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User Engagement with Mobile Health Applications for Self-management of Diabetes: A Principal Component Analysis Approach

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Background and Purpose: Diabetes is a non-communicable disease that can arise from a genetic predisposition or develop due to the unhealthy lifestyle of an individual. mHealth applications (apps) can potentially revolutionise diabetes management by empowering people diagnosed with diabetes to take better control of their condition, promoting effective self-management. User engagement and sustained usage are critical determinants of mHealth apps' success. The study reported in this paper investigated the extent to which the User Engagement Scale (UES) can be applied in evaluating user engagement with a mHealth app for self-management of diabetes.
Methods: A 30-item UES questionnaire was distributed through Diabetes South Africa (DSA), a non-governmental organisation that supports and advocates for people living with diabetes in South Africa. Participants, who are either diagnosed with Type 1 or Type 2 diabetes, rated their agreement with each statement in the UES using a 5-point Likert scale. Principal Component Analysis (PCA) was conducted on 55 responses to evaluate the UES's dimensionality.
Results: PCA suitability was confirmed by the Kaiser-Meyer-Olkin (KMO) measure of 0.650 and a significant Bartlett's test of sphericity, $\chi2(435) = 1124.16$, $p < 0.001$. A new factor, Incentive, emerged by combining Aesthetic Appeal and Reward, which impacted user engagement. Additionally, Focused Attention and Perceived Usability were identified as significant predictors of user engagement. A revised 25-item scale was produced after five items were removed due to low factor loadings.
Conclusions: This study validated the UES in a mHealth app context among South African participants, suggesting that the three-factor, 25-item solution is effective in evaluating user engagement in mHealth applications for self-management of diabetes.

Keywords: Diabetes self-management, mHealth, User engagement, User engagement scale, UES.

1 Introduction and Background

Diabetes affects society both clinically and economically [1]. According to Kumar et al. [2], there are an estimated 537 million people diagnosed with diabetes globally, and this number is expected to increase to 783 million by 2045 [2]. Diabetes, including other non-communicable diseases, will cost more than an estimated $47 trillion (R864 trillion) to manage worldwide in the next 20 years [3].

The two prevalent classifications of diabetes are Type 1 and Type 2. Type 1 diabetes is the complete loss of insulin-producing cells, a hormone that controls a person's blood glucose level. Without proper regulation of glucose emanating from food consumption, the build-up of glucose in blood cells leads to the onset of diabetes and further conditions such as hyperglycaemia [4]. Patients will typically experience long-term symptoms that include fatigue, skin conditions such as psoriasis and pruritus, as well as weight loss. There are further risks of more serious conditions associated with Type 1 diabetes, such as ketoacidosis, which occurs when there is an excessive level of ketones in the body due to a lack of sufficient insulin for the uptake of blood sugar by cells for energy [5]. This is a condition which may lead to coma in a patient or even death.

Type 2 diabetes is a progressive loss of the cells that produce insulin and is the most prevalent form of the disease. The onset of this type of diabetes is typically gradual and often associated with insulin resistance, where the body's cells do not respond effectively to insulin. Over time, the pancreas is unable to produce enough insulin to compensate for this resistance, leading to elevated blood glucose levels. Some

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of the risk factors for Type 2 diabetes include obesity, a sedentary lifestyle, poor diet and genetic predisposition to the disease [6]. In addition, the symptoms of Type 2 diabetes can be less pronounced initially but may include frequent urination, excessive thirst and persistent hunger.

According to Sifunda et al. [7], it is estimated that nearly 4.6 million people were living with diabetes in South Africa in 2019. However, the prevalence of the disease has increased significantly from about 4.5% in 2010 to 12.7% in 2019, with more than half of the people living with the disease not diagnosed. Hence, the term 'silent killer' is often used to refer to Type 2 diabetes. According to the WHO [8], in 2021, diabetes was one of the top 10 causes of death in South Africa and occupied position number five. At the same time, many countries from sub-Saharan Africa, including South Africa, have very low population-to-healthcare worker ratios [9].

The risks associated with diabetes can be mitigated by adopting healthier lifestyle changes like increased physical activities to reduce the onset of the disease [10]. Regular physical activity enhances insulin sensitivity, which allows cells to utilise glucose more effectively, thereby reducing blood sugar levels [11]. In conjunction with the traditional methods of diabetes management, technological advancements offer new opportunities for patient care and disease management. Mobile health (mHealth) involves leveraging mobile technology to improve healthcare services [12]. The use of mHealth applications (apps) can be harnessed to enhance the quality of healthcare service delivery. This enhancement can include various aspects of value, including the speed and precision of diagnosis, tailoring treatment plans to individual needs, and providing guidance for behavioural changes [13].

mHealth delivered through mobile devices could facilitate the provision of healthcare services to areas without access to basic health services due to geographical or resource constraints. Healthcare services can also be achieved at a more rapid rate, depending on the rollout of network infrastructure. The added benefits of mHealth include immediate and around-the-clock healthcare access [14]. Given the increasing prevalence of smartphone ownership, mHealth is positioned to have a significant impact on involving patients in self-care [15]. As of January 2024, there were 5.61 billion unique mobile phone users worldwide, equating to 69.4% of the global population [16]. This figure highlights the widespread adoption and access to mobile technologies, reinforcing the potential impact of mHealth apps in health-related fields. There is significant potential for mHealth to greatly enhance access to specialised clinical diagnostics and treatment guidance [13]. The increase in the ownership of smart mobile devices has been accompanied by the proliferation of mHealth apps, with a combined 300,000 health-related apps existing and about 200 being released daily [17]. One such mHealth application is MySugr, a free mHealth app that allows users to log meal intake, track physical activity and integrate data sources such as glucometers and fitness trackers. The MySugr app provides analytics aimed at the long-term management of diabetes. The app also generates reports that indicate whether a user is within their target blood glucose range or if corrective action is required.

Although promising, mHealth is also unfortunately subjected to factors within the Information Technology (IT) discipline that could affect the success of mobile apps [18]. For example, these factors include the complexity of the IT project being implemented, potentially resulting in failure [19]. Other factors include having a high number of bugs, which could lead to users abandoning the app [20]. Due to the potential failure of healthcare-related projects, it is important to consider the factors that could have an impact on the success of mHealth apps [2021]. Despite the high growth rate and availability of mHealth apps, there remains little investigation of the factors that affect their success [21]. This view is supported by Oakley-Girvan et al. [22] and Santos-Vijande et al. [23], with these researchers emphasising that user engagement, an essential aspect, is often overlooked in the design and evaluation of mHealth apps. Given this consideration, among the factors that influence the success of mHealth apps, such as usability and adoption [18], an important determinant of success is users' engagement and sustained use of mHealth apps [24]. User engagement entails a user's involvement in personal meaning and vigour, dedication, and absorption [25]. Previous studies have indicated that the underlying constructs of user engagement include usability, aesthetics, focused attention, novelty, and felt involvement endurability [26]. These factors were later refined to usability, aesthetics, focused attention, and reward [27]. These constructs indicate that user engagement relates to a psychological state which is affective, cognitive, and behavioural, and includes emotional elements [28].

Although previous studies have evaluated and measured user engagement, detailed knowledge regarding how to guide the development of apps to ensure that they possess the basic requirements of engagement and support user commitment to the app is lacking [29]. According to O’Brien and Toms [30], the

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complexity and abstract nature of user engagement add to the reasons why there is a sparseness of studies that focus on measuring user engagement. Consequently, the objectives of this study are:

1. To investigate the factors that could influence user engagement with mHealth apps for the self-management of diabetes.
2. To determine which of the User Engagement Scale (UES) factors, developed by O'Brien and Toms [30], can predict user engagement with mHealth apps for the self-management of diabetes.

The UES has been used in previous studies to measure user engagement with different mobile apps. The scale defines the full range of theoretical elements required in a technology to influence user engagement with an app to realise the intended benefits and return on investment. The scale has been applied to over 40 studies using different applications, including information search, online news, and online videos [31, 32]. The UES offers a robust measurement method to evaluate engagement with digital environments. In the context of this study, MySugr, a mobile mHealth app available on both iOS and Android platforms, was utilized as the mHealth app of choice because it is widely used and endorsed by Diabetes South Africa (DSA). This non-governmental organization supports and advocates for people living with diabetes in South Africa. It should be noted that the goal of this study is not to evaluate or test any software or application. Rather, the aim was to determine the extent to which the UES can be used to evaluate user engagement with mHealth applications that support the self-management of diabetes. Any mHealth application that supports self-management of chronic disease could have been selected for this purpose. The choice of MySugr is primarily because it is an app that has been endorsed for use by diabetes patients by DSA. As stated earlier, South Africa has a high prevalence of diabetes and a limited number of healthcare workforce. mHealth applications like MySugr can address local challenges but require sustained user engagement to succeed. Although widely used, the User Engagement Scale (UES) was originally developed for Western audiences. Hence, there is a need to investigate its applicability to the South African context.

2 Theoretical Framework

The research model for this study is based on the integration of two theories, the flow theory [33] and the theory of experience [34]. This study adopted the definition that user engagement is a quality of user experience and is characterised by attributes of the system [30]. According to O'Brien and Toms [30], the definition of an attribute is a characteristic that influences user engagement. The adopted definition [30] is informed by the synthesis of the two theories in sections 2.1 and 2.2.

2.1 The flow theory

User engagement research is informed by the flow theory [30]. Flow theory postulates that certain activities, such as gaming and writing [35], could have a user so captivated to the extent that little else matters in the user's environment [33]. The activity can be viewed as highly pleasurable or an end in itself. Flow is critical in user engagement because it represents a state of immersion and focus, where users are fully absorbed in the activity they are performing. This psychological concept is relevant in the context of user engagement with digital applications, including mHealth apps for self-management of diabetes, as it could help in explaining why users are motivated to use an app. According to O'Brien and Toms [30], attributes like feedback, control, challenge, attention, motivation, goal-directed behaviour, and meaningfulness are present in flow experiences. These attributes are also intrinsic to user engagement. A brief explanation of the attributes related to flow theory is provided in the following paragraphs:

- *Feedback* can be defined as the response from the environment or the system that transmits the appropriateness of the action taken [30].
- *Control* refers to how a user perceives their ability to manage their interactions with an app, or the extent to which they feel they are in control of their interactions with an app or a system [30].
- *Challenge* refers to a cognitive or navigability task given to a user. A cognitive challenge refers to how much mental effort is expended by a user when performing tasks, while a navigability challenge refers to the effort needed by a user when navigating an interface [30].
- *Focused attention* refers to the concentration of mental activity during the engagement [30]. A user's attention is either maintained or lost through the ability to communicate a specific message effectively.

- *Motivation* presents itself as the need to achieve a goal or have an experience with the interface. Flow experiences are intrinsically motivating. Meaning that pleasure is derived from the action itself, while in user engagement, this may not be the case.
- *Flow* requires a user to form specific goals during their experience. In contrast, user engagement does not specifically need the user to have a specific interaction goal.
- *User engagement* activities may offer a level of *meaningfulness*. This could be in the form of the experience being joyful or challenging [30]. This contrasts with flow, which stresses that the experience has meaning and the user is purposeful in the activity in which they are engaged with.

2.2 The theory of experience

The theory of experience by Dewey [34] was adapted for the field of education by McCarthy and Wright [36] to explain aspects of user experience with technology. Based on the philosophy of experience [33], the threads of experience decompose the user experience into sensual, emotional, compositional and spatiotemporal threads:

- The *sensual* threads address the visual feedback, the auditory cues, and the tactile sensations that users experience separately during their interaction with a system [33]. The sensual thread presents the information and graphical elements that promote engagement when it meets the customizable needs of the user [30].
- *Emotional thread* relates to a user's engagement with a product on an emotional level. It presents the affective experiences of users and how engagement is influenced. This thread is linked to the motivational and interest attributes that influence a user's engagement with a system.
- *The spatiotemporal* thread refers to the aspects of space and time during the experience. This includes the user's perception about being aware of their physical surroundings and links to focused attention and absorption (as explained in flow experiences).
- *Compositional thread* is woven around the sensual, emotional and spatiotemporal threads to articulate engagement as a process. The engagement process involves an initial engagement, followed by continued engagement, and eventually disengagement [30].

Building on the threads of experience, O'Brien and Toms [30] postulated that the theory of experience is relevant to user engagement and mapped the process of user engagement by aligning it with the threads of experience and identifying the attributes present at each stage of engagement. Therefore, this research aims to determine the applicability of the user engagement scale (UES) to predict users' engagement with the MySugr mHealth app, which is used for the self-management of diabetes.

2.3 Research hypothesis

The UES, developed by O'Brien and Toms [30], is informed by the flow and experience theories. Based on the results of a 2018 study, Santos-Vijande et al. [23] refined the UES from a six-factor to a four-factor, 30-item questionnaire [26]. The four factors, namely Focused Attention (FA), Perceived Usability (PU), Aesthetic Appeal (AE), and Reward (RW), formed the basis of the hypotheses that were tested in the research reported in the paper. The factors and applicable hypotheses for the study reported in this paper are:

- Focused attention (FA): Focused attention relates to how a user perceives time and the awareness of their physical environment while interacting with a digital system. O'Brien and Toms [26] indicated that a change in FA will influence user engagement. To evaluate the influence of FA on user engagement with a mHealth app that supports self-management of diabetes, the following hypothesis was developed:
  H1: Focused attention will have a positive effect on user engagement with the mHealth application that supports self-management of diabetes.
- Perceived usability (PU): Perceived usability deals with the subjective assessment of how easy a system is to use and how well it meets the user's needs [30]. The level of difficulty when using an app is also related to PU. For example, the ease with which a user can navigate a website to complete a task would influence the user's perceived usability. Control and how the user perceives this during their interaction is also related to PU. This construct measures the perceived effort, the ability to accomplish tasks and

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the emotions felt during the interaction, hence, the label 'perceived usability' [30]. To evaluate the influence of PU on user engagement with the mHealth app that supports self-management of diabetes, it is hypothesised that:

H2: Perceived usability will have a positive effect on user engagement with the mHealth application that supports self-management of diabetes.

- Aesthetic appeal (EA): Aesthetics is the visual appearance that relates to interface as it aligns to the design principles which are symmetry, balance, emphasis, harmony, proportion, rhythm and unity [30]. The construct relates to aspects that affect the interface, covering the screen design and the application's visual appeal [30]. This also includes the graphics that are presented to the user. EA is considered a stable indicator for predicting user engagement [27]. To determine the influence of EA on user engagement with the mHealth app that supports self-management of diabetes, it is hypothesised that:

  H3: Aesthetic appeal will have a positive effect on user engagement with the mHealth application that supports self-management of diabetes.
- Reward (RW): Reward refers to the hedonic features of experience and the overall success of the interaction. Reward originally consisted of three constructs, namely endurability, novelty and felt involvement [30]. These were later merged into the single construct of reward [27]. Endurability relates to the probability of a user endorsing a product to someone else, the perception of how successful the experience was and whether the user was able to complete tasks. Novelty relates to how much curiosity the platform generated. The app should at least present something new and unexpected for the user. Felt involvement relates to a user feeling 'caught up' in the experience of interacting with the app. There is also a relation to the fun experienced in the engagement. The reward construct measured well on reliability and is a robust predictor of engagement [27]. To determine the influence of reward on user engagement with a mHealth app that supports self-management of diabetes, the following hypothesis was developed:

  H4: Reward has a positive effect on user engagement with the mHealth application that supports self-management of diabetes.

The research model of the study regarding the factors affecting user engagement in mHealth applications that support diabetes self-management is illustrated in **Error! Reference source not found.**.

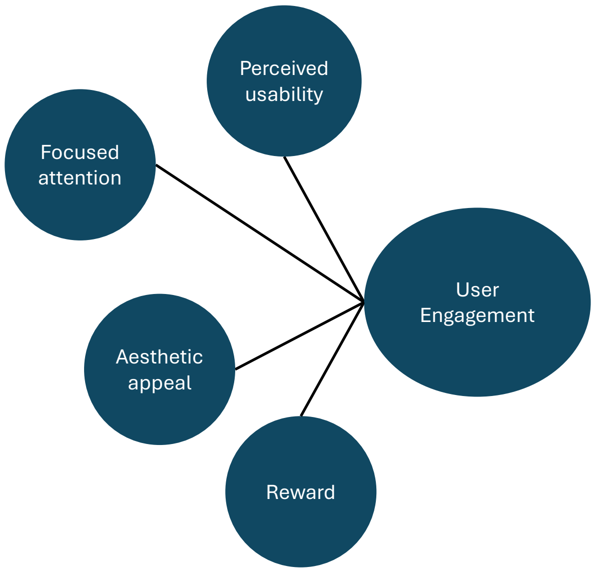

Figure 1. Research model

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3 Materials and Methods

3.1 Research design

The questionnaire and subscales adopted in this study were previously validated for their reliability by O'Brien [33]. The results of the reliability of each of the UES factors are shown in Table 9.

Table 9: UES Scale Reliability

Factor	*ω* MacDonald's Omega	Number of Items
Focused attention	0.92	7
Perceived usability	0.92	8
Aesthetic appeal	0.90	5
Reward	0.87	10

The research instrument was an online questionnaire through the survey strategy to collect the data from participants diagnosed with Type 1 or Type 2 diabetes who were using the MySugr app to manage their diabetes. Participants were recruited through the DSA, thus ensuring that only people who were living with diabetes completed the questionnaire. The questionnaire was distributed through DSA's social media channels with a link and QR code that participants could scan to complete the survey. A non-probability snowball sampling approach was used to ensure a good response rate. The data collection period lasted six weeks from July to mid-August 2023. The questionnaire was designed on the Qualtrics survey web platform. The questionnaire used a 5-point Likert scale, which participants used to indicate their agreement with each statement, with 5 being strongly agree and 1 being strongly disagree. All the questionnaire statements were set as mandatory in Qualtrics to ensure that there were no incomplete responses. However, to ensure that participation remains voluntary, study participants were asked to leave the survey by closing their browsers if they were no longer comfortable with continuing to participate in the study. A sample of the questionnaire is provided in Appendix A. Ethical clearance for the study was obtained from the Faculty of Economic and Management Sciences at the University of Pretoria.

3.2 Data analysis approach

Data from quantitative research can be analysed using descriptive or inferential methods. Both methods were adopted in this study through the normality of items with central tendency and the variability of the data with descriptive statistics, as well as correlation analysis and testing for inferential statistics. The survey responses were analyzed using the Statistical Package for the Social Sciences (SPSS) version 28. Before the analysis, the survey responses were prepared to ensure the accuracy of the research results. This preparation included converting the data into an interpretable format for input into the SPSS analysis tool, coding the data, checking for missing values and performing data transformation. Because each statement on the questionnaire was set as mandatory in Qualtrics, there were no missing values in participants' responses.

Some of the survey statements were negatively worded items, e.g., PU1: "I felt frustrated while using the MySugr mHealth application to manage diabetes" (see the survey instrument in Appendix A). Hence, these items were reverse coded during the data preparation stage, where a scale of 1 was changed to 5. Descriptive statistics include a measure of central tendency and a measure of variability (spread). Central tendency measures consist of the mean, median, and mode, while variability is assessed using standard deviation, variance, minimum and maximum values, kurtosis, and skewness [37]. The descriptive statistics indicated reasonable means, standard deviations, skewness and kurtosis, thus supporting the normality assumptions required for Principal Component Analysis (PCA) [38]. Based on the descriptive statistics provided in Table 10, the Kaiser–Meyer–Olkin (KMO) value of 0.650, and Bartlett's test of sphericity, which was significant at $\chi2(435) = 1124.16$, $p<0.001$, it was concluded that the research data were suitable for a PCA. The descriptive statistics indicate reasonable means, standard deviations, skewness, and kurtosis required for a PCA. The significant Bartlett's test [39] and acceptable KMO measure [40] further support the adequacy of the survey data for PCA.

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Table 10: Descriptive statistics per questionnaire item

Item	Mean	Median	Std. Deviation	Skewness	Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis
FA1	3.09	3.00	1.043	-0.301	0.327	-0.544	0.644
FA2	3.07	3.00	0.988	-0.275	0.325	-0.640	0.639
FA3	3.05	3.00	0.951	-0.380	0.322	-0.648	0.634
FA4	2.84	3.00	0.977	0.341	0.322	-0.276	0.634
FA5	3.05	3.00	0.931	0.317	0.322	-0.334	0.634
FA6	3.25	3.00	0.907	-0.073	0.322	-0.320	0.634
FA7	2.91	3.00	0.928	0.042	0.322	-0.240	0.634
PU1	3.60	4.00	1.011	-0.674	0.322	0.146	0.634
PU2	3.60	4.00	1.029	-0.597	0.322	-0.010	0.634
PU3	3.67	4.00	1.019	-0.707	0.322	0.243	0.634
PU4	3.67	4.00	0.982	-0.505	0.322	-0.168	0.634
PU5	3.60	4.00	1.047	-0.627	0.322	-0.112	0.634
PU6	3.65	4.00	1.022	-0.652	0.322	0.155	0.634
PU7	3.49	4.00	0.940	-0.736	0.322	-0.229	0.634
PU8	3.25	3.00	0.927	-0.105	0.322	-0.483	0.634
AE1	3.58	4.00	0.875	-0.775	0.322	0.513	0.634
AE2	3.55	4.00	0.899	-0.538	0.322	0.172	0.634
AE3	3.64	4.00	0.930	-0.630	0.322	0.187	0.634
AE4	3.65	4.00	0.799	-0.643	0.322	0.083	0.634
AE5	3.53	4.00	0.959	-0.603	0.322	0.348	0.634
RW1	3.69	4.00	0.858	-0.807	0.322	0.987	0.634
RW2	3.55	4.00	0.959	-0.265	0.322	-0.846	0.634
RW3	3.36	3.00	0.950	-0.265	0.322	-0.492	0.634
RW4	3.62	4.00	0.757	-0.551	0.322	0.077	0.634
RW5	3.71	4.00	0.936	-0.499	0.322	0.131	0.634
RW6	3.56	4.00	0.877	-0.201	0.322	-0.577	0.634
RW7	3.71	4.00	0.832	-0.603	0.322	0.012	0.634
RW8	3.53	4.00	0.940	-0.706	0.322	0.526	0.634
RW9	3.56	4.00	0.834	-0.408	0.322	-0.361	0.634
RW10	3.75	4.00	0.821	-0.321	0.322	-0.257	0.634
FA = Focused Attention PU = Perceived Usability AE = Aesthetic Appeal RW = Reward							

As stated in Section 1, the aim of the research was to determine the applicability of the UES to predict user engagement with mHealth apps for the self-management of diabetes. The PCA method was used to analyze the research data. PCA is particularly suitable when the goal is to reduce data dimensionality and highlight its main features. Previous studies have used PCA to evaluate the UES [41, 42]. In this study, PCA was used to evaluate the responses related to the subscales of FA, PU, AE and RW.

Another consideration was the sample size. During the data collection period, 55 participants completed the questionnaire. According to Jenkins and Quintana-Ascencio [43], a sample size of 50 is sufficient to perform regression analysis in the context of PCA. Similarly, Latif et al. [44] indicated that a sample size of 50 participants is acceptable in studies that utilize PCA. Following these guidelines, the sample size of 55 collected in this study was deemed adequate and suitable for factor analysis. This lower sample size challenge is not uncommon in medical-related research, where the median is 20 respondents [43].

Principal axis factoring computations were carried out with direct Oblimin rotation on the dataset. The items underwent analysis to identify factor loadings that were either notably high or low. The correlation between the variable and the underlying factor is referred to as the factor loading. There is no agreement among researchers regarding the appropriate cut-off for factor loadings. Some studies, such as Stevens [45],

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suggest a cut-off of less than 0.3, while others, including Hair [46], recommend a cut-off greater than 0.4. This study adopted the recommendation by Comrey and Lee [47] and Tabachnick et al [48], who recommended values < 0.4 as this is seen as being more rigorous.

To determine the number of factors to retain for analysis, the three criteria used were (i) retaining factors with an Eigenvalue > 1 [49], (ii) examining the Scree plot and performing a Scree test and, (iii) performing a parallel analysis to compare the observed Eigenvalues with those from random data [50]. After the initial factor analysis, several items exhibited cross-loading, specifically the following items: Item 7 FA7 ('During this experience, I let myself go'), Item 14 PU7 ('I felt in control while using MySugr'), Item 15 PU8 ('I could not do some of the things I needed to do while using MySugr'), Item 23 RW3 ('The experience of using MySugr did not work out the way I had planned') and Item 26 RW6 ('I continued to use MySugr out of curiosity'). These items were subsequently removed from the analysis due to their weak loadings (i.e., below the threshold of 0.4). The analysis was then re-run without these items to establish a better factor structure.

4 Results

4.1 PCA results and reliability of the user engagement scale

The 30 items of the UES were subjected to a PCA to determine how many factors were to be extracted using the Kaiser criterion [48], which determines the number of factors to retain. The results of the PCA analysis initially suggested that nine factors could be extracted (Eigenvalues > 1), explaining 76.88% of the variance in the data. This was seen as an impractical solution. The first factor was particularly strong, explaining 30.38% of the variance. Horn's parallel analysis was conducted, with the results suggesting that five factors could be extracted [51]. However, theoretically, four factors were mostly cited in previous studies that are similar to the current one. For instance, O'Brien et al. [27] confirmed a four-factor UES structure. Similarly, Banhawi and Mohamad Ali [52] and Wiebe et al. [53] also supported this four-factor model. The result of the five-factor solution was also notably not well-defined. Three items exhibited cross-loadings, meaning they have substantial loadings on more than one factor. Further analysis revealed that a four-factor solution was also not well-defined. The fourth factor contained only two items (PU4 and RW3), which is insufficient for a well-defined factor [54]. Additionally, one of the items exhibited significant cross-loading on another factor, which diluted its unique contribution to factor four. This cross-loading indicates that the item does not exclusively belong to factor four and shares variance with other factors, further weakening the definition and interpretability of factor four.

The next step was to explore a three-factor solution. The rotated pattern matrix is presented in Table 11 with loadings < 0.4 suppressed. The first factor was a combination of the Aesthetic Appeal and Reward items. Item 13 (from Perceived Usability) also showed a loading on this factor, with a cross-loading on the third factor. This factor was termed Incentive. 'Incentive' is an appropriate term to describe both Aesthetic Appeal and Reward because it conveys the idea of providing motivation or inducement for certain behaviours or actions.

Aesthetic Appeal can serve as an incentive by motivating individuals to engage with an application or system due to its visual aesthetic [55]. Similarly, Reward can function as an incentive by motivating people to achieve a specific goal or complete a task to obtain that Reward. This motivational aspect is central to understanding why the term 'Incentive' effectively encompasses both Aesthetic Appeal and Reward. All items from the original Focused Attention factor were included in the second factor. The third factor mostly contained factors from Perceived Usability, with one item from Aesthetic Appeal loading and one from Reward also loading here. These two factors were therefore well-identified in the current data set.

Table 11: The proposed three-factor solution

Pattern Matrix			
Subscale Items	Factor		
	1	2	3
RW10: The experience of using the MySugr mHealth application to manage my diabetes was fun.	0.875		

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RW7: The content of the MySugr mHealth application for the management of diabetes incited my curiosity.	0.721		
AE1: The MySugr mHealth application for diabetes management is attractive.	0.710		
AE4: The MySugr mHealth application for the management of diabetes is appealing to the visual senses.	0.633		
RW2: I consider my experience of using the MySugr mHealth application to manage my diabetes a success.	0.620		
AE2: The MySugr mHealth application for diabetes management is aesthetically appealing.	0.609		
RW8: I was really drawn into the experience of using the MySugr mHealth application to manage my diabetes.	0.597		
RW4: My experience of using the MySugr mHealth application to manage my diabetes is rewarding.	0.558		
RW9: I felt involved in the experience of using the MySugr mHealth application to manage my diabetes.	0.525		
AE3: I liked the graphics and images of the MySugr mHealth application for the management of diabetes.	0.491		
RW1: Using the MySugr mHealth application to manage my diabetes is worthwhile.	0.479		
PU6: This experience of the MySugr mHealth application to manage my diabetes was demanding.	-0.419		0.403
RW6: I continued to use the MySugr mHealth application for the management of diabetes out of curiosity.			
FA2: I was so involved in the experience of using the MySugr mHealth application to manage my diabetes that I lost track of time.		0.845	
FA4: While using the MySugr mHealth application to manage diabetes, I lost track of the world around me.		0.764	
FA1: I lost myself in the experience of using the MySugr mHealth application to manage my diabetes condition.		0.637	
FA3: I blocked out things around me while using the MySugr mHealth application to manage my diabetes condition.		0.589	
FA5: The time I spent using the MySugr mHealth application to manage my diabetes just slipped away.		0.585	
FA6: I was so absorbed in the experience of using the MySugr mHealth application to manage my diabetes.		0.488	
FA7: During this experience of using the MySugr mHealth application, I let myself go.			
RW3: The experience of using the MySugr mHealth application to manage my diabetes did not work out the way I had planned.			
PU2: I found the MySugr mHealth application confusing to use.			-0.948
PU1: I felt frustrated while using the MySugr mHealth application to manage diabetes.			-0.784
PU3: I felt annoyed while using the MySugr mHealth application to manage diabetes.			0.647
PU5: Using the MySugr mHealth application to manage my diabetes was taxing.			0.532
RW5: I would recommend the MySugr mHealth application for the management of diabetes to my family and friends.			-0.519
AE5: The screen layout of the MySugr mHealth application for the management of diabetes is visually pleasing.	0.438		-0.518

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PU4: I felt discouraged while using the MySugr mHealth application to manage diabetes.			0.466
PU7: I felt in control while using the MySugr mHealth application to manage my diabetes.			
PU8: I could not do some of the things I needed to do while using the MySugr mHealth application to manage my diabetes.			
Extraction Method: Principal Axis Factoring. Rotation Method: Oblimin with Kaiser Normalisation. a. Rotation converged in 22 iterations. FA = Focused Attention; PU = Perceived Usability; AE = Aesthetic Appeal; RW = Reward			

Items 7 (FA7), 14 (PU7), 15 (PU8), 23 (RW3) and 26 (RW6) did not show substantial loadings (> 0.4) on any of the factors and were subsequently removed. The removal of items aligns with similar health-related studies, for instance, Holdener et al. [56]. The reliability estimates for all factors exceeded the acceptable threshold of 0.7, indicating ideal internal consistency. Specifically, the factors of the Incentive, FA and PU subscales of the UES demonstrated high reliabilities, with Cronbach alpha values of 0.902, 0.822 and 0.884, respectively.

4.2 Correlation between constructs

The Pearson correlation coefficient between Focused Attention and Incentive is -0.228 with a *p-value* of 0.095. This indicates a small, negative correlation that is not statistically significant at the 0.05 level. The Pearson correlation coefficient between FA and PU is -0.270 with a *p-value* of 0.046, indicating a small, negative correlation that is statistically significant at the 0.05 level. This finding is aligned with a previous study by O'Brien et al [27], where a negative Focused Attention and Perceived Usability were also noted, where the authors found a surprising negative link between the two in online shopping. Focused Attention, which involves being fully absorbed in an activity, usually connects well with usability factors such as control and challenge. However, the laboratory setting and assigned tasks in the study by O'Brien et al [27] might have made it difficult for participants to achieve deep focus, leading to lower Focused Attention scores. Despite the negative relationship, both Focused Attention and Perceived Usability are important for the overall user experience, as shown by the analysis, which revealed that removing either factor made the model weaker, as per the findings by O'Brien [57].

4.3 Hypothesis testing

The hypotheses stated in section 2.3 were tested using the results obtained from the research data to determine the relationships between Focused Attention (FA), Perceived Usability (PU), Aesthetic Appeal (AE) and Reward (RW) in user engagement with MySugr, a mHealth app for self-management of diabetes.

To reiterate, the initial four hypotheses formulated were:

- H1: Focused Attention will have a positive effect on user engagement.
- H2: Perceived Usability will have a positive effect on user engagement.
- H3: Aesthetic Appeal will have a positive effect on user engagement.
- H4: Reward will have a positive effect on user engagement.

The AE and RW factors combined to form a single factor termed Incentive. Given this overlap, Hypotheses 3 and 4 were combined into a single hypothesis, i.e., H3:

- H3: Incentive will have a positive effect on user engagement.

H1: Focused attention and user engagement: The hypothesis that FA (H1) would have a positive effect on user engagement was supported by analysis of the research data. The standardized path coefficient was -0.32 and was significant *($p < .019$)*. This aligns with previous studies by O'Brien and Toms [30] in which focused attention was a significant predictor of engagement in digital experiences. However, as in the webcast study by O'Brien and Toms [26], the current study found that the level of FA was less influential than expected, possibly due to the structured and task-oriented nature of the MySugr app.

H2: Perceived usability and user engagement: The hypothesis that PU (H2) would have a positive effect on user engagement was supported by analysis of the research data and is consistent with the findings of

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O'Brien and Toms [30]. The standardized path coefficient was 0.81 and was significant *($p < .001$)*. This result underscores the critical role that usability plays in the effectiveness of mHealth apps, particularly in ensuring that users can easily navigate and interact with the app, which is crucial for sustained engagement.

H3 (combined hypothesis): Incentive and user engagement: Incentive was found to have a strong positive effect on user engagement. The standardized path coefficient was 0.73 and was significant *($p < .001$)*.

The results validated the dataset's suitability for a PCA analysis and informed the merging of Aesthetic Appeal and Reward into the 'Incentive' factor. This adjustment enhances the research relevance by addressing the role of visual and motivational elements in improving engagement. The exclusion of low-loading items strengthened the scale's reliability. Findings, such as the negative correlation between Focused Attention and Perceived Usability underscore the need to balance immersion and ease of use. These insights emphasize the importance of combining intuitive, aesthetic, and context-sensitive features into mHealth apps to improve engagement.

5 Discussion

As stated in section 1, the objectives of the research reported in this paper are as follows:

1. To investigate the factors that could influence user engagement with mHealth apps for the self-management of diabetes.

Based on the results of the analysis, Focused Attention (FA), Perceived Usability (PU), and Incentive (which combines Aesthetic Appeal and Reward) have a significant influence on user engagement. FA and PU were found to be strong predictors of user engagement, underscoring the critical role of these two factors in the design of effective mHealth apps. Incentive had a moderate positive impact, suggesting that while important, it must be carefully balanced with other elements.

2. To determine which of the User Engagement Scale (UES) factors, developed by O'Brien and Toms [30], can predict user engagement with mHealth apps for the self-management of diabetes.

The UES was adapted for a mHealth app in the context of this study, with modifications that enhanced its relevance to the self-management of diabetes. This adaptation facilitated a more accurate measurement of user engagement, indicating the UES's robust applicability across different contexts. The analysis confirmed that specific UES factors, notably Focused Attention and Perceived Usability, are significant predictors of user engagement. This suggests that the UES is suitable for predicting and enhancing engagement with mHealth apps. The UES demonstrated good internal consistency, with Cronbach's alpha values exceeding the acceptable threshold of 0.70–0.79. This confirms that the UES is a dependable scale for assessing user engagement in this specialized context.

The findings from this research have practical and theoretical contributions concerning mHealth applications for self-management of diabetes, including the following:

- The research results provide evidence on the factors that influence user engagement, particularly Focused Attention, Perceived Usability, and Incentive. This contributes to the improved understanding of user engagement with mHealth applications for self-management of diabetes.
- The research adapted the original four-factor, 30-item questionnaire and validated the new three-factor, 25-item UES for a mHealth app for self-management of diabetes to demonstrate the applicability and reliability of the UES in a new context.
- The study also has practical implications for designers of mHealth applications for self-management of chronic disease in general and diabetes in particular. Designers must prioritize the optimization of usability since Perceived Usability is strongly linked to engagement. Hence, designers must focus on intuitive navigation and reducing cognitive load on users. Secondly, designers should integrate visually appealing interfaces and motivational elements like gamification or progress tracking to sustain user engagement.

6 Conclusion

This study investigated the factors that could influence user engagement with mHealth apps for the self-management of diabetes using the UES developed by O'Brien and Toms [30]. Data was collected from 55

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participants living with diabetes who were using the MySugr mHealth app at the time of data collection. The Principal Component Analysis (PCA) method was used to analyse the research data. The results showed that Focused Attention and Perceived Usability are significant predictors of user engagement. In addition, Incentive was shown to have a moderate positive impact on user engagement. The study provides an improved understanding of the factors that could influence user engagement with mHealth apps for self-management of diabetes.

6.1 Study limitations and recommendations for future research

While the findings of this research are significant, they are subject to limitations which include the following:

- Sample size concerns: The study was carried out with a relatively small sample size – 55 participants. This limitation could affect the generalizability of the results as the small sample may not adequately represent the broader population of mHealth app users. Future studies would benefit from a larger cohort to validate and extend these findings. Future studies should expand their investigations across diverse demographic and geographic populations to enhance the robustness and applicability of the new three-factor, 25-item UES.
- Cross-sectional design: The cross-sectional design of this study limits the ability to establish causal relationships from the data. While significant correlations were identified, determining whether one factor directly influences another, or vice versa, remains beyond the scope of this study. Longitudinal research designs in future studies could help establish causal relationships and track changes in user engagement over time and its impact on health outcomes.
- Reliance on self-reported data: The use of self-reported measures to assess user engagement introduces the potential for bias. Participants may overestimate or underestimate their level of engagement due to social desirability or memory recall biases. Objective measures of engagement, such as usage logs or behavioural tracking in mHealth apps, could be employed in future research.

Closing remarks

The study reported in this paper provides insights into the evaluation of mHealth apps, offering evidence on the factors that enhance user engagement. The adaptation and validation of the revised three-factor, 25-item UES in a new context underscore the scale's applicability and relevance, paving the way for further research and development in this vital area of healthcare. These findings not only contribute to academic research but also provide practical guidance for developers aiming to create more engaging and effective mHealth solutions for self-management of diabetes. The 3-factor solution is supported by other recent surveys [41], highlighting the need for further research on the UES. Similar studies that have adopted the UES provide evidence supporting the multidimensionality and variability of user engagement in mHealth apps [56, 58]. Concerning the factor structure, studies have shown that there is variation within different contexts; initial studies confirm a six-factor structure in an information-searching context [42] while other studies – also using PCA analysis – noted that Perceived Usability and Felt Involvement are the most significant indicators of user engagement [59]. This study, therefore, echoes the findings from previous studies and calls for more studies to investigate user engagement with mHealth apps for the self-management of chronic diseases in different contexts.

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Conflict of interest

None

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