https://doi.org/10.54989/msd-2023-0011

DECIPHERING USER FEEDBACK: CLUSTERING OF DIGITAL WELL-BEING SYSTEM REVIEWS

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ABSTRACT: This research holds significant importance in the realm of digital well-being, addressing the increasing concern over digital addiction. By analyzing user feedback on digital well-being systems, the study provides valuable insights into the effectiveness of these systems in moderating digital habits. It contributes to understanding how digital detox applications can mitigate compulsive smartphone use, thereby enhancing mental health. The study stands out for its unique approach to clustering user feedback on two popular digital well-being systems, Space and Google Well-being app. This original approach provides a novel perspective on user interaction with digital well-being tools, distinguishing it from existing literature which primarily focuses on general usage patterns and the impact on mental health. The purpose of this research is to systematically analyze and cluster user feedback on digital well-being systems. It also incorporates information retrieval techniques like topic modeling to extract main topics from these reviews. This methodology allows for an in-depth understanding of user feedback, going beyond mere statistical analysis to capture the nuances of user experiences and expectations. The findings of this research have significant implications for software developers and stakeholders in the digital well-being domain.

KEY WORDS: digital well-being, user feedback, natural language processing, clustering.

1. INTRODUCTION

According to Edward Tufle, "There are only two sectors that call their customers 'users', the illegal drug industry and the software industry". Addiction is defined as "an inevitable desire and desire that arises as a result of repeated doses and increasing amounts of a substance without the aim of eliminating the symptoms of an organic disease. If it is cut, some mental and physical disorders occur". In recent years, digital well-being systems are designed to combat with digital addiction. User participation in a software system improves the quality of the software and provides adaptability to the system. Incorporating user feedback into the system design process is important, and thus a more user-centric approach is encouraged in software design (Ali, 2018). By providing insights into user feedback, we can enhance the quality and adaptability of software, ensuring that these tools effectively meet user needs. In addition, analyzing user feedback contributes to the broader discourse on digital health, suggesting ways in which digital tools can be optimized for better mental health outcomes.

The aim of the research is to cluster digital well-being reviews in order to understand the user feedback. In this study, the comments made by users about online software systems are evaluated. This research explores and clusters the feedback of two popular digital well-being systems, Space and Google Well-being app. Google Well-being and Apple Screen Time are examples of an emerging family of tools to help people have a healthier and more informed relationship with technology (McAlaney et al., 2020). It is introduced in Google Well-being as a program that displays daily statistical data of digital habits and controls behaviors aimed at reducing phone usage. This app lets you show how much time has been spent on the phone. It determines the usage times for the applications and ensures their restriction. It controls how many times the screen lock is opened and closed. It also has modes such as sleep mode and focus mode. Focus mode allows notifications to be stopped with a single button. Thus, it prevents the person from being distracted. Sleep mode allows notifications to be muted. In sleep mode, the screen is dimmed in grayscale.

Space app, developed with the concept of digital addiction in mind, is promoted as a personalized behaviour modification program designed to help you think about how you use your phone and how it affects your life. In the application, time usage is controlled according to personalized goals. In the Space application, it shows how much time is spent in other applications and the total time spent on the phone. At the same time, it is possible to continue using the phone by stopping the timer. Usage periods come as notifications. Time permission per day, number of unlocks allowed per day, etc. It has many features such as For example, daily time leave helps you to specify how many hours you want to spend on the phone and set the time accordingly. It can be seen how long the phone has been used in which location. Daily progress can be tracked. The number of times the screen is unlocked is recorded. At the end of the targeted time, the screen dimming feature is activated. Also, notifications can be blocked. All of these practices take their place in the literature as digital well-being practices.

The literature (Schmuck, 2020) shows that digital detox applications reduce the risk of compulsive smartphone use and that using social networking sites is an effective tool to prevent harmful effects on health. Requirements engineering is one of the most important and design-critical steps in software engineering. Understanding and analyzing the needs of the software system is extremely important for software quality. To improve quality, feedback from software system users must be properly understood at runtime and then used in system design. User feedback should be analyzed to improve software quality. In crowd feedback, users support by shaping a powerful software adaptation to capture and convey precise information that cannot be automatically displayed. In addition, software cannot be fully customized by designers at design time, yet designers must plan and stage software adaptation

(Ali et al., 2012, Ali et al., 2011a, 2011b). Software evaluation is a task done to efficiently and accurately achieve the software's own design purposes. The stakeholders of software evaluation include the people who use the software to achieve their needs and expectations. Thus, acceptance and effective use of the software by the users is the main subject of software evaluation. In a dynamic world, it's important for users to approve software. In order for the software to survive, it is imperative that it catches this dynamism throughout its life. In addition, software systems are required to have adaptability in order to automatically respond to changes. Ultimately, the aim is to respond efficiently, dynamically and accurately to user needs. Analysis of users' large-scale feedback about the software is important in this regard. In the literature, there are Digital addiction studies that evaluate software requirements (Ali et al. 2015, Alrobai et al., 2014) and studies that focus on the system in terms of digital motivation (McAlaney et al., 2020). According to Kahya Özyirmidokuz et al. (2021) explored the users' feedback with qualitative research and thematic analysis.

Software reviews are free text that may informally contain relevant information for the development team such as bugs or issues that need to be fixed, summaries of the user experience with certain features, requests for enhancements, ideas for new features, and comparison with other apps. Thus, not only do user reviews represent the simplest and fastest way end users have to express their opinions or report their suggestions, but also a powerful crowd feedback mechanisms that can be used by developers as a backlog for the development process, aiming to improve the success/distribution of their apps (Palomba et al., 2017). Galvis Carreño and Winbladh (2013) extracted the main topics from user reviews with information retrieval techniques including topic modeling and evaluating them on different publicly available data sets in requirements analysis. Pagano and Maalej (2013) explored over one million reviews from the Apple AppStore. They investigated how and when users provide feedback, inspected the feedback content, and analyzed its impact on the user community. They used content analysis technique. Kurtanovic´and Maalej (2017) studied 32,414 reviews for 52 software applications in the Amazon Store. Through a grounded theory approach and peer content analysis, they investigated how users argue and justify their decisions, e.g. about upgrading, installing, or switching software applications. They also studied the occurrence frequency of rationale concepts such as issues encountered or alternatives considered in the reviews and found that assessment criteria like performance, compatibility, and usability represent the most pervasive concept. They used the labeled review data set to explore how accurately they can mine rationale concepts from the reviews. They used Support Vector Classifier, Naive Bayes, and Logistic Regression, trained on the review metadata, syntax tree of the review text, and influential terms, achieved a precision around 80% for predicting sentences with alternatives and decisions, with top recall values of 98%. On the review level, precision was up to 13% higher with recall values reaching 99%. Palomba et al. (2017) introduced CHANGEADVISOR, a novel approach that analyzed the structure, semantics, and sentiments of sentences contained in user reviews to extract useful (user) feedback from maintenance perspectives and recommend to developers changes to software artifacts. They used natural language processing and clustering algorithms to group user reviews around similar user needs and suggestions for change. Lau et al. (2020) examined the breadth of therapeutic contents and features of psychosocial wellness and stress management apps available to self-help seekers for public download and determined which of these apps have original research support. A systematic review was applied. Solymosi et al. (2020) systematically reviewed the articles that use crowdsourced or app-based measures to explore perceptions of crime. Yang et al. (2021) presented a literature review for web-based software architecture clustering models that are categorized into software architecture recovery, software architecture metric measurement, and software architecture reusability. Kahya Özyirmidokuz et al., (2021) used the same data source to understand the happiness and well-being concepts in data. They used qualitative research, thematic analysis to visualize the categories of the happiness and well-being properties in softwares depending on these user reviews.

Researchers also studied digital addiction and user feedback in recent years. Nguyen et al. (2022) provided insights into the prevalence of motivations and strategies for reducing digital addiction applications among individuals. Additionally, it provided information on how different sociodemographic groups experience digital disconnection. A national survey was conducted with 1163 Internet users in Switzerland in November 2020. Thematic coding of open-text responses revealed that people's understanding of 'balanced digital media use' primarily revolves around subjective appropriate usage, purposeful usage, social connections, absence of addiction, and time allocated for 'real life.' Through principal component analysis, they presented a classification of the types of motivations for digital disconnection and the strategies employed by individuals. Persistent age differences indicated the importance of adopting a lifespan approach when studying digital disconnection. Neale et al. (2022) assessed end users' views and experiences of the SURE Recovery application, exploring how it could be improved, and presenting findings on its usage and engagement. Engagement was enhanced when the app generates positive feelings, and individuals are unlikely to download or use the app if they cannot relate to or identify with its content. Therefore, incorporating user feedback into app design and establishing a network of supportive partners (advocating for the app) seemed to boost usage and engagement among individuals facing alcohol and substance use issues. Achieving the full potential of addiction recovery apps required improved digital literacy and access to devices, but it was essential not to evaluate these apps solely based on observable changes in substance use behaviors. Conroy et al. (2023) explored the smartphone usage, particularly in the context of digital well-being and efforts to combat digital addiction. They provided an in-depth qualitative exploration into the experiences of British young adults regarding smartphone overreliance and their efforts to disconnect. The study involved fourteen university students aged between 18 to 30 years and utilized semistructured interviews, which were analyzed through interpretative phenomenological analysis.

This research explores the software labels of digital well-being available in online user feedback. Large volumes of feedback from software system users are analyzed. The aim of the study is to group the user reviews of digital well-being softwares that meet the existing software applications in terms of user comments of the popular screen time applications (Google Well-Being and Space) used by users to combat digital addiction. We automatically cluster the users’ review about software labels. Section 2 presents the method and the data collection. Section 3 briefly explains our results. Last section concludes the research.

2. APPLICATION

In this study, we systematically gathered all online user reviews for the Space application and the Google Well-Being digital well-being software up to April 1, 2020. The data collection process was automated, resulting in a comprehensive dataset. For the Space application, we amassed a total of 28,130 user comments. Similarly, for the Google Well-being application, a substantial number of 210,837 English comments from users were compiled. In our focused analysis, all feedback relevant to theories of digital addiction, well-being, and happiness were meticulously selected, following a grounded theory approach as outlined by Creswell (2013). This selection process led to the inclusion of 3,477 user feedbacks from the Space App and 4,673 user comments from the Google Well-being feedbacks. These comments provided a rich source of user perspectives and experiences, forming the foundation of our study's empirical analysis. According to Table 1, for the Space app, a total of 3,477 English comments were analyzed, while the Google Well-being app had a slightly higher number at 4,673 comments. The Space app received 289 one-star and 242 two-star reviews. This suggests a notable portion of users were dissatisfied with the app. For the Google Well-being app, there were 1,230 one-star reviews, indicating a significant level of dissatisfaction among its users. However, it had a relatively small number of two-star reviews (106), which is significantly lower than the Space app. The Space app had 356 three-star reviews, while the Google Well-being app had 229. These numbers suggest a moderate level of satisfaction, indicating areas of the apps are meeting user expectations but also have room for improvement. The Space app garnered 881 four-star and 1,709 five-star reviews, indicating a high level of user satisfaction. This suggests that a significant number of users found the app beneficial and effective. For the Google Well-being app, 476 users gave four stars, and a notably high number of 2,632 users gave five stars. This demonstrates a strong positive reception among a majority of its users. The Google Well-being app, despite having more total reviews, has a higher proportion of five-star reviews compared to the Space app. This could imply higher overall user satisfaction or effectiveness in addressing user needs. The Space app, while having fewer total reviews, shows a more evenly distributed range of satisfaction levels, indicating varied user experiences and perceptions. In summary, these star distributions reflect user satisfaction levels and provide valuable feedback for the respective app developers. While both apps have areas of strength, as indicated by the number of high ratings, they also have aspects that could be improved, as suggested by the lower star ratings. This feedback is crucial for further development and enhancement of the apps in catering to user well-being and managing digital addiction.

Table 1. Star distribution of the comments

Stars	Number of English comments for Space app.	Number of English comments for Google Well-being app.
1	289	1230
2	242	106
3	356	229
4	881	476
5	1709	2632
Total	3477	4673

The most liked comment is, "Being a student I just love the focus mode to keep away distracting apps. It can be improved a little as it counts the Google Ambient Display in the screen time which makes the overall screen time ridiculously high." with 1725 times for Google Wellbeing app. Users also liked the "Great app. Too bad 'I'm' terrible at listening to it lol!" comment more than a thousand about Space app. The most liked Space comment with 300 likes; "Great for increasing awareness about phone use The app makes me so much more aware of how much I am on my phone and really helps me to decrease my phone usage. The app is quite customizable so you can change features to work better for you to stop being addicted to your phone. I 'would've' rated it 5 stars but it has some bugs that need worked out. Also, the user-interface is not very pretty."

The star table of the selected comments is given in Table 1 (Kahya Özyirmidokuz et al., 2021). Our corpus is formed of 4673 Google Well-being app and 3477 Space app user comments which are collected until 01.May.2020. We manually select comments about software labels and 1124 of 3477 comments are about Space app., 659 of 4673 comments are about Google Well-being software labels.

The collected unstructured big data were analyzed using qualitative and NLP (Natural Language Processing) methods. Python NLTK was used for Natural Language Processing. Descriptive statistics and grouping analyzes of unstructured data were performed using NLP algorithms. The TF-IDF (Term Frequency - Reverse Document Frequency) method was used while the data was processed with natural language processing techniques. After tokenizing the data, all data is converted to lowercase. *WordNetLemmatizer()* is used to lemmatize the words. HTML codes are removed. Table 2 presents some rows of the data matrix after NLP process.

Table 2. Data examples

App	Relikes	Comments
Well-being	5	['thx']
Well-being	5	['good']
Well-being	145	['needs', 'work.', '\ndo', 'you', 'guys', 'train', 'somewhere', 'to', 'be', 'this', 'bad', 'at', '\nyour', 'job?', 'all', 'this', 'pie', 'is', 'a', 'disaster.', 'and', 'you', 'keep', '\nspamming', 'with', 'more', 'useless', 'apps', 'to', 'eat', 'memory', 'and', 'battery', 'to', 'clse', 'MY', 'apps,', 'creating', 'more', 'ways', 'to', 'make', 'shure', 'old', 'ones', 'would', 'stop', 'working...', 'bravo', 'Google', 'you', 'are', 'Microsoft', 'now!']
Well-being	1	['do', 'you', 'really', 'want', 'your', 'digital', '\nhabbit', 'mapped?']
Well-being	4	['when', 'i', 'close', 'the', 'app', 'and', 'imediately', 'open', 'it', 'again', '\nthen', 'the', 'timings', 'are', 'changed', '?', 'why', 'is', 'it', 'so?']
Well-being	2	['It', "doesn't", 'work', 'on', 'my', 'Pixel', '2.', "\nI've", 'been', 'able', 'to', 'activate', 'the', 'gray-scale', 'for', 'a', 'couple', '\nof', 'moments,', 'but', 'my', 'phone', 'seems', 'to', 'think', 'that', 'sunrise', 'is', 'in', 'the', 'middle', 'of', 'the', 'night', 'or', 'something.']
Well-being	4	['cool']
Space	10	['Amazing', 'app!', 'Really', 'helps', 'you', 'stay', 'away', 'from', 'your', 'phone.', 'I', 'was', 'looking', 'for', 'a', 'mobile', 'de', 'addiction', 'app', 'since', 'couple', 'of', 'months', 'now.', "Didn't", 'really', 'get', 'the', 'flexibility,', 'which', 'this', 'app', 'offers.', 'Very', 'helpful!!']
Space	3	["It's", 'pretty', 'good', 'It', 'does', 'what', 'it', 'advertises,', 'but', 'I', "can't", 'get', 'the', 'schedule', 'to', 'work.', 'I', 'have', 'it', 'set', 'for', 'work', 'hours,', 'but', "it's", 'after',

		'hours', 'and', "it's", 'still', 'on.', "I'd", 'love', 'to', 'improve', 'the', 'score,', 'if', 'it', 'would', 'work', 'or', 'have', 'more', 'instructions.']
Space	5	['im', 'free!!', 'before', 'I', 'didnt', 'ever', 'knew', 'how', 'often', 'i', 'checked', 'my', 'phone,', 'i', 'was', 'using', 'it', 'about', '200!!', 'times', 'a', 'DAY,', 'now', 'i', 'check', 'it', 'about', '200', 'a', 'WEEK', 'thx', 'soo', 'much', 'for', 'curing', 'me']
Space	4	['Nice', 'tool', 'Would', 'be', 'great', 'to', 'be', 'able', 'to', 'check', 'the', 'specific', 'hours', 'spent', 'on', 'previous', 'days,', 'as', 'well', 'as', 'the', 'Times', 'with', 'must', 'phone', 'usage']

The word clouds presented in Figures 1, 2, and 3 offer insightful visual representations of user feedback for the Google Well-being app and the Space app. Figure 1 presents the word cloud of the users' feedback including likes of the comments. Figure 2 shows the word cloud of the Google Well-being app and Figure 3 presents the word cloud of the Space app users' feedback about software labels.

Figure 1. Word cloud of the users' feedback

Figure 2. Word cloud of the Google Well-being app users' feedback about software labels

Figure 3. Word cloud of the Space app users' feedback about software labels

In the word clouds, the "uninstall " word is seen, it was repeated 656 times in the Google Well-being app users' feedback corpus (Figure 2). The comments are about uninstalling the app and easy to use, e.g.for Google Well-being a comment is as follows, " for installing public version .. it says uninstall beta version.. but now it doesn't give any option to uninstall beta version of the same", "A wellbeing app is useful, but this specific app breaks Gen1 Google Pixels, and is a HUGE pain to uninstall. The stress and frustration I feel from figuring out how to remove this app, so my Pixel works will ALWAYS end up outweighing any health benefits this app could have potentially hypothetically delivered. If I could list it lower than 1 star, I would.", "let me uninstall". Prevalence of the Word "Uninstall": The frequent appearance of "uninstall" in the Google Well-being app feedback suggests a significant level of dissatisfaction or challenges among users, particularly regarding uninstallation issues. This high frequency indicates that addressing the uninstallation process might be a critical area for improvement for the app developers. The difficulty in uninstalling the app and the negative impact of the app on user experience, especially on Gen1 Google Pixel devices is crucial as it points to specific technical and user experience issues that need addressing. The comment about the app causing stress and frustration, outweighing its potential health benefits, is particularly telling. It underscores the importance of ensuring that well-being apps, which are designed to improve user health and wellness, do not inadvertently cause adverse effects. This kind of feedback is vital for developers to consider in future updates or designs, ensuring that the app's core functionality aligns with user expectations and experiences.In the study, the k-medoids clustering algorithm is employed to categorize the user comments into distinct groups based on their content, which is related to various aspects of software functionality. This method is particularly advantageous for its ability to minimize the influence of outliers and noise on the classification of data. K-medoids is not restricted to numerical data and can be applied to categorical data as well, as long as an appropriate dissimilarity measure is defined. In addition, k-medoids algorithm tends to be more stable in the presence of noise and outliers, which means the results are more reliable and repeatable when the same data is clustered multiple times. The number of clusters is predefined at four (k=4), with the Euclidean distance metric being utilized to measure the similarity between data points.

Following the application of the k-medoids algorithm, the comments are allocated into four clusters with the following sizes:

- Cluster 0: This cluster groups 501 comments, which are mainly focused on the challenges users face when attempting to remove or uninstall the app. In addition, this cluster gathers opinions about the software's battery usage. On a less frequent basis, it includes remarks about the focus mode feature, suggesting this is a less common concern among users.
- Cluster 1: Comprising 481 comments, this cluster is characterized by discussions surrounding Google Play, Google Pixel devices, and the software's settings. This indicates that users are actively engaging with the software on these devices and are concerned with its configuration and functionality within the Google ecosystem.
- Cluster 2: With 175 comments, this cluster is associated with user feedback on pop-up notifications, the driving mode feature, and the app's interaction with Google Maps.

These comments reflect user experiences and feedback on how the app behaves during navigation and driving scenarios.

- Cluster 3: The largest cluster, with 625 items, encompasses comments related to the timer functionality of the app and a variety of other topics, such as updates and privacy concerns. This suggests a broad range of user feedback areas that extend beyond specific features to include general app behaviour and user preferences.

The model's effectiveness is quantified using a performance vector, which, in this context, likely represents the model's ability to accurately cluster comments. A performance vector index of 0.989 indicates that the clustering model is performing with a high degree of precision, effectively grouping user comments in a way that accurately reflects the various themes and concerns mentioned by the users.

This analytical process of clustering user comments provides a structured approach to understanding the multitude of user feedback, which is critical for the continuous improvement of the software and ensuring that it aligns with user needs and experiences. The centroid plot views of clusters can be seen from Fig. 4. A performance vector is applied to count the number of support vectors of the model. The performance vector of the model's cluster number index is 0.989.

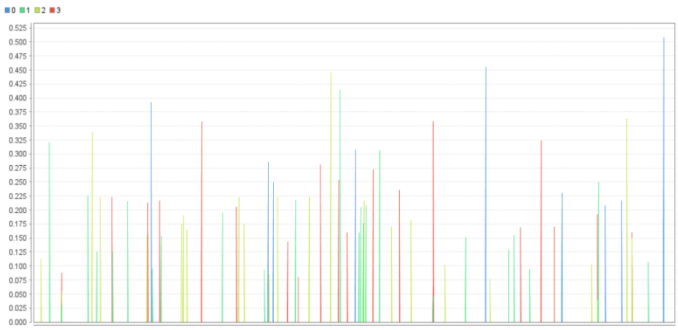

Figure 4. Plot histogram of cluster model

5. CONCLUSIONS

In this study, we embarked on an automated exploration of user reviews of digital well-being applications, specifically focusing on popular Android software such as Space and Google Well-being. By leveraging Natural Language Processing (NLP) algorithms, we systematically collected and processed user feedback, which enabled us to classify the reviews into four distinct clusters. This classification provides a clearer understanding of the various user perspectives on the digital well-being system's features and performance. Our research marks a pioneering step in the automated analysis of user feedback within the realm of digital well-being systems. Through the methodology employed, we reveal patterns and commonalities in user experiences that have not been systematically compiled before. For developers and designers of digital well-being software, the insights gleaned from these user reviews can inform the iterative design process, leading to enhancements that are more closely aligned with user needs and preferences. This is particularly relevant for the ongoing development of features like app usage timers, focus modes, and battery management, which have been highlighted as areas of user concern. By integrating user feedback in real-time, software developers can foster a more participatory design approach. This could lead to the creation of digital well-being tools that are not only reflective of user feedback but also evolve with user input, ensuring that the tools remain relevant and effective as digital habits and technologies change. In conclusion, this study serves as a foundational work, demonstrating the feasibility and value of using automated NLP techniques to analyse user feedback on digital well-being applications. The use of such advanced analytical methods holds the promise of enhancing user satisfaction and contributing to the broader goal of improving digital health.

ACKNOWLEDGEMENTS

This research is supported by Erciyes University (BAP) Project, Project id: **SBA-2017-7195**, Project title: "Dijital bağımlılık önleme konusunda kültür farkındalık tasarımı (Culture Aware Design for Digital Addiction Prevention)".

REFERENCES

1. Ali, R. (2018) *Digital Motivation, Digital Addiction and Responsibility Requirements*. In 2018 1st International Workshop on Affective Computing for Requirements Engineering (AffectRE) (pp. 27–27). Banff, AB, Canada. https://doi.org/10.1109/AffectRE.2018.00011.
2. Ali, R.; Solis, C.; Salehie, M.; Omoronyia, I.; Nuseibeh, B.; Maalej, W. (2011a) *Social Sensing: When Users Become Monitors*. In the proceedings of the New Ideas Track of the joint meeting of the European Software Engineering Conference and the ACM SIGSOFT Symposium on the Foundations of Software Engineering (ESEC/FSE 2011), Szeged, Hungary, September 5-9, 476-479.
3. Ali, R.; Jiang, N.; Phalp, K.; Muir, S.; McAlaney, J. (2015) *The Emerging Requirement for Digital Addiction Labels*. The 21st International Working Conference on Requirements Engineering: Foundation for Software Quality (REFSQ 2015), Springer. Essen, Germany, March 2015, pp 198-213.
4. Ali, R.; Solis, C.; Dalpiaz, F.; Maalej, W.; Giorgini, P.; Nuseibeh, B. (2011b) *Social Software Product Lines*. In the proceedings of the 1st international Workshop on Requirements Engineering for Social Computing (RESC 2011), 2011, co-located with the 19th IEEE International Requirements Engineering Conference. Trento, Italy, August 29th 2011, 14-17.
5. Ali, R.; Solis, C.; Omoronyia, I.; Salehie, M.; Nuseibeh, B. (2012) *Social Adaptation: When Software Gives Users a Voice*. In the proceedings of the 7th International Conference on Evaluation of Novel Approaches to Software Engineering (ENASE 2012), Best Paper Award. Wroclaw, Poland, June 29-30, 75-84.
6. Alrobai, A., Phalp, K., Ali, R. (2014). *Digital Addiction: A Requirements Engineering Perspective*. In: Salinesi, C., van de Weerd, I. (eds) Requirements Engineering: Foundation for Software Quality. REFSQ 2014. Lecture Notes in Computer Science, vol 8396. Springer, Cham. https://doi.org/10.1007/978-3-319-05843-6_9.
7. Creswell, J.W. (2013). *Qualitative inquiry and research design. Choosing among five approaches* (3e éd.).

London: Sage. Approches inductives, 2015, Hakim Ben Salah, Note de lecture : 1-4.
8. Galvis Carreño, L.V.; Winbladh, K. (2013) *Analysis of User Comments: An Approach for Software Requirements Evolution*. In ACM/IEEE International Conference on Software Engineering (ICSE), 582–591.
9. Kahya Özyirmidokuz, E.; Çifçi, Ş.; Pak, E.; Yıldız, A.; Andaç, E. (2021) Dijital iyi olma sistemlerinde kullanıcı geribildirim analizi. *Bilişim Sistemleri ve Yönetim Araştırmaları Dergisi*, 3(1).
10. Kurtanovic´, Z.; Maalej, W. (2017) *Mining User Rationale from Software Reviews*. IEEE 25th International Requirements Engineering Conference, 61-70. DOI 10.1109/RE.2017.86.
11. Lau, N.; O'Daffer, A.; Colt, S.; Yi-Frazier, J.P.; Palermo, T.M.; McCauley, E.; Rosenberg, A.R. (2020) Android and iPhone Mobile Apps for Psychosocial Wellness and Stress Management: Systematic Search in App Stores and Literature Review. *JMIR Mhealth Uhealth*, 8(5), e17798. doi: 10.2196/17798.
12. McAlaney, J.; Almourad, M. B.; Powell, G.; Ali, R. (2020) Perceptions and Misperceptions of Smartphone Use: Applying the Social Norms Approach. *Information*, 11(11), 513.
13. Neale, J.; Bowen, A. M. (2022) Lessons for Uptake and Engagement of a Smartphone App (SURE Recovery) for People in Recovery From Alcohol and Other Drug Problems: Interview Study of App Users. *JMIR Human Factors*, 9(1), e33038.
14. Nguyen, M. H.; Büchi, M.; Geber, S. T. (2022) Everyday disconnection experiences: Exploring people's understanding of digital well-being and management of digital media use. *New Media & Society*. https://doi.org/10.1177/14614448221105428.
15. Palomba, F.; Salza, P.; Ciurumelea, A.; Panichella, S.; Gall, H.; Ferrucci, F.; De Lucia, A. (2017) *Recommending and Localizing Change Requests for Mobile Apps based on User Reviews*. IEEE/ACM 39th International Conference on Software Engineering, 106-117. DOI 10.1109/ICSE.2017.18.
16. 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 (8), 526-532.
17. Solymosi, R.; Buil-Gil, D.; Vozmediano, L.; Guedes, I.S. (2020) Towards a Place-based Measure of Fear of Crime: A Systematic Review of App-based and Crowdsourcing Approaches. *Environment and Behavior*, 1-32.
18. Yang, T.; Jiang, Z.; Shang, Y.; Norouzi, M. (2021) Systematic review on next-generation web-based software architecture clustering models. *Computers and Communication*, 167, 63-74.