-Out, Abstain, Unplug. A Systematic Review of the Voluntary Digital Disconnection Literature." *Telematics and Informatics* 81: 101980.

Negara, E. S., and D. Triadi. 2021. "Topic Modeling Using Latent Dirichlet Allocation (LDA) on Twitter Data With Indonesia Keyword." *Bulletin of Social Informatics Theory and Application* 5, no. 2: 124–132.

Nguyen, M. H., M. Büchi, and S. Geber. 2024. "Everyday Disconnection Experiences: Exploring people's Understanding of Digital Well-Being and Management of Digital Media Use." *New Media and Society* 26, no. 6: 3657–3678.

Olson, J. A., D. A. Sandra, É. S. Colucci, et al. 2022. "Smartphone Addiction Is Increasing Across the World: A Meta-Analysis of 24 Countries." *Computers in Human Behavior* 129: 107138.

Pahwa, B., S. Taruna, and N. Kasliwal. 2018. "Sentiment Analysis-Strategy for Text Pre-Processing." *International Journal of Computers and Applications* 180, no. 34: 15–18.

Percha, B., Y. Garten, and R. B. Altman. 2012. "Discovery and Explanation of Drug-Drug Interactions via Text Mining." *Biocomputing* 2012: 410–421.

Radtke, T., T. Apel, K. Schenkel, J. Keller, and E. von Lindern. 2022. "Digital Detox: An Effective Solution in the Smartphone Era? A Systematic Literature Review." *Mobile Media and Communication* 10, no. 2: 190–215.

Rennie, L. J., P. R. Harris, and T. L. Webb. 2014. "The Impact of Perspective in Visualizing Health-Related Behaviors: First-Person Perspective Increases Motivation to Adopt Health-Related Behaviors." *Journal of Applied Social Psychology* 44, no. 12: 806–812.

Roffarello, A. M., and L. De Russis. 2019. "The Race Towards Digital Wellbeing: Issues and Opportunities." In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–14.

Roffarello, A. M., and L. De Russis. 2023. "Achieving Digital Wellbeing Through Digital Self-Control Tools: A Systematic Review and Meta-Analysis." *ACM Transactions on Computer-Human Interaction* 30, no. 4: 1–66.

Ross, M. Q., A. Gilbert, J. Klingelhoefer, et al. 2024. "Mapping a Pluralistic Continuum of Approaches to Digital Disconnection." *Media, Culture and Society* 46, no. 4: 851–862.

Sadeghi Moghadam, M. R., H. Safari, and N. Yousefi. 2019. "Clustering Quality Management Models and Methods: Systematic Literature Review and Text-Mining Analysis Approach." *Total Quality Management and Business Excellence* 32, no. 3–4: 241–264.

Santiago Walser, R., A. De Jong, and U. Remus. 2022. "The Good, the Bad, and the Missing: Topic Modeling Analysis of User Feedback on Digital Wellbeing Features." In *Proceedings of the 55th Hawaii International Conference on System Sciences*. Manoa, Hawaii: Shidler College of Business, University of Hawaii.

Schmuck, D. 2020. "Does Digital Detox Work? Exploring the Role of Digital Detox Applications for Problematic Smartphone Use and Well-Being of Young Adults Using Multigroup Analysis." *Cyberpsychology, Behavior, and Social Networking* 23, no. 8: 526–532.

Semper, H. M., R. Povey, and D. Clark-Carter. 2016. "A Systematic Review of the Effectiveness of Smartphone Applications That Encourage Dietary Self-Regulatory Strategies for Weight Loss in Overweight and Obese Adults." *Obesity Reviews* 17, no. 9: 895–906.

Sharma, A. K., and R. Sharma. 2024. "Detox for Success: How Digital Detoxification Can Enhance Productivity and Well-Being." In *Business Drivers in Promoting Digital Detoxification*, 71–90. Hershey, PA: IGI Global.

Sreeja, I., J. V. Sunny, and L. Jatian. 2020. "Twitter Sentiment Analysis on Airline Tweets in India Using R Language." In *Journal of Physics: Conference Series*, vol. 1427, No. 1, 12003. England: IOP Publishing.

Sullivan, L., and P. Reiner. 2021. "Digital Wellness and Persuasive Technologies." *Philosophy and Technology* 34: 413–424.

Sunday, O. J., O. O. Adesope, and P. L. Maarhuis. 2021. "The Effects of Smartphone Addiction on Learning: A Meta-Analysis." *Computers in Human Behavior Reports* 4: 100114.

Swendeman, D., N. Ramanathan, L. Baetscher, et al. 2015. "Smartphone Self-Monitoring to Support Self-Management Among People Living With HIV: Perceived Benefits and Theory of Change From a Mixed-Methods Randomized Pilot Study." *JAIDS Journal of Acquired Immune Deficiency Syndromes* 69: S80–S91.

Tian, J., J. Y. Zhao, J. M. Xu, et al. 2021. "Mobile Phone Addiction and Academic Procrastination Negatively Impact Academic Achievement Among Chinese Medical Students." *Frontiers in Psychology* 12: 5561.

Trivedi, S. K., and A. Singh. 2021. "Twitter Sentiment Analysis of App Based Online Food Delivery Companies." *Global Knowledge, Memory and Communication* 70, no. 8/9: 891–910.

Vialle, S. J., T. Machin, and S. Abel. 2023. "Better Than Scrolling: Digital Detox in the Search for the Ideal Self." *Psychology of Popular Media* 13, no. 4: 687–695.

Wacks, Y., and A. M. Weinstein. 2021. "Excessive Smartphone Use Is Associated With Health Problems in Adolescents and Young Adults." *Frontiers in Psychiatry* 12: 762.

Wankhade, M., A. C. S. Rao, and C. Kulkarni. 2022. "A Survey on Sentiment Analysis Methods, Applications, and Challenges." *Artificial Intelligence Review* 55, no. 7: 5731–5780.

Wilcockson, T. D., A. M. Osborne, and D. A. Ellis. 2019. "Digital Detox: The Effect of Smartphone Abstinence on Mood, Anxiety, and Craving." *Addictive Behaviors* 99: 106013.

Zhou, B., J. Li, Y. Yang, and J. Hu. 2024. "A Model for Risk Factors Harms and of Smartphone Addiction Among Nursing Students: A Scoping Review." *Nurse Education in Practice* 103874: 103874.