PERSONALIZATION IN MOBILE HEALTH APPLICATIONS FOR BEHAVIOR CHANGE: A LITERATURE-BASED PREFERENCE MATRIX, EMPIRICAL VALIDATION, AND ONTOLOGY DEVELOPMENT

La Personnalisation dans les Applications Mobiles de Santé pour le Changement de Comportement : une Matrice de Préférences Basée sur la Littérature, une Validation Empirique et un Développement d'Ontologie

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Geneva School of Economics and Management,
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by
Laetitia GOSETTO

Under the direction of

Prof. Gilles FALQUET, supervisor and

Dr Frédéric EHRLER, co-supervisor

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Jury members:

Prof. Katarzyna WAC, Chair, University of Geneva
Prof. Sylvia PELAYO, University of Lille, France
Prof. Giovanna DI MARZO SERUGENDO, University of Geneva

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Dean
Salvatore DI FALCO

Impression d’après le manuscrit de l’auteur

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Abstract

Unhealthy behaviors, including physical inactivity, poor diet, tobacco use, and alcohol misuse, continue to be significant contributors to global mortality, highlighting the pressing need for effective, scalable interventions to promote sustained health behavior change. In recent years, mobile health (mHealth) applications have emerged as promising tools for promoting such change, offering cost-effective, accessible, and personalized solutions. However, despite their potential, many mHealth applications still adopt a "one-size-fits-all" approach, which fails to account for the considerable variability in user characteristics that influence engagement and behavioral outcomes.

This thesis addresses the challenge of personalization in mHealth by proposing a structured, empirically validated framework that links user profiles to mechanisms. The work is grounded in established behavior change theories and gamification principles. It identifies key dimensions relevant to personalization, including personality traits (e.g., Big Five), player types (e.g., Hexad, BrainHex), and demographic variables (e.g., age, gender). A multi-stage research process was conducted. An initial scoping review established a comprehensive preference matrix linking user types to mechanisms. This matrix was subsequently validated through an empirical study involving self-reported profiling and mechanism selection tasks.

In order to operationalize these findings, the thesis introduces two major contributions. First, it proposes a preference matrix that systematically maps user characteristics to mechanisms, providing practical guidance for developers and researchers aiming to design adaptive mHealth interventions. Secondly, it presents a formal ontology that encodes these relationships in a semantic framework, thereby enabling advanced querying, reuse, and future integration with broader behavior change ontologies.

The findings suggest a substantial degree of convergence between literature-derived predictions and empirical user preferences, thereby substantiating the external validity of the proposed framework. Furthermore, the work delves into the methodological and ethical considerations associated with user profiling, advocating for the utilization of validated instruments over opaque, automated inference systems. The limitations of the study are acknowledged, including the exclusion of some dimensions, such as message framing and social norms, which are proposed as avenues for future research.

In summary, this thesis presents a principled, extensible approach to user-centered personalization in mHealth for behavior change. The integration of theoretical models, empirical data, and semantic tools is a significant contribution to the development of more engaging, effective, and individualized mhealth interventions.

Résumé

Les comportements à risque, tels que le manque d'activité physique, une alimentation déséquilibrée, le tabagisme et la consommation excessive d'alcool, demeurent des facteurs prépondérants de la mortalité mondiale. Cette constatation met en exergue la nécessité impérieuse de mettre en œuvre des interventions efficaces et adaptables visant à promouvoir des changements de comportement durables en matière de santé. Ces dernières années, les applications de santé mobile (mHealth) ont émergé comme des outils prometteurs pour favoriser cette transition, en proposant des solutions économiquement viables, accessibles et individualisées. Cependant, malgré leur potentiel, de nombreuses applications de santé mobile adoptent encore une approche « universelle », qui ne tient pas compte de la grande variabilité des caractéristiques des utilisateurs. Cette variabilité influence leurs changements comportementaux.

Cette thèse aborde le défi de la personnalisation dans le domaine des mHealth en proposant un cadre structuré et validé empiriquement qui relie les profils des utilisateurs à des mécanismes de. Ce travail s'appuie sur des théories établies en matière de changement de comportement et sur les principes de la gamification. Il identifie les dimensions clés pertinentes pour la personnalisation, notamment les traits de personnalité (par exemple, les cinq grands traits de personnalité du modèle Big-five), les typologies de joueurs (par exemple, Hexad, BrainHex) et les variables démographiques (par exemple, l'âge, le sexe). Un processus de recherche en plusieurs étapes a été mené. Une première analyse exploratoire a permis d'établir une matrice complète des préférences reliant les types d'utilisateurs aux mécanismes d'engagement. Cette matrice a ensuite été validée par une étude empirique comprenant des tâches de profilage autodéclaré et de sélection de mécanismes.

Dans le cadre de la mise en œuvre des résultats obtenus, la thèse présente deux contributions majeures. En premier lieu, elle présente une matrice de préférences qui établit systématiquement un lien entre les caractéristiques des utilisateurs et les mécanismes, offrant ainsi des recommandations pratiques aux développeurs et aux chercheurs désireux de concevoir des interventions numériques adaptatives. En deuxième lieu, elle propose une ontologie formelle qui encode ces relations dans un cadre sémantique. Cette approche permet des requêtes avancées, la réutilisation et l'intégration future avec des ontologies plus larges sur le changement de comportement.

Les résultats suggèrent un degré important de convergence entre les prédictions issues de la littérature et les préférences empiriques des utilisateurs, confirmant ainsi la validité externe du cadre proposé. En outre, cette étude examine les considérations méthodologiques et éthiques associées au profilage des utilisateurs, préconisant l'emploi d'instruments validés plutôt que de systèmes d'inférence automatisés opaques. Il convient de souligner que l'étude présente des limites inhérentes à toute recherche scientifique. En effet, certaines dimensions ont été délibérément écartées du champ d'analyse, notamment en ce qui concerne le cadrage des messages et les normes sociales. Ces dernières sont proposées comme pistes de recherche pour les travaux futurs, afin d'enrichir et d'approfondir la compréhension des phénomènes étudiés.

En somme, cette thèse propose une méthodologie structurée autour de principes généraux, avec une capacité d'extension vers une personnalisation centrée sur l'utilisateur dans le secteur des mHealth, visant à induire des changements comportementaux. L'intégration de modèles

théoriques, de données empiriques et d'outils sémantiques représente une avancée majeure dans le développement d'interventions de santé numérique qui se distinguent par leur attractivité, leur efficacité et leur personnalisation accrue.

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Chapter 1

1. Introduction

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1.1 Context and Motivation

It has been demonstrated that a significant proportion of global mortality can be attributed to the presence of unhealthy behaviors. According to the World Health Organization (2009), the five leading behavioral and metabolic risk factors associated with premature death are as follows: elevated blood pressure (accounting for approximately 13% of global deaths), tobacco use (9%), elevated blood glucose levels (6%), physical inactivity (6%), and overweight or obesity (5%) (World Health Organization, 2009). The significance of encouraging healthier lifestyle choices among populations is underscored by these modifiable risk factors.

In this context, the adoption of health-promoting behaviors emerges as a crucial public health strategy. Engaging in regular physical activity, following a balanced and nutritious diet, maintaining a healthy body weight, refraining from tobacco use, and consuming alcohol in moderation have all been consistently linked to increased life expectancy and reduced disease burden. The evidence suggests that these behaviors contribute to measurable reductions in all-cause mortality. Furthermore, they collectively enhance overall quality of life and mitigate the very risk factors identified by the WHO (Li et al., 2020; Wingard et al., 1982).

1.1.1 Importance of mHealth

Achieving this objective may be best served by the development and implementation of mobile health (mHealth) applications. In recent years, there has been a substantial increase in the number of mobile applications designed to support individuals in adopting and maintaining healthier behaviors. This proliferation has led to the emergence of thousands of new applications annually. In 2018, the number of health-related applications available for download exceeded 35,000. (Aitken et al., 2017). The pervasive adoption of smartphones has thus engendered novel opportunities for promoting health-related behaviors through digital means.

Mobile health (mHealth) applications offer a number of significant advantages. Firstly, there is a broad consensus regarding their cost-effectiveness (Iribarren et al., 2017; Khosravi & Azar, 2024; M. S. Marcolino et al., 2018). The utilization of these tools has the potential to contribute to a reduction in healthcare expenditures by decreasing patient and provider transportation costs, expediting diagnostic times, and enhancing diagnostic accuracy. These tools maintain the central role of healthcare professionals in the diagnostic process. For example, they enable home patient monitoring, which has the potential to reduce hospital admissions and decrease the frequency of in-person clinical visits (Schweitzer & and Synowiec, 2012; Steinhubl et al., 2013).

Secondly, these applications frequently enable patients to input personal health data, which can be synchronized with personal technologies such as smartphones and wearable devices. These technologies have seen significant advancements in their capacity to continuously monitor long-term physical parameters (e.g., sleep quality, physical activity), psychological states (e.g., stress levels), and other clinically relevant outcomes with increasing accuracy. Such capabilities have the potential to facilitate more personalized patient monitoring and may contribute to an enhancement in overall quality of life (QOL) (Khosravi & Azar, 2024; Natalucci et al., 2023; Yen, 2021). For example, a recent study demonstrated that the integration of smart wearable devices with mobile applications for physical exercise, stress management, and quality of life enhancement resulted in a substantial enhancement in outcomes (Yen, 2021). Furthermore, a recent review has demonstrated that the impact of wearable technology on various domains has been shown to have positive implications. The domain of cardiac rehabilitation, for instance, has witnessed significant advancements in the realm of monitoring hypertension, detecting arrhythmias, and facilitating cardiac rehabilitation. In the domain of neurology, wearable technology has demonstrated considerable promise in the identification of seizures and the management of Parkinson's disease (Jafleh et al., 2024).

Thirdly, mHealth solutions hold significant promise for improving access to healthcare, particularly in remote, underserved, or low-resource settings. Evidence from Sub-Saharan Africa indicates that mobile health (mHealth) interventions, including SMS reminders, remote consultations, and mobile data collection, can effectively address significant barriers such as geographic isolation, limited health infrastructure, shortages of healthcare workers, and social stigma. The efficacy of these interventions has been demonstrated in facilitating patient follow-up, enhancing communication between health professionals, and supporting adherence to treatment. Consequently, these interventions have been demonstrated to contribute to enhancing continuity and quality of care in hard-to-reach areas (Betjeman et al., 2013).

These applications are currently being utilized across a broad spectrum of health-related domains and have exhibited encouraging results in terms of effectiveness. Reviews (Mair et al., 2023; Zhao et al., 2016) highlighted that mobile health (mHealth) apps have demonstrated significant positive outcomes in various domains. For instance, in the context of alcohol addiction, one study found that an application grounded in the principles of motivational enhancement led to a marked increase in the number of abstinent days among individuals with alcohol use disorder over a six-week intervention period, when compared to participants in a control group.

Other studies have also demonstrated the efficacy of mHealth apps in promoting physical activity, regulating body weight, and supporting dietary behavior change. In regard to the matter of medication adherence, research findings have indicated the potential benefits thereof. For example, in a study focusing on adherence to antidepressant treatment among university students, (Hammonds et al., 2015) observed a notable trend suggesting that the use of a medication reminder application could significantly improve compliance with prescribed treatments.

The aforementioned reviews (Mair et al., 2023; Zhao et al., 2016) also identified evidence of effectiveness in several other health areas, including diabetes management, cardiac rehabilitation, smoking cessation, medication management, and pain management. Collectively, these findings illustrate the broad applicability and clinical value of mobile health technologies in supporting patient engagement, self-management, and health outcomes across diverse medical conditions.

1.1.2 Behavior change theory

A comprehensive understanding of how individuals adopt, maintain, or abandon health-related behaviors is imperative for the development of effective and sustainable health interventions. To this end, behavior change theories offer structured frameworks that explain the psychological, social, and contextual factors influencing human behavior. These theories are particularly pertinent in the context of mobile health (mHealth) technologies, which aim to deliver personalized and scalable interventions via mobile devices.

A growing body of research underscores the significance of theoretical frameworks and the necessity of translating these constructs into practical, implementable components. In such cases, the employment of Behavior Change Techniques (BCTs) becomes paramount. According to Michie et al., (2013a), BCTs are defined as the active, replicable ingredients of interventions that are intended to modify behavior. Examples of such strategies include goal setting, self-monitoring, feedback, and social support. These techniques function as a conduit between abstract theoretical principles and real-world application (Michie et al., 2013).

To systematize the application of BCTs across different health domains, Michie et al. (2013) developed a comprehensive taxonomy of 93 Behavior Change Techniques, organized into a hierarchical structure. This taxonomy has become a foundational tool in behavioral science, enabling researchers and practitioners to design, evaluate, and replicate interventions with greater precision.

A critical challenge, however, lies in addressing the intention–behavior gap, the discrepancy between what individuals intend to do and the actions they ultimately perform. Conner and Norman (2022) highlight the central role of intention strength in bridging this gap: strong intentions are more predictive of behavior and more stable over time, yet they may also be harder to modify and can bias subsequent information processing. This duality underscores that interventions must do more than foster the mere formation of intentions; they must also employ BCTs that consolidate and operationalize intentions into sustained behaviors. Relevant strategies include action planning, self-commitment, and implementation intentions, which can strengthen the translation of motivation into consistent practice (Conner & Norman, 2022).

In the context of mHealth, this insight has direct implications. Mobile applications can be designed to integrate multiple BCTs in real time and in a personalized manner that both supports the creation of intentions and reinforces their enactment. By incorporating mechanisms such as dynamic goal setting, contextualized reminders, or adaptive feedback loops, apps can reduce the intention–behavior gap while simultaneously enhancing user engagement and intervention effectiveness. Consequently, a theory- and technique-driven approach is imperative for the advancement of digital health.

This section presents a detailed overview of the major behavior change theories, their core components, and how they inform the application of behavior change techniques in mHealth interventions.

1.1.2.1 Overview of Major Behavior Change Theories

1.1.2.1.1 Health Belief Model (HBM)

The Health Belief Model explains behavior through individual perceptions of health threats and the evaluation of recommended health behaviors. Its foundational components include perceived susceptibility, which refers to a person's belief about the likelihood of acquiring a health condition, and perceived seriousness, which reflects their understanding of the potential consequences of a health condition. The integration of these two constructs engenders the perceived threat. The model also emphasizes perceived benefits, defined as the belief that a specific health action will reduce risk or severity, weighed against perceived barriers, which are the physical, emotional, or logistical costs associated with taking that action. Another critical component is cues to action, which are defined as triggers. Triggers can be classified as either internal, such as symptoms, or external, such as reminders. These triggers serve to activate the decision-making process (Rosenstock, 1974).

1.1.2.1.2 Theory of Planned Behavior (TPB)

The Theory of Planned Behavior posits that behavior is determined by behavioral intentions, which are influenced by three main constructs: attitude toward the behavior, subjective norms, and perceived behavioral control (Ajzen, 1991). Attitude is defined as the individual's evaluation of behavior, which is based on expected outcomes and personal values. The assumption that positive results are the consequence of the behavior in question will result in a more favorable attitude on the part of the individual. Subjective norms are defined as the perceived social pressures to engage or abstain from a certain behavior, derived from the expectations of significant referents such as friends, family, or professionals. Perceived behavioral control is defined as the individual's perception of their capability to perform the behavior, including the presence of facilitators or obstacles.

An illustrative example of TPB-based design is the FitBack mobile-Web intervention wich was evaluated by Irvine et al. (2015). This intervention was developed to support self-management of nonspecific low back pain (NLBP). The program encouraged participants to engage in self-tailored strategies and was designed to influence their beliefs and intentions around adopting healthier back care behaviors. A four-month follow-up revealed that FitBack users exhibited superior improvements in all critical domains when compared to the control group. These domains encompassed physical condition, health behaviors, and workplace functioning. In comparison with a control group receiving alternative care, FitBack participants exhibited a reduced prevalence of current back pain and more positive behavioral and occupational health outcomes. Furthermore, FitBack users exhibited stronger patient activation and more positive shifts in cognitive and motivational factors, including attitudes toward pain and key constructs associated with behavioral intention. These findings underscore the efficacy of a theoretically founded, self-directed digital intervention in promoting health outcomes and behavioral engagement.

1.1.2.1.3 Social Cognitive Theory (SCT)

Social Cognitive Theory posits a dynamic interplay between cognitive, behavioral, and environmental influences (Bandura, 1977). A core construct is observational learning, which refers to the process by which individuals acquire new behaviors by observing others, particularly if those others are perceived as similar or competent. This phenomenon is accompanied by outcome expectations, which refer to beliefs about the anticipated consequences of behavior, and self-efficacy, defined as the belief in one's capacity to execute the behavior successfully across situations.

A practical example of SCT implementation is found in the MyBehavior app, evaluated by Rabbi et al. (2015). This mobile health application employs SCT principles by enabling users to monitor physical activity and dietary habits through a combination of manual and automatic logging. The platform utilizes an advanced decision-making algorithm that generates low-effort, personalized, and contextualized suggestions based on the user's behavior and environment. These personalized recommendations have been shown to support self-regulation by reinforcing existing healthy behaviors and encouraging small, achievable changes. These changes, in turn, contribute to building self-efficacy. By empowering users to determine which suggestions to adhere to and the timing of their implementation, the application cultivates autonomy and a perception of behavioral agency. The randomized pilot study demonstrated that users receiving personalized suggestions exhibited a significant increase in walking behavior compared to those receiving non-tailored suggestions. Additionally, users rated the app's recommendations as more actionable and relevant. These findings suggest that SCT-based feedback systems in mHealth can effectively enhance user engagement and support sustainable behavior change.

1.1.2.1.4 Transtheoretical Model (TTM)

The Transtheoretical Model conceptualizes behavior change as a staged process (Prochaska & Velicer, 1997). It includes six stages: precontemplation, contemplation, preparation, action, maintenance, and termination. In the precontemplation stage, individuals are not yet considering change and may be unaware of the risks associated with their behavior. In the contemplation stage, they begin to recognize the problem and weigh the pros and cons of change, though they remain ambivalent. The preparation stage involves planning and intention to take action soon, typically within a month. In the action stage, individuals have recently adopted the behavior and are actively working to sustain it. The maintenance stage refers to sustained behavior change over time, and the termination stage is reached when the individual no longer feels tempted to relapse.

1.1.2.1.5 Self-Determination Theory (SDT)

Self-Determination Theory focuses on the quality of motivation behind behavior (Deci & Ryan, 2000). The distinction between intrinsic motivation, which is driven by internal satisfaction, and extrinsic motivation, which is driven by external rewards or pressures, is a fundamental aspect of human motivation. According to SDT, the three fundamental psychological needs of autonomy, competence, and relatedness must be met to cultivate intrinsic motivation and enduring behavioral change. Autonomy is defined as the experience of choice and volition in one's actions. When individuals feel that their actions align with their personal values and interests, they tend to exhibit greater motivation, which is often more sustained over time. Competence is defined as a sense of mastery and effectiveness in performing tasks. The enhancement of this skill is particularly evident when individuals experience success and receive clear, constructive feedback. The concept of relatedness is predicated on the notion of interconnectedness and a sense of affiliation with others, which has the potential to galvanize motivation through the establishment of emotional and social bonds.

In their randomized clinical trial, Gustafson et al. (2014) evaluated the efficacy of a smartphone application called A-CHESS (Addiction–Comprehensive Health Enhancement Support System). This application was designed to support individuals in recovery from alcohol dependence. The application under scrutiny was developed in accordance with the tenets of Self-Determination Theory (SDT). The objective of the application was to address the fundamental psychological needs of autonomy, competence, and relatedness. The findings indicated statistically significant enhancements in the intervention group in comparison to the control group. Participants who utilized A-CHESS reported a reduced number of risky drinking days and an elevated rate of abstinence over a 12-month period. During the 8-month intervention period and the subsequent 4-month follow-up, participants who used the A-CHESS application reported a significantly lower number of days involving risky alcohol consumption compared to those in the control group. These findings underscore the effectiveness of SDT-aligned features in enhancing motivation and sustaining long-term behavior change in digital health interventions.

An other article by Villalobos-Zúñiga & Cherubini (2020) investigated the extent to which mobile applications designed to promote behavior change support the three fundamental psychological needs delineated in SDT. To this end, the authors conducted a content analysis of 208 behavior-change applications available on the Apple App Store, with a focus on habits such as physical activity, hydration, and meditation. A taxonomy was developed based on the analysis, comprising 12 distinct application features. These features were categorized according to the psychological needs they address. Features that promote autonomy encompass various mechanisms, including the utilization of reminders, the establishment of goals, the dissemination of motivational messages, and the implementation of pre-commitments. Competence is enhanced by features that include activity feedback, history, self-monitoring, and rewards. Features that promote relatedness include social performance sharing, peer comparison, challenge peer messaging, and other related functions. However, an examination of the alignment of app design features with the principles of Self-Determination Theory revealed that merely approximately 25% of the analyzed applications addressed all three fundamental psychological needs. Among the applications that satisfied this criterion, a recurring design strategy emerged: users are first prompted to specify their behavioral objective (goal setting), then receive activity-related feedback (activity feedback), and subsequently given the option to disseminate their results via social media platforms (performance sharing).

1.1.2.1.6 COM-B Model

The COM-B model proposes that behavior is a result of the interaction between three essential elements: capability, opportunity, and motivation (Michie, van Stralen, et al., 2011). Capability is defined as the physical and psychological capacity to perform the behavior, including knowledge and skills. The term "opportunity" is defined as all external factors, whether physical or social in nature, that make the behavior possible or prompt it. Motivation encompasses both reflective processes, such as beliefs and intentions, and automatic processes, including impulses and emotions. The COM-B component is frequently utilized as the foundational element of the Behavior Change Wheel framework, which establishes a linkage between behavioral diagnosis and intervention functions, as well as policy categories. This approach facilitates the identification of the necessary changes for a specific behavior to occur, as well as the determination of the most relevant BCTs.

1.1.3 Gamification

Another promising strategy for enhancing the effectiveness of mHealth interventions in promoting behavior change involves the integration of gamification. The concept of gamification is a widely employed method for facilitating behavioral change (Bassanelli et al., 2022; Johnson et al., 2016). Gamification is defined as the integration of game design elements, including points, levels, challenges, and leaderboards, within non-game contexts (Deterding et al., 2011). This approach endeavors to capitalize on the motivational allure of gameplay to cultivate sustained user engagement and to promote health-related behaviors with greater efficacy.

A mounting body of evidence supports the efficacy of gamification in promoting behavioral change, particularly in the context of digital health. It has been widely recognized as a valuable tool for increasing user motivation, adherence, and enjoyment (Cugelman, 2013; Johnson et al., 2016). Recent research underscores the pivotal role of personalization in the efficacy of gamification, emphasizing the necessity of tailoring its components to align with individual user preferences (Altmeyer et al., 2020; R. Orji et al., 2018; Tondello et al., 2016a, 2017). Rather than implementing uniform game mechanics for all users, effective interventions are increasingly reliant on adaptive systems that align gamification strategies with user-specific motivations, personalities, and play styles.

This necessity for personalization has been thoroughly examined in a review that analyzes how adapting user experience (UX) and user interface (UI) design within gamified systems can enhance engagement (Klock et al., 2020). Their findings suggest that a one-size-fits-all approach to gamification may fail to meet the motivational needs of diverse user populations, thereby limiting its long-term impact on behavior change.

A practical illustration of gamification's mounting pertinence can be observed in a review that revealed that over half (52%) of the health-related applications examined incorporated at least one gamification component (Lister et al., 2014). Notably, the integration of gamified features was found to be positively correlated with users' inclination to adopt the application, particularly among young, healthy individuals, a demographic that has historically posed challenges in terms of engagement through conventional health messaging (Lee et al., 2018).

A critical component of enhancing the efficacy of gamified mHealth interventions pertains to the personalization of game components, which are tailored to individual user profiles or typologies. While the application of gamification has yielded positive outcomes in terms of engagement and health behavior, research has increasingly highlighted that individual differences in gaming motivation significantly influence user response to specific game mechanics (R. O. Orji, 2014; Tondello et al., 2016a). Consequently, several player classification models have been proposed to assist designers in more effectively aligning game elements with users' psychological profiles.

One of the earliest and most influential frameworks is Bartle’s Taxonomy of Player Types (Bartle, 1996), originally developed in the context of multiplayer online games. Bartle's seminal work identified four distinct core player types: Individuals who are motivated by success and measurable progress are considered "Achievers." Those who enjoy discovery and system mastery are considered "Explorers." Individuals who value interaction with others are considered "Socializers." Finally, those who derive satisfaction from competition and asserting dominance over others are considered "Killers." While the model is undoubtedly beneficial, its applicability to health interventions is somewhat limited in nature. This limitation stems from the model's assumption of a gaming environment based on virtual worlds and social play.

To address this, the Gamification User Types Hexad model (Tondello et al., 2016a), as been developed. This model extends Bartle's work and adapts it to gamified systems beyond entertainment, including health, education, and productivity. The Hexad taxonomy identifies six distinct user types:

- Philanthropists, who are intrinsically motivated to help others and contribute to a greater purpose.
- Socializers, who are driven by social interaction and collaboration.
- Free Spirits, who seek autonomy and creative freedom.
- Achievers, who aim to overcome challenges and reach mastery.
- Players, who are primarily extrinsically motivated by rewards, points, and incentives.
- Disruptors, who enjoy testing systems and provoking change.

Each of these types reflects a unique motivational orientation that can be aligned with specific BCTs and game elements. For instance, Achievers may respond well to challenge-based goals and performance feedback, while Socializers may be more engaged by team challenges or cooperative tasks within an app.

Another influential framework is Yee's Gamer Motivation Model (Yee, 2006), based on empirical data from thousands of gamers. Yee proposes three overarching motivational domains: Achievement, Social, and Immersion. Each of these domains is further subdivided into components. Achievement is defined by the presence of competition and advancement. Social encompasses relationships and teamwork. Immersion is characterized by exploration and role-playing. These motivations have been validated across diverse populations and are particularly useful for designing modular mHealth applications, where different modules can correspond to different user needs.

Additionally, the BrainHex model (Nacke et al., 2014) provides a typology informed by neuroscience, which categorizes players into seven types based on their emotional and cognitive engagement. It is evident that individuals can be categorized into various types based on their motivations and behaviors. These categories include seekers, who are driven by curiosity; survivors, who are motivated by fear and thrill; daredevils, who take risks; masterminds, who excel at strategic problem-solving; conquerors, who are driven by competitive challenges; socializers, who value social interaction; and achievers, who are driven to complete tasks. This model provides a more emotionally grounded lens for mapping user preferences to in-app experiences, which can be particularly effective in stress reduction or mental health interventions.

Collectively, these frameworks offer rich tools for personalization in gamified health interventions. Integration of validated typologies, such as the Hexad User Types, Yee's motivational profiles, or BrainHex categories, enables designers to adapt game mechanics, thereby increasing relevance and efficacy. For instance, an individual with a Free Spirit disposition may find exploratory features and unstructured learning paths more appealing, while a Player may be more responsive to a system of points and tangible incentives.

Furthermore, these typologies can inform the development of adaptive systems within mHealth platforms, thereby enabling real-time personalization. Systems capable of identifying a user's predominant type include brief onboarding questionnaires and in-app behavioral tracking. These systems are able to deliver customized content, feedback, and rewards accordingly. This strategy holds particular promise in enhancing adherence to long-term interventions, where personalization has been identified as a significant predictor of user retention (Edwards et al., 2016).

By adapting gamified features to align with these psychological profiles, designers can enhance both the perceived relevance and motivational strength of digital health interventions. This not only enhances immediate user engagement but also amplifies the probability of enduring behavioral modification, a fundamental challenge in mobile health intervention design.

1.1.4 Relevance of Personalization in mHealth

A growing body of research has emphasized the importance of systematically evaluating the quality of mobile health (mHealth) applications, particularly in relation to their potential for facilitating behavior change. In response to this need, several validated assessment tools have been developed. Among the most widely used is the Mobile App Rating Scale (MARS) (Stoyanov et al., 2016), which evaluates app quality across multiple domains, including engagement, functionality, aesthetics, information quality, and personalization. Similarly, the App Behavior Change Scale (ABACUS) (McKay et al., 2019) was meticulously engineered to evaluate the presence and potency of behavior change techniques (BCTs) in mHealth applications. In a similar vein, ABACUS underscores personalization as a pivotal quality indicator.

The incorporation of personalization within these scales underscores its central role in effective digital health interventions. Personalization can be defined as the adaptation of content, delivery, or interface based on individual user characteristics. Examples of these characteristics include demographic data, behavioral patterns, preferences, or psychological profiles. This adaptive approach is not merely a design enhancement; rather, it is a core determinant of user engagement, perceived relevance, and cognitive processing. The hypothesis is further substantiated by substantial empirical evidence. For instance, research by Hawkins et al. (Hawkins et al., 2008) demonstrated that tailored health messages, which incorporate user-specific variables (e.g., age, beliefs, health status), are significantly more likely to capture attention, be cognitively processed, and be retained in memory than generic or non-tailored messages. Tailored content was also found to be more personally meaningful, increasing the likelihood that it would be discussed with others and integrated into health-related decision-making.

Moreover, personalized interventions have been shown to engender heightened user satisfaction and adherence. According to Kreuter and Wray (Kreuter & Wray, 2003) the efficacy of communication that is tailored to the specific needs of the user is enhanced, thereby increasing the persuasive impact and behavioral effectiveness of the intervention. This is particularly salient in the context of behavior change, where individual variability in readiness to change, self-efficacy, and motivational drivers necessitates customized approaches.

Within the domain of mHealth platforms, personalization can manifests in diverse forms. These include the implementation of algorithms that adjust message frequency in accordance with user engagement, the adaptation of goal suggestions based on baseline activity levels, and the presentation of content utilizing preferred formats, such as text, video, and gamified feedback. The incorporation of these strategies, when deliberate, has been shown to enhance the perceived value of the application. For instance, research that adapted breast cancer educational pamphlets according to user characteristics, including age, ethnicity, insurance coverage, and constructs from the Health Behavior Preference matrix, reported significantly increased screening intentions among individuals who received the personalized materials (Jensen et al., 2012). Furthermore, these strategies have been demonstrated to facilitate the psychological processes underlying behavior change, including autonomy, competence, and relatedness, as outlined in Self-Determination Theory (Deci & Ryan, 2000).

1.1.4.1 Personalization According to User Profile

A significant challenge in the development of effective mHealth interventions is the heterogeneity of users. The implementation of a uniform behavior change strategy across a heterogeneous population may yield suboptimal outcomes, as each individual possesses a unique user profile comprising multiple interrelated characteristics. These include demographic variables (e.g., age, gender, education level), personality traits (e.g., Big Five, Myers-Briggs Type Indicator), cognitive styles (e.g., need for cognition, susceptibility to persuasive messaging), and attitudinal factors (e.g., prior engagement in health behaviors, health locus of control).

In this context, personality traits can be considered as a component of the user profile. The Five-Factor Model (Big-Five), encompasses five broad dimensions that encapsulate the predominant variations in human personality: The model under consideration includes the following dimensions: Openness to Experience (creativity and intellectual curiosity), Conscientiousness (organization and goal-directed behavior), Extraversion (sociability and assertiveness), Agreeableness (cooperativeness and compassion), and Neuroticism (emotional instability and negative affect).

This model has been widely used in health psychology to explain interindividual differences in motivation, intention, and adherence (John & Srivastava, 1999; McCrae & Costa, 2004). McCrae & Costa, (1997) advanced the notion that the Big Five model constitutes a universal framework for the description of human personality across diverse cultural contexts. In order to examine this claim, the Revised NEO Personality Inventory (NEO-PI-R), a psychometric instrument developed specifically for the assessment of the five major personality traits, was translated into six languages. The languages encompassed by this study include German, Portuguese, Hebrew, Chinese, Korean, and Japanese. Their findings consistently demonstrated that a five-factor structure consistently emerged across these linguistic and cultural contexts. Additional substantiation for the universality of the Big Five was furnished by a substantial, cross-cultural investigation undertaken by (McCrae et al., 2005). This study evaluated personality structure across 50 cultures from American, European, Arab, Asian, and African regions. The NEO-PI-R was translated into the native language of each participating country, and the sample consisted primarily of native citizens. Factor analyses indicated that the American-based structure of the NEO-PI-R (Form S, self-report) could be replicated across all cultures, with 94.4% of the factors demonstrating structural equivalence. These findings strongly support the cross-cultural validity of the Big five and have contributed to its widespread adoption in the field of personality psychology. As a reflection of its growing influence, the number of scientific publications related to the Big Five model increased markedly, from approximately 400 articles between 1990 and 1994 to around 1,600 between 2005 and 2009 (John et al., 2008a). Moreover, these personal characteristics are not merely descriptive; they play an active role in modulating how individuals perceive, process, and respond to behavioral interventions. For instance, studies (Rhodes et al., 2022; Rhodes & Courneya, 2003) demonstrated that individuals with high levels of conscientiousness and extraversion were more likely to establish robust behavioral intentions to engage in physical activity, thereby effectively augmenting the predictive capability of the Theory of Planned Behavior (TPB). This finding lends support to the notion that trait-based personalization can strengthen intention formation, a critical determinant of behavior in TPB-based interventions.

These findings support the cross-cultural validity of the Five-Factor Model and have contributed to its widespread adoption in personality research. This growing interest is evidenced by a significant increase in the number of publications related to the Big Five, which rose from approximately 400 between 1990 and 1994 to around 1,600 between 2005 and 2009 (John et al., 2008a).

Furthermore, cognitive profiles, such as the need for cognition, a trait reflecting an individual's tendency to engage in and enjoy effortful cognitive activity, have the potential to influence how users interact with app content. Individuals with a high need for cognition may demonstrate a preference for detailed, information-rich content and rational arguments, while those with a low need for cognition may exhibit a heightened responsiveness to visual prompts and emotional appeals (Cacioppo & Petty, 1982a).

This complexity reinforces the critical distinction between personalization and customization in digital intervention design. Personalization refers to system-initiated tailoring of content or interface based on pre-identified user characteristics (e.g., sending messages that match the user's name, goals, or user profile). Customization, in contrast, is user-driven, allowing users to adapt the interface, goals, or feedback mechanisms to suit their preferences (Kaptein & Eckles, 2012). While both strategies have their merits, personalization is particularly relevant when the objective is to anticipate and support user engagement without requiring additional cognitive load or effort from the user.

A substantial body of empirical evidence has emerged to support the efficacy of customized content in amplifying the impact of Behavior Change Techniques (BCTs). For instance, studies have demonstrated that customized messages incorporating the user's name or pertinent personal information enhance attention and recall (Hawkins et al., 2008), Additionally, the implementation of individualized goal setting has resulted in enhanced adherence in digital fitness programs (Michie et al., 2009). Feedback tailored to the user's progress or motivational profile has also proven more effective in sustaining engagement and promoting self-regulation compared to generic feedback (Noar et al., 2007).

Consequently, the design of mHealth applications that consider the psychological, demographic, and cognitive diversity of users is not merely a matter of user experience; it is a theoretical imperative grounded in evidence from behavioral science. The integration of validated models, such as the Big Five, can serve as a foundational basis for developing personalized intervention strategies, thereby enhancing the relevance, engagement, and efficacy of health behavior change efforts within mHealth environments.

This perspective suggests the necessity for a coherent framework that systematically links theoretical models, mechanisms, and user characteristics. The framework developed in this thesis addresses this need by organizing personalization along three complementary dimensions: (1) user profiles, encompassing psychological traits (e.g., Big Five), player typologies (e.g., Hexad, BrainHex), and demographic variables; (2) mechanisms, which integrate evidence-based approaches such as behavior change techniques (BCTs) and gamification strategies; and (3) mapping relations that connect specific user characteristics to the mechanisms most likely to foster engagement and sustain behavior change. The integration of these components establishes a structured foundation for the design and evaluation of personalized mHealth interventions. The subsequent research inquiries were thus formulated to refine, validate, and operationalize this framework.

1.2 Research Questions

Following the recognition of the importance of personalization in mHealth, we formulated four research questions to guide this thesis.

1.2.1 Defining Mechanisms and User Profiles for Personalization

RQ1. According to the literature, which dimensions should be considered when personalizing mHealth applications to support behavior change?

As a preliminary step, it was imperative to delineate the operationalization of personalization in mHealth applications. Specifically, the objective was to identify the types of personalization that can be recommended, and whether relationships could be established between user profiles (e.g., personality traits), mechanisms (e.g., gamification elements), and behavior change theories.

To address this, a thorough state-of-the-art review was conducted to identify the personalization dimensions applicable in the context of mHealth. Our review revealed the potential relationships between various user characteristics (e.g., personality traits, player types, and need for cognition) and a range of mechanisms used in digital health behavior change interventions (e.g., message framing, gamification techniques, app functionalities).

Given the extensive range of potential personalization dimensions, it was imperative to restrict the scope. Consequently, the present thesis focused specifically on mechanisms aligned with the Behavior Change Technique (BCT) taxonomy and gamification elements, and on three types of user profiling: personality (based on the Big Five model), player types (based on the Hexad scale and BrainHex), and demographic variables (age and gender). The exclusion of other profiling dimensions and mechanisms is explained in the discussion section.

Subsequent to the literature review, the subsequent step was to determine how to practically apply personalization based on the identified dimensions, which led to the formulation of the second research question.

1.2.2 Implementing Personalization in mHealth Applications

RQ2. How can personalization dimensions be applied within a mobile health application?

Once the relevant personalization dimensions were identified through the literature, we established explicit mappings between user profiles and preferences mechanisms. This led to the creation of a relation matrix, summarizing preferences for each profile dimension based on findings from the literature.

To validate and refine this matrix, we conducted an empirical study. Participants completed an online questionnaire assessing their personality traits, after which they were asked to select the mechanisms, they would prefer in a fitness app. This allowed us to both confirm and expand the literature-based relationships captured in the matrix.

1.2.3 Supporting mHealth Designers and Developers

RQ3. How can designers develop personalized mHealth applications for behavior change?

To answer these questions, we proposed a relation matrix for enabling personalization in mHealth design. Designers can rely on the relation matrix, grounded in both the literature and our empirical findings, to select appropriate mechanisms based on user profiles.

Furthermore, an ontology was developed to formalize these relationships and integrate empirical data, thereby supporting visualization, semantic queries, reusability, and future expansion. The ontology under consideration encompasses a range of instruments, including validated questionnaires designed for the evaluation of user profiles.

RQ4. How can a user's personality profile be integrated into a mobile health application?

We also explored two main approaches for integrating user profiling into mHealth apps:

- Questionnaire-based profiling: Users complete validated instruments (e.g., Big Five, Hexad) during onboarding or via the app settings, enabling the app to tailor content accordingly.
- Implicit profiling via usage data: Although promising, this approach raises significant privacy and data security concerns, which are discussed in detail.

These personalization strategies are further elaborated in the discussion sections of Chapters 5,6 and 7.

1.3 Thesis contributions

This thesis makes significant contributions to the field of personalized mHealth for behavior change design by introducing a structured and extensible approach to tailoring interventions based on user characteristics.

First, it establishes a classification framework for the mechanisms that can be integrated into mHealth applications, leveraging both the Behavior Change Technique (BCT) taxonomy and a gamification elements. This classification system organizes the design space of mHealth interventions, thereby demonstrating the feasibility of personalization based on user profiling dimensions, such as personality traits, using the Big Five model, and gamer typology, based on the Hexad player typology. This dual-perspective profiling facilitates a more nuanced adaptation of mHealth features to user predispositions.

Secondly, the thesis introduces a preference matrix that links mechanisms preferences according to user profile. This contribution facilitates the personalization of mHealth by providing guidance on which design elements are most suitable for different user types. In addition, the study we conducted validates and adds links to this matrix.

Finally, the thesis presents an ontology that models the matrix in a formal and visualizable structure. The ontology captures the relationships between user profiles and preferred mechanisms, as supported by scientific literature. It also integrates additional elements such as validated questionnaires used to assess user profiles and permit the incorporations of new relationships and mechanisms as they are identified in future research. This ontological representation enhances the maintainability, scalability, semantic queries, and interpretability of the personalization framework

Table 1.1. Synoptic Table of Dissertation Articles

	Article 1	Article 2	Article 3	Article 3	Article 4	Article 5	Article 6
Chapter	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Research Focus	**Matrix preference between mechanism preference and user profil**	**Matrix preference between mechanism preference and user profil**	**Validation of the protocol**	**Mechanisms preferences based on personality**	**Mechanisms preferences based on player typology**	**Mechanisms preferences based on age and gender**	**Ontology with the matrix reference**
Paper Title	Personalization Dimensions for MHealth to Improve Behavior Change: A Scoping Review	Personalizing mobile applications for health based on user profiles: A preference matrix from a scoping review	Personalization of Mobile Apps for Health Behavior Change: Protocol for a Cross-sectional Study	Personalizing Mobile Applications for Health Behavioral Change according to personality: cross-sectional validation of a Preference matrix	Model to Personalize Mobiles Applications according to the gamification user types for Health Behavioral Change	Personalizing Mobile Applications for Health Behavior-al Change according to age and gender	Towards an ontology of user preferences based on user profiles for mobile health applications: Formalization based on a scoping review
Authors	Laëtitia Gosetto, Gilles Falquet, Fréderic Ehrler	Laëtitia Gosetto, Gilles Falquet, Fréderic Ehrler	Laëtitia Gosetto, Gilles Falquet, Marta Pittavino, Fréderic Ehrler	Laëtitia Gosetto, Gilles Falquet, Fréderic Ehrler	Laëtitia Gosetto, Gilles Falquet, Fréderic Ehrler	Laëtitia Gosetto, Gilles Falquet, Fréderic Ehrler	Laëtitia Gosetto, Gilles Falquet, Fréderic Ehrler
Methodology	Scoping review	Scoping review	Protocol	Empirical research	Empirical research	Empirical research	Ontological presentation
Scientific Contribution	Produces a matrix preference	Produces a matrix preference	Develops new protocol	Validation of the matrix preference	Validation of the matrix preference	Validation of the matrix preference	Develops a new ontology
Published in peer-reviewed conference /journal	Integrated Citizen Centered Digital Health and Social Care	PLOS Digital Health	JMIR Research Protocol	JMIR Human Factor	SAGE Digital Health	EAI Pervasive Health 2025	Under consideration
Status	Published	Published	Published	Submitted	In review	Accepted for poster	To submit
Author contribution	**LG** carried out the scoping review with the help and advice of FE and GF and wrote the paper. FE and Gf supervised and provided feedbacks on the paper.	**LG** carried out the scoping review with the help and advice of FE and GF. FE and Gf supervised and provided feedbacks on the paper.	**LG** conceived the study with the involvement and advice of FE and GF. MP is involved with statistics. All authors were involved in writing, reading, and approving the final manuscript.	**LG** designed and conducted the study, analyzed the data and wrote the paper. FE and GF supervised and wrote the paper.	**LG** designed and conducted the study, analyzed the data and wrote the paper. FE and GF supervised and wrote the paper.	**LG** designed and conducted the study, analyzed the data and wrote the paper. FE and GF supervised and wrote the paper.	**LG** design the ontology and wrote the paper. FE and GF supervised and wrote the paper.

1.4 Thesis Outline

Table 1.1 presents an overview of the research articles (conferences, and journals) written during the thesis, their connection to the different chapters, and their description of relevant scientific contributions.

Chapter 2 presents the background and related work. It includes an initial literature review and the first version of the classification of the user profile and mechanisms, which was introduced through a paper published in a conference. This chapter was presented on the 2020 the European Federation for Medical Informatics (EFMI) and published on the Integrated Citizen Centered Digital Health and Social Care (Gosetto et al., 2020).

Chapter 3 builds upon this by providing an extended literature review, structured as a scoping review and pluabished as PLOS Digital Health (Gosetto et al., 2025b). This chapter offers a more comprehensive analysis of the current state of the art and defines the validated version of the personalization framework with a preference matrix, including its application in the mHealth domain.

Chapter 4 presents the protocol of our study designed to validate the data from the preference matrix introduced in Chapter 3. The protocol was published in *JMIR Research Protocols* (Gosetto et al., 2023).

Chapters 5, 6, and 7 present the empirical results of this single study. The findings are divided into three distinct chapters, each corresponding to a submitted article and focusing on a specific dimension of user profiling. All findings stem from the same experimental design and dataset described in Chapter 4.

- Chapter 5 explores results related to participants' personality traits using the Big Five model, submitted at JMIR Human Factor (Gosetto et al., 2025d).
- Chapter 6 presents findings based on participants' gamer profiles, as defined by the Hexad scale, submitted at SAGE Digital Health (Gosetto et al., 2025a).
- Chapter 7 addresses the influence of demographic variables, specifically age and gender, on mechanism preferences in mHealth applications, submitted at EAI Pervasive Health 2025 (Gosetto et al., 2025c).

Chapter 8 focuses on the ontology developed from the matrix and empirical results. This ontology formalizes the relationships between user profiles and preferred mechanisms as identified in the literature and our study. It also incorporates additional data such as questionnaires used to assess user profiles and is designed to be extensible for future integration of new findings.

Finally, Chapter 9 offers a general discussion of the thesis. It synthesizes the results presented in the previous chapters, discusses the limitations of the work, and outlines potential directions for future research.

Chapter 2

2. Article I : Personalization Dimensions for MHealth to Improve Behavior Change: a Scoping Review

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Chapter Contents

Abstract. Due to the large number of smartphone users, mHealth has become a popular support to foster users' health behavior change. Personalization is an important factor to increase the effectiveness of mHealth interventions. Based on a literature review, we have listed and categorized personalization concepts associated with behavior change in mHealth into 4 dimensions, users, system functionalities, information, and app properties. The users dimension refers to user-related characteristics such as personality, player profile, need for cognition and perception of social norms. The system functionalities contain the functionalities that can be found in applications such as reminders as well as gamification functionalities such as collectibles. The information dimension concerns the way information is transmitted, such as the source of the message must be expert or the type of feedback to be provided. Finally, there are app properties such as the aesthetics of the application. For the next part, it would be interesting to discover the links we can make between the dimensions.

2.1 Introduction

MHealth can be defined as the use of mobile computing and communication technologies in health care and public health (Free et al., 2010). About 79% of the European population used their smartphone in 2016 to go online (Eurostat, 2016). Smartphones possess some features, including apps text messaging, Bluetooth, and others, that can be useful to change user behavior towards healthier ones (WHO, 2011). Integrating behavior change theories (BCT) is one of the popular techniques employed in mHealth. BCT, is defined by Michie et al. as "like an observable, replicable, and irreducible component of an intervention designed to alter or redirect causal processes that regulate behavior" (Michie et al., 2013). Researchers are therefore integrating interventions such as goal setting or self-monitoring of behavior (Direito et al., 2014).

Personalization is another mechanism that can be incorporated into mHealth interventions to promote behavioral change (Wanyonyi et al., 2011). Personalization can be defined as the incorporation of recognizable aspects of a person into tailored content, such as a person's name (Dijkstra, 2008). The importance of personalization is already widely recognized since it is found as criteria in many rating scales for mobile health applications such as the Mobile Application Rating Scale (MARS) (Stoyanov et al., 2015), or the App Behavior Change Scale (ABACUS) (McKay et al., 2019).

Since personalization in mHealth can be applied in many different ways, from simply adding the user's name to adapting the content to the user's personality, one may ask on which dimensions can we customize?

The purpose of this article is to present the different dimensions of personalization of mHealth intervention to promote behavioral change based on a review of the literature.

2.2 Method

Searches were conducted on the ScienceDirect, ResearchGate online databases for articles from 2008 to 2020. 2008 being the release of the first smartphone and thus the current mHealth. The selected articles had to treat personalization and applications for behavioral change as well as the evaluation of applications for behavior change. They also had to be written in English.

The terms used for the search were: personalization, mHealth, gamification, personality, tailoring, app features, app functionality, scale app mHealth, guideline app. A first selection was made base on the reading of the titles and abstracts. Then, a second reading of the full article allowed to determine if the article met the eligibility criteria. We have then listed the personalization techniques found in these articles.

We have also listed the features that appear in different scales used to assess application for behavior change. We have selected four scales, the MARS (Stoyanov et al., 2015), the ABACUS (McKay et al., 2019), the persuasive system design (Wang et al., 2019) and the ergonomic criteria grid for the assessment of ergonomic persuasion (Nemery & Brangier, 2011).

All concepts were organized into a conceptual map helping us to regrouped them into several dimensions.

2.3 Results

1825 articles were extracted, and 27 articles met the eligibility criteria. From the 27 articles, we were able to extract a list of concepts that are used to personalize intervention. From this list, we organized them into a conceptual map and group them into four dimensions.

2.3.1 Definition of Dimensions

The literature presents 39 personalization concepts, ranging from the personality of the user to the characteristics of the messages. We have organized these personalization concepts into a concept map summarized in the form of a table (see Table 2.1). This helped us to identify several dimensions to characterize the personalization concepts. We defined 4 dimensions: user, system functionalities, information, and app properties. These dimensions are detailed below. We identified 39 concepts, 5 for the dimension user, 17 for the dimension system functionalities, 13 for the dimension information and 4 for the dimension app properties. We also indicated which concepts were present in the four scales used to assess application for behavior change.

2.3.1.1 User

This dimension contains all user-specific characteristics that can be used for personalization. The literature shows links between user personality and gaming characteristics [(R. Orji, Nacke, et al., 2017)]. Personality is measured using the Big Five (Mccrae & Costa, 1987), a model with five factors neuroticism, openness, conscientiousness, altruism, and extroversion, defining personality.

The profile of the players is another user characteristic for personalization of mHealth intervention derived from gamification theory. Several scales exist to define the user's type of player, as well as his preferences for the games. We have chosen two scales for this representation, Tondello's Hexad Scale (Tondello et al., 2016b) and the taxonomy of player motivation by Yee (Yee, 2006). Each one defines a type of player and the type of games or interaction he prefers. We chose these scales because according to the literature, there would be a link between the type of player and the gamification features (Tondello et al., 2016b) ; (Yee, 2006). For example, according to the Hexad Scale, philanthropists are motivated by a goal, are altruistic and willing to give without expecting a reward. It is therefore necessary to incorporate elements of collection and exchange into the game to appeal to this type of user (Tondello et al., 2016b).

Another interesting feature is the need for cognition (Cacioppo & Petty, 1982a). This characteristic defines people according to their individual differences in intrinsic motivation to engage in effortful cognitive endeavors (Cacioppo et al., 1984; Cacioppo & Petty, 1982a). It may be interesting to consider this characteristic, as for example, individuals with high need-for-cognition are more influenced by quality messages while low need-for-cognition are more influenced by peripheral cues (Axsom et al., 1987).

Finally, the last characteristic we have integrated is the perception of the subjective norm. This characteristic is common to many theories of behavior change, such as the Theory of planned Behavior (Ajzen, 1991) or the Integrated Behavior Mode (Fishbein & Yzer, 2003). This characteristic refers to the perceived social pressure to perform or not to perform the behavior. As a general rule, the more the subjective norm is in agreement with the behavior, the more the individual will intend to change behavior in accordance with this subjective norm (Ajzen, 1991).

2.3.1.2 System Functionalities

In this dimension we included the functionalities of applications that can be personalized according to the literature. Functionalities refer to the services the application provides to the user, such as reminders or self-monitoring. Self-monitoring as "occurring when an individual first self-assesses whether or not a target behavior has occurred, and then self-records the occurrence, frequency, duration, or so on of the target behavior"(Nelson & Hayes, 1981).

We have also included gaming features that can be personalized. Such as goal setting, rewards or levels and progression.

2.3.1.3 Information

This dimension groups together characteristics that are related to the transmission of information in an application. One part concerns the knowledge and information to be transmitted, such as the importance of relying on an expert source to provide the content, or to provide basic information about the desired behavior. These characteristics are extracted from different scales such as MARS (Stoyanov et al., 2015) or ABACUS (McKay et al., 2019).

Another part concerns feedback. Feedback consists in presenting individuals with information about themselves, obtained through the application. There are 3 types of feedback, descriptive (provides only a description of the user's behavior in relation to his data), evaluative (provides an interpretation based on the user's behavior) and comparative (provides feedback comparing the user with other people). Each may be more or less effective depending on the user. For example, comparative feedback will work best for a person who needs to have a high level of social norms (Hawkins et al., 2008a) .

2.3.1.4 App Properties

The App properties dimension, groups together features that are specific to mobile applications. In particular, it includes the aesthetic features, extracted from the MARS scale (Stoyanov et al., 2015). As well as one feature, customization. Customization means that "the user explicitly states interests and preferences through direct configuration of human-computer interfaces (HCI), system's options or screens" (Madeira et al., 2018).

Table 2.1. Representation of the dimension to personalize mHealth

Users	System Functionalities	Information	App Properties
Personality (e.g Big-Five) [12][13]	App Functionalities (e.g reminder, self-monitoring)** [21]	Knowledge and information (e.g. expert source, quantity of information) **** [8][9]	Aesthectics (Layout, visual appeal, graphics)* [8]
Gamer Profil (e.g Hexad scale) [14][15]	Gamification Features (e.g Rewards, cooperation)**** [12][14][15]	Feedbacks (evaluative, descriptive, comparative)* [22]	App Features (customizable ****) [23]
Need-for-cognition [16][17][18]			
Perception of the social norm [19][20]			

*present in one scale; **present in two scales; ***present in three scales; ****present in four scales

2.4 Discussion

From the literature, we have identified and classified personalization concepts into 4 dimensions, users, system functionalities, information, and app properties. From this classification, we can identify on which characteristics it is possible to personalize. For example, what kind of feedback to provide for each user etc...

It would be interesting as a future research to also be interested in the notion of design, such as design with empathy or emotional design. In particular, the emotional design that can give tracks to give personality to the application and make it more attractive to the user. It would be also interesting to represent the relationship between the characteristics that belong to different dimensions. For example, what kind of gamification features do people who fit the big-five's extroversion profile prefer? In this way, one could personalize features of the application according to the user's personality. It would also be interesting to define how to obtain information about the user in order to personalize according to the other dimensions.

Chapter 3

3. Article II : Personalizing mobile applications for health based on user profiles: A preference matrix from a scoping review

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Chapter Content

Abstract

The World Health Organization identifies unhealthy behaviors, such as smoking, as significant risk factors contributing to mortality and morbidity, underscoring the necessity to adopt healthier habits. The increasing prevalence of health applications (apps) presents opportunities for promoting healthier lifestyles. Notably, personalized mobile health (mHealth) interventions can enhance user engagement and their effectiveness. Our scoping review aims to contribute to guide the personalization of mHealth interventions for health behavior change by defining which mechanisms should be favored for a given user profile. Online databases were searched to identify articles published between 2008 and 2024 describing the topic of personalization, behavior change apps and mobile app mechanisms. Of 1806 articles identified, 18 articles were retained. We then categorized the mechanisms and user profiles described in the selected articles into existing taxonomies. Finally, the relationship between the user profiles and mechanisms were reported. The four user profiles identified included personality and gamer profiles. Twenty-one mechanisms extracted from the articles were categorized as behavioral change techniques, gamification or mobile app mechanisms, with limited numbers of preference relations between mechanisms and user profiles. The relation matrix was not complete and covered only 51% of possible relations: game mechanisms, 30%; behavioral change techniques, 16%; and app mechanisms, 5%. Two user profiles, the Big Five (18%) and Hexad scale (20%), covered 38% of relations, whereas the two remaining user profiles contributed to the remaining 13%. Social mechanisms, including competition, cooperation and social comparison, exhibit strong connections to user profiles and are pivotal in persuasive system design. Self-efficacy theory links mechanisms such as self-monitoring, social persuasion and rewards to behavior change. However, only 51% of potential relationships between profiles and mechanisms were identified. Adapting mHealth content based on user profiles requires reliable personality assessments and privacy-conscious data collection to enable personalized, profile-specific interventions for improved outcomes.

Author Summary

The promotion of healthy behavior, as well as addressing health risk factors that contribute to mortality, such as sedentary lifestyles, has led to a proliferation of mHealth apps. These apps have the potential to facilitate behavior change and offer a variety of features, including reminders, progress tracking and personalized interventions, which have been demonstrated to enhance user engagement and adherence. Personalization is of critical importance in the process of adapting interventions to align with the specific characteristics and needs of individual user profiles. The use of tailored messages and feedback has been demonstrated to be more effective than the use of generic ones, particularly in the context of promoting physical activity and weight loss. The incorporation of game design elements is also a prevalent feature in health apps, with evidence suggesting that it positively impacts on user engagement and motivation. However, there is a lack of comprehensive frameworks that provide guidance on their implementation in mHealth interventions. Here, we aim to optimize the effectiveness of interventions designed to facilitate health behavior change by defining game mechanisms, behavior change techniques and app mechanisms employed to personalize apps based on user profiles.

3.1 Introduction

Certain behaviors increase the risk factors for mortality. According to the World Health Organization, the five leading global risk factors contributing to mortality are hypertension (13% of deaths), smoking (9%), high blood glucose (6%), sedentary lifestyle (6%), and being overweight (5%) (World Health Organization, 2009). It is therefore vital to encourage individuals to adopt healthy behaviors, such as smoking cessation or regular exercise. For this reason, the number of mobile health (mHealth) applications (apps) entering the market with the objective to help individuals to adopt healthier lifestyles is increasing rapidly. As of June 2022, there were more than 318,000 health apps available (Aitken et al., 2017). Smartphone apps present novel opportunities to promote health-related behaviors by offering immediate access to health information, reminders for medication adherence, and support for tracking progress (Ernsting et al., 2017). A systematic review of the literature demonstrated the efficacy of mobile apps in addressing a range of health concerns, including chronic diseases, blood sugar regulation and smoking cessation (M. Marcolino et al., 2018). Similarly, they have been shown to be effective in promoting healthy eating behaviors (McCarroll et al., 2017). Notably, reviews on the impact of mHealth on obesity (Dombrowski et al., 2012; Lau et al., 2020) highlighted its efficacy in weight management, body mass index reduction, waist circumference and blood pressure improvement (Lau et al., 2020), thereby fostering desired behavior changes (Dombrowski et al., 2012). Most of these apps employ behavioral change techniques (BCT) to encourage healthy habits, with prevalent strategies encompassing self-monitoring, goal setting, feedback, social support and reminders (Bardus et al., 2016; Edwards et al., 2016; Hoffmann et al., 2017; Lau et al., 2020; Lee et al., 2018; Lister et al., 2014; M. Marcolino et al., 2018; McDonald et al., 2015; Michie et al., 2013; Sporrel et al., 2021). These techniques are defined in taxonomies such as CALO-RE (Michie, Ashford, et al., 2011). For example, self-monitoring includes recording specific behaviors, such as the maintenance of a food diary or tracking daily weight.

Nevertheless, it is challenging to use a single technique on an entire population as each individual possesses a particular user profile, which encompasses a multitude of characteristics that define an individual. These include demographic data (e.g., age, gender), personality traits (e.g., Big Five, Myers-Briggs Type Indicator), cognitive profiles (e.g., need for cognition, sensitivity to persuasion) and attitudes (e.g., strong engagement in health behavior). For example, personality traits can significantly moderate behavioral change. A study demonstrated that high levels of conscientiousness and extraversion moderated the intention component of the Theory of Planned Behavior. In other words, individuals scoring high on these traits exhibited stronger intentions to engage in physical exercise (Rhodes et al., 2002). This suggests that, personalizing the app according to the user's characteristics is certainly relevant. By contrast, the term "customization" pertains to the act of adapting the content by the user themself. Furthermore, several reviews have highlighted the advantages of providing tailored content based on the user profile's specifics (personalized messages with user name(Head et al., 2013) , tailored goals (Sporrel et al., 2021) or feedback (Lau et al., 2020)) to enhance the efficacy of BCT (Head et al., 2013; Lau et al., 2020; Sporrel et al., 2021).

In line with these findings, a substantial body of research has been dedicated to the topic of personalization using tailored messages. As evidenced by a meta-analysis, behavior change interventions are significantly more effective when tailored to demographic variables (Head et al., 2013). This effectiveness has been particularly evident in mHealth applications, where tailored goals have been more effective than generic goals to promote physical activity and weight loss (Sporrel et al., 2021). For instance, tailored feedback has shown promising results in obesity-related apps (Lau et al., 2020), and participants receiving tailored text messages experienced greater average weight loss than those who received generic messages (McCarroll et al., 2017). These findings align with behavioral change theories that emphasize the importance of aligning intervention components with individual determinants of behavior. Personalization, in this context, is not limited to demographics but can incorporate medical variables and behavioral change theories, thereby targeting psychological and contextual factors that influence health behavior. For example, a study that personalized breast cancer pamphlets based on variables such as age, ethnicity, access to insurance, and constructs from the Health Behavior Preference matrix found significantly higher screening intentions among recipients of the tailored version(Jensen et al., 2012). Furthermore, Jakob et al. demonstrated that personalization could not only increase user engagement and adherence to mHealth solutions (Jakob et al., 2022), but also enhance the effectiveness of mHealth interventions (Jakob et al., 2022; Wei et al., 2020). This relationship between personalization and improved outcomes can be further understood through the concept of "little e" engagement, as defined in the digital behavior change intervention (DBCI) framework by Cole-Lewis et al. This “little e” refers to the interaction the user has with the DBCI features, as well as with the behavior change intervention components/active ingredients specifically designed to influence behavior determinants. When users reach an optimal level of interaction with the digital tool and the behavior change components are appropriately aligned, the probability of achieving the desired behavioral outcome is increased (Cole-Lewis et al., 2019).

Another method for enhancing the efficacy of mHealth in promoting behavioral change is through the integration of game elements. The concept of gamification is a widely employed method for facilitating behavioral change (Bassanelli et al., 2022; Johnson et al., 2016). The term “gamification” is defined as "the use of game design elements in non-game contexts" (Deterding et al., 2011). More recently, research has emphasized the importance of aligning gamification strategies with user-specific gaming preferences, as a means of maximizing engagement and behavioral outcomes (Altmeyer et al., 2020; R. Orji et al., 2018; Tondello et al., 2016a, 2017). A review by Klock et al. addressed the issue of personalization, but in the context of user experience and user interface design in tailored gamification (Klock et al., 2020). Of note, Lister et al. reported that 52% of health apps reviewed incorporated at least one gamification element (Lister et al., 2014). This inclusion had a positive effect on the intention to use health apps, particularly among young individuals without health issues (Lee et al., 2018). In the context of gamified applications, it is therefore advisable to personalize the app according to user profiles. These profiles reflect distinct preferences for gameplay styles - such as competition, achievement, social interaction- which can be measured using validated typologies like the Gamification User Types Hexad Scale (Tondello et al., 2016a). By tailoring gamification features to match these user preferences, designers can enhance the perceived relevance and motivational appeal of the intervention.

Previous reviews on behavior changes using mHealth have predominantly concentrated on the assessment of the efficacy of diverse mechanisms for initiating health behavior modifications, such as feedback, gamification mechanisms or BCT (Edwards et al., 2016; Hoffmann et al., 2017; Lau et al., 2020; Lee et al., 2018; Lister et al., 2014; M. Marcolino et al., 2018; Michie et al., 2013). However, despite also reporting the significance of personalizing text messages to enhance their efficacy (Head et al., 2013; Lau et al., 2020), no framework has been proposed to direct the personalization of mobile apps for health behavior change, apart from one review - but in the context of gamification alone (Klock et al., 2020). In light of the aforementioned limitations, our study aims to contribute to the field by providing a framework in the form of a preference matrix for the personalization of mHealth interventions for health behavior by delineating the mechanisms that are most effective for a given user profile.

3.2 Methods

This scoping review follows the Preferred Reporting Items for Systematic reviews and Meta-Analysis extension for Scoping Reviews (PRISMA-ScR) checklist (Tricco et al., 2018).

3.2.1 Eligibility criteria

Inclusion criteria were articles published in English between 1 January 2008 and 31 December 2024 (with 2008 marking the creation of the App Store) in a journal, book chapter or conference proceeding and addressing the relationship between user profiles and BCT or mechanisms applied through mHealth. The user profile had to be a validated personality model. The mHealth intervention should not be restricted to a specific population (e.g., people suffering from cancer) in order to ensure the generalization of our framework. Exclusion criteria were articles pertaining to the personalization of information, such as recommendations or the personalization of medical procedures.

3.2.2 Information sources

On 19 August 2024, we conducted a search of the following databases as a scoping exercise to identify relevant publications: Science Direct, Psycnet APA, ACM, PubMed, Springer, JSTOR, IEE, and Web of Science.

3.2.3 Search

The following search terms were used and combined using Boolean operators and articles published after 2008 were filtered for ACM, PubMed, Psycnet APA, IEEE, Web of Science and Springer:

(“Personalization” OR “Tailoring” OR “Adaptative” OR “Customization” OR “Individualization” OR “Personalized” OR “Contextualization” OR “User-specific” OR “Adaptation” OR “User-centric” OR “Gamification”) AND (“Personality” OR “Gamers profile” OR “Big-five” OR “Hexad scale” OR “brainHex” OR “need for cognition” OR “user characteristics” OR “User attributes” OR “User data” OR “User identity”) AND (“mHealth” OR “mobile app” OR “mobile application” OR “eHealth” OR “Digital Health” OR “Mobile health” OR “health app”) AND (“Behavior change” OR “Persuasive technology” OR “Behavior modification” OR “Behavioral adjustment” OR “Habit change” OR “Behavior transformation” OR “Attitude change” OR “Behavioral adaptation”).

As the search functionality of JSTOR, Science Direct and Springer does not permit queries of such a length, we conducted a search of these databases using the following query, which was filtered and limited to articles published prior to 2008:

("Personalization" OR Gamification) AND ("Personality") AND (mHealth OR "mobile app" OR "eHealth" OR digital) AND (“behavior change”).

3.2.4 Selection of sources of evidence

Based on the inclusion and exclusion criteria, an initial selection based on a scan of the titles and abstracts was made independently by three reviewers. The full texts of the retained articles were then screened by two reviewers to ascertain their eligibility. Any discrepancies in the selection of studies were resolved through a process of consensus and discussion.

Concurrently, additional articles were incorporated through a 'snowballing' process. We included articles that cited or were cited by the initially selected papers and that were not identified through our search. Full text articles had to fulfill the established criteria.

Data charting process

As a first step, we undertook a comprehensive listing of all user profiles exhibiting preference relations to mechanisms identified in the selected articles. Subsequently, the aforementioned mechanisms were categorized according to the BCT taxonomy (Michie et al., 2013) or the game elements proposed by Werbach and Hunter (Werbach et al., 2012). Finally, a matrix was constructed to represent these relationships in tabular form.

Data items

The variables extracted included those pertaining to the user profile model used (four user profiles: Big Five, BrainHex, Hexad scale and gender), the mechanisms with preference relations (Table 3.2), the personalization type (e.g., on game elements, app mechanisms) and the media type (e.g., mobile app, video game, communication).

Synthesis of results

Articles were subjected to a three-stage analytical process. The first stage entailed the enumeration of all identified mechanisms and user profiles within the selected articles. Subsequently, taxonomies were sought that encompassed the retrieved mechanisms and profiles. The third stage involved regrouping the mechanisms according to the taxonomies. Finally, the interrelationships between the identified user profiles and the mechanisms were documented.

3.3 Results

3.3.1 Selection of sources of evidence

The literature search yielded a total of 1806 articles; 92 articles were selected based on their title and abstract. Among these, 56 were rapidly excluded by all reviewers following agreement, and 36 remained in disagreement between two reviewers. Following additional discussions between reviewers, 34/36 articles were excluded, and two were included among the articles selected based on their titles and abstracts. Following assessment of the full text of the articles, two met the established eligibility criteria. In addition, 16 articles were further incorporated into the review through the snowballing process. From the 18 articles, a list of mechanisms used to personalize interventions was extracted (Figure 1).

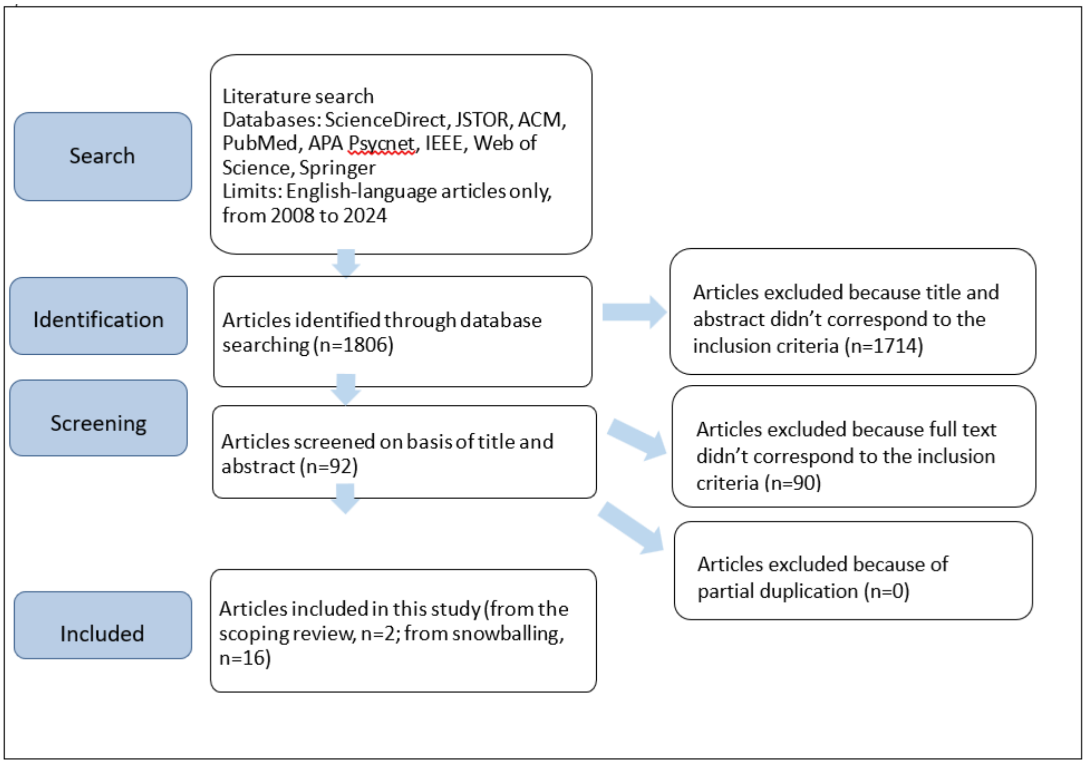

Figure 1. Source of evidence selection process.

3.3.2 Characteristics of the sources of evidence

The characteristics of the 18 articles selected are presented in Table 3.1.

Table 3.1. Characteristics and findings of the articles included in this review.

Number article	Article author (year)/country	Type*	Aim of the articles	User profile model	Personalization type	Media
1	Anagnostopoulou, E., et al. (2017) (Anagnostopoulou et al., 2017a) / Greece	EA	Examines the relation between persuasion, personality and mobility types in personalized mobility apps.	Big Five	Game elements and apps mechanisms	Mobile app and video game
2	Alqahtani, F. et al. (2022) (Alqahtani et al., 2022a) / Canada	EA	Explores the relationships between personality and features of a persuasive app for promoting mental and emotional well-being.	Big Five	Game elements, BCT mechanisms, and apps mechanisms	Mobile app
3	Altmeyer, M. et al. (2019) (Altmeyer et al., 2019) / Germany	EA	Investigates Hexad user types and behavior change intentions as factors to personalize gamified, persuasive fitness systems.	Hexad scale	Game elements	Mobile app
4	Codish, D. et Ravid, G. (2014) (Codish & Ravid, 2014) / Israel	EA	Highlights the potential influence that personality has on the perceived playfulness from gamification and ultimately the expected benefit from it.	Big Five	Game elements	Video game
5	Halko, S, et al. (2010) (Halko & Kientz, 2010a) / USA	EA	Explores the relation between personality and persuasive technologies in the context of health-promoting mobile apps.	Big Five	Game elements	Mobile app
6	Hallifax, S., et al. (2019) (Hallifax et al., 2019)/ France	EA	Investigates the preference of game elements according to the user's profile.	BrainHex, Big Five, Hexad scale	Game elements	Video game
7	Jia, Y., et al. (2016) (Jia et al., 2016)/ USA	EA	Investigates the relations among individuals' personality traits and perceived preferences for various motivational affordance used in gamification.	Big Five	Game element	Video game
8	Johnson, D., et al. (2012) (Johnson et al., 2012)/ Australia	EA	Explores relation between personality, video game preference and gaming experiences.	Big Five	Game elements	Video game
9	Klock, A.C.T, et al. (2020) (Klock et al., 2020)/ Finland	R	Presentation of a standardized terminology of the game elements used in tailored gamification and the most suitable game elements used in tailored gamification.	Hexad scale, Big Five, BrainHex,	Game elements	Video game
10	Ndulue, C. et al. (2022) (Ndulue et al., 2022)/ Canada	EA	Investigates whether the effectiveness of persuasive strategies varies across two distinct domains (healthy eating and smoking cessation) for people of distinct personality traits.	Big Five	Game element	Mobile app
11	Mora, A., et al. (2019) (Mora et al., 2019)/ Spain	EA	Investigates user types and preferences for different game design elements.	Hexad scale	Game elements	Video game
12	Orji, R. (2014) (R. Orji, 2014) / Canada	EA	Investigates differences in persuadability and the perceived persuasiveness of behavior change strategies between genders.	Gender	Game elements, BCT mechanisms, and apps mechanisms	Video game
13	Orji, R., et al. (2017) (R. Orji, Nacke, et al., 2017) / Canada	EA	Investigates how different personalities respond to persuasive strategies that are used in persuasive health games and gamified systems.	Big Five	Game element	Video game
14	Orji, R., et al. (2014)(R. Orji et al., 2014)/ Canada	EA	Investigates the efficacy of persuasive strategies for different gamer types in serious games for health.	BrainHex	Game element	Video game
15	Orji, R. et al. (2018) (R. Orji et al., 2018)/ Canada	EA	Investigates how different gamification user types responded to 10 persuasive strategies depicted in storyboards representing persuasive gameful health systems.	Hexad scale	Game element, app mechanism and BCT mechanism	Video game

16	Tondello G,. et al. (2017) (Tondello et al., 2017)/ Canada)	EA	Describes the characteristics of the users who are more likely to enjoy each group of design elements in terms of their gender, age, gamification user type, and personality traits.	Hexad scale, Big Five	BCT mechanism and app mechanism	Video game
17	Tondello,G,. et al. (2016) (Tondello et al., 2016a)/ Canada	EA	Presentation of the Hexad scale, a gamification user types' model. Presentation of the association between the Hexad user types with the Big Five.	Hexad scale, Big Five	Game elements	Video game
18	Tondello, G., et Nacke, L. (2020)(Tondello & Nacke, 2020) / Canada	EA	Validation of user preferences and effects of personalized gamification on task performance.	Hexad scale, Big Five	Game elements	Video game

*EA, experimental article; R, review.

3.3.3 Thematic presentation

3.3.3.1 User profiles

In the initial phase, we catalogued the user profiles identified in the literature. Five distinct types of user profile were identified, encompassing personality traits and player preferences. Personality was frequently assessed through various models, with the Big Five model being a prominent feature in 13/18 selected articles. These articles delineated personality based on five core dimensions: neuroticism, openness, conscientiousness, altruism and extroversion.

Derived from gamification theory, player profiles guide the process of mHealth personalization. The review revealed the existence of two distinct scales: BrainHex (featured in three articles) and Hexad scale (in 7 articles). Each scale defines player types and their preferred games or interactions, thereby offering insights into the gamification mechanisms that are favored by specific player archetypes. For example, according to the Hexad scale, philanthropic players who are motivated by goals and altruism respond well to collection and exchange elements within an app (Orji, Nacke, et al., 2017). Finally, the demographic profile, which included gender data from a single article, was incorporated into the personalization profiles. Figure 2 depicts the dimensions of the user profile.

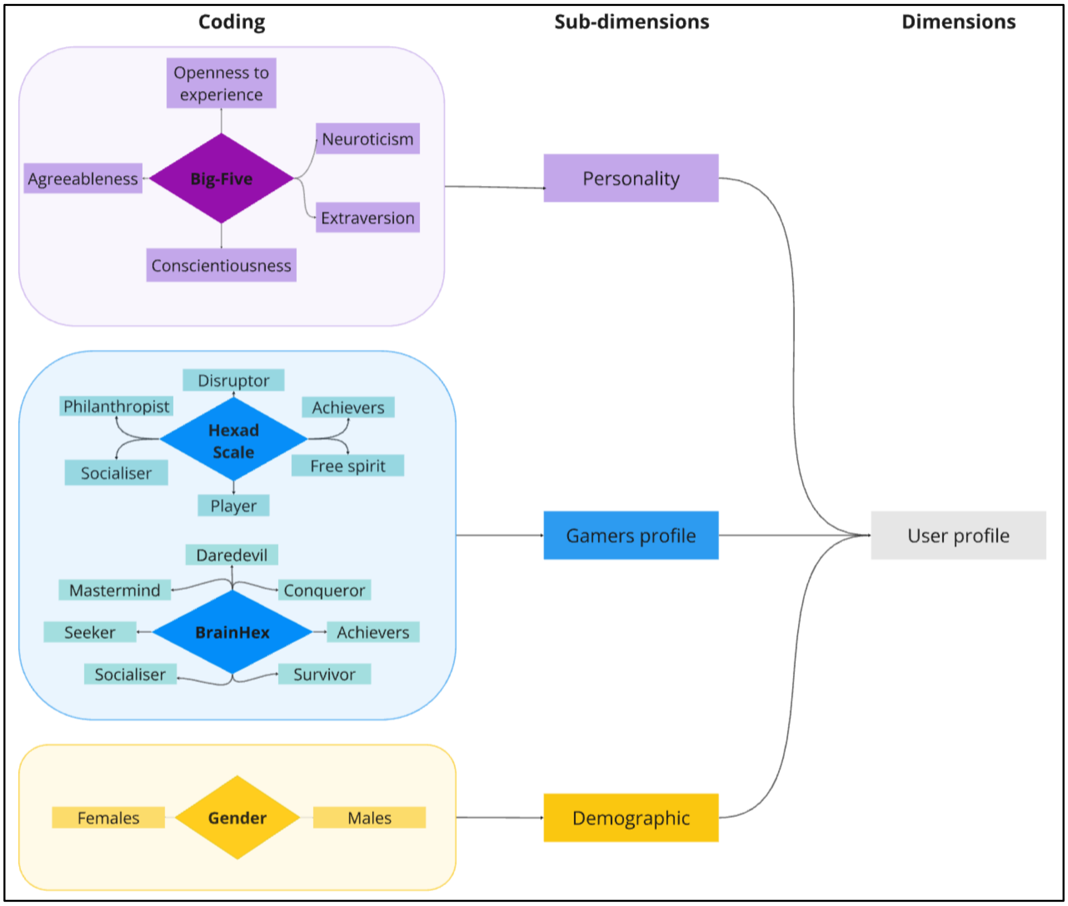

Figure 2. Diagram showing the user profile dimensions.

3.3.4 Mechanisms

The literature revealed that 15 mechanisms have been studied in association with user profiles. In our context, the term 'mechanism' is employed to denote the entirety of components that can be incorporated within an mHealth application with the objective of effecting behavioral change. This encompasses functionalities and gamification elements. Mechanisms are presented in order of their frequency of occurrence in the corpus (number of articles mentioning this mechanism), from the most to the least frequent (Table 3.2).

Table 3.2. List of mechanisms with their definition and frequency of occurrence in the corpus.

Mechanism	Frequency of occurrence in the corpus	Definition
Rewards	13	Virtual rewards offered to users for engaging in the target behavior (R. Orji, Mandryk, et al., 2017).
Competition	12	Users can compete to accomplish the desired behavior (R. Orji, Mandryk, et al., 2017).
Cooperation	12	Users collaborate to achieve a shared objective (R. Orji, Mandryk, et al., 2017).
Collection	12	Allows users to gather virtual objects.
Progression	11	Users can track their progression with steps through the system's purpose over time, visualized with mechanisms like stars or flags along a path (R. Orji, Mandryk, et al., 2017).

Customization	9	In contrast to personalization—which involves to adjust automatically the system to the user—customization refers to the user's ability to modify the content or functionalities of the mobile application according to their own preferences (R. Orji, Mandryk, et al., 2017). This approach enables users to actively tailor the system based on users' choices.
Social support	8	Enables communication between users, such as through chat or sharing activities with other users (Klock et al., 2020).
Challenge	7	Presents various situations that require effort from the user to be completed (Klock et al., 2020) (e.g., accomplishing 3 hours of physical activity per week).
Social comparison	7	An individual's perceptions of the prevailing beliefs and behaviors within a social group.
Self-monitoring	5	Users can track their behaviors, providing information on both past and current activities (R. Orji, Mandryk, et al., 2017)
Avatar	4	Allows users to share their data in the system without revealing their name (Klock et al., 2020).
Punishment	4	Virtually penalizes the user for not performing the desired behavior or reaching their goal (R. Orji, Nacke, et al., 2017).
Prompt and cues	3	Usually a message delivered to the user to prompt or recall a behavior at a specified time, with the app or user defining when the message should be sent (Villalobos-Zúñiga & Cherubini, 2020).
Demonstration of the behavior	3	Enables users to observe the cause-and-effect linkage of their behavior, such as seeing a simulation of their bodies after a diet (R. Orji, Mandryk, et al., 2017).
Quest	2	Users can enter or define the objectives targeted for the activity they will perform (Villalobos-Zúñiga & Cherubini, 2020).

The aforementioned mechanisms have been classified into the following three sub-dimensions.

3.3.4.1 BCT taxonomy

A total of six mechanisms have been aligned with the Behaviour Change Taxonomy (BCT taxonomy). The authors define BCT as "observable, replicable and irreducible components of an intervention designed to alter or redirect causal processes that regulate behavior; i.e., a technique is proposed to be an 'active ingredient' (e.g., feedback, self-monitoring, and reinforcement)." (Michie, Ashford, et al., 2011). The BCT taxonomy is a standardized, hierarchically-structured classification of 93 distinct BCT, each with labels, definitions and examples. Its objective is to provide a reliable and consensus-based method for specifying, interpreting and implementing the active components of behavior change interventions across various disciplines and domains, including health and the environment. The following mechanisms have been classified within this taxonomy: social comparison, self-monitoring of behavior, demonstration of behavior, punishment, prompt and cues and social support.

3.3.4.2 Gamification classification

In order to categorize the specific mechanisms of games and gamification, we relied on the classification of game elements proposed by Werbach and Hunter (Werbach et al., 2012). In their analysis of over 100 gamification implementations, the researchers identified the most prevalent elements, which they termed the "Points, Badges and Leaderboards (PBL triad)". The researchers then organized the remaining mechanisms into a category they termed 'game elements', defined as distinctive mechanisms inherent to video games. These game elements were subsequently classified into three principal categories pertinent to gamification named: Dynamics, Mechanics and Components, arranged in descending order of abstraction. *Dynamics* represent overarching aspects that are managed at a strategic level. *Mechanics* are fundamental processes that sustain engagement. *Components* are specific manifestations of mechanics or dynamics (Werbach et al., 2012).

Eight mechanisms were aligned with the game element classification. *Progression* is classified as a Dynamics category, while *competition, cooperation, challenge* and *rewards* are categorized as mechanics. The Components category includes *avatars, collections*, and *quests*.

3.3.4.3 Mobile app mechanism

One mechanism did not align with both the game elements and the BCT taxonomy. The category of customization encompasses mechanisms that are specific to mobile apps.

For a graphical representation of the dimensions for the mechanisms, see Figure 3.

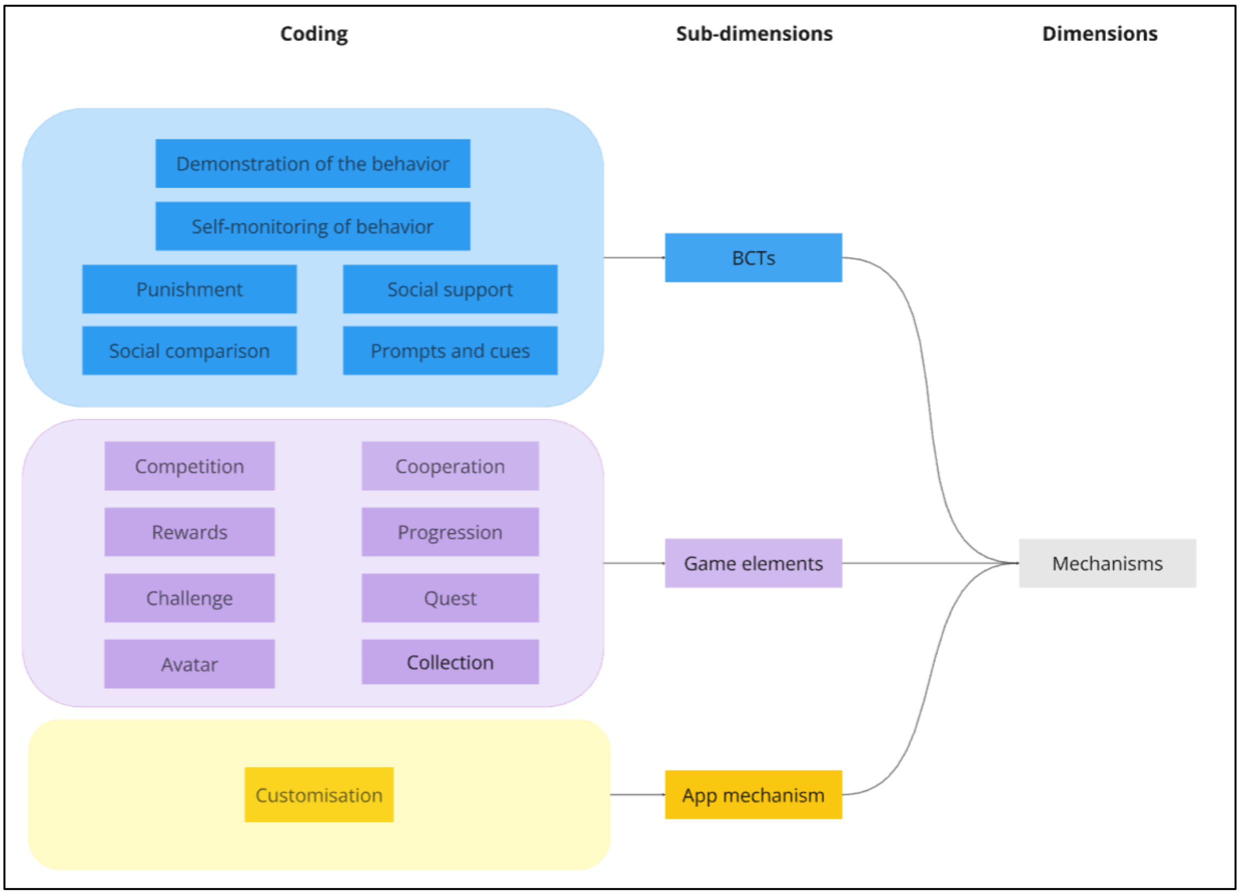

Figure 3. Diagram illustrating the mechanisms' dimensions.

3.3.5 Relations between dimensions

The selected articles identified and delineated the preference relations between the mechanisms and the user profiles. The aforementioned relations are summarized in Tables 3.3 and 3.4, with each relation referencing the corresponding article according to its number in Table 3.1. Most preference relations were positive, indicating a preference for a specific mechanism within a given profile. Negative relations indicate a rejection of a mechanism (represented by an asterisk in Tables 3.3 and 3.4). It should be noted that the relation matrix is not yet complete and out of 300 possible relations, only 154 were identified in the corpus, representing 51% of the preference matrix.

Our findings showed that two user profiles demonstrated a greater number of relations, i.e., the Big Five, representing 18% (55/300) of relations, and the Hexad scale comprising 20% (59/300) of relations (Table 3.3). In comparison, the BrainHex comprised 12% (35/300) of relations, while the gender comprised only 1% (4/300) of relations. The BCTs representing 16% (48/300) of relations, the Game elements 30% (90/300) relations, and app mechanism 5% (16/300) of relations.

Table 3.3. Relation between personality profiles and mechanisms.

			BCT mechanisms						Game elements								App mechanism
			Prompts and cues	Demonstration of the bahavior	Self-monitoring	Punishment	Social comparison	Social support	Progression	Competition	Cooperation	Collection	Rewards	Quest	Challenge	Avatar	Customization
Personality profile	**Big Five**	Openness to experience			[2, 13]	[13]	[13]	[2, 12]		[12, 13, 18] [5]*	[6, 13] [10]*	[12, 18]	[5, 13] [10]*				[9, 13, 16]
		Agreeableness	[2]	[13]	[1, 2, 13]	[12, 13]	[1, 13] [6]*	[6, 14, 2]	[12, 14]	[10, 13] [5, 6]*	[1, 10, 13]	[4, 18]	[1, 2, 10, 13]		[7, 14]		[1, 2, 13]
		Conscientiousness		[13]	[13] [1]*				[7]	[5, 4]	[5, 10]*		[4, 12]	[13]	[8]		[2]*
		Extraversion	[2]	[13]	[2, 13]	[13]	[13, 9, 7]	[9, 2]	[9, 7, 12, 14]	[7, 13,9]	[10, 13]	[9]	[2, 13, 9, 7, 5]	[13]	[8, 14]	[12]	[2, 13, 9] [1]*
		Neuroticism			[1]		[1]	[2]	[9]	[1] [10]*	[5]	[9, 16]	[9, 1, 2, 10]				[1]
Demographic profile	**gender**	Females		[12]							[12]		[12]				[12]
		Males															

*For inverse relations.

Table 3.4. Relation between gamer profiles and mechanisms.

			BCT mechanisms						**Game elements**									**App mechanism**
			Prompts and cues	**Demonstration of the bahavior**	**Self-monitoring**	**Punishment**	**Social comparison**	**Social support**	**Progression**	**Competition**	**Cooperation**	**Collection**	**Rewards**	**Quest**	**Challenge**	**Avatar**	**Customization**
Gamer profile	**Hexad scale**	Disruptor			[6] [15]*		[6]		[9, 6] [15]*	[6, 15, 1]			[16]		[9, 1]	[1]	[9, 15]
		Philanthropist		[15]				[1]	[9, 16]		[3, 11]	[18, 1]	[3]	[2]	[9]		[9]
		Socialiser		[15]	[15] [6]*	[15]	[9, 15, 1]	[16, 6, 9, 1]	[9, 15] [6]*	[9, 3, 15, 1]	[3, 15, 6, 1, 11]		[3, 15]	[2]	[9, 11]	[3]	[15]
		Player				[15]	[9, 15, 1]	[16]	[9, 3, 1, 18]	[9, 3, 15, 1, 11]	[3, 15]	[9, 3, 16, 1]	[9, 3, 15, 1]	[1]	[9, 3, 1, 11]	[3, 1]	[9]
		Free spirit						[1]	[9, 3, 1]		[3]		[3]	[2]	[9, 3, 1, 11]	[1]	[9, 1]
		Achiever					[9]		[9, 3, 16, 1]	[3]	[3]	[3, 1]	[3, 16, 1] [6]*	[2, 1]	[3, 9, 11, 1]	[1]	[9]
	BrainHex	Achievers			[14] [6]*				[9] [6]*		[14]		[14]		[9]		
		Conqueror		[14]	[14]		[9]			[14]	[6]						
		Daredevil		[14]	[14]*					[14]*		[6]	[6]				
		Mastermind		[14]	[14]					[14]							[14]
		Seeker								[14]			[14]				[14]
		Socialiser			[6, 14]*			[6]	[6]*	[14]	[14]		[14]*				[14]*
		Survivor			[14]		[6]*			[14] [6]*	[14]*		[14]*				[14]*

*For inverse relations.

Table 3.5 presents a classification of the number of relations per mechanism. The relative contributions of each mechanism to the preference matrix range from 1% to 6%. The mechanisms with the highest number of links are rewards, competition, customization and cooperation. It is evident that certain mechanisms exhibit relations with all traits present in a user profile. Rewards, competitions, customization, cooperation and self-monitoring demonstrate a connection with all five of the Big Five traits. Additionally, rewards, customization, progression and challenge exhibit a relationship with each of the Hexad scale traits. It has been demonstrated that other mechanisms exhibit strong relations with a user profile. Progression, social comparison, social support and collection have been found to be associated with four out of five Big Five traits. Furthermore, cooperation, quest, and avatar have been found to be associated with five out of six traits on the Hexad scale.

It is also worth noting that specific traits exhibit preference relations with nearly all mechanisms. Specifically: extraversion from the Big Five model exhibits relationships with all mechanisms; agreeableness from the Hexad model demonstrates relationships with 13/15 mechanisms; socializer from the Hexad model exhibits relationships with 13/15 mechanisms; and player from the Hexad model demonstrates relationships with 12/15 mechanisms. We can also observe that there is little relationship with gender. Only one article showed relations with gender, and only with women.

Finally, it was also observed that certain traits exhibit both preference and non-preference relationships for the same mechanism. For instance, the openness to experience trait exhibits a non-preference relationship with the cooperation mechanism, while the disruptor trait displays a non-preference relationship with the progression mechanism. This analysis reveals a total of 14 inconsistent relationships within the preference matrix.

Table 3.5. Representation of the number of relations per mechanism on the preference matrix and the number of relations per mechanism per user profile

Mechanisms	Percentage total on the preference matrix (number of relations/total relation possible on the preference matrix)	Percentage on the Big Five (number of relations/total relation possible on the Big Five)	Percentage on gender (number of relations/ total relation possible on gender)	Percentage on the Hexad scale (number of relations/total relation possible on the Hexad scale)	Percentage on the BrainHex (number of relations/ total relation possible on the BrainHex)
Rewards	6% (17/300)	100% (5/5)	50% (1/2)	100% (6/6)	71% (5/7)
Competition	5% (16/300)	100% (5/5)	0% (0/2)	67% (4/6)	86% (6/7)
Customisation	5% (16/300)	100% (5/5)	50% (1/2)	100% (6/6)	57% (4/7)
Cooperation	5% (15/300)	100% (5/5)	50% (1/2)	83% (5/6)	57% (4/7)
Self-monitoring	4% (13/300)	100% (5/5)	0% (0/2)	33% (2/6)	86% (6/7)
Progression	4% (12/300)	80% (4/5)	0% (0/2)	100% (6/6)	29% (2/7)
Challenge	3% (10/300)	60% (3/5)	0% (0/2)	100% (6/6)	14% (1/7)
Demonstration of the behavior	3% (9/300)	60% (3/5)	50% (1/2)	33% (2/6)	43% (3/7)

Social comparison	3% (9/300)	80% (4/5)	0% (0/2)	67% (4/6)	29% (2/7)
Social support	3% (9/300)	80% (4/5)	0% (0/2)	67% (4/6)	14% (1/7)
Collection	3% (8/300)	80% (4/5)	0% (0/2)	50% (3/6)	14% (1/7)
Quest	2% (7/300)	40% (2/5)	0% (0/2)	83% (5/6)	0% (0/7)
Avatar	2% (7/300)	20% (2/5)	0% (0/2)	83% (5/6)	0% (0/7)
Punishment	2% (5/300)	0% (0/5)	0% (0/2)	33% (2/6)	0% (0/7)
Prompts and cues	1% (2/300)	40% (2/5)	0% (0/2)	0% (0/6)	0% (0/7)

3.4 Discussion

In this study, a comprehensive review identified the preferred mechanisms for specific user profiles that can be employed in mobile apps to prompt behavioral change in health. The exploration revealed a variety of mechanisms including gamification mechanisms, mobile app mechanisms and BCT mechanisms. As a result, we have established connections between these user profiles and these mechanisms. A summary of the preferred and non-preferred mechanisms by user profile is provided in Table 3.6.

Personalized mobile health apps have been demonstrated to be more effective in inducing behavior change, particularly when the messages and goals are tailored to the individual rather than generic ones, as highlighted by Sporrel et al. (Sporrel et al., 2021). Accordingly, the development of mobile apps should be aligned with the user profile. The literature reveals three distinct user profiles: personality (utilizing the Big Five model), player profile (comprising the Hexad scale and BrainHex) and gender. Each profile categorizes users based on a variety of criteria. For instance, the Big Five model can be used to distinguish a user who exhibits high levels of extraversion and low levels of altruism. It is also notable that a single profile may exhibit a preference for all mechanisms or a preference and a rejection for a given mechanism. For example, the disruptor profile may prefer progression (Hallifax et al., 2019) or may reject this mechanism according to another article (R. Orji et al., 2018). This inconsistency in reports constitutes a minor proportion of the preference matrix (5%), yet it underscores the imperative for further investigation to resolve this discrepancy.

One review of the preference matrix addressed the concept of personalization within the context of gamification (Klock et al., 2020). Of note, 71% of the relations presented in this review were validated by other articles in the corpus, especially with all the relations with a BrainHex profile. The BrainHex profile, a construct of particular interest, is comparatively underdocumented, with only three articles in the corpus directly addressing its relationship. This paucity of documentation may partially account for the absence of corroboration from our corpus. Further research is therefore necessary to gather more data related to BrainHex. Conversely, this review encompasses a mere 13% of the potential relationships with our matrix (39/300). This finding underscores the significance of our scoping review, which offers a more extensive array of content and establishes connections between user profiles and mechanisms.

3.4.1 Social contact

A multitude of connections exist between the mechanisms associated with social contact and user profiles. It is noteworthy that social comparison, cooperation and competition, with 9, 15 and 16 relations, respectively, exceed the average number of relations per mechanism. This concept is of considerable significance, representing a category within the Persuasive System Design (PSD) framework that delineates the essential content and mechanisms for a persuasive system. Inclusion in the social support category of this framework further incorporates competition, cooperation and social comparison (Oinas-Kukkonen & Harjumaa, 2009). Notwithstanding meta-analyses that have affirmed the efficacy of interventions with a social network for behavioral change (Johnson et al., 2012; Lipnevich et al., 2021), social mechanisms are not frequently utilized in behavior change apps. Indeed, few apps in general include these social contact mechanisms. For example, of the 208 apps mechanism from Villalobos-Zuniga and Cherubini's taxonomy, less than 20% are related to social contact (Villalobos-Zúñiga & Cherubini, 2020). However, it can be reasonably deduced that encouraging the integration of these mechanisms within the domain of mobile health technology would prove to be a valuable undertaking.

3.4.2 Self-efficacy

A number of the most frequently retrieved mechanisms (with more than seven relations, representing the average number of relations per mechanism) can be associated with Bandura's theory of self-efficacy (Bandura, 1977), which has been demonstrated to influence both short- and long-term behavioral change (Strecher et al., 1986). The construct of self-efficacy is influenced by four primary sources: enactive attainment, vicarious experience, social persuasion and physiological/emotional states.

Enactive attainment entails observing one's past performance and providing an accurate assessment of one's abilities, which serves to encourage continued efforts. This is analogous to the self-monitoring mechanism, which enables individuals to evaluate their performance, such as by monitoring the number of daily steps. Furthermore, the self-monitoring mechanism is present in the PSD (Oinas-Kukkonen & Harjumaa, 2009) under the dialogue support category and also in another scale, the App Behavior Change Scale (McKay et al., 2019).

Vicarious experience can be defined as the process of gaining confidence through observation of others who are perceived to possess similar abilities engaging in the behavior in question. This experience can be facilitated by various mechanisms, including social comparison, which enables users to compare themselves with others, and the social network, which allows the sharing of performance and progress with other users.

Social persuasion entails the utilization of verbal reinforcement to motivate individuals to act in a manner that is perceived to enhance their ability to succeed. The provision of social support enables users to receive verbal encouragement and engage in supportive conversations.

Physiological/emotional states are used to describe their impact at the time of success or failure on one's sense of efficacy. A positive mood during a successful outcome leads to a more positive evaluation, whereas a negative mood during an unsuccessful outcome results in a lower sense of personal efficacy. It is therefore beneficial to cultivate a positive emotional state in users when they experience success. This can be achieved through the provision of rewards, such as badges or fictive coins.

3.4.3 Relation between BCT taxonomy and game elements

In the process of categorizing mechanisms within the BCT or game elements, it became evident that certain mechanisms could be placed in both taxonomies. For example, competition may be classified as social comparison within the BCT, while rewards may also be subsumed into the BCT reward and threat category. In instances where a mechanism was identified in both taxonomies, we retained it exclusively within the game elements' taxonomy. This decision was made in consideration of the comparison between gamification mechanisms and established behavioral change mechanisms that have been proven effective in digital health interventions (Cugelman, 2013).

3.4.4 Relation between BCT and engagement

Among the mechanisms we identified, those related to gamification can be considered as engagement-driven mechanisms. Various strategies, including targeted design features and evidence-based behavior change techniques, have been incorporated into mobile health (mHealth) applications to promote user engagement (Garnett et al., 2015). Consistent with these efforts, a recent systematic review reported significant associations between several mechanisms from our matrix and user engagement. Specifically, mechanisms such as goal setting, self-monitoring, social support, demonstration of the behavior, prompts and cues, and rewards were identified as being positively linked to enhanced engagement (Milne-Ives et al., 2023).

3.4.5 Persuasion strategies

The research conducted for this article revealed the potential for adapting Cialdini's six principles of persuasion (*liking, reciprocity, consensus, commitment and consistency*, *authority, scarcity*) according to the personality of the user. These principles have been extensively applied in the domains of marketing and persuasive technology (R. Petty et al., 2009) and identify six methods for requesting compliance with a particular course of action. For example, the principle of liking posits that requests made by individuals with whom we have a positive affinity are more likely to be complied with (Cialdini & Rhoads, 2001), or consensus posits that individuals are inclined to replicate the actions of others who share similar characteristics with them. However, we have elected to exclude these principles from our framework on the grounds that they are not mechanisms in themselves, but rather a means of personalizing messages. It would be beneficial for future research to consider the personalization of messages according to user profiles in the context of mHealth. In particular, research has demonstrated that personalized messages based on the recipient's personality are more effective (Hirsh et al., 2012).

3.4.6 Need for cognition

Our research has been expanded to encompass additional user profiles, including those pertaining to Need for Cognition (NFC). Indeed, this concept has been the subject of ongoing interest for researchers in the field of psychology (R. Petty et al., 2009) with over 8000 citations in articles following the original NFC article of Cacioppo et Petty published in 1982 (Cacioppo & Petty, 1982a). NFC is a construct that characterizes individuals based on their intrinsic motivation for engaging in cognitively demanding tasks (R. Petty et al., 2009). However, the articles on this topic did not present any relations with the identified mechanisms, thus precluding their inclusion in the scoping review. Individuals with high NFC demonstrate a preference for messages with robust arguments, whereas those with low NFC exhibit no preference between strong and weak arguments (Cacioppo et al., 1983). Furthermore, the Elaboration Likelihood Model (R. E. Petty & Cacioppo, 1986) posits that NFC may be linked to two distinct routes in the persuasion process. The central route pertains to the manner in which individuals pay attention to presented arguments, whereas the peripheral route involves the reliance on simple persuasive cues, such as the message's source, when motivation or processing abilities are low. Consequently, individuals with low NFC may be inclined to utilize the peripheral route, whereas those with high NFC may demonstrate a proclivity for the central route (Haugtvedt & Petty, 1989). It seems reasonable to suggest that the transmission of health behavior information and the formulation of feedback should be adapted on the basis of the user's NFC level. However, no articles were identified that examined relationships according to this profile.

3.4.7 Small number of relations

The articles selected for this review did not present a comprehensive account of the preference relations between all profile types and mechanisms. Indeed, 51% of potential relations were identified. This highlights an existing gap in knowledge although the limited number of articles included in this scoping review does not guarantee the comprehensive coverage of potential relations. Moreover, a considerable proportion of the studies included in this scoping review were conference proceedings rather than peer-reviewed journal articles. This prevalence may reflect the emerging nature of the field, but it also underscores a lack of robust, high-quality empirical research. The reliance on preliminary findings and non-archival sources highlights the urgent need for more rigorous, peer-reviewed investigations to establish a stronger evidence base in this area. It is also noteworthy that mHealth interventions identified in the literature rarely adapt their content based on user profiles. To identify additional relations, our search was expanded to include websites, video games, and various message types as these elements are commonly incorporated in mHealth.

3.4.8 Applying the approach

The use of the preference matrix in practice would require the completion of two distinct steps. The initial step will be to define the user profile for the application. The second step will be to adapt the content to align with the identified profile.

The first step, identification of the user profile, presents a significant challenge. This process typically involves having users complete standardized tests (e.g., the Big Five Inventory 10 Item Scale [BFI-10], Revised NEO Personality Instrument [NEO-PI-R]) and subsequently making adjustments to the app based on the user's scores. Nevertheless, this process has the potential to be time-consuming for the user. Some users may be reluctant to use the app if they are required to complete this type of questionnaire. Consequently, it is more rational to utilize automatic personality assessments. Research has demonstrated the feasibility of employing these assessments with existing data sources, including smartphone data (e.g., call duration, SMS, Bluetooth connection) (Chittaranjan et al., 2011; Staiano et al., 2012), demographic data (Azucar et al., 2018), social media (Azucar et al., 2018; Bai et al., 2012; Souri et al., 2018), user activities on YouTube (Yeo, 2010), language-based assessments (Park et al., 2015), and wearable activity trackers (Olguin & Gloor, 2009; Zufferey et al., 2023). However, such assessments necessitate the collection of data, which users often demonstrate reluctance to share, particularly when it comes to audio and video data (Kim et al., 2020). Privacy concerns related to excessive data collection may results in users to perceiving behavioral changes influenced by these assessments in a negative light, which could ultimately diminish the perceived accuracy of the assessments (Kim et al., 2020). Therefore, the most pragmatic approach is to make app personalization optional, allowing users to decide whether or not to engage with this functionality. Should the user express a desire for this functionality, they will be prompted to complete a brief personality questionnaire, utilizing the most concise version that has been empirically validated.

The second step would be to guarantee that the app contains solely the mechanisms that correspond to the dominant traits (which can be multiple) of the user's profile in accordance with our preference matrix. For instance, for participants exhibiting a high score on the Big Five conscientiousness scale, the app would include demonstration of the behavior, self-monitoring and, if the app is gamified, the progression, competition, cooperation, collection, rewards, quest and challenge mechanisms. It is also possible to personalize according to several user profiles. These profiles may be characterized by the Big Five personality model, gender, or the Hexad scale. Furthermore, it is possible to select mechanisms corresponding to a user's dominant traits for each of these profiles.

This process can be initiated at the time of account creation within the app. As an alternative, the option may be presented subsequent to the creation of the account. Should the user wish to trial an application that has been tailored to their profile, they may do so.

Table 3.6 Representation of the number of relations per mechanism on the preference matrix and the number of relations per mechanism per user profile

User profiles	Mechanisms preferred	Mechanisms non-preferred
Big Five		
Openness to experience	Self-monitoring, punishment, social comparison, social support, competition, cooperation, collection, rewards, customization.	Rewards, competition, cooperation
Agreeableness	Prompts and cues, demonstration of the behavior, self-monitoring, punishment, social comparison, social support, progression, competition, cooperation, collection, rewards, challenge, customization.	Social comparison, competition
Conscientiousness	Demonstration of the behavior, self-monitoring, progression, competition, collection, rewards, quest, challenge.	Self-monitoring, cooperation, customization
Extraversion	Prompts and cues, demonstration of the behavior, self-monitoring, punishment, social comparison, social support, progression, competition, cooperation, collection, rewards, quest, challenge, avatar, customization.	customisation
Neuroticism	Self-monitoring, social comparison, social support, progression, competition, cooperation, collection, rewards, customization.	competition
Demographic profile		
Female	Demonstration of the behavior, cooperation, rewards, customization	
Hexad scale		
Disruptor	Self-monitoring, social comparison, progression, competition, rewards, challenge, avatar, customization.	Self-monitoring, progression
Philanthropist	Demonstration of the behavior, social support, progression, cooperation, collection, rewards, quest, challenge, customisation	
Socialiser	Demonstration of the behavior, self-monitoring, punishment, social comparison, social support, progression, competition, cooperation, rewards, quest, challenge, avatar, customization.n	Self-monitoring, progression
Player	Punishment, social comparison, social support, progression, competition, cooperation, collection, rewards, quest, challenge, avatar, customization.	
Free spirit	Social support, progression, cooperation, rewards, quest, challenge, avatar, customization.	
Achiever	Social comparison, progression, competition, cooperation, collection, rewards, quest, challenge, challenge, avatar, customization.	Rewards
BrainHex		
Achievers	Self-monitoring, progression, cooperation, rewards, challenge.	Self-monitoring, progression
Conqueror	Demonstration of the behavior, self-monitoring, social comparison, competition, cooperation.	
Daredevil	Demonstration of the behavior, collection, reward.s	Self-monitoring, competition
Mastermind	Demonstration of the behavior, self-monitoring, competition, customization.	
Seeker	Competition, rewards, customization.	
Socializer	Self-monitoring, social support, competition, cooperation.	Self-monitoring, progression, rewards, customization
Survivor	Self-monitoring, competition.	Social comparison, cooperation, rewards, customization

3.4.9 Limitations

The decision was taken to categorize the mechanisms in question in accordance with the BCT taxonomy (Michie et al., 2013) and the game elements defined by (Werbach et al., 2012). Other taxonomies, such as PSD (Oinas-Kukkonen & Harjumaa, 2009), include also mechanisms such as rewards, social support and self-monitoring, but the BCT taxonomy was selected due to its extensive usage, with over 6000 citations. An alternative approach would have been to categorize the mechanisms according to the mechanisms of action (MoA), which appear to be a more relevant classification system (Carey et al., 2018). However, the BCT taxonomy is more detailed and allows for a more precise level of granularity than the MoA, thereby enabling a more accurate classification of the mechanisms identified in the literature.

The classification of mechanisms into the taxonomy was conducted by a single researcher. To mitigate research biases and enhance the credibility and validity of the taxonomy, it is recommended that validation by other researchers, specifically investigator triangulation, should be employed. The process of triangulation serves to confirm the accuracy of the taxonomy classification, identify instances of conflicting classification, rectify errors and enhance the overall accuracy of the taxonomy (Bans-Akutey & Tiimub, 2021). In order to corroborate this classification, it would be beneficial to engage in dialogue with experts in the field, such as focus groups comprising various specialists (e.g., app developers, healthcare professionals, health psychologists, BCT experts, etc.).

Another limitation is the addition of a snowballing process, which makes the process less reproducible. Surprisingly, after performing the scoping review, some articles frequently cited in article introductions were not in our corpus. We therefore decided to add this snowballing process as these articles met our criteria, although they did not stand out among the results of our searches in the various selected journals.

Finaly, the reliability of the relations is questionable, as studies are conducted in heterogenous manners. For instance, some of the studies were conducted with student populations (Codish & Ravid, 2014; Johnson et al., 2012; Tondello et al., 2016a). Second, the materials and procedures varied significantly between studies: while most asked participants to evaluate storyboards illustrating each mechanism (Altmeyer et al., 2019; Anagnostopoulou et al., 2017a; R. Orji et al., 2014, 2018; R. Orji, Nacke, et al., 2017), and one study involved participants selecting mechanisms they would prefer to use within a mobile application (Tondello & Nacke, 2020). Finally, the health-related issues addressed by the studies were heterogeneous, ranging from unhealthy alcohol consumption (R. Orji et al., 2014, 2018; R. Orji, Nacke, et al., 2017) to physical activity (Altmeyer et al., 2019) and mental health (Alqahtani et al., 2022a; Codish & Ravid, 2014), further limiting direct comparison.

3.5 Conclusions

Mobile apps represent an intriguing avenue for facilitating the adoption of healthier behaviors among individuals. To optimize the efficacy of these applications in influencing behavior, it is recommended that the content of the app be tailored to the specific profile of the user. This study permitted the delineation of diverse profiles, including those pertaining to personality and gamer profiles, with the Big Five and Hexad scale exhibiting the greatest number of associations. The preferred mechanisms for each of these profiles were then specified. Nevertheless, evidence was found for only 45% of the potential relations. Of note, several relations were identified in the domains of competition, collectibles, progression, customization and cooperation. To experimentally validate the findings of this scoping review, it would be valuable to conduct a study wherein participants' profiles are measured and they are subsequently asked to select their preferred mechanisms. Such an experiment would serve to corroborate the identified relations and explore any missing connections.

Conflicts of Interest

None declared.

Acknowledgments

LG carried out the scoping review with the help and advice of FE and GF. All authors participated in the writing and reading of the manuscript and approved the final version.

Data availability

Data sharing is not applicable to this article as no datasets were generated or analyzed during the study.

Chapter 4

4. Article III : Personalization of Mobile Apps for Health Behavioral Change: Protocol for a Cross-Sectional Study

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Chapter content

4.1 Abstract

Background:

Mobile health apps (mHealth) have the potential to motivate people to adopt healthier behavior, but many fail to maintain this behavior over time. However, it has been suggested that long-term adherence can be improved by personalizing the proposed interventions. Based on the literature, we created a conceptual framework for selecting appropriate functionalities according to the user's profile.

Objective:

This cross-sectional study aims to investigate if the relationships linking functionalities and profiles proposed in our conceptual framework are confirmed by user preferences.

Methods:

An online questionnaire comprising several sections was developed to determine the mobile app functionalities most likely to promote healthier behavior. First, participants completed questionnaires to define the user profile (Big Five Inventory-10, Hexad Scale and perception of the social norm using dimensions of the Theory of Planned Behavior). Second, participants were asked to select the five functionalities they considered to be the most relevant to motivate healthier behavior and to evaluate them on a score ranging from 0 to 100.

Results:

Data collection was conducted between July and December 2021. Analysis of responses began in January 2022, with the publication of results expected by the end of 2022.

Conclusions:

This study will allow to validate our conceptual model by defining the preferred functionalities according to user profiles.

Keywords: mHealth; personalization; mobile app; behavior change theory; gamification; functionalities

4.2 Introduction

Healthy lifestyle behaviors have increased the life expectancy of those who adopt them and help individuals to live not only longer, but better (Wingard et al., 1982). More specifically, adopting a healthy diet, maintaining a healthy weight, quitting smoking, drinking alcohol in moderation, and regular exercise are five behaviors associated with lower mortality. An increasing number of health apps aiming to help people adopt better health behaviors are reaching the market annually, with over 35,000 health apps available in 2018 (Aitken et al., 2017). Smartphone apps offer new opportunities to adopt health-related behaviors by providing immediate access to information about one's health, reminders to take medication, or help track one's progress (Ernsting et al., 2017).

Several scales exist to measure the quality of these health-related mobile apps, such as the Mobile App Rating Scale (Stoyanov et al., 2015) and the App Behavior Change Scale (Mckay et al., n.d.). A common feature of these scales is to consider a mobile app's personalization as a quality factor. Indeed, personalization is an important aspect to consider when creating an app that enables behavioral change. For example, it has been shown that messages tailored to the user tend to be read more, recalled more, attract more attention, be better remembered, be a topic of discussion with others, and be perceived as personally relevant compared to untailored messages (Skinner et al., 1999).

4.2.1 Development of a Mobile App Model for Behavior Change

Based on a previous literature review, we identified the personality traits more likely to adopt certain app functionalities (Gosetto et al., 2020). These findings led to the development of a model indicating the type of features preferred according to a user profile. When designing a mobile app aiming at behavior change for health, designers can refer to our model as a guideline to know what functionalities they should privilege for their applications, given the profile of the intended users. For example, if a person is extroverted according to the Big Five, it will be relevant to privilege functionalities allowing comparison and cooperation between users .

Our model contains 17 functionalities presented in detail in the Appendix 2. For the user profile, we relied on the most common classification dimensions found in the literature: personality profiles , game preference (Hallifax et al., 2019; Klock et al., 2020; Tondello et al., 2016a), and perception of social norm (Hawkins et al., 2008) (Table 4.1). Gender and age are also important and a recent review showed a difference in the type of functionality preferred according to gender, although no study in the review included individuals over 31 years (Klock et al., 2020).

One of the most popular scales to measure personality is the Big Five, which defines the user's personality according to 5 dimensions: openness, agreeableness, conscientiousness, neuroticism, and extraversion. Game preference was measured with the Hexad Scale model (Tondello et al., 2016a), which defines the user's gamer profile according to six dimensions: disruptor, achievers, free spirit, player, socializer, and philanthropist. For example, players motivated by extrinsic rewards who will do anything to earn a reward within a system. This type of profile is interesting to consider for apps that use gamification, which is also a concept widely used nowadays to incite behavioral change. We can define gamification as "the use of game design elements in non-game contexts" (Deterding et al., 2011). Indeed, gamification positively affects motivation, engagement and enjoyment (Hamari et al., 2014). Finally, the perception of social norm is the "individual's perception that other individuals important to the respondent believe that the respondent should perform the behavior of interest" (Harding et al., 2007). This perception can help or hinder the performance of the behavior, depending on how the user's entourage perceives it. Therefore, it is important to consider this factor and, depending on this perception, different functionalities can be included.

Table 4.1. Profiles taken into account in our conceptual framework.

Profiles	Scale
Personality	Big Five
Game's preferences	Hexad Scale (Tondello et al., 2016a)
Perception of social norms	Theory of Planned Behavior Action (Ajzen, 1991)

4.2.2 Objectives

This study aims to validate our conceptual framework by investigating if the proposed relationships between the functionalities and profiles are reflected in the preferences of our target population in an experimental setting.

4.3 Methods

4.3.1 Ethics Approval

The University Ethics Commission has approved this study for ethical research at the University of Geneva (CUREG_2021-04-38).

4.3.2 Study Design

We performed a cross-sectional study to address our aims. Participants responded to an online questionnaire to define their profile. Then, they were presented with a series of prototyped functionalities to be ranked according to their preferences to analyze if they corresponded to those defined in our conceptual framework. We have chosen to contextualize the functionalities of adopting healthy diet and fitness apps as these issues allow to target a generic public. Indeed, the desire to stay fit is a behavior that most adults want to adopt. All data are completely anonymous. This online survey is in accordance with the Checklist for Reporting Results of Internet E-Surveys (Eysenbach, 2004).

4.3.3 Outcomes

The primary outcome is the preferred functionalities given the user profile.

Secondary outcomes are the feature preferences related to past or current use of mobile health apps, and the preference of functionalities according to the participant's state of motivation to change behavior.

4.3.4 Study Population and Sample Size

The target population for this study included all individuals over 18 years who understood French. We chose to conduct the questionnaire in French as this population was not necessarily fluent in English and mainly native French speakers. An English language questionnaire would have introduced an element of bias as it might not have been correctly understood. Recruitment was conducted by posting messages on social networks (Facebook and Twitter) targeted at students at the University of Geneva, a young student population. The message indicated that we were seeking to recruit participants for an online study lasting 12 minutes as part of a research study conducted by the University of Geneva, with a focus on identifying user preferences based on their profile for a mobile app aimed at helping people get in shape. We also stated that the collected data remain completely anonymous.

For the calculation of the sample size, based on the hypothesis that altruistic people according to the Big Five prefer social networks (Hallifax et al., 2019; Klock et al., 2020), we used the multiple regression power calculation on R, with a u=3, f2=0.07, a significance level=0.05, a power=0.9, and a variance=202.403. To estimate variance, we relied on a previous study (Gosetto, 2018) investigating the preference of users classified according to the Big Five on posters. More specifically, we looked at the variance of altruistic participants (n=46) according to the Big Five on the average ratings of a poster representing a social network promoting blood donation (score from 0 to 100). Thus, we obtained a sample size of 206.

4.3.5 Procedure

Participants were asked to complete the online questionnaire developed by using Qualtrics software (Qualtrics, Provo, UT) (Appendix 1). First, they completed the consent form describing the purpose of the study and the procedure and informing them of their right to withdraw from the study. They were asked to confirm that they have read and understood the consent form and agree to have their responses used in our research and scientific publications. They can then access the rest of the questionnaire if they accepted these clauses. If not, they were informed that without their consent, we cannot collect their data and must terminate the survey. Next, participants were asked to answer demographic questions. In the case of a participant under 18 years old, we explain that only those over 18 years can participate and therefore we cannot continue with the questionnaire. Eligible participants continued to answer the questionnaire online where they had to (1) respond to scales to measure their profile, and then (2) look at the 17 features, select 5, and indicate on a score from 0 to 100 how much these features would motivate them to get back in shape.

4.3.6 Measures and Measurement

4.3.6.1 Demographic questions

Participants were asked to indicate their gender, age, occupation, and level of education.

4.3.6.2 Questions about their use of mobile health apps

Participants were asked if they use mobile apps aiming at behavior change (such as to help them eat healthier or exercise) to find out if they were already familiar with mHealth apps and whether they already like certain functionalities. If so, we asked them to select which functionalities they used most often and those they never used. These questions allowed us to observe whether participants already familiar with mHealth prefer certain features, as well as whether they prefer the same features among the 17 proposed.

4.3.6.3 Profile Assessment

4.3.6.3.1 Big Five

To assess participants' personalities, we relied on the Big Five Inventory-10 scale in French (BFI-10-Fr), translated and validated by Courtois (Courtois et al., 2020). This scale is composed of 10 items, two items per Big Five dimension. Participants are asked to indicate on a 5-point Likert scale whether they strongly approve or strongly disapprove of statements about themselves. For example, "I see myself as someone who is reserved" or "I see myself as someone who is easily anxious". The score for each dimension is calculated by adding the scores for the two statements concerning the dimension after reversing the items.

This scale was chosen because it has a factorial structure identical to that of the full version of the BFI-Fr (Courtois et al., 2020). Therefore, it has the advantage of effectively measuring personality with a small number of items. As our protocol contains several scales, we preferred to choose the shortest valid versions to avoid participant fatigue with a too-long questionnaire.

4.3.6.3.2 Gamer profile

To identify participants' gamer profiles, we chose the Hexad Scale created and validated by Tondello (Tondello et al., 2016a). This scale consists of 24 items, 4 per dimension. Users must rate how well each article describes them on a 7-point Likert scale. For example, there are items such as "I like competitions, where a prize can be won" or "Interacting with others is important to me". Items are presented in a randomized manner and the score is calculated by adding the scores for each dimension.

4.3.6.3.3 Perception of social norm

For the perception of social norm, we chose two items concerning this dimension of the Theory of Planned Behavior questionnaire of Ajzen (Ajzen, 1991). We adapted the items to the context of our mobile application, which is to eat healthier and do more physical activity. Thus, the two items are: "Most people who are important to me approve of the fact that I eat healthier and do more physical activity" and "Most people like me eat healthily and do physical activity". Participants were asked to respond to these statements on a 7-point scale ranging from “agree” to “disagree”. The calculation was done by adding up the scores, with a high score indicating a heightened social norm perception.

4.3.6.4 Choice of functionalities

4.3.6.4.1 Presentation of the functionalities

From the literature, we identified 17 functionalities commonly proposed in behavior change apps. We then created a prototype for each of these functionalities. All functionalities and their definition are presented in the Multimedia Appendix 2. We chose a visual design as neutral as possible for the prototypes, i.e., in black and white with no images, only icons. This aims to minimize the bias due to design preference (i.e., Figure 4). The 17 prototype screenshots were presented randomly to the participants to avoid a primacy or recency effect. During the study, participants discovered every functionality one-by-one by its representation in an image and accompanied by a short description. Then, they chose the five functionalities they considered to be the most motivating to stay fit.

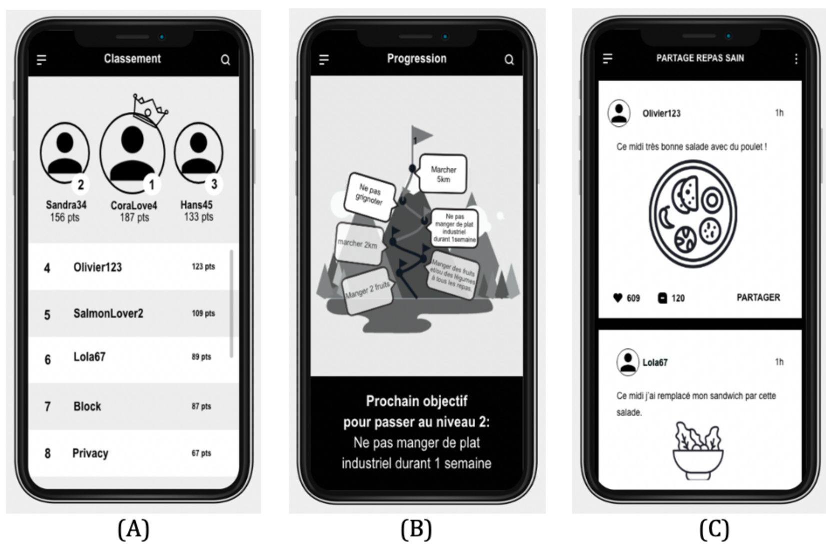

Figure 4. Example of screenshots of the prototype app, including the (A) functionality competition, (B) functionality level and progression, and (C) functionality social network.

4.3.6.4.2 Explanation of choice

For each functionality selected, participants were asked to indicate how much that functionality would motivate them to adopt healthier behavior on a scale of 0 to 100. Then, they were asked why they chose these functionalities. Excluded functionalities will default to a score of 0.

4.3.7 Analysis

Demographic characteristics of all participants will be presented using descriptive statistics (mean, standard deviations, or frequencies and range) in a table. A table will also provide responses about their use of mobile apps for health.

4.3.7.1 Quantitative data

Primary outcome

We will perform logistic regression with the functionalities as dependent variables and with scores of the three profile scales as predictors. This analysis will allow us to understand the effect of the participants' scores on each of the three scales (BFI-10-Fr, Hexad Scale, and perception of the social norm) on the five selected functionalities. By performing a logistic regression for each feature, it will be possible to determine whether the scores on the different scales predict the selection of the functionality.

In addition, we will perform a logistic ordinal regression with the motivation score of the functionalities chosen as dependent variables and with scores of the three profile scales as predictors. By performing this regression for each functionality motivation score, it will be possible to determine whether the scores on the different scales predict the functionality score.

Secondary outcome

To test whether there is a difference in functionality selection by age or gender, we will run logistic regressions with the choice of the functionality as the dependent variable and age or gender as the independent variable/s. In addition, we will perform an ordinal regression with the motivation score of the functionalities as the dependent variable and age or gender as the independent variable. There will be one regression per feature.

To test whether participants indicated that they preferred functionalities that are the same as the ones already used in their current mHealth app, we will run simple regressions with the feature they already use as the independent variable and whether this feature was chosen as the dependent variable. There will be one regression per feature.

We will use the Bonferroni correction for all our regressions to avoid a type 1 error.

Qualitative data

Qualitative analysis of the free text for the question regarding the explanation of their choice was performed and common themes extracted. Response categories will be defined when reading the responses.

4.4 Results

Recruitment and testing was conducted during July 2021. The deadline for the completion of the online questionnaire by participants was end of December 2021. We began analyzing the responses in January 2022 and the publication of results is expected at the end of 2022.

4.5 Discussion

This study will define the preferences of functionalities of users with a specific profile, e.g. what kind of functionalities are preferred by a user according to his/her personality. This protocol is important as its sample will enable to validate a model built on several previous studies and reviews. In turn, this will allow to build mobile apps that will be more efficient as adapted to each user. Thus, with this research, we will be able to better refine our conceptual framework, which will allow the mobile app designer to select features tailored to their users according to their profile and thus increase their involvement in the mobile health app.

The main interest of this research is that it gathers all the user profiles identified in the literature and all the functionalities generally implemented in mHealth. Indeed, we find studies allowing us to link personality and gamification elements , personality, gamer profile, and gamification elements (Hallifax et al., 2019), between personality and sensitivity to persuasion strategies (Anagnostopoulou et al., 2017a; R. Orji, Nacke, et al., 2017) or between personality and Need for Cognition (Haugtvedt & Petty, 1989). Moreover, these studies are not necessarily specific to the field of mobile apps for behavioral change. Some studies are more focused on preferences related to video games (Jia et al., 2016; Johnson et al., 2012) and others on the type of messages and feedback (Alkış & Taşkaya Temizel, 2015; Hawkins et al., 2008). Therefore, our research allows to combine what has been done previously in different studies and to corroborate their findings for mobile health apps regarding user preferences according to their specific profile.

4.5.1 Limitations

Our study has some limitations. We designed it to be as neutral as possible to limit preferences linked to the design of one of the prototyped functionalities. However, it is still possible that participants may prefer a certain functionality because they found it more visually attractive. Our results are also possibly not generalizable to the whole population. Indeed, since recruitment was done at the university and on social networks, it is expected that most participants were students aged 18-25 years. Moreover, as the questionnaire was in French language and only individuals living in the canton of Geneva and the surrounding area were included, it can only be generalized to this population, i.e., French-speaking people of Switzerland and France. Finally, the survey was not validated by a panel of experts for its content. Thus, it would be interesting for a future study to be validated by an expert in the field of health behavioral change in order to confirm if our questions are relevant and an expert in mHealth to know if our functionalities are representative. For this study, we preferred to rely on the literature, but such a validation would be a real advantage.

4.5.2 Conclusion

It is important to help people adopt better health behaviors. Mobile apps are an interesting channel to support this effort because they integrate functionalities such as goal setting or self-monitoring that have been proven to foster behavior change, but app efficiency can be improved by responding to user preferences according to their specific profiles. Our study will provide an additional evidence base to propose an accurate personalization conceptual framework for the development of future mHealth apps.

Data availability

The datasets generated during the current study are available from the corresponding author upon reasonable request.

Acknowledgments

We thank all participants for their valuable contribution

Authors' contributions

LG conceived the study with the involvement and advice of FE and GF. MP is involved in the statistical analysis. All authors participated in the writing and reading of the manuscript and approved the final version.

Conflicts of interest

None declared.

Appendices

- **Appendix 1** : Print version of the online questionnaire.
- **Appendix 2** : Presentation of the functionalities selected for our conceptual framework with their definitions and description of the screenshot.

Chapter 5

5. Article IV : Personalizing Mobile Applications for Health Behavioral Change according to personality: cross-sectional validation of a Preference matrix

Submitted to JMIR Human Factor

Chapter content

5.1 Abstract

mHealth apps are increasingly popular, offering tools like health tracking and personalized reminders to support these behaviors. Personalized messaging, tailored to the user's profile, has been shown to improve engagement and retention around health topics. Research links personality traits (based on the Big Five model) with preferred app mechanisms, leading to a preference matrix for personalizing health apps. This preference matrix includes 15 mechanisms, categorized by the Behavior Change Technique and gamification elements, guiding developers to optimize app engagement based on user profiles. This study aims to validate this preference matrix by assessing whether the associations between mechanisms and Big Five personality profiles proposed in the preference matrix align with the preferences of our population in an experimental context. This study employs a cross-sectional design. Participants completed an online survey, which collected data on demographic information, mobile health app usage, and personality. The average age of the 214 respondents (118 women, 89 men, 5 others), was 29.42. Logistic regression and logistic ordinal regression analyses, adjusted using the Bonferroni correction, assessed the influence of personality traits on mechanism preferences and motivation levels was statistically significant for three mechanisms. Conscientiousness significantly increased the likelihood of selection for collection (OR = 1.87). For competition, both conscientiousness (OR = 3.22) and altruism (OR = 1.93) emerged as strong predictors. For rewards, conscientiousness (OR = 1.97) and neuroticism (OR = 2.36) also showed a strong predictive value. The study found that four mechanisms, self-monitoring, progression, challenge, and quest, were favored by over half of the participants, suggesting these should be standard features in mHealth applications. Conscientious participants showed a preference for the collection mechanism, while both conscientious and altruistic individuals were drawn to competition. Neurotic and conscientious individuals preferred the reward mechanism. Conscientiousness consistently predicted preferences for all three gamification elements, highlighting its role in influencing engagement with mHealth features.

5.2 Introduction

Many studies have demonstrated the role of healthy lifestyle behaviors adoption to increase life expectancy. Specifically, the adoption of a healthy diet, maintenance of a healthy weight, cessation of smoking, consumption of alcohol in moderation, and regular exercise are associated with a reduction in mortality. The researchers discovered that the adoption of each healthy lifestyle behavior contributes to an enhanced quality of life and longevity (Wingard et al., 1982).

The number of health apps designed to assist individuals in adopting healthier behaviors is increasing annually, with new apps reaching the market every year. In 2018, there were over 35,000 health apps available for download (*Health-Tech-Mobile-Apps-Analytical-Report.Pdf*, n.d.). The advent of smartphone apps has created novel avenues for individuals to adopt health-related behaviors. These apps offer immediate access to health-related information, medication reminders, and tools for monitoring progress, which can collectively fostering healthier lifestyles (Ernsting et al., 2017).

Several scales have been developed to assess the quality of mHealth apps. For example, the Mobile App Rating Scale (MARS) (Stoyanov et al., 2015) and App Behavior Change Scale (Mckay et al., n.d.). One of the most salient features of these scales is the inclusion of personalization as a quality factor. Indeed, personalization represents a crucial consideration when developing an app designed to facilitate behavioral change. For example, one study has demonstrated that messages tailored to the user's specific characteristics are more likely to be read, recalled, and retained in memory, and are perceived as more personally relevant than untailored messages. Additionally, tailored messages tend to garner more attention, elicit more discussion, and be a topic of interest among others, compared to untailored messages (Skinner et al., 1999).

5.2.1 The preference matrix

Personalization of mobile app can be done according to the user's profile. In previous articles (Gosetto et al., 2025b), we identified from the literature preference relations between personality traits and mechanisms (components can be incorporated within a mHealth application). These findings related to the development of a preference matrix indicating the type of mechanisms preferred according to a user profile. The preference matrix can be used as a framework for the customization of mobile applications with the objective of encouraging behavioral change. When designing a mobile application aimed at facilitating behavior change for health-related purposes, designers can utilize our preference matrix to identify the mechanisms that are most efficient to achieve the desired outcomes, given the profile of the intended users. For instance, if an individual is classified as extroverted according to the Big Five personality traits, it would be relevant to prioritize mechanisms that facilitate social comparison and collaboration between users .

The preference matrix includes 15 mechanisms linked to Big five personality profile, which are presented in detail in Table 4.2. Regarding the user profile, we utilized one of the most prevalent classification systems for individuals, namely the Big Five personality profiles.

5.3 Personality measure: the Big-five

One of the most widely used instruments for the assessment of personality is the Big Five Model. The Big Five model characterizes an individual's personality based on five distinct traits, as illustrated in Table 5.1.

Table 5.1. Definition of the Big Five factors personality

Traits	**The five traits represent the tendency to** (Costa & Mccrae, 1992) **...**
Neuroticism	Worried, nervous, emotional, anxious, maladjusted, hypochondriac
Extraversion	Sociable, active, talkative, open to others, optimistic, fun-loving, affectionate
Openness	Curious, eclectic, creative, original, imaginative, non-conformist
Altruism	Compassionate, easy-going, trusting, helpful, indulgent, credulous, honest
Conscientiousness	Organized, reliable, hard-working, disciplined, punctual, meticulous, careful, ambitious, persevering

This model has the advantage of being frequently used in academic research. Between 1990 and 1994, the number of publications on this topic was approximately 400, while between 2005 and 2009, this figure rose to approximately 1,600 (John et al., 2008a).

The other advantage of this model is its universality. Five-factor model is universal in humans (Costa Jr. & McCrae, 1997). Indeed, the authors translated their personality questionnaire, the NEO-PI-R, into six languages belonging to the same language family as English (German, Portuguese, Hebrew, Chinese, Korean, and Japanese). The Big Five factors were found to emerge consistently.

In a further study, the researchers investigated whether the Big Five personality dimensions, as measured by the NEO-PI-R, are universal across 50 cultures, including American, European, Arabic, Asian, and African (McCrae et al., 2005). Accordingly, the NEO-PI-R was translated into the original language of the country in which it was administered. The participants were primarily students from the country in which the test was administered. The factor analysis demonstrated that the American structure of the NEO-PI-R self-report questionnaire (Form S) could be replicated in all cultures, with 94.4% of factors replicated. Furthermore, the structure was recognizable in all cultures studied.

5.3.1 Selection of the 15 mechanisms

Based on the hypothesis that people with different profile have different preference about components of mHealth applications aiming at facilitating behavioral change, a review of the literature identified 15 mechanisms that have been associated with user profiles. In our context, the term 'mechanism' is employed to denote the entirety of components that can be incorporated within an mHealth application with the objective of promoting behavioral change. We classified the mechanisms into two categories, the mechanisms linked to Behavior change techniques and the mechanisms linked to game elements. For further details and definition of mechanisms, refer to Table 5.2.

Table 5.2. List of mechanisms with their definition

Mechanism	Definition
BCT mechanisms	
Prompt and cues	Usually a message delivered to the user to prompt or recall a behavior at a specified time, with the app or user defining when the message should be sent (Villalobos-Zúñiga & Cherubini, 2020)
Demonstration of the behavior	Enables users to observe the cause-and-effect linkage of their behavior, such as seeing a simulation of their bodies after a diet (R. Orji, Mandryk, et al., 2017).
Self-monitoring	Users can track their behaviors, providing information on both past and current activities (R. Orji, Mandryk, et al., 2017)
punishment	Virtually penalizes the user for not performing the desired behavior or reaching their goal (R. Orji, Nacke, et al., 2017)
Social comparison	An individual's perceptions of the prevailing beliefs and behaviors within a social group.
social support	Enables communication between users, such as through chat or sharing activities with other users (Klock et al., 2020).
Game elements	
Progression	Users can track their progression with steps through the system's purpose over time, visualized with mechanisms like stars or flags along a path (R. Orji, Mandryk, et al., 2017).
Competition	Users can compete to accomplish the desired behavior (R. Orji, Mandryk, et al., 2017).
Cooperation	Users collaborate to achieve a shared objective (R. Orji, Mandryk, et al., 2017).
Collection	Allows users to gather virtual objects.
Rewards	Virtual rewards offered to users for engaging in the target behavior (R. Orji, Mandryk, et al., 2017).
Quest	Users can enter or define the objectives targeted for the activity they will perform (Villalobos-Zúñiga & Cherubini, 2020).
Challenge	Presents various situations that require effort from the user to be completed (Klock et al., 2020) (e.g., accomplishing 3 hours of physical activity per week).
Avatar	Allows users to share their data in the system without revealing their name (Klock et al., 2020).
App mechanism	
Customization	In contrast to personalization—which involves adjusting automatically the system to the user—customization refers to the user's ability to modify the content or functionalities of the mobile application according to their own preferences (R. Orji, Mandryk, et al., 2017). This approach enables users to actively tailor the system based on users' choices.

5.3.2 Preferences relations between big-five traits and mechanisms

The preference relations between the mechanisms and the big-five traits found in the literature enable us to build a preference matrix summarized in Tables 4.3, each cell of the matrix indicating the number of articles of the review containing a preference relation. Most of the preference relations were positive (71%, 53/75), indicating a preference for a specific mechanism within a given profile (represented by a plus sign). Negative relations indicate an aversion for a mechanism (represented by a minus sign in Tables 5.3) and represent 12% (9/75) of potential relations. It is worth noted that the relation matrix is not yet complete, as 73% (55/75) of potential relations were found in the literature review performed.

This study aims to corroborate or enrich this preference matrix with new preference relations the preference matrix displaying relations between mechanisms and personality traits by experimentally.

Table 5.3. Relation between big five traits and mechanisms

			BCT mechanisms						Game elements								App mechanism
			Prompts and cues	Demonstration of the bahavior	Self monitoring	Punishment	Social comparaison	Social support	progression	Competition	Cooperation	Collection	rewards	Quest	Challenge	avatar	customisation
Personality profile	**Big Five**	Openess to experience			++	+	+	++		+++ -	+ -	++	++ -				++ +
		Agreeableness	+	+	+++	++	++ -	+++	++	+++ -	+++	++	+++ +		++		+++
		Conscientiousness		+	+ -				+	++	- -		++	+	+		-
		Extraversion	+	+	++	+	+++	++	+++ +	+++	++	+	+++ ++	+	++	+	+++ -
		Neuroticism			+		+	+	+	+ -	+	++	+++ +				+

+ 1 article with a preference relation - 1 article with non-preference relation

5.4 Methods

This section comes from our previous published protocol article (Gosetto et al., 2023).

5.4.1 Ethics Approval

The University Ethics Commission has approved this study for ethical research at the University of Geneva (CUREG_2021-04-38).

5.4.2 Study Design

We performed a cross-sectional study to address our aims. Participants responded to an online questionnaire in accordance with the Checklist for Reporting Results of Internet E-Surveys (Eysenbach, 2004).

5.4.2.1 Outcomes

The primary outcome is the preferred mechanisms given the user profile.

5.4.2.2 Study Population

The target population for this study are individuals aged 18 and above who understands French. The recruitment process was conducted via social media platforms, specifically Facebook and Twitter, targeting students at the University of Geneva.

5.4.2.3 Sample Size calculation

We calculated the required sample size using a multiple regression power analysis in R. The parameters used were the number of predictors u=3, effect size f2=0.07, significance level α=0.05, power = 0.9, and estimated variance = 202.403. These estimates were based on the hypothesis that individuals with higher levels of altruism, as measured by the Big Five personality traits, show a preference for social networks (Hallifax et al., 2019; Klock et al., 2020).

To approximate the variance, we referred to a prior study (Gosetto, 2018) that assessed Big Five personality traits in relation to user preferences for social network posters. Specifically, we used the variance in Big Five trait ratings for altruistic participants (n = 46) based on their average scores for a poster promoting blood donation, which had a scoring range of 0–100. Using these parameters, we determined that a sample size of 206 would be sufficient for this study.

5.4.2.4 Procedure

The participants were requested to complete an online questionnaire, which was developed by the investigators using the Qualtrics software (Qualtrics, Provo, UT) (see Appendix 1). First, participants were required to complete a consent form that detailed the purpose of the study, the procedure to be followed, and their right to withdraw from the study at any time. It was compulsory for the participants to confirm that they had read and understood the form and agreed to its terms before to gain access to the questionnaire and for the investigators to utilize the data provided by the participants for the purposes of this study. Subsequently, participants were requested to respond to questions pertaining to their demographic characteristics. In order to access the rest of the survey, participants were required to confirm that they were over the age of 18. Eligible participants proceeded to complete the online questionnaire, which required them to (1) respond to a scale for measuring their personality profile and (2) examine the 15 mechanisms, select their five favorites, and indicate their likelihood of being motivated by a mechanism to get fit on a scale from 0 to 100.

5.4.3 Measures and Measurement

5.4.3.1 Demographic questions

The participants were requested to provide information regarding their gender, age, occupation, and level of education.

5.4.4 Profile Assessment

To assess the personality of the participants, we relied on the French version of the Big Five Inventory-10 scale (BFI-10-Fr), which was translated from English and validated by Courtois (Courtois et al., 2020). The internal reliability of the BFI-10 is low, as indicated by Cronbach's alpha coefficients ranging from 0.37 to 0.83. This is due to the fact that Cronbach's alpha is not an appropriate method for evaluating scales with a limited number of items (Courtois et al., 2020). The scale comprises 10 items, with two items pertaining to each of the five Big Five dimensions. Participants were requested to indicate on a 5-point Likert scale whether they approve or disapprove the statements pertaining to themselves. For example, the subject may indicate that they see themselves as reserved or as someone who is easily anxious. Subsequently, the score for each dimension is calculated by adding the scores for the two statements concerning the dimension, with the items reversed.

This scale was selected due to its factorial structure, which is identical to that of the complete version of the BFI-Fr (Courtois et al., 2020). Consequently, this approach offers the advantage of effectively measuring personality with a limited number of items. Given the number of scales included in our protocol, it was deemed preferable to select the shortest valid versions in order to avoid participant fatigue resulting from a questionnaire that was too lengthy.

5.4.5 Choice of mechanisms

Presentation and selection of the five favorites mechanisms

A mockup of each 15 mechanisms (see Appendix 2) was create. A comprehensive presentation of all mechanisms and their definitions can be found in the Appendix. In order to limit the potential bias due to design preferences, the visual design of the mockups was intentionally minimalistic. It relied only on a black and white color scheme with icons, in order to ensure neutrality and clarity. (Figure 6). To avoid any primacy or recency effects, the

15 mockups were randomly presented to the participants. During the study, participants were required to select the five mechanisms they considered the most motivating based on its mockup accompanied by a brief textual description.

5.4.6 Explanation of choice

For each of the 5 selected mechanisms, participants were requested to indicate the extent to which that mechanism would motivate them to engage in healthier behaviors on a scale of 0 to 100. Subsequently, participants were required to provide a free-form textual justification for their selection of the mechanisms. If a mechanism was excluded from the initial selection, it was assigned a score of zero.

5.4.7 Analysis

Preference matrix validation

In order to perform a comparative analysis of the experimental results and the initial preference matrix, the collected data were also organized into a matrix. The values of the initial matrix (M1) represent the number of preference relations observed in the literature following the scoping review that we conducted previously (Gosetto et al., 2025b). We modified this matrix by assigning a value of -1 to indicate an aversion relation. A value of 0 indicates that preferences and aversions were observed in the scoping review, and a null value is assigned when no relations were identified. The second matrix (M2) contains the data collected in this study. The value of the cell represents the score of the participants with the Big Five dimension for the mechanism on the line. In each cell, we calculated a mechanism discriminative score by summing the participants' scores, divided by the total number of participants.

$$C_{m,b} = round(\frac{\sum_{p=1}^{n} 1_{p,m} \cdot S_{p,b}}{\sum_{p=1}^{n} 1_{p,m}} - \frac{\sum_{p=1}^{n} 0_{p,m} \cdot S_{p,b}}{\sum_{p=1}^{n} 0_{p,m}})$$

$C_{m,b}$ represents the value in the cell corresponding to mechanism m (row) and the bigFive b (column).

$1_{p,m\_}$ is an indicator function equal to 1 if participant p has selected mechanism m, and 0 otherwise.

$0_{p,m\_}$ is an indicator function equal to 0 if participant p has selected mechanism m, and 1 otherwise.

$S_{p,b}$ is the score of participant p on the big five b dimension (1-5).

n is the total number of individuals.

A third matrix (M3) represents a comparison between the two matrices (M1, M2).

Statistical analysis

A logistic regression analysis was conducted to examine the relationship between the mechanisms and the personality profile scales. The objective of this analysis was to analyze if the participants' scores on the BFI-10-Fr significantly influences the choice of a mechanism. A logistic regression analysis was conducted for each mechanism to ascertain whether the BFI-10-Fr scores were predictive of the mechanism selection.

Furthermore, a logistic ordinal regression was conducted with the motivation scores of the selected mechanisms as the dependent variables and the BFI-10-Fr scores as the predictors. The regression was performed for each mechanism motivation score, with the objective of determining whether the scores on the scales predict the mechanism score.

To prevent a type I error, the Bonferroni correction was employed for all regression analyses.

5.5 Results

5.5.1 Demographics data

A total of 214 individuals responded to the questionnaire, comprising 118 women, 89 men, 5 individuals identified as other, and 2 individuals who did not provide a response. The mean age was 29.42 years (SD = 10.41). Further details can be found in Table 5.4.

Table 5.4 Demographics data

	N	**Mean**	**Standard deviation**
Age	214	29.42	10.41
	N	**%**	
Gender	214		
Women	89	41.6	
Men	118	55.1	
Others	7	3.3	
Education Level	211		
Mandatory education	53	24.8	
Bachelor’s degree	63	29.4	
Master’s degree	80	37.4	
Doctorate	15	7	
Smartphone use	214		
Not confortable	10	4.7	
Confortable	204	95.3	
Already used mHealth	135	63.1	

5.5.2 Characteristics of the participants on the big-five

The scores for the Big Five dimensions are recorded on a scale of 1 to 5. The distribution of the population on the Big Five is shown in Figure 5 (the line represents the median and the cross represents the mean).

The participants of this study are mainly altruistic (M=3.71, SD= 1.31), extravert (M=2.86, SD=1.17) and neurotic (M=3.12, SD= 1.23).

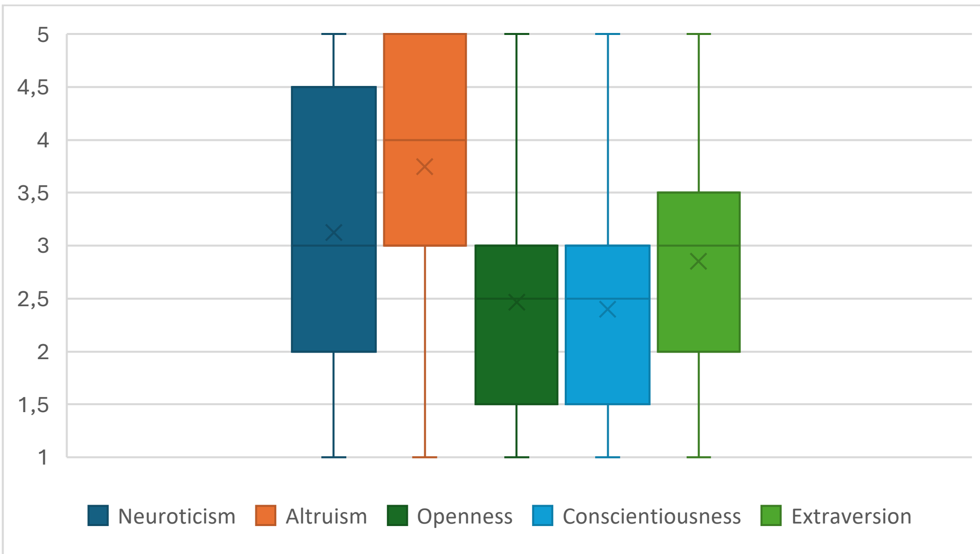

Figure 5. Boxplot of the representativeness of the participants on the big-five (N=214)

5.5.3 Characteristics of the participants on the selection for each mechanism

A total of four mechanisms were selected by more than half of the participants. These mechanisms included self-monitoring, progression, challenge, and quest (Table 5.5).

Table 5.5. Number of people who selected the mechanism (N=214)

Mechanisms	Number of people who selected the mechanism (percentage)	Mean Neuroticism (SD)	Mean Altruism (SD)	Mean Openness (SD)	Mean Consciousness (SD)	Mean Extraversion (SD)
Self-monitoring	149 (69.6%)	3.1 (1.2)	3.8 (1.3)	2.5 (1.0)	2.3 (1.0)	2.9 (1.1)
Progression	127 (59.3%)	3.1 (1.2)	3.7 (1.3)	2.6 (1.0)	2.3 (0.9)	2.9 (1.2)
Challenge	112 (52.3%)	3.2 (1.6)	3.7 (1.4)	2.4 (1.0)	2.4 (1.0)	2.9 (1.2)
Quests	111(51.9%)	3.0 (1.2)	3.8 (1.3)	2.6 (1.0)	2.3 (0.9)	2.9 (1.2)
Cooperation	70 (32.7%)	3.1 (1.2)	3.8 (1.3)	2.3 (1.0)	2.3 (0.9)	3.0 (1.3)
Demonstration of the behavior	61 (28.5%)	3.2 (1.2)	3.6 (1.3)	2.3 (0.9)	2.3 (1.0)	2.7 (1.2)
Prompt and cues	53 (24.8%)	3.3 (1.3)	3.6 (1.3)	2.6 (1.1)	2.4 (0.9)	2.8 (1.2)
Rewards	47 (22%)	3.4 (1.4)	3.6 (1.3)	2.5 (1.0)	2.8 (1.0)	2.8 (1.3)
Social comparison	44 (20.6%)	3.2 (1.2)	3.7 (1.3)	2.7 (1.0)	2.6 (0.9)	2.8 (0.9)
Collectible	41 (19.2%)	2.9 (1.3)	3.5 (1.6)	2.5 (1.0)	2.7 (1.0)	3.0 (1.2)
Avatar	29 (13.6%)	3.2 (1.3)	3.8 (1.5)	2.6 (0.9)	2.5 (0.8)	3 (1.3)
Competition	29 (13.6%)	2.8 (1.3)	3.9 (1.4)	2.4 (0.9)	2.8 (1.1)	2.7 (1.2)
Social support	20 (9.3%)	2.9 (1.2)	4.0 (1.0)	2.5 (1.0)	2.4 (1.1)	2.9 (1.1)
Punition	8 (3.7%)	3.3 (1.5)	3.5 (1.3)	2.2 (0.7)	2.3 (1.0)	3.1 (1.2)

Comparison between this study results and the preference matrix

The initial matrix (M1) presents 60% (42/70) of positive relation, 1% (1/70) of aversion relation, 10% (7/70) of no preference relations (preference and aversion were observed) and 29% (20/70) of missing relations (see M1 on Table 5.6).

The matrix of the selection mechanisms by participant (M2) presents 5% (4/70) of very high mechanism discriminative score (<4), 3% (2/70) of high selection mechanism (3), 17% (12/70) of medium selection mechanism (2), 74% (52/70) of low selection mechanisms (0-1) (see M2 on Table 5.6).

The matrix M3 shows the difference between M1 and M2. The higher the value, the greater the difference between the 2 matrices. We observe 27% (19/70) similar value in the 2 matrices (no differences), 38% (27/70) minimal difference of one, 24% (17/70) moderate difference of two, and 9% (7/70) significant difference of three and more (see M3 on Table 5.6).

Table 5.6 Matrices for the representation of preference relations on literature (M1), of the selection mechanisms by participants based on their Big-Five traits score (M2), and the difference between M1 and M2 (M3).

	M1 : preference relations on literature				
	Big-five traits				
Mechanisms	Neuroticim	Altruism	Openness	Conscientiousness	Extraversion
Prompts and cues	null	1	null	null	1
Demonstration of the Behavior	null	1	null	1	1
Self monitoring	2	3	2	0	2
Punishment	null	2	1	null	1
Social comparaison	1	0	1	null	3
Social support	1	3	2	null	2
Progression	1	2	null	1	4
Competition	0	0	0	2	3
Cooperation	1	3	0	-1	2
Collection	2	2	2	null	1
Rewards	4	4	0	2	5
Quest	null	null	null	1	1
Challenge	null	2	null	1	2
Avatar	null	null	null	null	1

5, 4, 3, 2, 1= preference relation on respectively 5 articles, 4 articles, 3 articles, 2 articles, 1 article, -1= aversion relation, 0= no preference relations (preference and aversion observed), null= no relation

	M2 : selection mechanisms by participant, based on their Big Five traits score				
	Big five traits				
Mechanisms	Neuroticim	Altruism	Openness	Conscientiousness	Extraversion
Prompts and cues	2	0	1	0	0
Demonstration of the Behavior	1	0	0	0	0
Self monitoring	0	2	2	0	0
Punishment	2	0	0	0	3
Social comparaison	1	0	2	2	0
Social support	0	3	1	0	1
Progression	0	1	1	0	0
Competition	0	2	0	5	0
Cooperation	0	1	0	0	2
Collection	0	0	0	4	1
Rewards	4	0	0	4	0
Quest	0	1	2	0	0
Challenge	2	0	0	0	1
Avatar	1	1	2	2	1

0 - 1= minimal selections of mechanism, 2= moderate selections of mechanism, 3= high selection of mechanism, 4+= very high selection of mechanism

	M3: Difference between M1 and M2				
	Big five traits				
Mechanisms	Neuroticim	Altruism	Openness	Conscientiousness	Extraversion
Prompts and cues	-2	1	-1	0	1
Demonstration of the Behavior	-1	1	0	1	1
Self monitoring	1	1	0	0	2
Punishment	-2	2	1	0	-2
Social comparaison	0	0	-1	-2	3
Social support	1	0	1	0	1
Progression	1	1	-1	1	4
Competition	0	-2	0	-3	3
Cooperation	1	2	0	-1	0
Collection	2	2	2	-4	0
Rewards	0	4	0	-2	5
Quest	0	-1	-2	1	1
Challenge	-2	2	0	1	1
Avatar	-1	-1	-2	-2	0

values represent diffence between M1 and M2

represent null relation in M1

5.5.4 Preferred mechanisms and big-five, statistical analysis

A logistic regression analysis was conducted for each mechanism to ascertain whether the scores on the scale were predictive of the mechanism selection. Furthermore, a logistic ordinal regression was conducted with the motivation scores of the selected mechanisms as the dependent variables and the BFI-10-Fr scores as the predictors. The logistic regression containing all predictors was statistically significant for three mechanisms.

5.5.4.1 Collection Mechanism

The logistic regression, conducted for each mechanism to ascertain whether the scores on the big-five scale, were predictive of the mechanism selection collection, was statistically significant, χ^2(5, N=207)= 13.07, p <.05, indicating that the regression was able to distinguish between respondents who selected and did not select the collection mechanism. The regression as a whole explained between .06% (Cox and Snell R square) and 10% (Nagelkerke R squared) of the variance in the selection of the mechanism collection, and correctly classified 83.1% of cases. As shows in Table 5.7, only one of the independent variables made a unique statistically significant contribution to the model, conscientiousness with an odds ratio of 1.87. This indicated that respondents who had a high level of conscientiousness were over 1.87 times more likely to select the mechanism collection than those who have a small level of conscientiousness, controlling for all other factors in the model.

Table 5.7 Logistic Regression Predicting Likelihood of selecting the mechanism Collection

	B	**S.E**	**Wald**	**Df**	**p**	**Odds Ratio**	**95,0% C.I for Odds Ratio**	
Openness	-.019	.193	.010	1	.920	.981	.672	1.432
Conscientiousness	.625	.198	9.987	1	**<.01**	1.868	1.268	2.752
Extraversion	.035	.168	.043	1	.836	1.035	.745	1.439
Altruism	-.165	.146	1.279	1	.258	.848	.637	1.129
Neuroticism	-.191	.163	1.376	1	.241	.826	.600	1.137
Constant	-2.089	1.093	3.654	1	.056	.124		

5.5.4.2 Competition Mechanism

The logistic regression was statistically significant, χ^2(5, N=200) = 31.49, p <.01, indicating that the model was able to distinguish between respondents who selected and did not select the mechanism competition. The regression explained between 15% (Cox and Snell R square) and 33% (Nagelkerke R squared) of the variance in the selection of the mechanism collection, and correctly classified 91.5% of cases. As shows in Table 5.8, four of the independent variables made a unique statistically significant contribution to the regression (neuroticism, conscientiousness, extraversion, and altruism). The strongest predictors of selecting the mechanism competition were conscientiousness with an odds ratio of 3.22 and altruism with an odds ratio of 1.93. The odds ratio of .43 for neuroticism and of .52 for extraversion, indicating that the respondents with a high level of neuroticism were over .42 times less likely to select this mechanism.

Table 5.8 Logistic Regression Predicting Likelihood of selecting the mechanism Collection

	B	S.E	Wald	df	p	Odds Ratio	95,0% C.I for Odds Ratio	
Openness	-.195	.286	.466	1	.495	.823	.469	1.441
conscientiousness	1.169	.318	13.532	1	**<.01**	3.220	1.727	6.003
Extraversion	-.660	.280	5.574	1	**<.05**	.517	.299	.894
Altruism	.660	.296	4.969	1	**<.05**	1.934	1.083	3.454
Neuroticism	-.854	.279	9.364	1	**<.01**	.426	.246	.736
Constant	-3.680	1.798	4.187	1	<.05	.025		

The logistic ordinal regression conducted for each mechanism to ascertain whether the scores on the big-five scale were predictive of the motivation score for competition mechanism was statistically significant, χ^2(5, N=214)= 11.16, p =.05, indicating that the model was able to distinguish between participants' scores for motivation to get fit using the competition mechanism. The model explained between 5% (Cox and Snell R square) and 8% (Nagelkerke R squared) of the variance in the selection of the mechanism competition. As shown in Table 5.9, two of the independent variables made a unique statistically significant contribution to the regression (neuroticism, and conscientiousness). The strongest predictor of selecting the mechanism competition was conscientiousness with an odds ratio of 1.63 and neuroticism with an odds ratio of 0.71.

Table 5.9 Logistic Regression Predicting Likelihood of score of the mechanism Competition

	B	S.E	Wald	df	p	Odds Ratio	95,0% C.I for Odds Ratio	
Openness	-.072	.207	.121	1	.728	.931	-.478	.553
conscientiousness	.487	.206	5.586	1	**.018**	1.628	.083	.892
Extraversion	-.272	.191	2.028	1	.154	.762	-.647	.102
Altruism	.206	.177	1.357	1	.244	1.229	-.141	.553
Neuroticism	-.345	.179	3.705	1	**.054**	.708	-.696	.006

5.5.4.3 Rewards Mechanism

The logistic regression was statistically significant, χ^2(5, N=204)= 35.29, p <.001, indicating that the model was able to distinguish between respondents who selected and did not select the mechanism rewards. The regression explained between 16% (Cox and Snell R square) and 27% (Nagelkerke R squared) of the variance in the selection of the mechanism rewards, and correctly classified 81.4% of cases. As shown in Table 5.10, two of the independent variables made a unique statistically significant contribution to the model (neuroticism, and conscientiousness). The strongest predictors of scoring the mechanism competition were conscientiousness with an odds ratio of 2.36 and neuroticism with an odds ratio of 1.97. The odds ratio indicating that the respondents with a high level of neuroticism were over 1.97 times more likely to select this mechanism and respondents with high level of conscientiousness were over 2.36 times more likely to select this mechanism.

Table 5.10. Logistic Regression Predicting Likelihood of selecting the mechanism rewards

	B	S.E	Wald	df	p	Odds Ratio	95,0% C.I for Odds Ratio	
Openness	.060	.194	.095	1	.758	1.061	.726	1.551
conscientiousness	.858	.220	15.262	1	**<.01**	2.360	1.534	3.630
Extraversion	-.220	.187	1.392	1	.238	.802	.557	1.157
Altruism	.068	.161	.177	1	.674	1.070	.781	1.466
Neuroticism	.679	.190	12.696	1	**<.01**	1.971	1.357	2.864
Constant	-5.919	1.327	19.897	1	<.01	.003		

The logistic ordinal regression was statistically significant, χ^2(5, N=214)= 14.36, p =.01, indicating that the model was able to distinguish between participants' scores for motivation to get fit using the reward mechanism. The regression explains between 6% (Cox and Snell R square) and 9% (Nagelkerke R squared) of the variance in the selection of the mechanism rewards. As shows in Table 5.11, two of the independent variables made a unique statistically significant contribution to the regression (neuroticism, and conscientiousness). The strongest predictors of scoring the mechanism rewards was conscientiousness with an odds ratio of 1.66 and neuroticism with an odds ratio of 1.38.

Table 5.11 Logistic Regression Predicting Likelihood of the score the mechanism rewards

	B	S.E	Wald	df	p	Odds Ratio	95,0% C.I for Odds Ratio	
Openness	.025	.170	.023	1	.881	1.026	-.307	.358
conscientiousness	.504	.176	8.199	1	**<.01**	1.66	.159	.849
Extraversion	-.031	.156	.040	1	.842	.969	-.336	.274
Altruism	-.083	.132	.389	1	.533	.921	-.342	.177
Neuroticism	.320	.149	4.606	1	**<.05**	1.378	.028	.61

5.6 Discussion

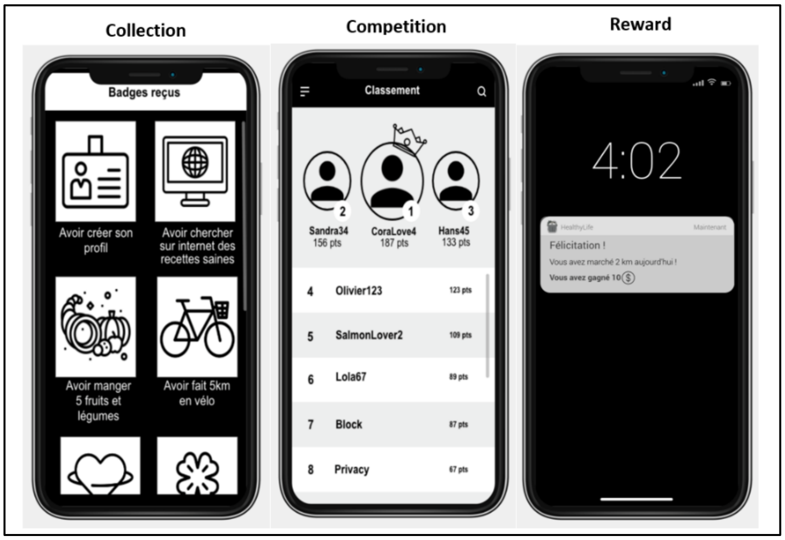

Figure 6. Preferred mechanisms according to personality profiles

The objective of this study was to validate the preference matrix obtained through a previous literature review by observing if we obtain similar relations within this study.

It was observed that four mechanisms were selected by more than half of the participants: self-monitoring (N=149), progression (N=127), challenge (N=112), and quest (N=111). No significant relationship was identified between these mechanisms and the Big Five dimensions. It can thus be inferred that these four mechanisms are appreciated by any type of participants and should be included in each mHealth application independantly of the profile of its users.

5.6.1 Comparison between M1 and M2

The comparison between matrices M1 and M2 reveals several noteworthy developments in the identification of potential relationships between mechanisms and Big Five personality traits. In M2, new possible associations emerge that were not identified in M1, particularly between neuroticism and mechanisms such as prompts and cues, demonstration of behavior, punishment, quest, challenge, and avatar. Similarly, openness is newly associated with prompts and cues, progression, quest, and challenge, while conscientiousness shows novel relations with social comparison and avatar, and a notably strong association with collection in M2. These findings suggest an evolving understanding of how specific personality traits may align with certain mechanisms.

Furthermore, while M1 lacked a clear consensus regarding the relationships between mechanisms and traits such as altruism and openness, M2 suggests emerging relations, particularly between altruism and competition, and between openness and rewards.

Conversely, several relationships identified in M1 do not reappear in M2. For example, extraversion was previously associated with a wide range of mechanisms in M1, including prompts and cues, demonstration of behavior, self-monitoring, punishment, social comparison, social support, progression, competition, cooperation, collection, rewards, and quest, but these associations are not observed in M2. A similar decline in associations is seen for altruism, which in M1 was linked with prompts and cues, demonstration of behavior, punishment, collection, challenge, and especially rewards. However, significant results were only found for the mechanisms collection, competition, and rewards. Three of the five significant relationships found in this study were present in the preference matrix M1, conscientiousness with competition, conscientiousness with reward and neuroticism with rewards.

Two have not a consensus on the preference matrix M1 with articles observed preference and non-preference relations between neuroticism with competition, and altruism with competition.

This study permits to enrich the preference matrix with the addition of one new significative relation between conscientiousness with collection. And to confirm when literature observe incongruent data, we clarify with our results a preference relation for neuroticism with competition, and altruism with competition.

Below we explore in more detail the three mechanisms that yielded significant regressions. Figure 6 depicts the three mechanisms, which were presented to participants in the questionnaire with a brief description.

5.6.2 Collection

In our context, the term "collection" refers to a set of items or badges that are accumulated over time. The act of collecting as a mechanism that can serve as a motivational tool for stay fit (Werbach et al., 2012). In our study conscientious participants selected 1.87 times collection than those who have a small level of conscientiousness.

These findings are corroborated by the existing literature. In the preference matrix M1, the collection mechanism was preferred by all big-five traits (Codish & Ravid, 2014; Jia et al., 2016; Klock et al., 2020; Tondello et al., 2017; Tondello & Nacke, 2020).

5.6.3 Competition

The competition mechanism can be defined as the fact that users are able to engage in a competitive process with one another in order to perform the desired behavior (R. Orji, Mandryk, et al., 2017).

This mechanism is related to all Big Five traits in the preference matrix M1. But in this study, individuals exhibiting conscientious (OR= 3.22) and altruistic tendencies (OR=1.93) were more likely to identify this mechanism as a motivating factor in maintaining their health than participant who have a small level of these dimensions. In contrast, extroverts (OR=.42) and individuals with neurotic tendencies (OR=.52) exhibited a reduced propensity to select this mechanism. Furthermore, respondents exhibiting high levels of conscientiousness (OR=1.63) assigned higher ratings to this mechanism, whereas those with neurotic personalities (OR=0.71) assigned lower ratings.

These differences can be explained by a controversial preference for this mechanism. Some participants said they preferred individual mechanisms that didn't involve other users, they involved personal, individual efforts to motivate to stay fit. The results is in line with previous research that found similar reasons against competition with their participants (R. Orji, Nacke, et al., 2017).

[P14] "No comparison with others because it stresses me out if I don't win. I'm more motivated by the idea of doing myself good".

[P39] "I choose for myself, not for others, so there's no competition or comparison with others."

[P129] "I've excluded those that involve other people because I prefer autonomy."

[P134] "I no longer have anything to prove to anyone but myself".

[P112] "The individuality aspect. In my opinion, when you do something, you do it for yourself and not for others".

[P140] "I think the principle of fitness should be personal and not a competition with others."

While other participants said they found competition more motivating:

[P44] "I find competition very enjoyable, it pushes me to excel."

[P176] "Comparing myself to others pushes me to do better."

[P192] "I'm very competitive and I like it when people show me that I've made progress. It encourages me to keep going. »

The preference matrix (M1) further indicates that altruistic and conscientious individuals tend to prefer competition . However, it also demonstrates a relation of preference with the profiles of extraversion and neuroticism (Anagnostopoulou et al., 2017a; Klock et al., 2020; Ndulue et al., 2022; R. Orji, Nacke, & Di Marco, 2017), whereas our study results indicate that extraverted and neurotic individuals select this mechanism with lower frequency. However, preference matrix (M1) also indicates a non-preferred relation for individuals with neuroticism profiles. The results of our experiment provide further corroboration of this relation.

5.6.4 Rewards

The reward mechanism entails the provision of virtual incentives to users for the completion of the desired action (R. Orji, Mandryk, et al., 2017). It differs from the concept of collection in that the rewards are not necessarily part of a set of collectible items.

Individuals with high levels of neuroticism (OR=1.97) and conscientiousness (OR=2.36) demonstrated a greater propensity to select the rewards mechanism. Additionally, they assigned a higher motivation score to this mechanism ($OR_{Conscientiousness}$=1.66; $OR_{Neuroticism}$=1.38).

Preference matrix (M1) reveals a preference relation between these two profiles and the rewards (Alqahtani et al., 2022; Anagnostopoulou et al., 2017a; Codish & Ravid, 2014; Klock et al., 2020; Ndulue et al., 2022; R. Orji, 2014).

5.6.5 Big five dimensions

It is noteworthy that the conscientiousness trait is a significant predictor of all three mechanisms.

No significant results were obtained regarding openness of participants, despite the existing literature indicating a preference for specific mechanisms like collection and competition.

No significant preference results were obtained with the extraversion traits. Our preference matrix, however, does exhibit relations for all mechanisms. A summary of results and preference matrix is presented on table 5.12.

Table 5.12. Mechanisms preferred and non-preferred per big-five dimension (in bold congruent finding between our test and the literature, in italic incongruent).

Big-five dimension	Mechanisms prefered on this study	Mechanisms non-preferred on this study	Mechanisms prefered on prefererence matrix (M1)	Mechanisms non-preferred on preference matrix (M1)
Openess to experience	-	-	Self-monitoring, punishment, social comparison, social support, **competition**, cooperation, **collection**, **rewards**, customization.	Rewards, *competition*, cooperation
Agreeableness	***Competition***	-	Prompts and cues, demonstration of the behavior, self-monitoring, punishment, social comparison, social support, progression, **competition**, cooperation, collection, rewards, challenge, customization.	Social comparison, *competition*
Conscientiousness	**Collection** ; **Competition** ; **Rewards**	-	Demonstration of the behavior, self-monitoring, progression, **competition**, **collection**, **rewards**, quest, challenge.	Self-monitoring, cooperation, customization
Extraversion	-	*Competition*	Prompts and cues, demonstration of the behavior, self-monitoring, punishment, social comparison, social support, progression, *competition*, cooperation, collection, rewards, quest, challenge, avatar, customization.	customisation
Neuroticism	**Rewards**	***Competition***	Self-monitoring, social comparison, social support, progression, *competition*, cooperation, collection, **rewards**, customization.	**competition**

5.6.6 Applying the Preference Matrix in Practice

Implementing the preference matrix involves two main steps: identifying the user profile and tailoring the app content accordingly. While user profiling often relies on validated questionnaires (e.g., BFI-10, NEO-PI-R), these can be time-consuming and may deter users. As a more practical alternative, automatic profiling based on smartphone (Chittaranjan et al., 2011; Staiano et al., 2012) or social media data (Azucar et al., 2018; Bai et al., 2012; Souri et al., 2018) has shown promise, though privacy concerns remain a significant barrier. To address this, we recommend making personalization optional, offering users the choice to complete a brief, validated personality questionnaire if they opt in.

Once the profile is established, app content can be adapted by selecting mechanisms aligned with the user's dominant traits, as outlined in the preference matrix. Personalization can be based on various models, and may occur during or after account creation, depending on user preference.

5.6.7 Limitations

The fact that participants had to select five mechanisms out of fifteen was a limitation. Some participants may have selected mechanisms they didn't find motivating because they had to select five. Others, on the contrary, might have selected more.

Our population is not representative of the general population, due to its high inclusion of university students, a demographic that is typically considered to be relatively young (M_{age}=29.42, SD_{age}=10.41).

We also observe that, despite our sample size calculation, it appears that it did not allow for proper discrimination, as we obtained significant results for only 3 out of 14 mechanisms. Therefore, this calculation should be reconsidered.

It was not feasible to assess the customization mechanism, given its expansive scope and the consequent challenges in representing it in the format of a conventional mockup screen.

5.7 Conclusion

The entire preference matrix could not be validated experimentally. Significant relations were identified for three mechanisms: collection, competition, and rewards. The preference relations are corroborated by the preference matrix M1, apart from preference relation for collection mechanism and conscientiousness and the non-preference relation for competition regarding the extraversion trait, which is significant in this study but, according to the preference matrix M1, is a preference relation. The neuroticism trait is significant for competition as non-preferred, yet the preference matrix studies demonstrated a preference and non-preference relation for this trait. Considering these findings, it can be concluded that a non-preference relation is corroborated. It would be interesting to replicate this study with a larger, less student-dominated panel to get better representation and more significant results on mechanism preference relations by Big Five traits.

Data availability

The data sets generated during the current study are available from the corresponding author on reasonable request.

Acknowledgment

None declared.

Authors' contributions

LG conceived the study with the involvement and advice of FE and GF. MP is involved with statistics. All authors were involved in writing, reading, and approving the final manuscript.

Conflicts of interest

None declared.

Appendix

Appendix: Print version of the online questionnaire

Chapter 6

6. Article V: Model to Personalize Mobiles Applications according to the gamification user types for Health Behavioral Change

Chapter content

6.1 Abstract

Background
Adopting healthy habits improves longevity and well-being. Mobile health (mHealth) apps support such behaviors, with over 35,000 available as of 2018. Personalization and gamification are recognized as effective strategies to enhance user engagement and behavioral outcomes in mobile health (mHealth) applications.

Objectives
This cross-sectional study explores links between user typologies (Hexad scale) and preferences for 15 game and behavior change mechanisms.

Methods
A preference matrix, derived from the literature, was tested on data from 214 respondents (Mage = 29.42; 118 women, 89 men, 5 other). Demographics and Hexad-based user typologies were recorded. Participants selected their top five mechanisms from 15 randomized mockups with brief descriptions. Logistic and ordinal logistic regressions, with Bonferroni correction, were used to assess associations

Results
Significant associations were observed for five mechanisms. Philanthropists were less likely to prefer collection (OR = 0.77, $p < .01$), whereas players favored it (OR = 1.11, $p < .05$) and showed strong preferences for rewards (OR = 1.39, $p < .01$) and, to a lesser extent, self-monitoring (OR = 0.88, $p < .05$). Socializers preferred cooperation (OR = 1.14, $p < .01$) but were less inclined toward demonstration of behavior (OR = 0.92, $p < .05$). Free spirits favored demonstration of behavior (OR = 1.25, $p < .01$), while achievers were less likely to prefer it (OR = 0.86, $p < .05$). Four mechanisms, self-monitoring, progression, challenge, and quest were selected by over 50% of participants.

Conclusion
This study validated the preference matrix, highlighting four mechanisms - self-monitoring, progression, challenge, and quest - as broadly appealing across user profiles for mHealth design. Three novel profile–mechanism associations were identified, refining the model and underscoring the need for replication with a more diverse sample.

Keywords: mHealth, Behavior Change Technique, Personalization, Gamification, Hexad scale

6.2 Introduction

Embracing healthy lifestyle habits has been shown to extend life expectancy. In particular, following a balanced diet, maintaining a healthy weight, quitting smoking, moderating alcohol intake, and engaging in regular physical activity are linked to lower mortality rates. Researchers have found that each of these behaviors individually contributes to improved quality of life and increased longevity (Li et al., 2020; Wingard et al., 1982).

The number of health apps aimed at supporting individuals in adopting healthier habits has been growing every year, with new apps regularly entering the market. By 2018, over 35,000 health apps were available for download (*Health-Tech-Mobile-Apps-Analytical-Report.Pdf*, n.d.). Smartphone apps have opened new pathways for individuals to engage in health-focused behaviors, providing instant access to health information, medication reminders, and progress-tracking tools that collectively promote healthier lifestyles (Ernsting et al., 2017).

Various tools have been created to evaluate the quality of mobile health applications, such as the Mobile App Rating Scale (MARS) (Stoyanov et al., 2015) and the App Behavior Change Scale (Mckay et al., n.d.). A common criterion across these evaluation frameworks is the emphasis on personalization. This aspect is considered essential, especially in the context of designing apps aimed at promoting behavioral change. This aspect is considered essential, especially in the context of designing apps aimed at promoting behavioral change. For instance, one study has demonstrated that health messages customized using individual-specific factors (e.g., age, beliefs, health status) were significantly more effective than non-tailored messages in attracting attention, facilitating cognitive processing, and enhancing memory retention. Such personalized content was also perceived as more personally relevant, which increased the likelihood of interpersonal discussion and incorporation into health-related decisions (Skinner et al., 1999).

An other strategy used to encourage behavioral change is the inclusion of gamification (Hamari et al., 2014), defined as "the application of game design elements in non-game contexts" (Klock et al., 2020). Notably, Lister et al. found that 52% of reviewed health apps included at least one gamification feature (Lipnevich et al., 2021). Gamification can be effective for a variety of healthcare issues, such as medication adherence (Tran et al., 2022), behavior change for diabetics patients (Cechetti et al., 2019), self-efficacy, nursing education (Mehraeen et al., 2025) and motivation to quit smoking (Rajani et al., 2021). Indeed, gamification has a positive impact on time spent on the app (Xu et al., 2022), on behavior, user experience and a positive influence on health and wellbeing (Johnson et al., 2016). Therefore a review by Klock et al addressed the issue of personalization, but in the context of user experience and user interface design with gamification (Klock et al., 2020).

Linking personality to game mechanics

Personalization refers to the adaptation of mechanisms to the user's profile, whereas customization allows the user to actively choose the mechanisms they prefer. A common strategy for personalization is to use player or user typologies to identify individual preferences (Gosetto et al., 2025b) A previous study reviewed the literature to identify associations between user typologies and specific mechanisms that can be integrated into mHealth applications. Based on these insights, a preference matrix was developed, mapping preferred mechanisms to user profiles. This matrix serves as a tool to support the personalization of mobile health apps aimed at promoting behavior change. By aligning app features with user characteristics, developers can enhance engagement and effectiveness. For example, for users identified as socialiser based on the Hexad scale model, it would be beneficial to emphasize features that encourage cooperation (Altmeyer et al., 2019).The preference matrix includes 15 mechanisms linked to players personality profile, which are presented in detail in Table 2. Regarding the user typologies, we utilized one of the most prevalent classification systems for individuals, namely the Hexad Scale (Alqahtani et al., 2022b; Altmeyer et al., 2019; Hallifax et al., 2019; Klock et al., 2020; Mora et al., 2019; R. Orji et al., 2018; Tondello et al., 2016a, 2017; Tondello & Nacke, 2020).

Gamification User typologies: Hexad scale

Multiple models have been proposed in the literature to identify individual preferences for game mechanisms, like the BrainHex model (Nacke et al., 2014), Bartle's taxonomy (Bartle, 1996) and Yee's player motivations (Yee, 2006). One of the most widely utilized instruments included on the preference matrix for the assessment of player typologies is the Hexad Scale Model. The Hexad Scale model characterizes an individual's player typologies based on six distinct typologies (Tondello et al., 2016a), as illustrated in Table 6.1. The scale assigns a score to each dimension, reflecting the extent to which each typology is present in a given user.

Table 6.1. Definition of the Hexad scale player typologies

User types	Definition
Philantropists	Motivated by purpose. Altruistic and willing to give without expecting a reward.
Socialisers	Motivated by relatedness. Want to interact with others and create social connections.
Free Spirits	Motivated by autonomy. Freedom to express themselves and act without external control. Like to create and explore within a system.
Achievers	Motivated by competence. Seek to progress within a system by completing tasks or prove themselves by tackling difficult challenges.
Players	Motivated by extrinsic rewards. Will do whatever to earn a reward within a system, independently of the type of the activity.
Disruptors	Motivated by triggering of change. Tend to disrupt the system either directly or through others to force negative or positive changes. They like to test the system’s boundaries and try to push further.

Selection of the 15 mechanisms

A review of the literature identified 15 processes that have been linked to user typologies (Gosetto et al., 2025b), based on the idea that people with different profiles have varying preferences regarding elements of mHealth applications that attempt to facilitate behavioral change. The word 'mechanism' in our case refers to all of the elements that might be included in a mHealth application that aims to modify behavior. We divided the mechanisms into two groups: those associated with gaming components and those associated with behavior change strategies. See Table 6.2 for more information and a definition of the mechanisms.

Table 6.2. List of mechanisms with their definition

Mechanism	Definition
BCT mechanisms	
Prompt and cues	Usually a message delivered to the user to prompt or recall a behavior at a specified time, with the app or user defining when the message should be sent (Villalobos-Zúñiga & Cherubini, 2020)
Demonstration of the behavior	Enables users to observe the cause-and-effect linkage of their behavior, such as seeing a simulation of their bodies after a diet (R. Orji, Mandryk, et al., 2017).
Self-monitoring	Users can track their behaviors, providing information on both past and current activities (R. Orji, Mandryk, et al., 2017)
punishment	Virtually penalizes the user for not performing the desired behavior or reaching their goal (R. Orji, Nacke, et al., 2017)
Social comparison	Highlight others' performance to enable comparison with one's own (Michie et al., 2013)
social support	Enables communication between users, such as through chat or sharing activities with other users (Klock et al., 2020).
Game elements	
Progression	Users can track their progression with steps through the system's purpose over time, visualized with mechanisms like stars or flags along a path (R. Orji, Mandryk, et al., 2017) .
Competition	Users can compete to accomplish the desired behavior (R. Orji, Mandryk, et al., 2017) .
Cooperation	Users collaborate to achieve a shared objective (R. Orji, Mandryk, et al., 2017) .
Collection	Allows users to gather virtual objects. Groups of rewards or badges to earn (Werbach et al., 2012)
Rewards	Virtual rewards offered to users for engaging in the target behavior (R. Orji, Mandryk, et al., 2017).
Quest	Users can enter or define the objectives targeted for the activity they will perform (Villalobos-Zúñiga & Cherubini, 2020) .
Challenge	Presents various situations that require effort from the user to be completed (Klock et al., 2020) (e.g., accomplishing 3 hours of physical activity per week).
Avatar	Allows users to share their data in the system without revealing their name (Klock et al., 2020).
App mechanism	
Customization	In contrast to personalization—which involves adjusting automatically the system to the user—customization refers to the user's ability to modify the content or functionalities of the mobile application according to their own preferences (R. Orji, Mandryk, et al., 2017) . This approach enables users to actively tailor the system based on users' choices.

Preferences relations between Hexad scale player typologies and mechanisms

Based on this literature review, a preference matrix could be generated, which is presented in Table 3, using the preference relations between the mechanisms and Hexad scale player typologies that were discovered in the literature. Each cell of the matrix indicates the number of articles that had a preference connection. A preference for a particular mechanism within a certain profile was indicated by a plus sign for the majority of the potential preference relations, which were positive (67%, 60/90). Negative relations, which make up 6% (5/90) of all possible relations, show an aversion to a mechanism (shown by a minus sign in Table 6.3). It should be mentioned that only 67% (60/90) of the possible linkages were discovered during the literature review, therefore the relation matrix is still incomplete.

This study aims to corroborate and potentially expand the existing preference matrix (Table 6.3), which maps relationships between game elements and BCT mechanisms with the Hexad model, by identifying new preference relations through experimental testing.

Table 6.3. Preference relations between gamer profile Hexad scales and mechanisms (+ represent preference relation and - an aversion relation)

			BCT mechanisms						**Game elements**								**App mechanism**
			Prompts and cues	**Demonstration of the**	**Self-monitoring**	**Punishment**	**Social comparison**	**Social support**	**Progression**	**Competition**	**Cooperation**	**Collection**	**Rewards**	**Quest**	**Challenge**	**Avatar**	**Customization**
Gamer profile	**Hexad scale**	Disruptor			+ -		+		++ -	+++			+		++	+	++
		Philanthropist		+				+	++		++	++	+	+	+		+
		Socialiser		+	+ -	+	+++	++++	++ -	++++	+++++		++	+	++	+	+
		Player				+	+++	+	++++	+++++	++	++++	++++	+	++++	++	+
		Free spirit						+	+++		+		+	+	++++	+	++
		Achiever					+		++++	+	+	++	+++ -	++	++++	+	+

+ 1 article with a preference relation - 1 article with non-preference relation

6.3 Methods

This section comes from our previous published protocol article (Gosetto et al., 2023).

6.3.1 Ethics Approval

The University Ethics Commission has approved this study for ethical research at the University of Geneva (CUREG_2021-04-38).

6.3.2 Study Design

We conducted a cross-sectional study to test and expand the existing preference matrix (Table 6.3), which maps relationships between gamification mechanisms and player typologies. This design was chosen to allow simultaneous collection of participants' user profile data (via the Hexad scale) and their experimentally assessed preferences for specific mechanisms. The goal was to determine whether the preference patterns identified in our prior scoping review (Table 6.3) could be corroborated in a controlled, experimental setting and whether new preference relations could be uncovered.

Participants completed an online questionnaire designed in accordance with the Checklist for Reporting Results of Internet E-Surveys (Eysenbach, 2004). The survey included two core tasks: (1) completion of the Hexad scale to assess user typology, and (2) selection and rating of motivational potential for five preferred mechanisms from a set of 15 mockups. These mechanisms were drawn from our previous work and represented diverse engagement strategies in mHealth applications.

6.3.2.1 Outcomes

The primary outcome is the preferred mechanisms given the user typologies.

6.3.2.2 Study Population

The target population for this study are individuals aged 18 and above who understands French. The recruitment process was conducted via social media platforms, specifically Facebook and Twitter, targeting students at the University of Geneva.

6.3.2.3 Sample Size calculation

As part of a larger study on the Big Five personality traits, the required sample size to identify a significant difference in preference was estimated using a multiple regression power analysis in R (u = 3, f^2 = 0.07, α = 0.05, power = 0.90). The variance estimate (202.403) was derived from prior research linking altruism, as measured by the Big Five, to preferences for social network content (Hallifax et al., 2019; Klock et al., 2020). Specifically, we used variance data from altruistic participants' responses (n = 46) to a blood donation poster (score range: 0–100) (Gosetto, 2018). Based on these parameters, a minimum of 206 participants was determined to be adequate.

6.3.2.4 Procedure

Participants were invited to complete an online survey developed by the research team using Qualtrics software (Qualtrics, Provo, UT) (see Appendix 2). The process began with an informed consent form outlining the study's purpose, procedures, and participants' right to withdraw at any time. Participants were required to confirm that they had read and understood the form and agreed to its terms before accessing the questionnaire, allowing the researchers to use their responses for the study.

Next, participants provided demographic information and were asked to confirm that they were at least 18 years old to proceed. Those who met the age requirement continued to the main part of the questionnaire, which involved two tasks: (1) completing a Hexad scale assessment and (2) reviewing 15 proposed mechanisms, selecting their five preferred ones, and rating the extent to which each would motivate them to adopt healthier behaviors on a scale from 0 to 100.

6.3.2.5 Measures and Measurement

Demographic questions

The participants were requested to provide information regarding their gender, age, occupation, and level of education.

6.3.3 Profile Assessment

Hexad Scale profil

To assess participants' gamification user type, we relied on Hexad Scale created and validated by Tondello (Tondello et al., 2016a). The internal scale reliability is good with Cronbach's alpha coefficient for each dimension ranging from 0.70 to 0.89 (Tondello et al., 2016a). This scale consists of 24 items, 4 per dimension. Users must rate how well each article describes them on a 7-point Likert scale. For example, there are items such as "I like competitions, where a prize can be won" or "Interacting with others is important to me". Items are presented in a randomized manner and the score is calculated by adding the scores for each dimension.

6.3.4 Choice of mechanisms

Presentation and selection of the five favorites mechanisms

Mockups representing each of the 15 mechanisms (see Appendix 1) were developed. A detailed description and definition of each mechanism is available in the Multimedia Appendix. To minimize potential bias related to aesthetic preferences, all mockups were designed using a deliberately simple and neutral visual style, limited to a black-and-white palette and basic icons. The order of presentation was randomized for each participant to prevent primacy or recency effects. During the study, participants were asked to select the five mechanisms they found most motivating, based on both the visual mockup and an accompanying brief textual explanation.

Motivation score

Participants were asked to rate on a scale of 0 to 100% how motivated these mechanisms made them feel to get back in shape for each of the five mechanisms they had previously selected.

Explanation of choice

For each mechanism selected, participants were asked to rate its perceived motivational potential in encouraging healthier behaviors using a scale ranging from 0 to 100. In addition, they were invited to provide an open-ended justification explaining their choices. Mechanisms that were not selected were automatically assigned a score of zero.

6.3.4.1 Analysis

Preference matrix validation

In order to perform a comparative analysis of the experimental results and the initial preference matrix, the collected data were also organized into a matrix. The values of the initial matrix (M1) represent the number of preference relations observed in the literature following the scoping review that we conducted previously (Gosetto et al., 2025b). We modified this matrix by assigning a value of -1 to indicate an aversion relation. A value of 0 indicates that a similar number of preferences and aversions were observed in the scoping review, and a null value is assigned when no relations were identified. The second matrix (M2) contains the data collected in this study. The value of the cell represents the score of the participants with the Hexad Scale dimension for the mechanism on the line. In each cell, we calculated a mechanism discriminative score by summing the participants' scores, divided by the total number of participants.

$$C_{m,b} = round\left(\frac{\sum_{p=1}^{n} 1_{p,m} \cdot S_{p,b}}{\sum_{p=1}^{n} 1_{p,m}} - \frac{\sum_{p=1}^{n} 0_{p,m} \cdot S_{p,b}}{\sum_{p=1}^{n} 0_{p,m}}\right)$$

$C_{m,b}$ represents the value in the cell corresponding to mechanism m (row) and the Hexad Scale b (column).

$1_{p,m\_}$ is an indicator function equal to 1 if participant p has selected mechanism m, and 0 otherwise.

$0_{p,m\_}$ is an indicator function equal to 0 if participant p has selected mechanism m, and 1 otherwise.

$S_{p,b}$ is the score of participant p on the Hexad scale b dimension (4-28).

n is the total number of individuals.

A third matrix (MC) represents a comparison between the two matrices (M1, M2). The values are computed by the difference on the score of both matrices.

6.3.4.2 Statistical analysis

A logistic regression analysis was conducted to examine the relationship between the mechanisms and the player profile scales. The objective of this analysis was to analyze if the participants' scores on the Hexad scale significantly influences the choice of a mechanism. A logistic regression analysis was conducted for each mechanism to ascertain whether the Hexad scale scores were predictive of the mechanism selection.

Furthermore, a logistic ordinal regression was conducted with the motivation scores of the selected mechanisms as the dependent variables and the Hexad scale scores as the predictors. The regression was performed for each mechanism motivation score, with the objective of determining whether the scores on the scales predict the mechanism score.

To prevent a type I error, the Bonferroni correction was employed for all regression analyses.

6.4 Results

6.4.1 Demographics data

214 individuals responded to our questionnaire, including 118 women, 89 men, 5 others and 2 didn't answer. The average age was 29.42 years (SD=10.41). More details are given in Table 6.4.

Table 6.4. Demographics data

	N	**Mean**	**Standard deviation**
Age	214	29.42	10.41
	N	**%**	
Gender	214		
Women	89	41.6	
Men	118	55.1	
Others	7	3.3	
Education Level	211		
Mandatory education	53	24.8	
Bachelor's degree	63	29.4	
Master's degree	80	37.4	
Doctorate	15	7	
Smartphone use	214		
Not confortable	10	4.7	
Confortable	204	95.3	
Already used mHealth	135	63.1	

6.4.2 Representativeness of the participants on the Hexad Scale

The scores for the Hexad Scale dimensions are recorded on a scale of 4 to 28. The distribution of the population on the Hexad Scale is shown in Figure 7 (the line represents the median and the cross represents the mean).

The participants of this study are mainly philantropist (M=23.23, SD= 24.50), Free spirit (M=22.93, SD=24.00), Achiever (M=21.99, SD= 21.50), Socialiser (M=19.35, SD=16) and Player (M=19.11, SD=17.50)). They are lower Disruptor (M= 15.22, SD=14.50).

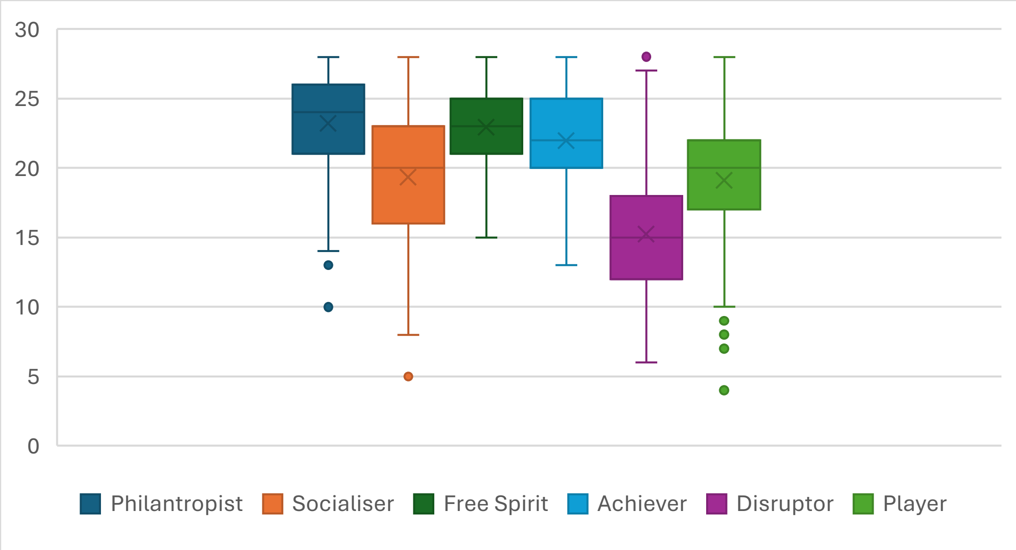

Figure 7. Boxplot of the representativeness of the participants on the Hexad Scale (N=214)

6.4.3 Characteristics of the participants on the selection for each mechanism

Four mechanisms, self-monitoring, progression, challenge, and quest, were selected by more than half of the participants, indicating a broad, cross-participant preference for these features (Table 6.5).

Tableau 6.5. Number of people who selected the mechanism (N=214)

Mechanisms	Number of people who selected the mechanism	Percentage
Self-monitoring	149	69.6
Progression	127	59.3
Challenge	112	52.3
Quests	111	51.9
Coopération	70	32.7
Demonstration of the behavior	61	28.5
Prompt and cues	53	24.8
Rewards	47	22
Social comparaison	44	20.6
Collectible	41	19.2
Avatar	29	13.6
Competition	29	13.6
Social support	20	9.3
Punition	8	3.7

6.4.4 Comparison between this study results and the preference matrix

The initial matrix (M1) presents 60% (50/84) of positive relation, 0% of aversion relation, 6% (5/84) of non-congruent relations (preference and aversion were observed) and 35% (29/84) of missing relations with no evidence found in our review (see M1 on Figure 8). Therefore, it is evident that the initial matrix derived from the scoping review is incomplete, with 35% of relationships remaining unaccounted for and potentially addressable explored through this research. Moreover, the predominance of positive relationships within this matrix highlights a gap in the literature, which has paid limited attention to documenting aversion-based relationships toward specific mechanisms.

The matrix of the selection mechanisms by participant of this study according on their Hexad Scale traits score (M2) presents 11% (9/84) of very high mechanism discriminative score (>4), 7% (6/84) of high selection mechanism (3), 15% (13/84) of medium selection mechanism (2), 67% (56/84) of low selection mechanisms (0-1) (see M2 on Figure 8). Consequently, we observe a minimal prevalence of high and medium selection mechanisms, accounting for a mere 33% of the total. The preponderance is predominantly characterized by weak selection mechanisms, which account for an overwhelming 66% of the observed cases.

In the matrix of presenting the difference between M1 and M2, the higher the value, the greater the difference between the 2 matrices. We observe 25% (21/84) similar value in the 2 matrices (0), 33% (28/84) minimal difference of one, 18% (15/84) moderate difference of two, and 24% (20/84) significant difference of three and more (see M3 on Figure 8). We observe a 25% similarity between the two matrices, representing roughly one quarter of their content and indicating a relatively low to moderate level of overlap. Therefore, it is expected that the results of our study will partially align with those of matrix M1, which reflects the outcomes of the scoping review. Additionally, the objective is to identify novel and substantial results that are not present in matrix M1, given the observed discrepancies between the two matrices, which account for 75% of the difference matrix M3.

	M1 : preference relations on literature					
	Hexad Scale traits					
Mechanisms	**Disruptor**	**Philantropist**	**Socialiser**	**Player**	**Free spirit**	**Achiever**
Prompts and cues	null	null	null	null	null	null
Demonstration of the Behavior	null	1	1	null	null	null
Self monitoring	0	null	0	null	null	null
Punishment	null	null	1	1	null	null
Social comparaison	1	null	3	3	null	1
Social support	null	1	4	1	1	null
Progression	0	2	0	4	3	4
Competition	3	null	4	5	null	1
Cooperation	null	2	5	2	1	1
Collection	null	2	null	4	null	2
Rewards	1	1	2	4	1	0
Quest	null	1	1	1	1	2
Challenge	2	1	2	4	4	4
Avatar	2	1	1	1	2	1

5, 4, 3, 2, 1= preference relation on respectively 5 articles, 4 articles, 3 articles, 2 articles, 1 article, -1= aversion relation, 0= no preference relations (preference and aversion observed), null= no relation

	M2 : selection mechanisms by participant, based on their Hexad Scale traits score					
	Hexad Scale traits					
Mechanisms	**Disruptor**	**Philantropist**	**Socialiser**	**Player**	**Free spirit**	**Achiever**
Prompts and cues	3	1	1	0	1	0
Demonstration of the Behavior	1	1	2	1	0	1
Self monitoring	1	0	1	2	0	0
Punishment	2	1	1	5	1	5
Social comparaison	0	0	0	0	3	2
Social support	0	1	1	1	4	1
Progression	0	0	0	0	2	1
Competition	1	0	1	2	2	5
Cooperation	2	1	2	1	0	0
Collection	2	2	0	1	1	2
Rewards	0	0	0	5	1	1
Quest	4	2	3	3	0	0
Challenge	1	3	0	1	1	5
Avatar	0	1	4	3	5	1

0 - 1= minimal selections of mechanism, 2= moderate selections of mechanism, 3= high selection of mechanism, 4+= very high selection of mechanism

	M3: Difference between M1 and M2					
	Hexad Scale traits					
Mechanisms	**Disruptor**	**Philantropist**	**Socialiser**	**Player**	**Free spirit**	**Achiever**
Prompts and cues	-3	-1	-1	0	-1	0
Demonstration of the Behavior	-1	0	-1	-1	0	-1
Self monitoring	-1	0	-1	-2	0	0
Punishment	-2	-1	0	-4	-1	-5
Social comparaison	1	0	3	3	-3	-1
Social support	0	0	3	0	-3	-1
Progression	0	2	0	4	1	3
Competition	2	0	3	3	-2	-4
Cooperation	-2	1	3	1	1	1
Collection	-2	0	0	3	-1	0
Rewards	1	1	2	-1	0	-1
Quest	-4	-1	-2	-2	1	2
Challenge	1	-2	2	3	3	-1
Avatar	2	0	-3	-2	-3	0

values represent diffence between M1 and M2

represent null relation in M1

Figure 8. Matrices for the representation of preference relations on literature (M1), of the selection mechanisms by participants based on their Hexad scale score (M2), and the difference between M1 and M2 (M3).

6.4.5 Preferred mechanisms and Hexad Scale

The full model containing all predictors was statistically significant for five selections of mechanism.

6.4.5.1 Mechanism collection

The full model was statistically significant, χ^2(6, N=205)= 22.16, p <.05, indicating that the model was able to distinguish between respondants who selected and did not select the mechanism collection. The model as a whole explained between 10% (Cox and Snell R square) and 17% (Nagelkerke R squared) of the variance in the selection of the mechanism collection, and correctly classified 82.9% of cases. As shows in Table 6.6, two of the independent variables made a unique statistically significant contribution to the model (philanthropist and player). The strongest predictors of selecting the mechanism collection were player with an odds ratio of 1.11. The odds ratio of .76 for philantropist was less than 1, indicating that the respondents with a high level of philantropist were over .76 times less likely to select this mechanism.

Table 6.6. Logistic Regression Predicting Likelihood of selecting the mechanism Collection

	B	**S.E**	**Wald**	**df**	**p**	**Odds Ratio**	**95,0% C.I for Odds Ratio**	
Philantropist	-.271	.075	13.134	1	**<.01**	.763	.659	.883
Socialiser	.071	.052	1.827	1	.177	1.073	.969	1.189
Free_Spirit	.096	.084	1.290	1	.256	1.101	.933	1.298
Achiever	-.049	.067	.548	1	.459	.952	.836	1.085
Disruptor	-.026	.053	.244	1	.621	.974	.878	1.081
Player	.106	.052	4.092	1	**<.05**	1.112	1.003	1.232
Constant	.345	1.836	.035	1	.851	1.412		

6.4.5.2 Mechanism cooperation

The full model was statistically significant, χ^2(6, N=209)= 17.87, p <.01, indicating that the model was able to distinguish between respondants who selected and did not select the mechanism cooperation. The model as a whole explained between 8% (Cox and Snell R square) and 11% (Nagelkerke R squared) of the variance in the selection of the mechanism cooperation, and correctly classified 67.5% of cases. As shows in Table 6.7, two of the independent variables made a unique statistically significant contribution to the model (socializer and free spirit). The strongest predictors of selecting the mechanism cooperation were socialiser with an odds ratio of 1.1. The odds ratio of .88 for free spirit was less than 1, indicating that the respondents with a high level of free spirit were over .88 times less likely to select this mechanism.

Table 6.7. Logistic Regression Predicting Likelihood of selecting the mechanism Cooperation

	B	**S.E**	**Wald**	**df**	**p**	**Odds Ratio**	**95,0% C.I for Odds Ratio**	
Philantropist	.070	.061	1.314	1	.252	1.073	.951	1.210
Socialiser	.128	.042	9.365	1	**<.01**	1.137	1.047	1.234
Free_Spirit	-.125	.068	3.424	1	.064	.882	.773	1.007
Achiever	.051	.052	.964	1	.326	1.052	.951	1.165
Disruptor	-.020	.039	.250	1	.617	.981	.908	1.059

Player	-.050	.037	1.761	1	.185	.952	.884	1.024
Constant	-1.949	1.442	1.827	1	.176	.142		

The full model was statistically significant, χ^2(6, N=211)= 13.01, p <.05, indicating that the model was able to distinguish between participants' scores for motivation to get fit using the cooperation mechanism. The model as a whole explained between 6% (Cox and Snell R square) and 7% (Nagelkerke R squared) of the variance in the selection of the mechanism cooperation. As shown in Table 6.8, independent variables socialiser made a unique statistically significant contribution to the model. The predictors socialiser of scoring the mechanism cooperation with an odds ratio of 1.10.

Table 6.8. Logistic Regression Predicting Likelihood of score of the mechanism Cooperation

	B	**S.E**	**Wald**	**df**	**p**	**Odds Ratio**	**95,0% C.I for Odds Ratio**	
Philantropist	.062	.057	1.161	1	.281	1.064	-.051	.175
Socialiser	.095	.038	6.346	1	**<.05**	1.100	.021	.170
Free_Spirit	-.075	.063	1.408	1	.235	.928	-.199	.049
Achiever	.031	.049	.411	1	.522	1.032	-.064	.127
Disruptor	-.029	.037	.603	1	.437	.972	-.102	.044
Player	-.050	.035	2.000	1	.157	.951	-.120	.019

6.4.5.3 Mechanism rewards

The full model was statistically significant, χ^2(6, N=208)= 38.67, p <.01, indicating that the model was able to distinguish between respondants who selected and did not select the mechanism rewards. The model as a whole explained between 17% (Cox and Snell R square) and 26% (Nagelkerke R squared) of the variance in the selection of the mechanism cooperation, and correctly classified 78.8% of cases. As shows in Table 6.9, independent variables Player made a unique statistically significant contribution to the model. The predictors Player of scoring the mechanism rewards were with an odds ratio of 1.39.

Table 6.9. Logistic Regression Predicting Likelihood of selecting the mechanism Rewards

	B	**S.E**	**Wald**	**df**	**p**	**Odds Ratio**	**95,0% C.I for Odds Ratio**	
Philantropist	.047	.066	.503	1	.478	1.048	.921	1.192
Socialiser	-.052	.048	1.152	1	.283	.950	.864	1.044
Free_Spirit	-.121	.082	2.173	1	.140	.886	.754	1.041
Achiever	-.081	.064	1.590	1	.207	.922	.814	1.046
Disruptor	.051	.051	1.027	1	.311	1.053	.953	1.163
Player	.329	.065	25.932	1	**<.01**	1.390	1.225	1.578
Constant	-4.362	1.800	5.870	1	.015	.013		

The full model was statistically significant, χ^2(6, N=211)= 31.65, p <.01, indicating that the model was able to distinguish between participants' scores for motivation to get fit using the rewards mechanism. The model as a whole explained between 14% (Cox and Snell R square) and 18% (Nagelkerke R squared) of the variance in the selection of the mechanism rewards. As shown in

Table 6.10, independent variables Player made a unique statistically significant contribution to the model. The predictors Player of scoring the mechanism cooperation with an odds ratio of 1.31.

Table 6.10. Logistic Regression Predicting Likelihood of score of the mechanism Rewards

	B	S.E	Wald	df	p	Odds Ratio	95,0% C.I for Odds Ratio	
Philantropist	.003	.060	.002	1	.961	1.003	-.115	.121
Socialiser	-.033	.045	.550	1	.458	.967	-.121	.054
Free_Spirit	-.050	.075	.435	1	.510	.952	-.197	.098
Achiever	-.087	.059	2.168	1	.141	.916	-.203	.029
Disruptor	.023	.047	.245	1	.621	1.024	-.069	.116
Player	.273	.056	23.586	1	**<.01**	1.314	.163	.383

6.4.5.4 Mechanism self-monitoring

The full model was statistically significant, χ^2(6, N=209)= 14.89, *p* <.05, indicating that the model was able to distinguish between respondants who selected and did not select the mechanism self-monitoring. The model as a whole explained between 6.9% (Cox and Snell R square) and 9.8% (Nagelkerke R squared) of the variance in the selection of the mechanism cooperation, and correctly classified 70.3% of cases. As shows in Table 6.11, independent variables Player made a unique statistically significant contribution to the model. The predictors Player of scoring the mechanism self-monitoring were with an odds ratio of .88.

Table 6.11. Logistic Regression Predicting Likelihood of selecting the mechanism Self-monitoring

	B	S.E	Wald	df	p	Odds Ratio	95,0% C.I for Odds Ratio	
Philantropist	-.016	.056	.079	1	.779	.984	.881	1.099
Socialiser	-.030	.040	.569	1	.451	.971	.898	1.049
Free_Spirit	.032	.068	.223	1	.637	1.033	.903	1.181
Achiever	.041	.053	.596	1	.440	1.041	.940	1.154
Disruptor	-.072	.041	3.061	1	.080	.931	.859	1.009
Player	-.126	.042	8.989	1	**<.05**	.881	.811	.957
Constant	3.764	1.500	6.302	1	.012	43.133		

6.4.5.5 Mechanism Demonstration of the behavior

The full model was statistically significant, χ^2(6, N=208)= 23.01, *p* <.01, indicating that the model was able to distinguish between respondants who selected and did not select the mechanism demonstration of the behavior. The model as a whole explained between 11% (Cox and Snell R square) and 15% (Nagelkerke R squared) of the variance in the selection of the mechanism demonstration of the behavior, and correctly classified 73.1% of cases. As shows in Table 6.12, three of the independent variables made a statistically significant contribution to the model (socializer, free spirit and achiever). The strongest predictors of selecting the mechanism demonstration of the behavior were socialiser with an odds ratio of .91, free spirit with an odds ratio of 1.25, and achiever with an odds ratio of .86. The independent variable philanthropist made a statically tendential contribution with an odds ratio of 1.13.

Table 6.12. Logistic Regression Predicting Likelihood of selecting the mechanism Demonstration of the behavior

	B	S.E	Wald	df	p	Odds Ratio	95,0% C.I for Odds Ratio	
Philantropist	.122	.064	3.594	1	.058	1.130	.996	1.282
Socialiser	-.088	.038	5.275	1	**<.05**	.915	.849	.987
Free_Spirit	.224	.075	8.902	1	**<.01**	1.251	1.080	1.449
Achiever	-.155	.057	7.497	1	**<.05**	.856	.766	.957
Disruptor	-.034	.041	.692	1	.405	.967	.892	1.047
Player	-.061	.040	2.273	1	.132	.941	.870	1.018
Constant	-2.342	1.576	2.209	1	.137	.096		

The full model was statistically tendential, χ^2(6, N=211)= 12.25, p=0.06, indicating that the model was able to distinguish between participants' scores for motivation to get fit using the demonstration of the behavior mechanism. The model as a whole explained between 6% (Cox and Snell R square) and 7% (Nagelkerke R squared) of the variance in the selection of the mechanism demonstration of the behavior. As shown in Table 6.13, independent variables Free Spirit made a unique statistically significant contribution to the model. The predictors Free Spirit of scoring the mechanism cooperation with an odds ratio of 1.17.

Table 6.13. Logistic Regression Predicting Likelihood of score of the mechanism Demonstration of the behavior

	B	S.E	Wald	df	p	Odds Ratio	95,0% C.I for Odds Ratio	
Philantropist	.067	.058	1.364	1	.243	1.070	-.046	.180
Socialiser	-.050	.036	1.979	1	.160	.951	-.120	.020
Free_Spirit	.162	.068	5.691	1	**<.05**	1.176	.029	.295
Achiever	-.093	.050	3.371	1	.066	.911	-.192	.006
Disruptor	-.032	.038	.692	1	.405	.969	-.107	.043
Player	-.040	.037	1.119	1	.290	.961	-.113	.034

6.5 Discussion

The aim of this study was to validate the preference matrix derived from a prior literature review by assessing whether similar relationships emerge within this research. Either if the relationships of M1 are found experimentally.

Findings indicate that four mechanisms were selected by more than half of the participants: self-monitoring (N=149), progression (N=127), challenge (N=112), and quest (N=111). No significant associations were identified between these mechanisms and the Hexad scale dimension except for self-monitoring. Therefore, it can be inferred that these four mechanisms are universally appreciated by participants, regardless of their individual profiles, and should be systematically incorporated into mHealth applications. With the exception of self-monitoring, which could be integrated solely for player users.

6.5.1 Comparison between preference matrix from the scoping review (M1) and preference matrix based on the results' study (M2)

Three of the eight significant relationships identified in this study were absent from the original preference matrix M1: the association between players and self-monitoring, free spirits and demonstration of behavior, and achievers and demonstration of behavior.

Therefore, this study contributes to the refinement of the preference matrix M1 by incorporating these three newly identified significant relationships.

In the following section, we provide a more detailed analysis of the five mechanisms that yielded significant regression results. Figure 9 illustrates these five mechanisms, as they were presented to participants in the questionnaire, accompanied by brief descriptions.

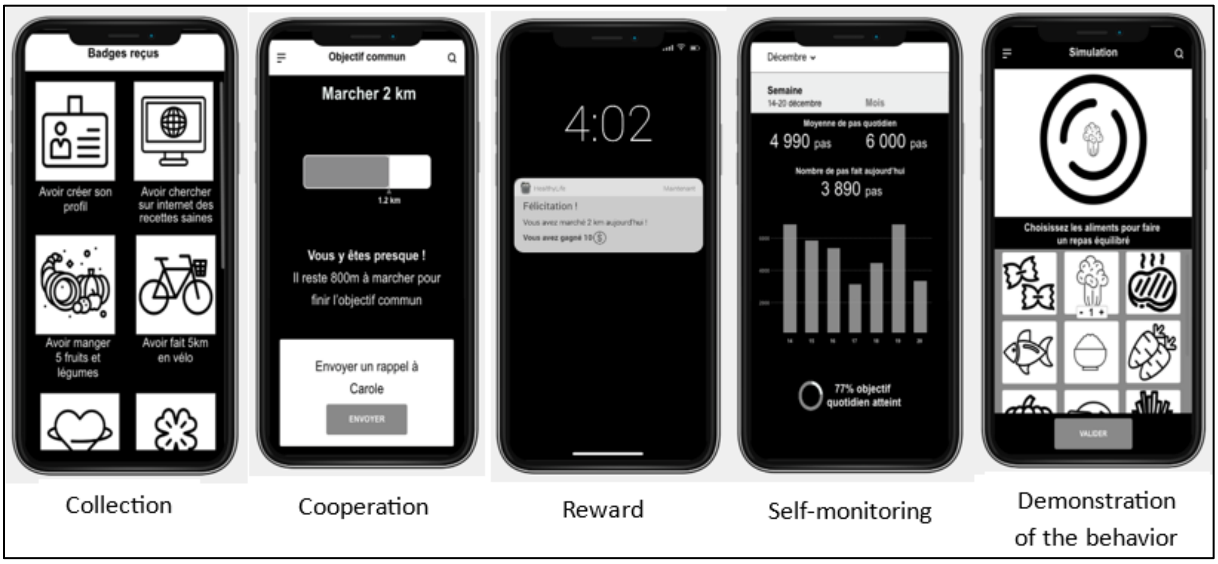

Figure 9. Preferred mechanisms according to user typologies

6.5.2 Collection

In our study, the term "collection" denotes an assemblage of items or badges accumulated progressively over time. Our findings indicate player (OR=1.11, p<.05) participants exhibited a stronger preference for the collection mechanism compared to other mechanisms and that philanthropist (OR=.77, p<.01) exhibited an aversion preference for this mechanism.

These results align with existing literature for player but is incongruent for philantropist. Within the preference matrix M1, the collection mechanism was favored by philanthropists (Tondello et al., 2016a; Tondello & Nacke, 2020), players (Altmeyer et al., 2019; Klock et al., 2020; Tondello et al., 2016a, 2017), and achievers (Altmeyer et al., 2019; Tondello et al., 2016a).

The pronounced tendency of player participants to opt for the collection mechanism may be attributed to their motivation by extrinsic rewards, such as badges.

6.5.3 Cooperation

The cooperation mechanism refers to the collaboration between app users to achieve a common goal, such as walking a predefined distance per day (R. Orji, Mandryk, et al., 2017). Our results indicate that socializer participants selected the cooperation mechanism more frequently than other mechanisms (OR=1.14, p<.01) and assigned it a higher motivational score (OR=1.10, p<.05).

This finding is strongly supported by five studies in the preference matrix M1(Altmeyer et al., 2019; Hallifax et al., 2019; Mora et al., 2019; R. Orji et al., 2018; Tondello et al., 2016a, 2017). Furthermore, it seem to be consistent with the characteristics of this profile, which describes players who are primarily motivated by interactions with other users.

6.5.4 Rewards

The reward mechanism involves granting virtual incentives to users upon the successful completion of a targeted action (R. Orji, Mandryk, et al., 2017) . Unlike the collection mechanism, rewards do not necessarily belong to a predefined set of collectible items.

Players exhibited a higher tendency to select the reward mechanism (OR=1.39, p<.01) and assigned it a greater motivational value (OR=1.31, p<.01).

The preference matrix (M1) highlights a preferential association between these participant profiles and the reward mechanism (Altmeyer et al., 2019; Klock et al., 2020; R. Orji et al., 2018; Tondello et al., 2016a). This preference may also be attributed to the characteristics of this profile, which is primarily driven by extrinsic rewards.

6.5.5 Self-monitoring

The self-monitoring mechanism enables users to track their health-related behaviors by providing information about their activities, such as displaying the number of steps taken in a day (R. Orji, Mandryk, et al., 2017) .

Our results indicate that player participants selected this mechanism less frequently (OR=.88, p<.05). However, this finding is not supported by the preference matrix M1. Therefore, these results introduce a new entry into the matrix.

6.5.6 Demonstration of the behavior

The demonstration of behavior mechanism simulate the causes and effects of users' actions, such as simulating a meal and its impact on their diet (R. Orji, Mandryk, et al., 2017) .

In our study, free spirit participants selected this mechanism more frequently than other mechanisms (OR= 1.25, p<.01) and assigned it a higher motivational score (OR=1.18, p<.05). These findings are not present in the preference matrix M1, thereby introducing a new relationship into the matrix.

Two profiles, socializers (OR=.92, p<.05) and achievers (OR=.86, p <.05) selected this mechanism less frequently than other mechanisms. The lack of preference between this mechanism and socializers contradicts the preference matrix M1, which previously indicated a positive association (R. Orji et al., 2018). In contrast, the aversion relationship between achievers and this mechanism constitutes a new entry in the preference matrix M1.

6.5.7 Relations according to profil

This study did not yield significant results for the Disruptor profile. Moreover, the mean participant scores were lowest on this profile (M= 15.22, SD=14.50), which may partly explain the absence of observable preferences among individuals scoring high in this dimension. Additionally, the Disruptor profile reflects a tendency to challenge the system and push its boundaries. However, none of the mechanisms implemented in our study were designed to elicit or measure such behaviors.

Our findings indicate that all mechanisms yielding significant results are consistently associated with the Player profile. This profile characterizes individuals who are motivated by rewards in game-based contexts, which may account for the observed relationship with the collection and reward mechanism. However, this does not fully explain its associations with the other three mechanisms—cooperation, self-monitoring, and demonstration of the behavior. It is possible that the Player profile is broadly responsive to various types of mechanisms, a hypothesis supported by the M1 preference matrix, which reveals numerous connections with findings in the existing literature. A summary of results and preference matrix is presented on table 6.14.

Table 6.14, Mechanisms preferred and non-preferred per Hexad-scale dimension (in bold congruent finding between our test and the literature, in italic incongruent)

Hexad scale dimension	Mechanisms prefered	Mechanisms non-preferred	Mechanisms prefered on litteratures	Mechanisms non-preferred on litteratures
Disruptor			Self-Monitoring, Social Comparison, Progression, Competition, Rewards, Challenge, Avatar, Customization	Self-monitoring, Progression
Philanthropist	**Demonstration of the behavior**	*Collection*	Demonstration of the Behavior, Social support, Progression, Cooperation, Collection, Rewards, Quest, Challenge, Customization	
Socialiser	Collection, **Cooperation**	*Demonstration of the behavior*	Demonstration of the Behavior, Self-monitoring, Punishment, Social comparison, Social support, Progression, Competition, Cooperation, Rewards, Quest, Challenge, Avatar, Customization	Self-monitoring, Progression
Player	**Rewards, Collection**	*Self-monitoring*	Punishment, Social comparison, Social support, Progression, Competition, Cooperation, Collection, Rewards, Quest, Challenge, Avatar, Customization	
Free spirit	Demonstration of the behavior		Social Support, Progression, Cooperation, Rewards, Quest, Challenge, Avatar, Customization	
achiever		Demonstration of the behavior	Social comparaison, Progression, Competition, Cooperation, Collection, Rewards, Quest, Challenge, Avatar, Customization	Rewards

6.5.8 Operationalizing the Preference Matrix

To apply the preference matrix in real-world settings, two steps are required: first, identifying the user's typologies; second, tailoring the app's features accordingly. While personality assessments typically involve standardized questionnaires, these can be burdensome and may reduce user engagement. Automatic profiling methods, using data such as smartphone usage (Chittaranjan et al., 2011; Staiano et al., 2012), social media activity (Azucar et al., 2018; Bai et al., 2012; Souri et al., 2018), or wearable data (Olguin & Gloor, 2009; Zufferey et al., 2023), offer alternatives, though they raise privacy concerns. To balance personalization and user autonomy, we suggest offering this feature as optional, using a short, validated questionnaire when users opt in.

Based on the identified profile, the app would then activate only the mechanisms relevant to the user's dominant traits, as indicated by the matrix. Personalization can target different profiling approaches and can be introduced either during onboarding or later, depending on user choice.

From a policy perspective, the refined preference matrix can guide the development of mHealth programs that are both evidence-based and user-centered. Prioritizing broadly appealing mechanisms such as self-monitoring and progression can maximise engagement across diverse user groups, while targeted adaptations for underrepresented profiles can help reduce digital health disparities. Scaling such personalization will require compliance with privacy regulations and clear consent processes, but offers the potential to improve both reach and effectiveness of publicly funded digital health interventions.

6.5.9 Limitations

A number of limitations should be acknowledged. First, the requirement for participants to select exactly five mechanisms out of fifteen may have introduced bias. Some participants may have included mechanisms they did not find particularly motivating simply to meet the selection quota, while others might have been inclined to select more than five if permitted. In light of empirical findings, we adopted a fixed-choice format to avoid extending the questionnaire's length, a factor known to significantly raise abandonment rates (Ganassali, 2008; Manfreda et al., 2002). Limiting the selection to five also compels participants to prioritize, reducing common rating biases such as acquiescence, social desirability, or consistency motif (Podsakoff et al., 2003).

Second, the sample was not representative of the general population, as it included a disproportionate number of university students, a demographic typically characterized by younger age (Mage = 29.42, SDage = 10.41). This homogeneity may limit the generalizability of the findings. However, evidence from digital behaviour change and web-based health interventions indicates that age does not mediate the observed effects on health behaviours (Lustria et al., 2013; Perski et al., 2017). Evidence from systematic reviews indicates that demographic moderators such as age, sex, and education generally exert weak or inconsistent effects on these techniques (Lustria et al., 2013). Furthermore, individuals most likely to use health applications tend to be younger and have higher incomes (Krebs & Duncan, 2015), characteristics that align closely with our sample, further supporting the applicability of our results.

Third, although a priori power analysis was conducted, the resulting sample size appears to have been insufficient for detecting effects across the full set of mechanisms. Indeed, significant results were obtained for only 5 out of 14 mechanisms, suggesting that the initial power calculation may need to be revisited in future studies.

Finally, the customization mechanism could not be adequately assessed. Due to its broad and complex nature, it was not feasible to represent this mechanism effectively within the constraints of standard mockup screens.

6.6 Conclusion

This study sought to validate the preference matrix (M1) by examining whether similar preference patterns could be observed in an experimental setting. Four mechanisms, self-monitoring, progression, challenge, and quest, were selected by more than half of participants, suggesting they have broad, cross-profile appeal. These mechanisms should be prioritized for integration in mHealth applications aiming for wide user engagement. Significant associations between user typologies and five mechanisms were identified, with three newly observed relationships, Player–self-monitoring, Free Spirit–demonstration of behavior, and Achiever–demonstration of behavior, not present in the original matrix. These findings contribute to refining and expanding the existing preference model. The Player profile showed the strongest and most consistent associations, aligning with its sensitivity to reward-driven and interactive features. Conversely, no significant associations were found for the Disruptor profile, likely due to both its lower representation and the absence of mechanisms designed to engage system-challenging behaviors. It would be interesting to replicate this study with a larger, less student-dominated panel to get better representation and more significant results on mechanism preference relations by Hexad scale.

6.7 Statements and declaration

Acknowledgments
None declared.

Authors' contributions
LG conceived the study with the involvement and advice of FE and GF. All authors were involved in writing, reading, and approving the final manuscript.

Ethical considerations

The University Ethics Commission has approved this study for ethical research at the University of Geneva (CUREG_2021-04-38).

Informed consent

Informed consent was obtained from all participants involved in the study.

Declaration of conflicting interest

None declared.

Funding statement

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Data availability

The data sets geénerated during the current study are available from the corresponding author on reasonable request.

6.8 Supplementary Material

Appendix 1: Print version of the online questionnaire

Chapter 7

7. Article VI : Personalizing Mobile Applications for Health Behavioral Change according to age and gender

Submitted to EAI Pervasive Health 2025

Chapter content

Abstract. Mobile health technologies have become increasingly relevant in promoting behavior change, particularly for chronic disease prevention and management. However, uniform solutions are limited by user diversity in age, gender, and personality. Prior research highlights the importance of tailoring content to user-specific characteristics to increase engagement and efficacy. The aim of this study is to investigate whether preferences for specific mechanisms vary as a function of participants' age or gender. Based on a literature review, 15 mechanisms were identified. This study employs a cross-sectional design. Participants completed an online survey, which collected data on demographic information, and preference selection of mechanisms. The average age of the 214 respondents (118 women, 89 men, 5 others), was 29.42. Logistic regression and logistic ordinal regression analyses, adjusted using the Bonferroni correction, assessed the influence of age and gender on mechanism preferences and motivation score. The study identified four mechanisms, self-monitoring, progression, challenge, and quests, as universally preferred across age and gender groups, suggesting their potential as core features in mHealth applications. However, notable differences emerged: older adults favored rewards *(OR=.37, p<.001*) but were less receptive to prompts and cues *(OR=1.52, p=.05),* while women showed lower preferences for social comparison *(OR=.44, p<.05)*, and competition *(OR=.34, p<.05)* and higher preference for avatar *(OR=2.39, p=.05).* These findings, underscore the importance of accounting for user characteristics in the design of personalized mHealth tools to improve engagement and intervention effectiveness.

Keywords: mHealth, personalization, age, gender, behavior change.

7.1 Introduction

In recent years, mobile health (mHealth) technologies have emerged as powerful tools in the promotion of behavioral change, particularly in the context of chronic disease prevention and management. As smartphones and wearable devices become increasingly ubiquitous, mHealth interventions offer scalable, real-time, and personalized solutions to support healthier behaviors across diverse populations (World Health Organization, 2021). These technologies harness mobile apps, SMS reminders, wearable sensors, and telehealth platforms to deliver health information, track behaviors, and facilitate self-monitoring and feedback, key mechanisms known to influence sustained behavior change (Free et al., 2013).

Applying a uniform intervention technique across an entire population presents considerable limitations, given the diversity of individual user profiles. Each user is characterized by a unique combination of factors, including demographic variables (such as age and gender), personality dimensions (e.g., the Big Five traits), cognitive tendencies (e.g., need for cognition), and attitudinal dispositions (e.g., degree of engagement in health-related behaviors). As such, adapting digital health applications to align with these individual differences is both appropriate and potentially beneficial. Prior research reviews have emphasized the effectiveness of tailoring app content, such as personalized messages including the user's name, customized goal-setting, and individualized feedback, based on user-specific attributes to increase the impact of behavior change techniques (Head et al., 2013; Lau et al., 2020; Sporrel et al., 2021). Moreover, differences can be observed depending on the age or gender of users, for example, younger users consistently favor interactive elements, such as gamification, with rewards (Hartzler et al., 2016) and do not like sharing their data on social network (Dennison et al., 2013). In addition, some studies note that women tend to appreciate social support features (Ehlers & Huberty, 2014; Jones et al., 2024). These findings suggest that offering customizable features can help accommodate the differing needs of users across age and gender groups.

Grounded in the assumption that individuals with varying profiles may exhibit distinct preferences regarding the features of mHealth applications designed to support behavioral change, a review of the existing literature identified 15 relevant mechanisms associated with user characteristics (Gosetto et al., 2025b). In this study, the term *mechanism* refers broadly to the various components that can be integrated into an mHealth application with the aim of promoting behavioral modification. These mechanisms were categorized into two main groups: those derived from behavior change techniques (BCTs) and those inspired by game design elements. A detailed description and classification of the mechanisms are provided in Table 7.1.

Table 7.1. List of mechanisms with their definition

Mechanism	Definition
BCT mechanisms	
Prompt and cues	Usually a message delivered to the user to prompt or recall a behavior at a specified time, with the app or user defining when the message should be sent (Villalobos-Zúñiga & Cherubini, 2020)
Demonstration of the behavior	Enables users to observe the cause-and-effect linkage of their behavior, such as seeing a simulation of their bodies after a diet (R. Orji, Mandryk, et al., 2017)
Self-monitoring	Users can track their behaviors, providing information on both past and current activities (R. Orji, Mandryk, et al., 2017)
punishment	Virtually penalizes the user for not performing the desired behavior or reaching their goal (R. Orji, Nacke, et al., 2017)
Social comparison	An individual's perceptions of the prevailing beliefs and behaviors within a social group.
social support	Enables communication between users, such as through chat or sharing activities with other users (Klock et al., 2020).
Game elements	
Progression	Users can track their progression with steps through the system's purpose over time, visualized with mechanisms like stars or flags along a path (R. Orji, Mandryk, et al., 2017)
Competition	Users can compete to accomplish the desired behavior (R. Orji, Mandryk, et al., 2017)
Cooperation	Users collaborate to achieve a shared objective (R. Orji, Mandryk, et al., 2017)
Collection	Allows users to gather virtual objects.
Rewards	Virtual rewards offered to users for engaging in the target behavior (R. Orji, Mandryk, et al., 2017)
Quest	Users can enter or define the objectives targeted for the activity they will perform (Villalobos-Zúñiga & Cherubini, 2020).
Challenge	Presents various situations that require effort from the user to be completed (R. Orji, Mandryk, et al., 2017) (e.g., accomplishing 3 hours of physical activity per week).
Avatar	Allows users to share their data in the system without revealing their name (R. Orji, Mandryk, et al., 2017).
App mechanism	
Customization	Users can adapt himself the mobile app's content and functionality to their needs or choices (R. Orji, Mandryk, et al., 2017). As opposed to personalization, which is adapting to the user without allowing them to control it.

The aim of this study is to investigate whether preferences for specific mechanisms vary as a function of participants' age or gender.

7.2 Methods

This section comes from our previous published protocol article (Gosetto et al., 2023).

7.2.1 Ethics Approval

The University Ethics Commission has approved this study for ethical research at the University of Geneva (CUREG_2021-04-38).

7.2.2 Study Design

We performed a cross-sectional study to address our aims. Participants responded to an online questionnaire in accordance with the Checklist for Reporting Results of Internet E-Surveys (Eysenbach, 2004).

7.2.3 Outcomes

The primary outcome is the preferred mechanisms given the user profile.

7.2.4 Study Population

The target population for this study are individuals aged 18 and above who understands French. The recruitment process was conducted via social media platforms, specifically Facebook and Twitter, targeting students at the University of Geneva.

7.2.5 Sample Size calculation

Given that this study is part of a larger study in which the sample size was calculated based on the Big Five. We calculated the required sample size using a multiple regression power analysis in R. The parameters used were the number of predictors u=3, effect size f2=0.07, significance level α=0.05, power = 0.9, and estimated variance = 202.403. These estimates were based on the hypothesis that individuals with higher levels of altruism, as measured by the Big Five personality traits, show a preference for social networks (Hallifax et al., 2019; Klock et al., 2020).

To approximate the variance, we referred to a prior study (Gosetto, 2018) that assessed Big Five personality traits in relation to user preferences for social network posters. Specifically, we used the variance in Big Five trait ratings for altruistic participants (n = 46) based on their average scores for a poster promoting blood donation, which had a scoring range of 0–100. Using these parameters, we determined that a sample size of 206 would be sufficient for this study.

7.2.6 Procedure

Participants completed an online questionnaire created with Qualtrics (Qualtrics, Provo, UT), following informed consent. After confirming their age (≥18) and providing demographic information, participants completed a personality assessment and reviewed 15 behavioral change mechanisms, selecting their five preferred ones and rating their motivational impact on a 0–100 scale for promoting healthier behavior.

7.2.7 Measures and Measurement

7.2.7.1 Demographic questions

The participants were requested to provide information regarding their gender, age, occupation, and level of education.

7.2.7.2 Choice of mechanisms

Participants were presented with black-and-white mockups of 15 behavioral mechanisms, each accompanied by a brief description. To reduce design bias, the visuals were intentionally minimalistic, and the order of presentation was randomized to prevent primacy or recency effects. Participants were asked to select the five mechanisms they found most motivating and indicate their likelihood of being motivated by these five mechanisms to get fit on a scale from 0 to 100.

7.2.8 Analysis

A logistic regression analysis was conducted to examine the relationship between the mechanisms and the age and gender of participant. The objective of this analysis was to analyze if the age and gender significantly influences the choice of a mechanism. A logistic regression analysis was conducted for each mechanism to ascertain whether the age and gender were predictive of the mechanism selection.

Furthermore, a logistic ordinal regression was conducted with the motivation scores of the selected mechanisms as the dependent variables and the age and gender as the predictors. The regression was performed for each mechanism motivation score, with the objective of determining whether age and gender predict the mechanism score.

To prevent a type I error, the Bonferroni correction was employed for all regression analyses.

7.3 Results

7.3.1 Demographics data

214 individuals responded to our questionnaire, including 118 women, 89 men, 5 others and 2 didn't answer. The average age was 29.42 years (SD=10.41). More details are given in Table 7.2.

Table 7.2. Demographics data

	N	**Mean**	**Standard deviation**
Age	214	29.42	10.41
	N	**%**	
18-24 years	90	42.1%	
25-34 years	81	37.9%	
35 – 65 years	43	20.1%	
Gender	214		
Women	118	55.1	
Men	89	41.6	
Others	7	3.3	
Education Level	211		
Mandatory education	53	24.8	
Bachelor's degree	63	29.4	
Master's degree	80	37.4	
Doctorate	15	7	
Smartphone use	214		
Not confortable	10	4.7	
Confortable	204	95.3	
Already used mHealth	135	63.1	

Characteristics of the participants on the selection for each mechanism

A total of four mechanisms were selected by more than half of the participants. These mechanisms included self-monitoring, progression, challenge, and quest (Table 7.3).

Table 7.3. Number of people who selected the mechanism (N=214)

Mechanisms	Number of people who selected the mechanism	Percentage
Self-monitoring	149	69.6
Progression	127	59.3
Challenge	112	52.3
Quests	111	51.9
Coopération	70	32.7
Demonstration of the behavior	61	28.5
Prompt and cues	53	24.8
Rewards	47	22
Social comparaison	44	20.6
Collectible	41	19.2
Avatar	29	13.6
Competition	29	13.6
Social support	20	9.3
Punition	8	3.7

7.3.2 Preferred mechanisms and age

The full model containing all predictors was statistically significant for three mechanisms.

7.3.2.1 Mechanism Prompts and cues

The logistic regression model was statistically significant, $\chi^2(1, N = 214) = 4.02$, $p = .05$, indicating that the model reliably distinguished between participants who selected and did not select the Prompts an cues mechanism. The model explained between 2% (Cox & Snell R^2) and 3% (Nagelkerke R^2) of the variance in mechanism selection and correctly classified 75.2% of cases. The odds ratio of 1.52, indicating that the respondents with older were over 1.52 times less likely to select this mechanism.

The full model was statistically significant, $\chi^2(1, N=214)= 4.2$, $p <.05$, indicating that the model was able to distinguish between participants' scores for motivation to get fit using the prompts and cues mechanism. The model as a whole explained between 2% (Cox and Snell R square) and 2% (Nagelkerke R squared) of the variance in the selection of the mechanism prompt and cues. The predictors age of scoring the mechanism prompts and cues with an odds ratio of 1.53.

7.3.2.2 Mechanism Reward

The logistic regression model was statistically significant, $\chi^2(1, N = 214) = 16.27$, $p<.001$, indicating that the model reliably distinguished between participants who selected and did not select the reward mechanism with an odds ratio of 0.37. The model explained between 7% (Cox & Snell R^2) and 11% (Nagelkerke R^2) of the variance in mechanism selection and correctly classified 78% of cases.

The full model was statistically significant, χ^2(1, N=214)= 18.78, p <.001, indicating that the model was able to distinguish between participants' scores for motivation to get fit using the reward mechanism. The model as a whole explained between 8% (Cox and Snell R square) and 11% (Nagelkerke R squared) of the variance in the selection of the mechanism reward. The predictors age of scoring the mechanism reward with an odds ratio of .35.

7.3.3 Preferred mechanisms and gender

The full model containing all predictors was statistically significant for three mechanisms.

7.3.3.1 Mechanism Social comparison

The logistic regression model was statistically significant, χ^2(1, N = 207) = 5.86, p< .05, indicating that the model reliably distinguished between participants who selected and did not select the social comparison mechanism. The model explained between 3% (Cox & Snell R^2) and 4% (Nagelkerke R^2) of the variance in mechanism selection and correctly classified 78.7% of cases. The odds ratio of .44, indicating that the women respondents were over .44 times less likely to select this mechanism.

The full model was statistically significant, χ^2(1, N=214)= 5.2, p <.05, indicating that the model was able to distinguish between participants' scores for motivation to get fit using the social comparison mechanism. The model as a whole explained between 2% (Cox and Snell R square) and 3% (Nagelkerke R squared) of the variance in the selection of the mechanism social comparison. The predictors gender of scoring the mechanism self-monitoring with an odds ratio of .56.

7.3.3.2 Mechanism Avatar

The logistic regression model was statistically significant, χ^2(1, N = 207) = 3.87, p=.05, indicating that the model reliably distinguished between participants who selected and did not select the avatar mechanism. The model explained between 2% (Cox & Snell R^2) and 3% (Nagelkerke R^2) of the variance in mechanism selection and correctly classified 87% of cases. The odds ratio of 2.39, indicating that the women respondents were over 2.39 times more likely to select this mechanism.

The full model was statistically significant, χ^2(1, N=214)= 5.39, p <.05, indicating that the model was able to distinguish between participants' scores for motivation to get fit using the avatar mechanism. The model as a whole explained between 3% (Cox and Snell R square) and 4% (Nagelkerke R squared) of the variance in the selection of the mechanism cooperation. The predictors gender of scoring the mechanism self-monitoring with an odds ratio of 2.89.

7.3.3.3 Mechanism Competition

The logistic regression model was statistically significant, χ^2(1, N = 207) = 6.94, p< .05, indicating that the model reliably distinguished between participants who selected and did not select the competition mechanism. The model explained between 3% (Cox & Snell R^2) and 6% (Nagelkerke R^2) of the variance in mechanism selection and correctly classified 86% of cases. The odds ratio of .34, indicating that the women respondents were over .34 times less likely to select this mechanism.

The full model was statistically significant, $\chi^2(1, N=214)= 6.5$, $p <.05$, indicating that the model was able to distinguish between participants' scores for motivation to get fit using the self-monitoring mechanism. The model as a whole explained between 3% (Cox and Snell R square) and 5% (Nagelkerke R squared) of the variance in the selection of the mechanism competition. The predictors gender of scoring the mechanism self-monitoring with an odds ratio of .35.

7.3.3.4 Mechanism Self-monitoring

The full model was statistically significant, $\chi^2(1, N=214)= 5.02$, $p <.05$, indicating that the model was able to distinguish between participants' scores for motivation to get fit using the self-monitoring mechanism. The model as a whole explained between 2% (Cox and Snell R square) and 3% (Nagelkerke R squared) of the variance in the selection of the mechanism self-monitoring. The predictors gender of scoring the mechanism self-monitoring with an odds ratio of .55.

7.4 Discussion

Our results highlight four mechanisms, self-monitoring, progression, challenge, and quests, that were consistently selected by participants regardless of age or gender. This finding suggests that these mechanisms may serve as core components that should be systematically integrated into mobile health applications aimed at promoting behavior change.

In addition, our findings reveal age and gender related preferences for specific app features. Older participants showed a higher preference and assigned more favorable ratings to the rewards mechanism *(OR=.37, p<.001*). This result contrasts with findings from previous studies conducted with women (Jones et al., 2024), smokers (Hartzler et al., 2016). Conversely, older participants selected and rated prompt and cues less favorably *(OR=1.52, p=.05)*. This observation appears to be novel, as it has not been reported in prior studies.

With regard to gender, we observed a specific preference among women in our study for the avatar mechanism *(OR=2.39, p=.05)*. However, this finding has not been corroborated by existing literature. Women also selected and rated the social comparison mechanism less favorably *(OR=.44, p<.05)*. Similarly, women selected and scored the competition mechanism lower *(OR=.34, p<.05)*, although we did not identify any existing studies reporting a similar pattern. Finally, women in our sample gave lower ratings to self-monitoring, *(OR=.55, p<.05),* which contradicts the broader consensus in the literature that this mechanism is generally well-received across populations. Moreover, self-monitoring was the most frequently selected mechanism across the entire sample (N= 149), supporting prior research indicating a widespread preference for this feature (DeSmet et al., 2019; Ehlers & Huberty, 2014; Hoj et al., n.d.; Kahriz et al., 2023) and underscoring its critical role in the design of mobile health behavior change interventions.

7.4.1 Limitation

A key limitation of this study is the restricted age range of the sample (M_{age}=29.42, SD_{age}=10.41). The oldest participant was 65 years old, which limits the generalizability of the findings to populations above this age threshold. This age distribution is largely due to the predominantly student-based composition of our participant pool. Future research should consider including older adults to enable comparisons across age groups and to assess whether similar patterns emerge in a more age-diverse population.

Requiring participants to choose exactly five mechanisms from a set of fifteen represents a methodological limitation. This constraint may have led some individuals to include mechanisms they did not find particularly motivating simply to meet the selection quota. Conversely, other participants might have preferred to select more than five mechanisms but were restricted by the imposed limit.

7.5 Conclusion

This study aimed to determine whether users exhibit preferences for specific types of mechanisms within mobile health applications designed to support behavior change. The results identified four mechanisms, self-monitoring, progression, challenge, and quests, that were consistently favored across all participant groups, irrespective of age or gender. These consistently preferred features may represent foundational elements to be systematically incorporated into mobile health interventions targeting behavior change. Findings revealed also significant differences in preferences for several mechanisms. Older participants showed a greater preference for rewards, while expressing less interest in prompts and cues (i.e., reminder-based features). In contrast, female participants demonstrated a lower preference for self-monitoring, social comparison, and competition mechanisms. Some of these results are consistent with prior literature, while others diverge, highlighting the need for continued research in this area. Such investigations are essential to further validate user preferences and support the development of more personalized mobile health applications, ultimately enhancing their adoption and effectiveness.

Acknowledgment

None declared.

Authors' contributions

LG conceived the study with the involvement and advice of FE and GF. All authors were involved in writing, reading, and approving the final manuscript.

Conflicts of interest

None declared.

Chapter 8

8. Article VII: Towards an ontology of user preferences based on user profiles for mobile health applications: Formalization based on a scoping review

Not submitted, under consideration for submission.

Chapter content

8.1 Abstract

The personalization of mobile health (mHealth) interventions has been demonstrated to enhance user engagement and improve behavioral outcomes. However, existing personalization frameworks frequently exhibit a lack of formal semantic required to facilitate interoperability, reasoning, and integration with user profiles and motivational strategies. The present study proposes an OWL 2 ontology that formalizes user preferences for health behavior change, as derived from a structured scoping review. The ontology integrates psychological traits (e.g., Big Five), gamer profiles (e.g., BrainHex, Hexad), and demographic attributes with gamification mechanisms and behavior change techniques. It has been determined that there are over 300 instances that link user profiles to engagement mechanisms. Each of these instances is grounded in bibliographic references, enabling traceable and evidence-informed personalization. The ontology was validated using the HermiT reasoner and supports SPARQL-based queries for adaptive intervention design. A comparative analysis with the Behavior Change Intervention Ontology (BCIO) illuminates the complementary nature of our approach, with a stronger emphasis on gamification and user-centric modeling. Subsequent endeavors will concentrate on formal evaluation, and incorporation into a prototype mHealth system.

8.2 Introduction

It has been determined by the (World Health Organization, 2009) that certain behaviors have a significant impact on global mortality risk. Among the leading modifiable factors identified are physical inactivity, poor diet, and smoking. In response to this challenge, the proliferation of mobile health (mHealth) applications, with a total exceeding 318,000 as of mid-2022 (Aitken et al., 2017), has created new opportunities for promoting healthy behaviors through features such as real-time health tracking, reminders, and informational support (Ernsting et al., 2017). Many evidences from the literature suggests that mobile health (mHealth) applications have the potential to be efficient in the management of chronic conditions, the promotion of physical activity, the facilitation of dietary modifications, and the attainment of weight loss, often through the incorporation of behavior change techniques (BCTs). These techniques include, but are not limited to, goal setting, self-monitoring, and feedback (Bardus et al., 2016; Edwards et al., 2016; Hoffmann et al., 2017; Lau et al., 2020; Lee et al., 2018; Lister et al., 2014; M. Marcolino et al., 2018; McDonald et al., 2015; Michie et al., 2013; Sporrel et al., 2021).

However, the efficacy of these interventions can be influenced by user-specific characteristics, including demographics, personality traits, cognitive profiles, and attitudes. Research suggests that personalization or adapting intervention, enhances the efficacy of BCTs, particularly in domains like physical activity and weight management. Indeed, tailored goals, messages, and feedback have been demonstrated to yield superior outcomes in comparison to the utilization of non-personalized content. These outcomes include enhanced weight reduction and elevated levels of engagement (Sporrel et al., 2021) Lau et al., 2020(McCarroll et al., 2017).

Beyond demographic tailoring, effective personalization can also incorporate psychological constructs and contextual variables. This approach has been validated in studies demonstrating that customized interventions utilizing frameworks grounded in behavioral theory result in improved behavioral intentions and health outcomes (Jensen et al., 2012). Personalization has further been linked to increased user engagement through mechanisms described in digital behavior change intervention (DBCI) models, particularly by enhancing users' interaction with intervention components (Cole-Lewis et al., 2019).

Gamification, defined as the application of game elements in non-game contexts (Deterding et al., 2011), is another strategy increasingly used to improve motivation and adherence in mHealth apps (Bassanelli et al., 2022; Johnson et al., 2016). Recent research emphasizes the importance of aligning gamified features with user-specific preferences, such as competition or narrative orientation, which can be assessed using typologies like the Gamification User Types Hexad Scale (Altmeyer et al., 2020; R. Orji et al., 2018; Tondello et al., 2016a, 2017). Although personalization and gamification have individually demonstrated potential in improving engagement and behavioral outcomes (Lister et al., 2014).

Most reviews on mHealth interventions have targeted the evaluation of the effectiveness of individual components, such as feedback, gamification, and behavior change techniques (BCTs)(Edwards et al., 2016; Hoffmann et al., 2017; Lau et al., 2020; Lee et al., 2018; Lister et al., 2014; M. Marcolino et al., 2018; Michie et al., 2013). While certain studies have emphasized the advantages of customized messaging (Head et al., 2013; Lau et al., 2020), only one review providing a framework to facilitate personalization within mHealth contexts but confined to the context of gamification (Klock et al., 2020). As an attempt to be more generic a work by Gosetto and al. proposes a personalization matrix that maps behavior change techniques, gamification strategies, and app functionalities to specific user profiles, with the aim of optimizing health behavior change through individualized mHealth interventions (Gosetto et al., 2025b). A study was conducted to validate this matrix revealed additional relationships and validated others (Gosetto et al., 2025a, 2025d, 2025b).

To further enhance the personalization and scalability of mHealth interventions, the use of ontologies offers significant advantages in both modeling and interoperability. Ontologies provide a formal and shared representation of concepts and relationships within a specific domain, enabling consistent annotation, reasoning, and knowledge integration across heterogeneous systems (Bodenreider, 2008). For instance, standardized ontologies allow for the alignment of behavioral change taxonomies, such as the Behavior Change Intervention Ontology (BCIO), with user traits or contextual data, enabling adaptive interventions that are both clinically relevant and technically portable (Michie et al., 2021).

Several ontologies have been developed to support semantic modeling in the domain of digital health. These ontologies have applications ranging from user profiling to behavior change interventions. For instance, the Behavior Change Intervention Ontology (BCIO) offers a structured framework for representing intervention components, behavioral outcomes, and contextual factors. This enables more effective analysis, comparison, and replication of behavior change interventions across studies (Michie et al., 2021). The SNOMED CT ontology, a widely utilized tool in the realm of clinical informatics, facilitates standardized representation of health conditions, treatments, and patient attributes, thereby enabling seamless integration with electronic health records (EHRs) and other health information systems (Donnelly, 2006). The alignment of these ontologies through semantic web technologies (e.g., RDF, OWL) enables reasoning across datasets and platforms, facilitating dynamic personalization and ensuring consistency across disparate app ecosystems. Consequently, the integration of domain ontologies not only enhances the granularity and adaptability of mHealth personalization but also contributes to the long-term sustainability and interoperability of digital health ecosystems.

This study aims to develop a domain ontology focused on user preferences for personalized health behavior change interventions, building upon the recognized utility of ontologies for structuring knowledge and enabling interoperability in mHealth systems. The proposed ontology is grounded in the preference matrix introduced by (Gosetto et al., 2025b).

8.3 Methodology

8.3.1 Objectives of the ontology

The ontology developed in this study supports current and future research on the relationship between user characteristics, particularly personality traits and gamer profiles, and behavioral and gamification mechanisms used in mobile applications to promote behavior change. The ontology formally encodes empirical findings on user preferences and aversions toward specific mechanisms (e.g., feedback, competition, and self-monitoring) to enable personalized system design and automated reasoning.

A primary objective of the ontology is to aggregate research findings into structured, reusable preference models. For example, it allows researchers to create a matrix that shows how different personality types respond to various mechanisms, which can guide the design of adaptive, user-centered interventions.

Another important goal is to help researchers and developers retrieve empirical evidence aligning with the specific traits of their target users. This capability supports evidence-based decision-making in developing mHealth tools, enabling more precise and scientifically grounded personalization.

Finally, the ontology is designed to be easily extendable, allowing new empirical results and bibliographic references to be added as research in the field evolves. This feature ensures the ontology remains up to date and continues to serve as a living resource that grows alongside the scientific community.

8.3.2 Data source: the preference matrix

The primary data source for this research is a preference matrix developed to support the personalization of mHealth interventions. This matrix synthesizes evidence from 18 peer-reviewed publications and conference proceedings, mapping associations between user profiles, such as Big Five personality traits, Hexad gamification types, BrainHex gaming archetypes, and gender, and 15 commonly used behavior change and mechanisms. These mechanisms were subsequently categorized into three overarching classifications: behavior change techniques (BCTs), gamification mechanisms, and app-specific functionalities. A total of 300 potential profile-mechanism combinations were identified; however, only 154 of these (51%) were documented in the existing literature. This finding underscores the fragmented and incomplete nature of the extant empirical evidence (Gosetto et al., 2025b).

8.3.3 Construction method of the matrix in the review

The construction of the matrix followed a structured thematic synthesis methodology. Initially, user profile variables and engagement mechanisms were extracted from the included studies. Subsequently, the mechanisms were categorized utilizing established taxonomies: Michie et al.'s BCT taxonomy for behavioral strategies (Michie et al., 2013), Werbach and Hunter's gamification framework (Werbach et al., 2012), and a third residual category for app-specific features not covered by these models. User profiles were similarly coded according to validated psychological and gamification theories, including the Big Five model, the Hexad player type scale, BrainHex typology, and gender identity. The cells of the matrix are intended to represent the findings of each study, indicating whether the study reported a user preference or aversion toward a given mechanism (Gosetto et al., 2025b).

8.3.4 Experimental validation of the preference matrix

To validate the matrix-derived assumptions, a cross-sectional study was conducted, in which participants completed validated psychological questionnaires (e.g., Big Five Inventory, Hexad scale) and rated their motivation across the 15 engagement mechanisms (Gosetto et al., 2025a, 2025d, 2025b). The results of this study have also been added to the ontology.

8.3.5 Ontology construction

The ontology underpinning the preference matrix was constructed using a hybrid methodological approach, combining both bottom-up extraction and top-down structuring principles, as recommended by the Methontology framework (Fernández López et al., 1997). The bottom-up phase commenced with the manual extraction of key concepts from the scoping review, which led to the identification of core entities such as user profiles (e.g., personality traits, gamification types), mechanisms (e.g., feedback, rewards, narrative), and the nature of their associations (preferences, aversions). The modeling process was implemented in its entirety using the Protégé ontology editor (Musen, 2015) and encoded in OWL 2 (Web Ontology Language). This approach enabled formal reasoning, semantic validation, and potential integration into decision-support systems. This rigorous methodological integration of bottom-up evidence synthesis and top-down formalization ensures both empirical grounding and semantic coherence in the resulting ontology.

The resulting conceptualization is as follows**:**

- Demographic data → :Demographic ⊑ :User_profile
    - This class refers to the demographic profile of users, such as their :age and :gender.
- Personality traits → :Big-FiveTrait ⊑ :Personality ⊑ :User_profile
    - Personality refers to a set of stable psychological traits and individual differences that influence users’ behaviors, motivations, and preferences in digital interventions. This class typically includes dimensions derived from validated psychological models such as the Big Five.
- Gamers Profile ⊑ :User_profile
    - This class represents user characteristics related to gameplay preferences as defined by established player typologies, such as the :HexadScale and :BrainHex scales. It captures the motivational dispositions and interaction styles that influence how users engage with gamified systems.
- Mechanism → :

- This class concerns the entirety of components that can be incorporated within an mHealth application with the objective of effecting behavioral change such as :Game_elements, :App_Mechanisms.
- Bibliographic_concept → :ArticleTitle, :Author, :Journal, :Publication ⊑ :references
    - This class concerns bibliographic references present in the results.
- Results → :
    - Members of this class are scientific results reported in a referenced work. The result presents in this ontology are about relations, such as preference or dislike, between user traits and mechanisms.
- *Psychometric Measures* This class contains frequently used psychometric measures such as BFI-10, :BFI-44, :BFI-fr,:BrainHex_Questionnaire, :Hexad_User_Types_Scale, :NEO-PI-R on :measures
- Relations
    - This class contains the relations between a (category of) participants and mechanism that have been found by scientific studies focus on the preference and dislike relationships.

8.3.6 Ontology Reasoning and Validation with HermiT

After the formal modeling phase, the ontology underwent validation using the HermiT reasoner, a Description Logic (DL) reasoner integrated within the Protégé environment. The utilization of HermiT entailed a multifaceted approach aimed at ascertaining the logical coherence of the ontology, identifying unsatisfiable classes, and deriving implicit relationships through the application of axioms and object properties that had been explicitly defined (Glimm et al., 2014). This reasoning process enabled the detection of modeling errors, such as contradictory class definitions or incorrect domain and range specifications. In particular, disjointness axioms between user profile types (e.g., Big Five vs. Hexad) and between mechanism (e.g., gamification elements vs. BCTs) were tested to ensure the integrity of the class hierarchy. Inferred relations, such as transitive associations between user traits and higher-level engagement strategies, were also evaluated to validate the expressiveness and deductive power of the ontology.

8.4 Results

The ontology under consideration comprises 24 class and 478 individuals, encapsulating semantic relationships among mechanisms, user characteristics, and referenced studies.

The database contains a total of 304 instantiated results, with each result correlating a specific mechanism to one user profiles. These results are supported by a literature references.

Each *:resXXX* individual is semantically linked to a *biblio#Publication* via the reference property. The mechanisms in question are described through conceptual properties that support reasoning and flexible queries.

Ontology structure

Class hierarchy

The ontology is structured around a well-defined class hierarchy, which organizes conceptual domains such as user profiles, mechanisms, and bibliographic references. This hierarchy facilitates the process of inheritance and reasoning over user traits and design strategies. The following diagram (see Figure 10) and structure presents the aforementioned hierarchy.

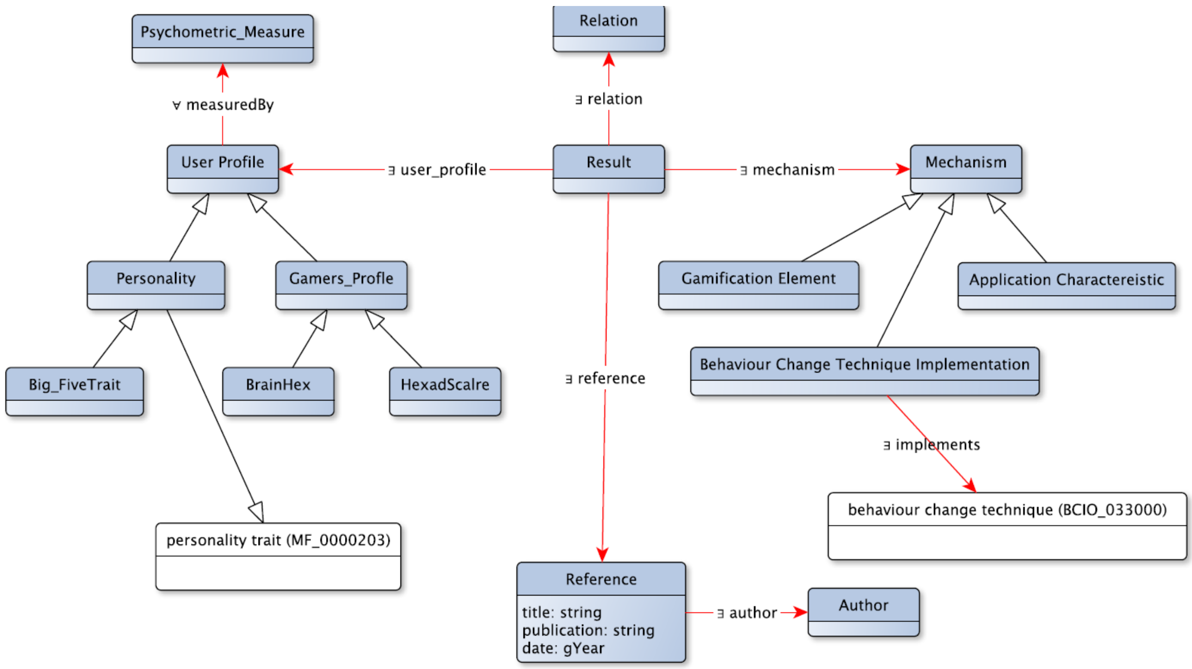

Figure 10. Diagramm of the ontology

```
:User_profile
        :Demographic
                :age
                :gender
        :Personality
                :Big-FiveTrait
        :Gamers_profile
                :BrainHex
                :HexadScale

:Mechanisms
        :App_Mechanisms
        :Behavior_Change_Technique_Implementation
        :Game_Elements

:Relation

:Psychometric_Measures

:Result

:Bibliographic_Concept
        :ArticleTitle
        :Author
        :Journal
        :Publication


:BCIO_Concept
        :Behaviour_Change_Technique
```

Key ontological properties

The ontology delineates a set of fundamental properties that establish semantic relations between individuals and classes across the user profile and game mechanism domains. The properties in question can be categorized into two distinct classes: object properties, which establish a connection between entities, and data type properties, which facilitate the association of entities with literal values.

Object Properties

- *mechanism:* associates a result instance with one mechanism.
- *relation:* expresses the type of connection (e.g., *preference*, *dislike*) between user characteristics and mechanisms.
- *reference:* connects a result to its bibliographic source.
- *gender, age*: used to specify demographic.
- *User_profile:*
    - *personality*: used to specify personality trait.
    - *gamer_profile*: links user-related results to player typologies (e.g., *conqueror*, *seeker*).
- *hasAuthor, hasJournal, hasTitle, hasYear:* define the structure of bibliographic entries.

Datatype Properties

- *name*: used for labeling authors.

- *titleText*: provides the literal title of a referenced publication.
- *journalName:* specifies the name of the publication venue.
- *date:* marks publication or assertion dates.

Example of instantiation

The following instantiation models a behavioral change technique. The individual *:Res1* represents an empirical result linking the mechanism *:demonstration_of_the_behavior* with the personality trait *:agreeableness*, based on a preference relation and supported by an academic reference *:pub_2.*

```
:res1 rdf:type owl:NamedIndividual ,
          :Result ;
    :mechanism :demonstration_of_the_behavior ;
    :personality :agreeableness ;
    :reference :pub_2 ;
    :relation :preference .
```

SPARQL Use Case

According to the present instantiation, it is possible to formulate a SPARQL query to retrieve all results associating the Self-monitoring of the behavior mechanism with a given personality trait. This approach facilitates the targeted extraction of empirical patterns encoded in the ontology.

```
PREFIX : <http://www.semanticweb.org/laetitiagosetto/ontologies/2021/3/modele_these/>
PREFIX biblio: <http://example.org/biblio#>

SELECT ?result ?reference
WHERE {
  ?result a :results ;
        :mechanism :Self-monitoring_of_the_behavior ;
        :personality :agreeableness ;
        :relation :preference ;
        :reference ?reference .
}
```

Model building queries

The following query aggregates research results to construct a preference matrix mechanism * user profile → relation count, positive count, negative count where user profile is a BrainHex gamer profile, positive count is the number of studies that found a ‘preference’ relation between the mechanism and the user trait and negative count is the number of studies that found a ‘dislike’ relation.

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX : http://cui.unige.ch/isi/onto/mhap/
SELECT ?p ?m (count(?r) as ?c) (sum(?pref) as ?cpref) (sum(?dis) as
?cdis)
  WHERE { ?result :user_profil ?p ;  :mechanism ?m  ;  :relation ?r.
   ?p a :BrainHex.
   BIND(IF(?r = :preference, 1, 0) AS ?pref)
   BIND(IF(?r = :dislike, 1, 0) AS ?dis)
}
group by ?p ?m
order by ?p ?m
```

Typical result rows are :

Profile	Mechanism	#Relations	#Positive	#Negative
achiever	cooperation	1	1	0
achiever	customisation	1	1	0
achiever	rewards	4	3	1
achiever	social_comparison	1	1	0
socialiser	progression	3	2	1
socialiser	demonstration_of_the_behavior	2	2	0
socialiser	quest	1	1	0
socialiser	self-monitoring_of_the_behavior	2	1	1

The following query aggregates research results to obtain references mentioning links to the Big Five personality profile extroversion

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX : <http://cui.unige.ch/isi/onto/mhap/>
SELECT DISTINCT ?r  ?title
WHERE { ?r :personality :extraversion ; :reference ?ref . ?ref :hasTitle/:titleText ?title}
```

Results :

http://cui.unige.ch/isi/onto/mhap/res86
"Personality-targeted persuasive gamified systems: exploring the impact of application domain on the effectiveness of behaviour change strategies"^^<http://www.w3.org/2001/XMLSchema#string>

http://cui.unige.ch/isi/onto/mhap/res98
"Towards Personality-driven Persuasive Health Games and Gamified Systems"^^<http://www.w3.org/2001/XMLSchema#string>

http://cui.unige.ch/isi/onto/mhap/res71
"Personality-based approach for tailoring persuasive mental health applications"^^<http://www.w3.org/2001/XMLSchema#string>

http://cui.unige.ch/isi/onto/mhap/res94
"Personality, Genre and Videogame Play Experience"^^<http://www.w3.org/2001/XMLSchema#string>

http://cui.unige.ch/isi/onto/mhap/res81
"Exploring the Persuasiveness of Behavior Change Support Strategies and Possible Gender Differences"^^<http://www.w3.org/2001/XMLSchema#string>

http://cui.unige.ch/isi/onto/mhap/res96
"Exploring the Persuasiveness of Behavior Change Support Strategies and Possible Gender Differences"^^<http://www.w3.org/2001/XMLSchema#string>

http://cui.unige.ch/isi/onto/mhap/res92
"Personality & Persuasive Technology: An Exploratory Study on Health-Promoting Mobile Applications"^^<http://www.w3.org/2001/XMLSchema#string>

Etc. ...

Validation with HermiT

The ontology demonstrated a degree of semantic robustness and computational soundness upon successful completion of the reasoning checks, thereby qualifying it for incorporation into decision-support systems and adaptive mHealth platforms.

8.5 Discussion

8.5.1 Conceptual and Methodological Contributions

This study presents a novel formalization of user preferences in the domain of mHealth applications, grounded in a structured scoping review (Gosetto et al., 2025b). The resulting ontology provides a modular, extensible, and interoperable framework for representing a wide spectrum of user characteristics relevant to digital personalization, particularly in the context of behavior change support.

The ontology is structured around a series of conceptual pillars, including personality traits (particularly the Big Five), gamer profiles (BrainHex and Hexad), demographic variables, behavioral change techniques, gamification mechanisms, and app-specific features. These elements are interconnected through semantically defined object properties, including *:preference* and :*dislike*, thereby enabling the ontology to express nuanced relationships between user profiles and mechanisms. Furthermore, each empirical assertion is linked to a bibliographic source via the *:Bibliographic_Concept* property, ensuring traceability and evidence-based modeling.

To illustrate, consider the instantiated individual *:res1*, which links the mechanism :*demonstration_of_the_behavior* to the personality trait *:agreeableness* through the *:preference* property. This relation is substantiated by a particular publication that is referenced using the *:reference* property. This assertion suggests that individuals with high agreeableness scores may exhibit a greater positive response to demonstration of the behavior features, such as simulation. In a similar vein, other instantiated results associate conqueror users (BrainHex profile) with competition mechanisms, or free spirits with customization features (Hexad scale profile).

These examples underscore the ontology's capacity to facilitate granular, evidence-driven personalization by explicitly modeling how specific user traits map to well-defined mechanisms. Rather than relying on broad or generic categories, the ontology encodes fine-grained distinctions, such as the differential responsiveness of agreeable individuals to demonstration of the behavior techniques, or the preference of conqueror-type users for competitive structures, backed by empirical findings. This level of detail enables adaptive systems to surpass surface-level personalization, such as demographic tailoring, and instead implement psychologically grounded, trait-sensitive interventions.

By establishing these associations within a logically consistent and machine-readable structure, the ontology enables digital systems to dynamically infer which strategies are likely to be most effective for a given user profile. The result is a personalization process that is both explainable and justifiable, as each recommendation or adaptive behavior can be traced back to a documented empirical relation. This approach not only facilitates technical implementation but also fosters ethical transparency and user trust, particularly in health-related or behaviorally sensitive contexts.

In practical terms, this signifies that the system is capable of differentiating not only between different users, but also between why a certain mechanism may be more effective for one individual than another, thereby establishing the foundation for personalization that is both evidence-based and precise.

This capacity is imperative for facilitating the dynamic integration of the ontology into real-time personalization engines within mHealth applications and conversational agents. By leveraging reasoning over the ontology, systems can infer which content formats, delivery strategies, or motivational framings are most likely to resonate with a given user profile, allowing for the adaptation of interfaces and interventions in real time. The aforementioned factors result in a highly personalized system that is not only adaptive and effective, but also explainable, justifiable, and aligned with behavioral science and ethical design principles.

In addition to supporting real-time reasoning, the ontology also enables advanced semantic queries that aggregate empirical evidence across studies. For instance, it is possible to construct a mechanism-by-user profile matrix that tallies the number of reported *:preference* and *:dislike* relations between specific engagement mechanisms and BrainHex gamer profiles. This query type enables researchers and designers to ascertain the extent of consensus in the literature, as well as identify areas where conflicting or limited evidence persists. By establishing quantitative relationships between these concepts, the ontology can facilitate the development of data-driven preference models. These models can serve as valuable inputs for decision-making processes in research and application development. This illustrates the ontology's function not only as a reasoning layer for individual-level personalization, but also as a tool for synthesizing evidence, thereby integrating disparate empirical findings into actionable design insights.

Finally, the ontology has been explicitly designed to support extensibility by enabling the straightforward addition of new empirical findings and bibliographic references. As research in user personalization and behavior change continues to evolve, researchers can incorporate novel results by following the established structure of the ontology. Specifically, new instances of the *:Results* class can be created to encode the relationship between a user trait (e.g., a personality dimension or gamer profile) and a behavioral or gamification mechanism, using object properties such as *:personality, :mechanism*, and the relation type *(:preference or :dislike*). Each new result can then be linked to a publication through the *:Bibliographic_concept* class, thereby maintaining the ontology's traceability and scientific grounding. For instance, a novel finding suggesting a correlation between the personality trait of extraversion and the social support mechanism can be incorporated by creating a new results individual and citing the relevant source. The ontology is maintained as a dynamic and living resource through a modular and repeatable process that ensures its continuous enrichment by evidence accumulated across literature.

8.5.2 Comparison with the BCIO

In order to contextualize the present ontology within existing semantic frameworks, a comparison is made with the Behavior Change Intervention Ontology (BCIO), a comprehensive ontology designed to model interventions, mechanisms of action, and outcomes in behavioral science (Michie et al., 2021)

The BCIO offers a comprehensive formalization of behavior change techniques, context, delivery, and population characteristics. While it demonstrates notable aptitude in the representation of structured health interventions, the system exhibits a notable degree of lack with regard to the specific requirements of digital gamification, player typologies that are employed in behavior change intervention.

In contrast, the present ontology focuses specifically on the intersection between user traits (e.g., gamer profiles, personality) and mechanisms (e.g., competition, rewards, social comparison). The text synthesizes empirical evidence from the extant literature, establishing a correlation between each mechanism and specific user profiles, with the support of pertinent references. In contrast to BCIO, it encompasses the following:

- Fine-grained gamer typologies such as BrainHex and Hexad;
- Mechanisms aligned with game design;
- Explicit preference or impact relationships based on literature-derived results.

Furthermore, while both ontologies exhibit common elements (e.g., behavior change techniques such as self-monitoring or prompts and cues), our model integrates these into a gamified context and supports dynamic reasoning over user personalization strategies, a capability that BCIO does not explicitly model. A promising avenue for integration lies in the potential alignment between the behavior change techniques from the BCIO. Consequently, the Behavior_Change_Technique_Implementation class has the following subclass: implements *some* "behavior modification techniques."

The two ontologies can be regarded as complementary: BCIO furnishes a generalized behavioral foundation, whereas our ontology proffers a gamification-specific layer that has the capacity to enrich personalized mHealth interventions with scientific litterature. Consequently, our ontology could be seen as an additional module to the BCIO.

8.5.3 Limitation, Future Directions and Applications

To extend the impact and robustness of the ontology, several improvements and applications are planned for future development.

First, the ontology will undergo a formal evaluation to assess both its logical consistency and conceptual completeness by qualitative assessments through domain expert review. This will particularly serve to validate the behavioral change techniques and mechanisms modeled within the ontology.

Secondly, a notable aspect of the ontology's design is its consideration of modular extensibility. The system facilitates straightforward enrichment through the addition of new individuals, classes, and object properties, a functionality that is particularly useful for integrating findings from future scientific publications. Furthermore, the ontology could be enhanced by incorporating more precise details from the cited references, such as the specific nomenclature of mechanisms employed in studies, numerical effect sizes, statistical significance levels, and the nature of statistical relationships (e.g., correlation, regression). These additions would not only enrich the informational depth of the model but also enable more nuanced reasoning, filtering, and ranking of interventions based on empirical strength. Such progressive enrichment would contribute to maintaining the ontology as a living, evidence-informed resource, aligned with ongoing developments in the behavioral and research communities.

Thirdly, a pragmatic proof of concept will be formulated in the form of a prototype application, such as a mobile health app or chatbot. This system will demonstrate ontology-based reasoning for content personalization and dynamic adaptation of intervention strategies based on user profiles. For example, one may consider a user interacting with a health chatbot for stress management purposes. A preliminary evaluation of the subject's responses to a brief onboarding questionnaire suggests that the individual in question exhibits high levels of neuroticism, moderate agreeableness, and a mastermind gamer profile. Utilizing ontology-based reasoning, the chatbot dynamically selects a combination of behavioral change techniques, such as social support and self-monitoring, while excluding others, such as competition, which are contraindicated for this specific profile. The feasibility and performance of the ontology in a real-time context will be assessed using both system-level metrics (e.g., query execution time, responsiveness) and user-centered evaluations (e.g., usability and personalization effectiveness).

These steps are essential to establish the ontology not only as a conceptual artifact but also as a functional asset for adaptive and evidence-based mHealth interventions.

8.6 Conclusion

This paper presents a semantically rich ontology for modeling user preferences in the context of personalized mHealth interventions. The ontology is grounded on empirical literature and structured around psychological and gamification-based user profiles, thereby capturing meaningful relationships between users and behavior change mechanisms. In contrast to existing behavior change ontologies, such as BCIO, this model emphasizes the personalization dimension, providing precise representations of user traits, game mechanisms, and evidence-based preferences. The ontology provides a foundation for reasoning, querying, and system-level adaptation, thereby bridging the gap between theoretical personalization frameworks and practical implementation. The utilization of reasoning tools for its validation ensures semantic robustness, while the incorporation of real-world instantiations enables immediate applicability. In the future, the ontology will undergo formal evaluation, and be integrated into a prototype mHealth intervention. These steps will support its use as both a research tool and a technological asset for adaptive, evidence-based, and user-centered mHealth design.

Chapter 9

9. General Discussion

Chapter content

The various articles we have submitted or published provide answers to our various research questions.

9.1 Defining Mechanisms and User Profiles for Personalization

RQ1. According to the literature, which dimensions should be considered when personalizing mHealth applications to support behavior change?

To address this research question, a multi-stage process was followed. The initial phase entailed conducting a comprehensive literature analysis of the domain. To synthesize the data extracted from this extensive literature review, particularly the potential connections between mechanisms relevant to mobile health applications and dimensions that could characterize user profiles, an initial concept map was developed (available at this link). However, it was soon apparent that the concept map was overly complex and difficult to interpret. The system incorporated an excessive number of mechanisms and user profile types, in addition to references to guidelines evaluating the quality of mobile health applications.

In response, a restructuring of the model was implemented, whereby its concepts were organized into four overarching categories: user characteristics, system functionalities, information content, and app properties (see Figure 11). Within each of these categories, relevant concepts were grouped and integrated with the elements from the original concept map. Additionally, the guideline-based information was maintained, indicating whether specific mechanisms were considered essential for high-quality applications because several guidelines have stipulated their necessity. This was accomplished through the implementation of a color-coding system. The number of colors of a given mechanism's representation in the literature served as a proxy for its perceived significance. The initial version of the model, which did not yet incorporate explicit connections between user profiles and mechanisms, was outlined in Chapter 2.

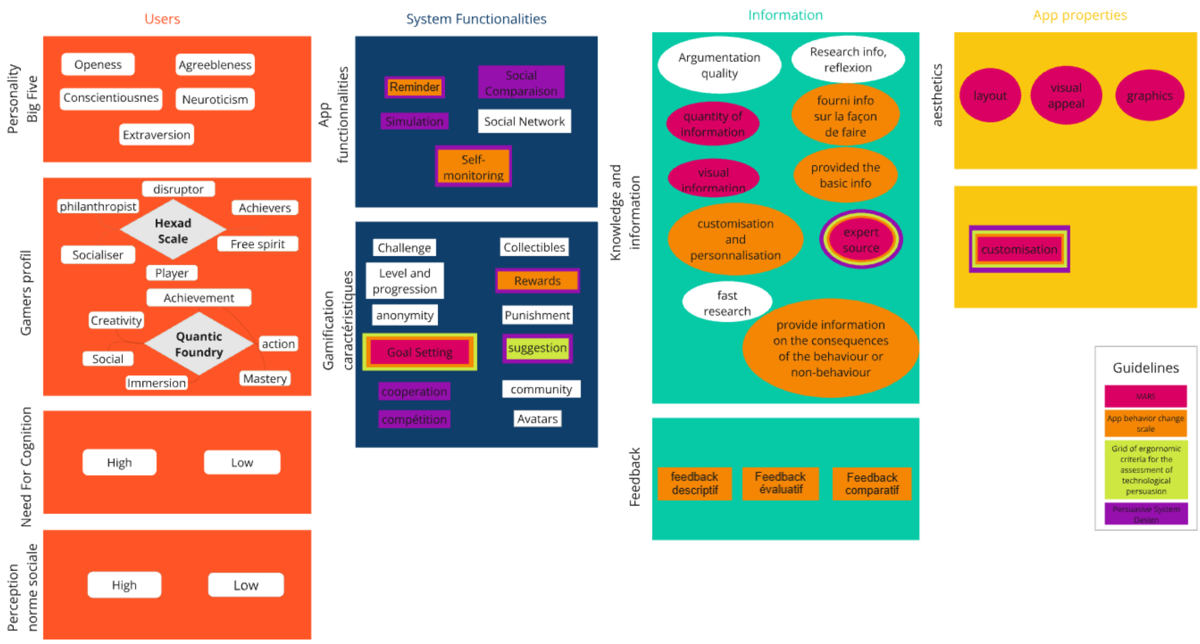

Figure 11. First model representation of the dimensions

Subsequently, to clarify and refine the model while introducing explicit preference relationships between user profiles and engagement mechanisms, we conducted a more focused scoping review, presented in Chapter 3. This refined review enabled us to delineate the salient dimensions pertinent to personalization in mobile health applications that facilitate behavior change. We were able to identify specific user profiles that could be meaningfully associated with particular mechanisms. Consequently, the range of dimensions was constrained, and the rationale behind the exclusion of specific elements from the original matrix is elucidated in the limitations section of this thesis.

Furthermore, we sought to enhance the conceptual rigor of the model by aligning the identified mechanisms with established frameworks from the literature. Specifically, we mapped certain mechanisms to the Behavior Change Technique taxonomy (BCT) and others to recognized gamification design elements. This step enabled the consolidation and reclassification of the mechanisms into a final, structured set, which formed the basis of both the preference matrix and the resulting ontology.

We further discuss in the Limitations and Future Work sections how the ontology could be expanded and refined. Future enhancements may include the integration of more granular evidence from source articles the integration of emerging findings in the literature, and the development of a user-friendly web interface to enhance the accessibility and actionability of the ontology for non-expert users.

9.2 Implementing Personalization in mHealth Applications

RQ2. How can personalization dimensions be applied within a mobile health application?

A preference matrix was developed based on the findings of the scoping review presented in Chapter 3. This matrix offers a comprehensive overview of the relationships between user profiles and motivational mechanisms, facilitating the identification of strategies associated with specific user types.

To validate this matrix, an empirical study was conducted (detailed in Chapter 4), which enabled a comparison of user-reported preferences with the associations previously identified in the literature. The findings (detailed in Chapter 5, 6 and 7) indicated a substantial convergence between the literature-based predictions and the patterns observed in the experimental data. This finding supports the reliability and external validity of the matrix as a foundation for personalization strategies in mobile health interventions.

Having established this empirical robustness, it is equally important to consider the contextual boundaries of the present work. The current investigation centered on a preventive health behavior, namely the selection of motivational features to promote increased physical activity. It is reasonable to hypothesize that user preferences for mHealth functionality may vary depending on the nature of the behavior being managed, particularly in cases involving chronic conditions such as diabetes. However, a recent meta-analysis of digital health interventions for the prevention and management of noncommunicable diseases suggests that the most effective BCTs are largely consistent across these contexts (Mair et al., 2023). For instance, in the domain of cardiovascular disease interventions, diabetes or chronic condition, self-monitoring and prompts/cues were identified as the most effective strategies. Preventive interventions similarly underscored goal setting, self-monitoring, and prompts/cues as pivotal catalysts for behavioral modification, with goal setting constituting the sole salient distinction when juxtaposed with management-focused programs. These findings are consistent with the results of our own study, in which more than half of the participants selected self-monitoring and the Quest mechanism (our operationalization of goal setting) as preferred mechanisms. Collectively, these results indicate that while the health context (prevention versus chronic disease management) may influence specific aspects of user preference, the fundamental set of effective BCTs exhibits remarkable similarity. This observation underscores the significance of our preference matrix and ontology for a wide range of mHealth applications.

9.3 Supporting mHealth Designers and Developers

RQ3. How can designers develop personalized mHealth applications for behavior change?

To operationalize the personalization dimensions identified in the scoping review, we chose to represent them in the form of a preference matrix, summarized in these matrices presented on chapter 3 (see Tables 3.3 and 3.4), which indicate whether specific user profiles exhibit preferences, or aversions, toward particular motivational mechanisms. This structured format enables researchers seeking to apply the model to mobile health interventions to readily identify which mechanisms are most suitable for inclusion, based on prior empirical findings. Moreover, by referring directly to the cited studies, researchers can verify the contextual validity of each preference relationship and determine whether it aligns with the specific needs of their target population or application domain.

In addition to the aforementioned matrix, an ontology (presented on chapter 8) was developed to represent the same data in a more structured and flexible way. While the matrix offers a useful summary of how different user profiles relate to various behavior change mechanisms, the ontology provides a more detailed and interactive view of this information. This approach facilitates comprehension of the context underlying each finding and enables the reusability of the data in other research endeavors or applications. A primary benefit of the ontology is its capacity to facilitate more sophisticated semantic querying. To illustrate, it enables users to identify all studies that examined a specific user profile, employed a particular gamification strategy, or were published in a designated year. Furthermore, it facilitates the investigation of the study authors, the robustness of the reported preferences, and the users' preferences to particular mechanisms. This kind of flexible access to the data is useful not only for researchers reviewing the literature, but also for developers looking to design more personalized mHealth. In essence, the ontology functions not merely as a storage medium for data but as a framework that facilitates the interpretation and understanding of the data. By transforming disparate research results into a cohesive and searchable knowledge base, it facilitates more informed decisions in both scientific and practical contexts. This approach enables researchers and designers to discern patterns, evaluate concepts, and develop interventions that are more aligned with the diverse needs and preferences of various user groups. Moreover, the model has been intentionally designed to be flexible and easily updatable as new research becomes available. As research in the fields of behavior change and user personalization continues to expand, the integration of novel findings becomes increasingly feasible by adhering to a systematic structure. The establishment of each new association, along with its source in the scientific literature, ensures the transparency and empirical foundation of the information. For instance, if a study indicates that individuals with a high extraversion score respond positively to social support features, this finding can be articulated in a clear and systematic manner. This modular approach enables the resource to evolve over time, continuously integrating new knowledge from the field and maintaining its relevance for researchers and practitioners.

RQ4. How can a user's personality profile be integrated into a mobile health application?

One of the major challenges in this field lies in defining user profiles in order to offer them mechanisms that align with their preferences. As discussed in Chapters 5 and 6, several approaches are available to researchers and mobile app developers for this purpose, each accompanied by specific challenges. These include the trade-offs between self-reported questionnaires and automatic personality assessments, as well as issues related to user burden, privacy, and data reliability.

In light of the intricacies inherent in this issue and the ethical considerations involved, a more cautious approach is adopted, favoring the utilization of validated questionnaires for the assessment of user profiles. Consequently, our ontology incorporates a selection of empirically validated personality instruments drawn from the extant literature, which can be administered directly to users.

While the use of validated questionnaires provides a rigorous means of assessing user profiles, it is important to acknowledge that certain profile dimensions are not necessarily stable over time. For instance, a longitudinal investigation of the gamification user types Hexad scale revealed that the majority of participants underwent a change in their predominant user type within a period of six months. Furthermore, all six sub-scales exhibited significant shifts in mean scores, effects that were particularly pronounced among female participants (Santos et al., 2021). In contrast, substantial evidence indicates that core personality traits exhibit considerable temporal stability in adulthood, particularly after the age of 30 (Atherton et al., 2022; Hampson & Goldberg, 2006; Rantanen et al., 2007; Robins et al., 2001; Terracciano et al., 2010). These findings underscore the importance of maintaining mechanisms for user-driven customization and the need for periodic reassessment of dynamic constructs such as player-type profiles. Rather than treating these constructs as fixed attributes throughout prolonged app use, it is prudent to reassess them periodically.

9.4 Limitation and Future work

9.4.1 Choice of Mechanisms

A significant constraint of this study is the narrow scope of the mechanisms examined. Specifically, the modeling was deliberately restricted to mechanisms that could be aligned with Michie's Behavior Change Technique (BCT) taxonomy (Michie et al., 2013) and widely accepted gamification elements (Werbach et al., 2012). Consequently, a complete dimension concerning message characteristics was excluded from the preference matrix and ontology. This encompasses variations in feedback style, message framing, source credibility (e.g., expert vs. peer), and overall message quality (e.g., structured, evidence-based, persuasive). This was the Information dimension from the first model presented on Figure 11. This decision was made to preserve conceptual focus and maintain tractability, as the message-related literature is extensive and multidimensional. The incorporation of this dimension would necessitate a dedicated research effort, with the potential to serve as the foundation for a future thesis project. However, it is acknowledged that individual differences in message receptivity are pertinent to personalization, and that such features could significantly influence user engagement and intervention effectiveness. For instance, previous studies have demonstrated that specific personality traits, such as altruism, are correlated with a heightened predilection for credible message sources (Alqahtani et al., 2022a). These findings suggest promising opportunities for future work to extend the current ontology by incorporating dimensions related to communication strategy, potentially including message tone, sender identity, personalization depth, or emotional framing.

9.4.2 Selection of Dimensions to Include in the Preference Matrix

A secondary constraint pertains to the inadequate scope of user dimensions as delineated in extant literature. While a wide range of user characteristics relevant to personalization were retrieved during the scoping review, it was not feasible to incorporate all of them within the scope of this work. A series of strategic decisions were made to narrow the focus and avoid tackling an overly broad and heterogeneous personalization landscape.

Consequently, several potentially significant dimensions were excluded from the present version of the matrix and ontology. These omissions were not due to a lack of relevance; rather, they were a deliberate choice to maintain conceptual clarity and feasibility within the confines of this thesis. However, these dimensions could be explored in greater depth and formally integrated into future iterations of the ontology.

The primary user-related dimensions that were omitted are presented in the following section. These dimensions represent promising areas for the extension of the model, particularly in efforts aimed at achieving more holistic and fine-grained personalization in mobile health interventions.

9.4.2.1 Need for cognition

The construct of need for cognition is defined as the motivation that individuals inherently possess to engage in and derive pleasure from effortful cognitive activities. (Cacioppo et al., 1984; Cacioppo & Petty, 1982a). This individual difference is of particular pertinence in the context of message processing. Individuals with a high need for cognition tend to be more responsive to the strength and quality of arguments, while those with a low need for cognition are more influenced by peripheral cues (Axsom et al., 1987).

One of the primary reasons for the exclusion of this dimension from both the matrix and the ontology pertains to the publication timeframe of the pertinent literature. As early as the 1980s, fundamental studies addressing constructs such as the need for cognition and their influence on behavioral change and message processing were published. However, the present matrix is based on a scoping review restricted to literature published from 2008 onward, in order to align with the emergence and evolution of mobile health applications.

Given that the objective of the review was to identify personalization mechanisms applicable to mobile app environments, studies predating the widespread adoption of smartphones and app ecosystems were excluded by design. Consequently, although seminal theoretical frameworks such as the Need for Cognition have been firmly entrenched in the domain of psychology concerning persuasion and decision-making, they fell outside the purview of the inclusion criteria employed in this study. However, these earlier insights could be reconsidered and integrated in future extensions of the ontology, especially if their relevance can be demonstrated in contemporary mHealth contexts.

9.4.2.2 Social norm

Another dimension that was initially explored during the early stages of this research and included in the first version of the preference matrix was the concept of social norm. Social norms are frequently incorporated within behavior change theories, including the Theory of Planned Behavior. These norms represent the perceived social pressure to engage or refrain from engaging in specific behaviors (Ajzen, 1991). For instance, an individual surrounded by non-smoking family and friends who encourage cessation is more likely to engage in quitting, provided the social influence is perceived as salient and supportive.

A preliminary review of the extant literature suggests a correlation between a high social norm orientation and a preference for comparative feedback mechanisms (Hawkins et al., 2008a). By "comparative feedback mechanisms," we refer to feedback that positions the user's performance in relation to that of others (Smith & Lipnevich, 2018). Furthermore, the empirical data gathered through the questionnaire of this thesis indicated that individuals with high social norm scores expressed stronger preferences for mechanisms such as cooperation (OR=1.29, p=.03) and the demonstration of behavior (OR=1.32, p=0.1).

Notwithstanding the promising evidence, the decision was ultimately made to exclude this dimension from the final version of the preference matrix derived from the scoping review. This determination was informed by a synthesis of conceptual and empirical considerations. Conceptually, social norms were regarded as context-dependent, socially constructed factors, rather than as intrinsic user characteristics, such as personality traits or motivational orientations. Empirically, the extant literature yielded only a single preference link involving social norm, and this was specifically related to message framing, a dimension that was excluded from the scope of the final model, as discussed earlier. Nevertheless, these preliminary findings suggest that social norms could be a valuable addition in future extensions of the ontology, particularly in contexts where social dynamics and peer influence play a critical role in behavior change.

9.4.2.3 Selection of models for evaluation

After thorough examination of the extant literature, it was determined that the inclusion of two categories of user characteristics within the matrix would be the most efficacious utilization of available data. The two categories selected for inclusion were personality traits and player profile types, as these dimensions were the most frequently linked to motivational preferences in the extant literature. However, within each category, further selective decisions regarding the theoretical models to be retained had to be made.

With regard to personality assessment, we chose to exclude certain frameworks, including the Myers-Briggs Type Indicator (MBTI), due to ongoing controversies surrounding its psychometric validity and scientific reliability (Pittenger, 2005). Conversely, the present study opted to prioritize the Big Five model, a framework that continues to dominate the field of personality psychology, as evidenced by its widespread acceptance and empirical validation. This model has been a staple in behavioral change research, underscoring its significance in the academic and clinical domains.

With respect to player typologies, the extant literature proposes a variety of models. In the final matrix, only those that emerged through the scoping review were included, namely, the Hexad scale and BrainHex model. Two additional player models, Bartle's taxonomy (Bartle, 1996) and Yee's player motivations (Yee, 2006), were considered but ultimately excluded from the final model. The Bartle model was not retained due to the absence of any preference links in the extant literature connecting it to the mechanisms in our framework. For the Yee model, only limited and inconclusive associations were identified, insufficient to justify its inclusion at this stage.

Moreover, we encountered practical constraints related to questionnaire length and respondent burden when attempting to empirically validate the matrix. The implementation of comprehensive player profile and personality assessments would have resulted in a substantial prolongation of the study's duration, potentially leading to participant fatigue, diminished data quality, and heightened rates of attrition. Consequently, the Hexad scale was selected for inclusion in the study, as it was the most extensively represented model in the literature-derived matrix. Nevertheless, the BrainHex model, which was also represented in the matrix, remains a promising alternative and could serve as the basis for a complementary validation study in future work.

9.4.3 Contextual and Social-Ecological Considerations

A further limitation of this thesis is that personalization strategies were primarily modeled at the individual level, without fully addressing the broader social and environmental context emphasized in social-ecological and social-determinants frameworks. Social-ecological models underscore that health behaviors emerge from the dynamic interplay of multiple layers of influence, encompassing individual, interpersonal, organizational, community, and policy factors (McLeroy et al., 1988). The review indicates that most health promotion interventions remain focused on individual and interpersonal levels, with limited attention to organizational, community, or policy factors, largely due to resource constraints, evaluation challenges, and the dominance of individually oriented theories (Golden & Earp, 2012). The World Health Organization's framework on the social determinants of health (SDH) similarly underscores that the conditions in which people are born, grow, live, work, and age, including access to healthcare, are fundamental drivers of health outcomes and behaviors (WHO Commission on the Social Determinants of Health, 2008). The existence of disparities in access to power, resources, and opportunities has been demonstrated to contribute to unequal exposure to health risks. These disparities also serve to limit the ability of individuals to maintain healthy behaviors. A low socioeconomic position can restrict access to nutritious food, exercise equipment, or safe transportation, reducing both time and energy for self-care and hindering health literacy, the capacity to acquire, understand, and apply health information. Socioeconomic disadvantage has been demonstrated to be associated with chronic stressors, including financial strain, job insecurity, and social exclusion. These factors have been shown to further impede the development of healthy habits and to lead to an increased reliance on coping behaviors, such as smoking or overeating (Bartley, 2004). Consequently, while the present ontology provides a framework for individual-level tailoring, effective long-term personalization in mHealth should also account for these contextual determinants, integrating information about users' social environment, community norms, and structural constraints to better support sustainable behavior change.

9.4.4 Intention–behavior gap and insights from the validation study

A significant constraint of the present study pertains to the well-documented intention–behavior gap, wherein stated preferences or intentions do not invariably translate into sustained real-world utilization (Conner & Norman, 2022). The literature employed to construct the preference matrix and the present experiment primarily assessed intentions and feature appreciation, rather than long-term behavioral adoption. To address this concern, participants from our validation study first reported any previous mHealth use and the mechanisms they had actually engaged with. Logistic regressions were utilized to compare experienced and non-experienced users, revealing that prior mHealth users exhibited a lower propensity to select the Challenge feature (*OR*= *–0.58*, *p* = *.05*). The study also found that the participants assigned a lower rating to Challenge *(OR= 0.55, p <. .05)* and a higher rating to Self-Monitoring (*OR = 1.83, p <.05).* A thorough examination of the concordance between previously utilized mechanisms and current selections yielded a discernible pattern of alignment. The findings of the study indicated that participants who had previously utilized Prompts and cues were more inclined to select them again *(OR = 2.08, p <.01),* like for Self-Monitoring *(OR = 1.07, p <.05).* Additionally, those who had experienced Rewards demonstrated a higher propensity for its selection *(OR = 2.43, p < .05)*. Finally, participants who had previously engaged with Social Comparison exhibited a renewed preference for it *($OR = 1.46$, $p < .05$)*. In contrast, participants who had never used Social Comparison were, paradoxically, more likely to select it *($B = 20.11$, $p <.01$)*. Conversely, those who had never used Competition or Challenge were less likely to choose them (Competition: $OR = -19.54$, $p < .01$; Challenge: $OR = -0.90$, $p < .05$).

These supplementary findings, derived from the validation study, were not incorporated into the submitted manuscripts for publication but provide valuable context. The findings suggest that when participants have concrete prior experience with particular mHealth mechanisms, their stated preferences largely mirror their actual usage patterns. However, given that the primary outcome remains self-reported intention rather than objective, longitudinal engagement, the possibility of an intention–behavior gap underscores the need for future studies incorporating real-world usage data and long-term follow-up.

9.4.5 Issues and improvements to our questionnaire

As elaborated in Chapters 5, 6, and 7, the experimental phase revealed several methodological limitations. These limitations emerged from post-hoc reflection on the study design, data collection process, and statistical outcomes. They offer useful directions for refinement in future iterations.

Initially, participants were instructed to select precisely five mechanisms from a predetermined list of fifteen, a procedure that may have introduced a forced-choice bias. It is possible that some individuals may have included mechanisms that they did not genuinely find motivating, with the sole intention of meeting the quota. Alternatively, it is plausible that others may have been constrained by the artificial ceiling of five choices. This limitation may have reduced the ecological validity and nuance of the collected preference data. Nevertheless, this fixed-choice format was deliberately adopted to keep the questionnaire concise and limit participant burden, as longer surveys are well known to increase abandonment rates (Ganassali, 2008; Manfreda et al., 2002). Moreover, asking participants to restrict their selections to five required them to rank their preferences, which can help mitigate common rating biases such as acquiescence, social desirability, and consistency effects (Podsakoff et al., 2003). A potential solution for future studies would be to replace categorical selection with a continuous rating scale, thereby allowing participants to assign scores (e.g., from 1 to 7) to each mechanism. This approach would facilitate more nuanced analyses, enabling the assessment of relative preference strength across diverse user profiles without the use of arbitrary cutoffs.

Secondly, the composition of the sample gives rise to concerns regarding generalizability. The study population was predominantly composed of university students, resulting in a relatively narrow demographic profile in terms of age, education, and likely digital familiarity ($M = 29.42$, $SD = 10.41$). This homogeneity may limit the applicability of findings to broader or more diverse populations, particularly individuals from different sociocultural backgrounds or age groups. Nevertheless, evidence from research on digital behavior change and web-based health interventions suggests that age does not significantly influence the impact of these interventions on health behaviors (Lustria et al., 2013; Perski et al., 2017). Systematic reviews likewise show that demographic factors such as age, sex, and education typically have only minimal or inconsistent moderating effects (Lustria et al., 2013). Moreover, people who are most inclined to use health applications are generally younger and possess higher incomes (Krebs & Duncan, 2015), a profile that closely matches our participant sample and thus reinforces the relevance of our findings. This recruitment imbalance was primarily attributable to practical constraints. Despite outreach efforts via various social media platforms and flyer distribution in public areas, it became necessary to recruit extensively within the university setting to meet the minimum sample size requirements. This issue underscores the necessity for more diversified recruitment strategies in future replications.

Thirdly, although an a priori power analysis was conducted, the final sample size appeared insufficient to detect subtle differences across all mechanisms. Statistically significant associations were identified for a mere three out of the fourteen mechanisms examined, thereby suggesting that initial assumptions regarding effect size and variance may have been excessively optimistic. Future research endeavors should consider employing more conservative power calculations and exploring the use of alternative analytical approaches, such as mixed models or Bayesian methods, which have the potential to offer greater sensitivity in capturing individual variability.

Consequently, the efficacy of the customization mechanism could not be adequately assessed, despite its acknowledged significance within the domain of gamification research. The inherent breadth and user-defined nature of customization rendered it particularly challenging to represent it in the format of static mockup screens used in this study. It is recommended that subsequent studies take into account the incorporation of interactive or adaptive prototypes, which have the capacity to more accurately simulate the customization experience. This would facilitate a more precise evaluation of user engagement with such features.

9.4.6 Adaptation of the ontology

An ontology was created, containing exclusively the results of the aforementioned matrix from the scoping review. Subsequent research endeavors will entail the extension of this ontology by incorporating all extant results from the extant literature that were not necessarily identified in our scoping review, including more recent articles. However, it is also crucial to consider the dimensions that were excluded from this matrix, such as the integration of specific messages or social norms.

This ontology is in the preliminary stages of development, exhibiting considerable promise for future refinement. A promising direction for future research would be to incorporate more granular information from the referenced studies. This could include details such as the type of statistical analysis performed, the strength of the reported associations, the specific behavioral or gamification mechanisms tested, the target population characteristics, and the type of health behavior addressed. Integrating such metadata would enhance the precision, and interpretability, of the ontology, allowing for more nuanced evidence synthesis and personalized intervention design.

In future iterations, the proposed ontology could be aligned with the Behavior Change Intervention Ontology (BCIO) (Michie et al., 2021), a large-scale semantic framework developed within the Behaviour Change Intervention Ontology initiative. The BCIO is designed to provide a formal representation of behavior change interventions, capturing entities such as intervention components, target behaviors, populations, contexts, mechanisms of action, and outcomes. It serves as a foundational ontology within the broader Behavior Change Knowledge System and is intended to support evidence synthesis, intervention evaluation, and policy decision-making.

However, the BCIO alone does not account for variability in user receptiveness or motivational alignment. In such circumstances, the bottom-up perspective assumes paramount importance. The ontology developed in this study serves as a complementary framework to the BCIO, offering comprehensive representations of individual user profiles. These profiles encompass psychological traits, gamer types, and empirically substantiated preferences concerning specific mechanisms. This affords the system the capacity to ascertain, for instance, that a specific user may exhibit a marked predilection for collaborative challenges, while concurrently demonstrating disengagement from competitive tasks or punitive feedback.

The developed ontology provides a pragmatic pathway for seamless integration into mobile health (mHealth) applications by functioning as a structured knowledge base that client applications can query in real time to drive personalization. Upon registering or updating their profile, the mobile application can automatically transmit pertinent information, to the designated service. The inference engine linked to the ontology can then match user profiles to specific BCTs and gamification elements, returning a set of recommended mechanisms. These outputs can be utilized by the application to dynamically configure the interface, select appropriate mechanisms (e.g., self-monitoring, prompts and cues, quests without requiring manual updates from developers. The ontology's machine-readability (e.g., OWL/RDF) facilitates interoperability with existing personalization frameworks and analytics pipelines, enabling continuous refinement. As the user interacts with the application, engagement data feeds back into the system, updating individual profiles and fine-tuning recommendations. This architecture enables automated, evidence-based personalization that can scale across diverse user populations while maintaining consistency with the theoretical foundations encoded in the ontology.

Finaly, it would be advantageous to develop a website that would facilitate convenient access to the results of this ontology for application developers. To illustrate, developers have the option of selecting the user profile and personality dimension of their users from a drop-down menu. In turn, they will obtain a list of the mechanisms that this profile prefers or dislikes, along with the corresponding literature.

9.5 Conclusion

The present thesis has sought to address a series of interrelated research inquiries concerning the personalization of mobile health (mHealth) applications to facilitate behavior modification. A comprehensive literature synthesis, empirical validation, and semantic modeling were used to propose and evaluate a framework for tailoring motivational mechanisms to individual user profiles.

To identifies which dimensions should be considered when personalizing mHealth applications to support behavior change, a multi-phase literature review was conducted, which culminated in the development of a structured model of personalization dimensions. The model was grounded in theoretical taxonomies, such as the Behavior Change Technique (BCT) taxonomy, and gamification design principles, as well as empirical evidence. The resulting conceptual framework was formalized into a preference matrix and subsequently encoded into an ontology, offering a semantic representation of user-mechanism associations.

For the application of personalization in mHealth applications, we operationalized the identified personalization dimensions within a preference matrix and empirically validated it through a study. The alignment between observed preferences and literature-based predictions demonstrated the external validity of the matrix, underscoring its utility in guiding the development of adaptive mHealth systems.

In order to facilitate the development of personalized mHealth applications for behavioral modification by design professionals, the findings of the study were translated into a series of practical resources for designers and developers. We accomplished this by providing a structured preference matrix and an ontology that enables dynamic querying and integration. These tools function not only as repositories of personalization knowledge but also as foundations for automated decision-making in system design.

To explore how a user's personality profile can be effectively integrated into mHealth applications, we investigated methodologies for integrating personality assessment into mHealth applications, emphasizing the utilization of validated psychometric instruments to ensure data quality and ethical compliance. The ontology was enriched with metadata linking mechanisms to reliable measurement tools, thereby facilitating user-tailored interventions while maintaining scientific rigor.

Despite these contributions, several limitations were acknowledged, particularly concerning the exclusion of potentially relevant dimensions (e.g., message characteristics, social norms, and need for cognition) and the constraints associated with questionnaire design and sample composition. These limitations delineate a clear path for future research, which should aim to expand the ontology, enhance methodological robustness, and address broader user diversity.

In summary, the present thesis offers a foundational step toward a principled and empirically grounded approach to personalization in mHealth for behavior change. By establishing relations between user characteristics and mechanisms within a structured semantic framework, preference matrix and ontology, this thesis contributes to the advancement of knowledge in the field and establishes the foundation for the development of next-generation, personalized mHealth interventions for behavior change.

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