Designing for diversity: Dynamic persuasive strategies in mHealth app development

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Abstract
This study examines the impact of persuasive system design (PSD) in mobile health (mHealth) apps, focusing on how personalized persuasive strategies, based on users' psychological characteristics can enhance engagement, behavior change and efficacy. With the ubiquity of mobile devices reshaping behavior and perspectives, there's a growing need to personalize digital health technologies to individual users' characteristics. This approach challenges the conventional 'one size fits all' model, recognizing the diversity in user needs and motivations. This research employed a multiphase experimental design, developing and evaluating 25 mHealth app screens using PSD principles. This involved rigorous prototyping, expert review, and iterative design, ensuring that each screen effectively incorporated persuasive elements tailored for diverse user groups. The study's findings highlight the effectiveness of combining primary task support and dialogue support in mHealth screens to maximize user engagement. Furthermore, the research underscores the importance of system credibility and social support in persuasive design, although these elements require careful implementation due to users' varying perceptions of persuasiveness among users. This work significantly contributes to the field by providing insights into how digital health technologies can be optimally designed to cater to the dynamic psychological makeup of users, ultimately enhancing user engagement with a focus on behavior change.

Keywords
Persuasive Design, User Engagement, User-Centric Design, Digital Health Interventions

1. Introduction

The evolution of Behavior Change Systems (BCS) reflects a dynamic journey, from early behaviorism ideas to the modern combination of psychology, data science, and user-centric design, revealing a remarkable story of adaptation and creativity. The potential of BCS to motivate and support individuals is promising; however, there needs to be more explicit research on behavioral theory and evidence-based solutions [1]. Mobile health (mHealth) apps have proven highly effective in encouraging positive health-related behavioral changes among users [2]. Notably, the persuasive system design framework (PSD) plays a crucial role in guiding

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the use of persuasive technology, especially in mobile health applications [3, 4]. Recently, mHealth interventions have gained interest as an innovative strategy to combat disease in a cost-effective manner [5]. Regular evaluation of persuasive features within these mHealth apps is essential, and the PSD model serves as a valuable tool for accomplishing this task. The benefits of persuasive technologies in mHealth engagement, capable of educating, convincing, and encouraging users throughout their behavioral change, particular in health behavior, are significant and should not be overlooked [2]. The ubiquity of mobile devices has reshaped our actions and thoughts, making it valuable and relevant for us to learn and understand the importance of persuasive technology [6]. The word persuasive refers to synonyms like effective, cueing, convincing, and compelling. At its root, persuasion is simply an attempt to influence and convince others on various subjects [7].

Given the diverse range of individuals and their unique needs, the "one size fits all" approach to solutions has been accepted as often counterproductive and outdated. Individuals vary significantly in their needs, reflecting the diversity and uniqueness of their personal characteristics and backgrounds [8]. It is important to accommodate cultural differences, including race, gender, socioeconomic status, age, and sex, instead of applying one-size-fits-all solutions in an effort to foster behavior change [9]. By embracing diversity and understanding individual differences, we can achieve better outcomes, increased efficiency in innovation [10], and better satisfaction [8]. Examining how individual psychological traits like self-efficacy, health consciousness, and personality types influence user engagement with mHealth screens highlights the importance of personalized digital health strategies [11].

2. Background

Digital health behavior change interventions have emerged as potent catalysts for positive behavioral shifts among healthcare professionals, patients, and the public [12]. Mobile health applications are evolving, with an increasing implementation of persuasive design features aimed at enhancing behavior change [2]. A wide array of ideas, concepts, and approaches comprises the behavior change interventions. These include, but are not limited to, the theory of reasoned action, the theory of planned behavior, the technology of acceptance model, the self-efficacy theory, the social cognitive theory, the elaboration likelihood model, cognitive dissonance theory, goal setting theory, and computer self-efficacy [4]. In addition, the majority of theories on cognitive health outline the possible connections between psychosocial elements and healthful conduct [13]. Mobile applications target various health behaviors, including increasing physical activity, smoking cessation, healthy eating, weight loss, and blood pressure control, among others [14].

A systematic review of controlled trials in mobile health interventions revealed noteworthy outcomes for therapies delivered via smartphones and tablets [15]. The findings indicate that intervention participants demonstrated a heightened success rate in changes across a spectrum of health behaviors and related outcomes. However, the implementation of mobile health interventions faces significant challenges, such as user engagement, theoretical underpinnings, pace and efficiency, effectiveness evaluation, regulation, and ethics. To address these problems and maximize possibilities, a diverse range of academic disciplines, involving behavioral, computer, and engineering sciences, as well as user-centered design, will need to collaborate and share their skills [12]. Integrating behavior change interventions into mobile and social technologies enables real-time, continuous evaluation, offering advantages over outdated, data-poor, and infrequent methods.

A recent study focusing on computational models of habit formation proposed a method in health applications for situations where actions are repeated continually; in promoting healthy lifestyles, one of the obstacles to effective transformation is the process of breaking poor old habits and developing healthy new ones [16].Previous research and development in persuasive technology often adapted a one-size-fits-all approach [17]. Considering that individuals have different motivations and beliefs, there is a need for digital health technology to become more personalized [10]. In this literature review, we aim to explore the concept of personalization, understanding diversity across different industries, and the importance of finding solutions that are tailored to personal needs. One size does not fit all, especially when tailoring Persuasive Technology (PT) to an individual [9]. Since persuasive systems aim to target behavior and shape it into a desired behavior [18], understanding individual needs and adapting to various user characteristics is essential.

Psychologically, consumer engagement improves when a mHealth app aligns with individual user preferences, sparking interest and fostering sustained interaction and commitment. This view, as discussed by Tarute et al., emphasizes how the consumers' focus is drawn to brands or enterprises that resonate with their interests, thereby encouraging cognitive, emotional, and behavioral engagement [19]. This includes maintaining commitment and taking corresponding actions. Notably mHealth apps predominantly attract young adults, with older adults showing less interest. This demographic skew, highlighted by Mustafa et al. and Askari et al., narrows the consumer age range, since the elderly often show resistance to adopting health apps [20, 21]. A significant challenge for mHealth apps lies in sustaining or even initiating consumer interest. Factors contributing to this issue include missing elements within the apps, lack of enjoyment, confusion regarding usage, and the need to evaluate multiple apps to find the most effective ones [21].

There exists a paradigm shift in literature where researchers extended the qualifications for engagement. Researchers began to home in on the principle of user engagement being driven by the quality of the users/patients experience [22-24]. While others also measured engagement by the interaction with digital health technologies, often driven by attributes that naturally evoke interest in the consumer, which was frequently believed to be reflected by behavior change in the user [25, 26]. Engagement is also seen as a synergized relationship between digital health technology and the consumer, in which the consumer is fully immersed and aligned with the activity [27].

User engagement is also driven by user characteristics. For example, emotional (i.e. motivation) and behavioral (i.e. response to rewards) characteristics are considered driving factors for the time and energy users are willing to expend [28]. Breaking from previous more experience-oriented perspectives of engagement, current engagement concepts require the users to give their undivided attention to the digital health technology [25]. Achieving synergy between digital health technologies and consumers is often considered the highest form of user engagement [27]. As smartphones and other conduits for the delivery of digital health technologies become more ubiquitous, designers are capable of incorporating customization features to engage users/patients [24].

While the positive influence that persuasion has on changing an individual's attitude and behavior has been established [29, 30], researchers have contended the need for personalized systems that address the individual's personality to increase the effectiveness of digital health technologies [31, 32]. One-size-fits-all digital health technologies that target behavioral change to improve the user's health often fail because they do not target the psychological traits that drive an individual’s motivations and behaviors, due in part to the lack of guidance intervention designers and data scientists with numerous options face [8].

A dynamic personalized approach to the development of persuasive technologies is imperative as research has shown that strategies that may influence change in an individual with one type of psychological type may dissuade another individual with a different psychological type [9]. Our review of the literature revealed a void in the literature with scientists seeking a more intimate view of the consumer and how they interact with persuasive principles in order to help guide the design processes. The design process is furthered impaired by the lack of an understanding of the psychological characteristics of digital health technology users [33].

The common use of ‘Argumentum Ad Populum’ (“appeal to the majority”) in persuasive technology becomes less effective over time as it fails to address the dynamic characteristics of mHealth app users [34, 35]. Persuasive technology features become obsolete over time because designers do not address the multivariate, dynamic characteristics of mHealth app users [36]. Given the flawed nature of the design process, to leverage the benefits of successfully engaging the users of digital health technologies, it is desirable that dynamic features driven by user characteristics are amalgamated into the design process to better serve the context of user engagement [37, 38]. A methodical approach which intersects dynamic data driven design facilitated by persuasive technology will allow researchers and designers of persuasive technologies to predict the persuasive features that will successfully engage users, thus enabling effective engagement. The following research study aims to address the challenge of designing persuasive technology-grounded mHealth app screens that reflect the intended persuasive characteristics of the designer.

With increasing application of user engagement in digital health technologies, the benefits of enhanced outcomes are increasingly informed by mixed method approaches driven by data science [39]. The integration of data science and psychological characteristics has led to significant advances in predicting individual differences and similarities [40]. The use of data science allows a user’s personality to be leveraged to anticipate his or her potential needs [41]. Contrast mining can identify the significant personality characteristic differences that may lead to enhanced persuasiveness among groups of users and patients. By using this information, designers of digital health technologies can establish enhanced guidelines for the conceptualization of personalized persuasive intervention design for a given group; this, in turn, would lead to improved engagement of users. The recognition of additional differences will in turn allow designers of digital health technologies to better engage users and establish guidelines in each user/patient group which would help in the conceptualization of a personalized persuasive intervention design.

3. Methodology

3.1. Design process

To identify factors influencing engagement and intent to use a mHealth application, a multiple-phase experiment was conducted during the Summer 2020. This experiment utilized a survey-based approach, examining 25 mHealth app screens designed with persuasive principles to promote physical activity. This study was conducted with the approval of the Institutional Review Board (IRB) at the University of South Alabama, ensuring adherence to ethical standards for research involving human participants. This research focuses on the design and validation of the mHealth app screens. These screens were designed by adhering to the Persuasive System Design (PSD) categories and principles delineated by Oinas-Kukkonen and Harjumaa [42]. The screens were all developed with a unifying theme focused on enhancing and promoting physical exercise. Contrast Mining was used to evaluate the screens, identifying significant differences in user responses based on the interrelationships of the combinations of persuasive principles and individual characteristics of the users [43]. Contrast mining is a subarea of data mining that focuses on finding contrasting patterns that express significant differences in multiple datasets or classes, often comparing cases with a desired outcome against those with an undesired outcome [44].

The development process started with creating wireframe prototypes [45] for the mHealth screens. In this phase, preliminary designs were sketched on paper, with each sheet serving as a canvas for one mHealth app screen. Each prototype was thoroughly documented. Documentation included the persuasive system category, the (primary) design principle as from Oinas-Kukkonen's framework [42], targeted implantation, details about the mockup, and the mockup name that would be used throughout the study. Table 1 shows an example of the initial prototype development. Accompanying this documentation was a detailed description of each screen's features, which was used to guide the assignment of a unique reference name for each screen. This name was consistently used throughout the phases of questionnaire development and subsequent analysis. The final step in this phase was the creation of a sketch for each prototype, ensuring a visual representation of what each mHealth screen would encompass.

In the final development phase, BuildFire [46], a mobile application development tool was used. Buildfire was used to create digital, high-fidelity prototypes for each mHealth app screen. These advanced prototypes were instrumental in actualizing the design objectives set forth during the wireframe stage. After development, still images of the mHealth screens were captured using an iPhone XS Max. This technique was chosen to ensure that the captured images would authentically represent the user's experience on a mobile device. The images were then transferred from the iPhone to a laptop via email, for further analysis.

Table 1

Examples of the Initial Prototype Development Steps

Persuasive System Category	Design Principle	Targeted Implementation	Mockup	Mockup Name
Primary Task Support	Tunneling	Guiding people in a process step-by-step to meet a goal	Fitness program with step by step workout plan. Once daily/weekly goals are reached, the next set of steps are given.	Burpee-Squat

System Credibility Support	Trustworthiness	Application should appear to be truthful, fair, and unbiased	Display information guaranteeing HIPAA compliance to reassure users that information will not be shared with 3rd party organizations.	HIPAA

3.2. mHealth screen validation

In the final stage of the development process, the mHealth screen prototypes underwent a rigorous evaluation by two distinguished experts in persuasive technology. This evaluation used a blind review format for objective and unbiased assessment. The expert panel included one reviewer with an extensive 12-year background in the field of persuasive technology and another with 9 years of experience.

Following the expert inspection and blind review, a consultation was held with the expert review panel where notes and suggestions were reviewed. The review and modification process continued until the developer and reviewers reached a consensus. The mHealth screens were iteratively evaluated, modified, and improved following each expert inspection and blind review.

For the first round, twenty-three mHealth screens were developed: Add, Start, Burpee-Squat, Increase, Mountain, Target, Trophy, Late, Calories, Dinner Chat, Tracker, About Us, Stories, Leaderboard, Journal, Partners, Ads, Strategy, CDC, HIPAA, Contact, Before After, and Yoga. The developer and reviewers identified eleven mHealth screens with conflicting persuasive technology principles that required modification: Target, Dinner Chat, About Us, Journal, Partners, Strategy, HIPAA, Contact, Before After, Yoga, and CDC. There were discrepancies in the intended persuasive technology principle and the identified principle which necessitated modifications in the mHealth app screen to ensure coherence in the application of persuasive principles. The revised mHealth screens were resubmitted for review. CDC was dropped during the first round because the designed persuasive category was not seen by either of the two reviewers and the category that was identified was seen in another screen.

The Apple mHealth screen was created to replace CDC and submitted with revisions for round 2. A consensus was reached on the twenty-three mHealth screens during the second round. Additionally, three paper and high-fidelity prototypes were created for the remaining persuasive technology principles following the methods stated above. The additional mHealth screens (SSL, Avatar, and Recreation) were iteratively evaluated, modified, and improved using expert inspection and blind review methods used during rounds one and two. The iterative process resulted in twenty-five mHealth screens designed for the questionnaire that were agreed upon through the blind review process and one mHealth screen prototype being discarded. The mHealth screen acceptance by round is shown in Table 2. The X indicates which round the mHealth screen was accepted and N/A indicates that the screen had not been developed during the particular round.

Table 2
mHealth Screen Acceptance by Round

Screen Name	Round 1	Round 2	Round 3
Add	X		
Start	X		
Burpee-Squat	X		
Increase	X		
Mountain	X		
Target		X	
Trophy	X		
Late	X		
Calories	X		
Dinner Chat		X	
Tracker	X		
About Us		X	
Stories	X		
Leaderboard	X		
Journal		X	
Partners		X	
Ads	X		
Strategy		X	
Cdc	Dropped	N/A	N/A
Hipaa		X	
Contact		X	
Before After		X	
Yoga		X	
Apple	N/A	Replaced Cdc	
Ssl	N/A	N/A	X
Avatar	N/A	N/A	X
Recreation	N/A	N/A	X

4. Results

The iterative process yielded twenty-five mHealth screens used in a comprehensive research questionnaire.

Table 3 presents the final testing iteration, detailing the principles and principle categories (PT = primary task support, DS = dialogue support, SC = system credibility support and SS = social support) for each screen. Figure 1 displays two of the final mHealth screens (Start and Contact) that were developed.

Table 3
Mobile App Screen Name with Persuasive principles and Categories

Screen Name	Principle 1 (Primary)	Principle 2	Principle 3
Add	(PT) Tailoring	(PT) Tunneling	
Start	(PT) Reduction	(PT) Tunneling	
Burpee-Squat	(PT) Tunneling	(PT) Reduction	
Increase	(DS) Praise		
Mountain	(PT) Rehearsal	(DS) Suggestion	
Target	(DS) Praise	(PT) Personalization	
Trophy	(DS) Rewards	(DS) Praise	
Late	(DS) Reminders		
Calories	(DS) Suggestion		
Dinner Chat	(DS) Social Role	(DS) Praise	
Tracker	(PT) Self-Monitoring		
About Us	(SC) Expertise	(SC)Trustworthiness	(SC) Authority
Stories	(SS) Recognition	(PT) Simulation	(DS) Praise
Leaderboard	(SS) Competition		
Journal	(SS) Social Learning	(SS) Social Comparison	(SC)Social Facilitation
Partners	(SC) Trustworthiness	(SC) Expertise	(SC) Authority
Ads	(SC) Surface Credibility		
Strategy	(SC) Authority	(SC) Expertise	
Apple	(SC) Verifiability	(SC) Expertise	(SC) Authority
HIPAA	(SC) Trustworthiness	(SC) Surface Credibility	
Contact	(SC) Real-World Feel		
Before After	(SC) Normative Influence	(PT) Simulation	
Yoga	(SS) Cooperation	(DS) Praise	(SS)Social Comparison
SSL	(SC)Third-party Endorsements	(SC) Trustworthiness	
Avatar	(DS) Similarity	(DS) Liking	

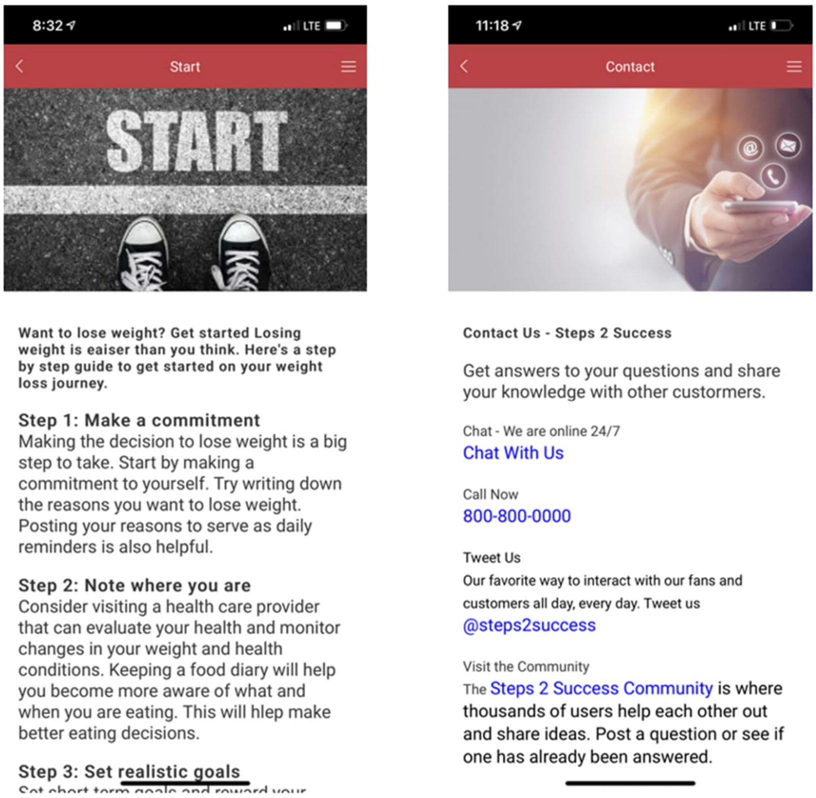

Figure 1: Sample mHealth screens developed and accepted during review

Among the 25 screens developed, 5 (20%) featured a primary principle from the primary task support category, 7 (28%) from the dialogue support category, 8 (32%) from the system credibility support category, and 5 (20%) from the social support category.

Contrast mining, not driven by hypothesis, effectively uncovers strong correlations between predictors, guiding future research. This method produced a concise set of rules predicting the persuasiveness of mHealth screens' primary categories: primary task support, dialogue support, system credibility support, or social support would be persuasive. The primary task support scores exceeded the average perceived persuasiveness score, with screens from the system credibility category closely matching or surpassing the average score.

This study introduces contrast mining as a novel solution to the gap in PSD frameworks' lack of systematic data driven decisions. Contrast mining offered a multi-layer insight into its impact on perceived persuasiveness at the screen level. The Primary Task Support category ranked highest in the weighted perceived persuasiveness bin. This finding contradicts Drozd [47], who found no significant relationship between primary task support and perceived persuasiveness. Screens from the System Credibility category achieved mid-level weighted perceived persuasiveness scores. The findings that primary task support and system credibility increase perceived persuasiveness are supported by Lehto [48], who found that primary task support and system credibility both significantly impact perceived persuasiveness directly. Screens from the Social Support category scored in the lowest perceived persuasiveness bin. Figure 2 illustrates the bins of perceived persuasiveness rules generated by Contrast Mining.

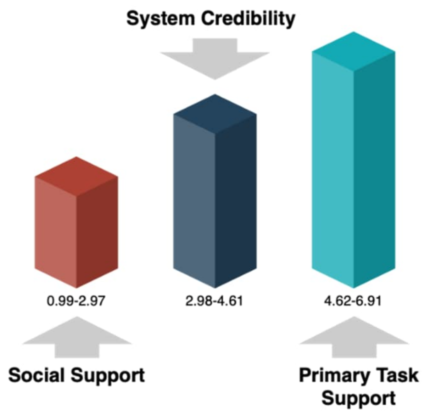

Figure 2: Contrast mining category results

The findings suggest that practitioners seeking to develop persuasive digital health technologies should develop screens using techniques in the primary task support or system credibility categories. Screens that employ techniques from the social support category need to be “strongly personalized” in order to achieve perceived persuasive-ness as these produced low perceived persuasiveness scores in our study. The contrast mining findings also suggest practitioners should use techniques from the dialogue support category when developing digital health technologies.

Little is known about the impact of psychological characteristics and the combination of multiple persuasive techniques on perceived persuasiveness. Drozd et al. [47] discovered that Primary Task Support and Dialogue Support together significantly impacted perceived persuasiveness. Additional studies that examine the primary and secondary categories are needed to determine whether or not the combination of additional categories is driving the perceived persuasiveness.

5. Discussion

Incorporating accurate persuasive design principles into a mHealth design process involves a detailed and multifaceted approach [42]. This strategy involves seamlessly blending these principles into the user experience of the digital health technology.

The Primary Task Support category plays a crucial role in simplifying the user's journey by breaking down complex tasks into simpler, more manageable steps. This was achieved through the reduction principle (Start), which simplified the steps involved in starting the weight loss journey, and the tunneling method (Burpee Squat), which guided users step-by-step in the process of completing an exercise. The design also incorporated tailoring (Add), adapting the app’s interface and functionality to individual user needs, interests, and personalities, creating a more customized experience. To enhance engagement and motivation, personalization (Target) was a key focus, ensuring that users received timely suggestions, praise, and rewards. Additionally, self-monitoring (Tracker) features were integrated, allowing users to easily track their progress and performance. The app also included simulation (Before After) and rehearsal

(Mountain), which depicted a video with a coach showing users how to properly perform an exercise.

Similarly, the Dialogue Support category enriches the interaction between humans and digital health technologies, rendering the application more captivating and reactive. This included integrating aspects like praise and rewards (Increase, Trophy), with the app providing various forms of positive feedback and visual rewards for task completion and reaching health milestones. In addition, the app included reminders (Late) and tailored suggestions (Calories), where reminders helped users stay on track with their health goals and personalized suggestions offered advice based on individual user data. The design also focused on the principles of similarity (Avatar) and liking (Avatar), ensuring that the app was not only visually appealing but also relatable to the users.

The System Credibility category aims to build trust and reliability within the system. Achieving this involved certifying the app's trustworthiness (Partners), presenting it as honest and unbiased to the user. To demonstrate expertise (About Us), the app included content from knowledgeable and reputable health organizations. Surface credibility (Ads) was also a focus, achieved through a competent and visually credible ad free design that resonated with users. Additionally, the app provided a real-world feel (Contact) by connecting users with the organizations and individuals responsible for the content, thereby enhancing the authenticity of the information provided. Authority (Strategy) was leveraged by incorporating inputs from recognized experts and authorities in the field such as the CDC and leading weight loss authorities, thereby bolstering user trust. To further solidify credibility, the app included third-party endorsements (SSL) and features for verifiability, allowing users to cross-check and confirm the safety of their health data with external sources.

Finally, the Social Support category leverages social influence to motivate users. This is accomplished through the social learning (Journal) principle, which allow users to see others engaging in target behaviors, creating a sense of community and shared goals. Additionally, the app incorporates social comparison (Journal) principle, enabling users to measure their performance against that of their peers, which serves as a motivational tool. The use of normative influence (Before After) is also employed, harnessing peer pressure in a positive way to encourage desired behaviors, by sharing before and after pictures of users that lost more than fifty pounds. Social facilitation (Journal) is integrated to give users the feeling of being part of a collective effort by allowing them to participate alongside others. The mHealth app screens also tapped into the innate human tendencies towards cooperation (Yoga) and competition (Leaderboard), encouraging both collaborative and competitive activities which are designed to increase engagement. Furthermore, the app includes features for recognition (Stories), publicly acknowledging user achievements, which not only rewards but also motivates users to continue their health journey.

Each of these categories and principles is interwoven into the design process to create a persuasive, engaging, and effective digital health technology that resonates with users on multiple levels, encouraging positive behavior change and sustained engagement.

6. Conclusion

This study aimed to investigate the effectiveness of persuasive design principles in mHealth applications and how they contribute to user engagement and perceived persuasiveness. This research advances the field of persuasive technology by focusing on the user-centric design and validation of mHealth app screens, employing data-driven methods to assess their effectiveness in engaging users and influencing behavior change. The use of dynamic data-driven capabilities is important to advancing perceived persuasiveness which has the potential to successfully engage users of digital health technologies. A significant limitation of this study was the use of static screens. Developing a fully developed app will allow researchers to evaluate the engagement of the digital health tool. Running these studies in tandem will allow researchers to evaluate engagement on both of those to see if higher perceived persuasiveness leads to higher engagement.

While this study has provided valuable insights into the application of persuasive design principles in mHealth applications, further clarification is needed regarding the extent of personalization in these designs. Understanding how various levels of personalization influence user engagement and the effectiveness of persuasive strategies could significantly enhance the development of more tailored and impactful digital health interventions. Future research in this area should explore the nuances of personalization, examining its potential to meet diverse user needs and preferences more effectively.

References

[1] A. C. King et al., "Effects of Three Motivationally Targeted Mobile Device Applications on Initial Physical Activity and Sedentary Behavior Change in Midlife and Older Adults: A Randomized Trial," PLoS One, 11(6): e0156370 (2016). doi: 10.1371/journal.pone.0156370.

[2] J. Matthews, K. T. Win, H. Oinas-Kukkonen, and M. Freeman, "Persuasive Technology in Mobile Applications Promoting Physical Activity: a Systematic Review," J Med Syst, 40(3): 72 (2016). doi: 10.1007/s10916-015-0425-x.

[3] A. Hussian, A. Mateen, F. Amin, M. A. Abid, and S. Ullah, "Health Monitoring Apps: An Evaluation of the Persuasive System Design Model for Human Wellbeing," Information, 14(7), (2023). doi: 10.3390/info14070412.

[4] H. Oinas-Kukkonen, "A foundation for the study of behavior change support systems," Personal and Ubiquitous Computing, 17(6): 1223-1235, (2012). doi: 10.1007/s00779-012-0591-5.

[5] S. Sittig, A. McGowan, and S. Iyengar, "Extensive Review of Persuasive System Design Categories and Principles: Behavioral Obesity Interventions," J Med Syst, 44(7): 128, (2020). doi: 10.1007/s10916-020-01591-w.

[6] B. J. Fogg, "Creating Persuasive Technologies: An Eight-Step Design Process," presented at the Proceedings of the 4th International Conference on Persuasive Technology - Persuasive '09 (2009).

[7] H. A. A. Spelt, J. H. D. M. Westerink, L. Frank, J. Ham, and W. A. Ijsselsteijn, "Physiology-based personalization of persuasive technology: a user modeling perspective," User Modeling and User-Adapted Interaction (2022). doi: 10.1007/s11257-021-09313-8.

[8] E. Engl, P. Smittenaar, and S. K. Sgaier, "Identifying population segments for effective intervention design and targeting using unsupervised machine learning: an end-to-end guide," Gates Open Res, 3:1503, (2019), doi: 10.12688/gatesopenres.13029.2.

[9] A. M. Abdullahi, K. Oyibo, R. Orji, and A. A. Kawu, "The Influence of Age, Gender, and Cognitive Ability on the Susceptibility to Persuasive Strategies," Information, 10(11), (2019). doi: 10.3390/info10110352.
[10] R. Orji, "Exploring the persuasiveness of behavior change support strategies and possible gender differences," presented at the 2nd International Workshop on Behavior Change Support Systems, BCSS 2014, Padua; Italy, (2014).
[11] A. McGowan, S. Sittig, D. Bourrie, R. Benton, and S. Iyengar, "The Intersection of Persuasive System Design and Personalization in Mobile Health: Statistical Evaluation," (in English), JMIR Mhealth Uhealth, 10(9): e40576, (2022). doi: 10.2196/40576.
[12] S. Michie, L. Yardley, R. West, K. Patrick, and F. Greaves, "Developing and Evaluating Digital Interventions to Promote Behavior Change in Health and Health Care: Recommendations Resulting From an International Workshop," J Med Internet Res, 19(6):1-13, (2017). doi: 10.2196/jmir.7126.
[13] F. Taj, M. C. A. Klein, and A. Van Halteren, "Motivating Machines: The Potential of Modeling Motivation as MoA for Behavior Change Systems," Information, 13(5), (2022). doi: 10.3390/info13050258.
[14] C. Ernsting et al., "Using Smartphones and Health Apps to Change and Manage Health Behaviors: A Population-Based Survey," J Med Internet Res, 19(4):e101, (2017). doi: 10.2196/jmir.6838.
[15] W. T. Riley, D. E. Rivera, A. A. Atienza, W. Nilsen, S. M. Allison, and R. Mermelstein, "Health behavior models in the age of mobile interventions: are our theories up to the task?," Transl Behav Med, 1 (1):53-71, (2011). doi: 10.1007/s13142-011-0021-7.
[16] C. Zhang, J. Vanschoren, A. van Wissen, D. Lakens, B. de Ruyter, and I. J. WA, "Theory-based habit modeling for enhancing behavior prediction in behavior change support systems," User Model User-adapt Interact, 32(39):389-415, (2022). doi: 10.1007/s11257-022-09326-x.
[17] A. M. Abdullahi, R. Orji, and A. A. Kawu, "Gender, Age and Subjective Well-Being: Towards Personalized Persuasive Health Interventions," Information, 10(10), (2019), doi: 10.3390/info10100301.
[18] V. Mylonopoulou, "Design for health behavior change supportive technology," presented at the Proceedings of the 10th Nordic Conference on Human-Computer Interaction - NordiCHI '18, 2018.
[19] A. Tarute, S. Nikou, and R. Gatautis, "Mobile application driven consumer engagement," Telematics and Informatics, vol. 34, no. 4, pp. 145-156, 2017, doi: 10.1016/j.tele.2017.01.006.
[20] M. Askari, N. S. Klaver, T. J. van Gestel, and J. van de Klundert, "Intention to use Medical Apps Among Older Adults in the Netherlands: Cross-Sectional Study," J Med Internet Res, vol. 22, no. 9, p. e18080, Sep 4 2020, doi: 10.2196/18080.
[21] A. S. Mustafa, N. Ali, J. S. Dhillon, G. Alkawsi, and Y. Baashar, "User Engagement and Abandonment of mHealth: A Cross-Sectional Survey," Healthcare (Basel), vol. 10, no. 2, Jan 24 2022, doi: 10.3390/healthcare10020221.
[22] S. Taki et al., "Assessing User Engagement of an mHealth Intervention: Development and Implementation of the Growing Healthy App Engagement Index," JMIR Mhealth Uhealth, vol. 5, no. 6, p. e89, Jun 29 2017, doi: 10.2196/mhealth.7236.

[23] M. Holdener, A. Gut, and A. Angerer, "Applicability of the User Engagement Scale to Mobile Health: A Survey-Based Quantitative Study," JMIR Mhealth Uhealth, vol. 8, no. 1, p. e13244, Jan 3 2020, doi: 10.2196/13244.
[24] M. Lalmas, H. O'Brien, and E. Yom-Tov, Measuring User Engagement (Synthesis Lectures on Information Concepts, Retrieval, and Services). Morgan & Claypool, 2014.
[25] X. Ren, C. Silpasuwanchai, and J. Cahill, "Human-Engaged Computing: the future of Human–Computer Interaction," CCF Transactions on Pervasive Computing and Interaction, vol. 1, no. 1, pp. 47-68, 2019, doi: 10.1007/s42486-019-00007-0.
[26] N. Zagalo, "From Experience to Engagement," in Engagement Design: Designing for Interaction Motivations. Cham: Springer International Publishing, 2020, pp. 11-30.
[27] K. Salehzadeh Niksirat et al., "Approaching Engagement towards Human-Engaged Computing," presented at the Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems, 2018.
[28] H. L. O'Brien, J. Arguello, and R. Capra, "An empirical study of interest, task complexity, and search behaviour on user engagement," Information Processing & Management, vol. 57, no. 3, 2020, doi: 10.1016/j.ipm.2020.102226.
[29] P. MScMed and F. G. BOccTher, "Persuasive technology and behaviour change in parent-focused eHealth interventions supporting child health: A scoping review protocol," New Zealand Journal of Physiotherapy, 47(1): 36-48 (2019).
[30] R. Orji and K. Moffatt, "Persuasive technology for health and wellness: State-of-the-art and emerging trends," Health Informatics J, 24(1):66-91 (2018). doi: 10.1177/1460458216650979.
[31] M. Kaptein, P. Markopoulos, B. de Ruyter, and E. Aarts, "Personalizing persuasive technologies: Explicit and implicit personalization using persuasion profiles," International Journal of Human-Computer Studies, vol. 77, pp. 38-51, 2015, doi: 10.1016/j.ijhcs.2015.01.004.
[32] H. J. Wall, C. C. Campbell, L. K. Kaye, A. Levy, and N. Bhullar, "Personality profiles and persuasion: An exploratory study investigating the role of the Big-5, Type D personality and the Dark Triad on susceptibility to persuasion," Personality and Individual Differences, 139:69-76, (2019). doi: 10.1016/j.paid.2018.11.003.
[33] M. Tuman and A. Moyer, "Health intentions and behaviors of health app owners: a cross-sectional study," Psychol Health Med, 24(7):819-826, (2019). doi: 10.1080/13548506.2019.1576911.
[34] E. Anagnostopoulou, E. Bothos, B. Magoutas, J. Schrammel, and G. Mentzas, "Persuasive technologies for sustainable mobility: State of the art and emerging trends," Sustainability, 10(7):2128, (2018).
[35] R. Orji and R. L. Mandryk, "Developing culturally relevant design guidelines for encouraging healthy eating behavior," International Journal of Human-Computer Studies, 72(2):207-223, (2014).
[36] H. Oinas-Kukkonen, "Personalization Myopia: A Viewpoint to True Personalization of Information Systems," presented at the Proceedings of the 22nd International Academic Mindtrek Conference on - Mindtrek '18, (2018).
[37] J. A. Naslund et al., "Health behavior models for informing digital technology interventions for individuals with mental illness," Psychiatr Rehabil J, 40(3):325-335, (2017). doi: 10.1037/prj0000246.

[38] D. Spruijt-Metz and W. Nilsen. (2014, July-Sept. 2014) Dynamic Models of Behavior for Just-in-Time Adaptive Interventions. IEEE Pervasive Computing 13-17.
[39] R. K. Britt, J. Maddox, S. Kanthawala, and J. L. Hayes, "The impact of mHealth interventions," in Technology and Health, pp. 271-288, (2020).
[40] W. Bleidorn and C. J. Hopwood, "Using Machine Learning to Advance Personality Assessment and Theory," Pers Soc Psychol Rev, 23(2):190-203, (2019). doi: 10.1177/1088868318772990.
[41] A. Souri, S. Hosseinpour, and A. M. Rahmani, "Personality classification based on profiles of social networks' users and the five-factor model of personality," Human-centric Computing and Information Sciences, 8(1), (2018). doi: 10.1186/s13673-018-0147-4.
[42] H. Oinas-Kukkonen and M. Harjumaa, "Persuasive Systems Design: Key Issues, Process Model, and System Features," Communications of the Association for Information Systems, 24, (2009). doi: 10.17705/1cais.02428.
[43] Contrast. (2018). GitHub. Accessed: 08/13/2021. [Online]. Available: https://github.com/parsahosseini/contrast
[44] G. Dong and J. Bailey, Contrast data mining: concepts, algorithms, and applications. CRC Press, (2012).
[45] E. Rosenzweig, Successful user experience : strategies and roadmaps. Amsterdam: Elsevier, (2015).
[46] Buildfire Corporation. https://buildfire.com/
[47] F. Drozd, T. Lehto, and H. Oinas-Kukkonen, "Exploring Perceived Persuasiveness of a Behavior Change Support System: A Structural Model," in Persuasive Technology. Design for Health and Safety, (Lecture Notes in Computer Science, ch. 14, pp. 157-168, (2012).
[48] T. Lehto, H. Oinas-Kukkonen, and F. Drozd, "Factors affecting perceived persuasiveness of a behavior change support system," (2012).