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Assessing Interventional Components in a Weight Loss App

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Abstract

Many mHealth interventions for health behavior change are considered effective for improving health outcomes. However, there is a limited understanding of the role of the components in an intervention on its effectiveness. Insights into intervention components such as content and software features are needed to design efficient and effective interventions. In this study, we conducted an exploratory analysis of objective data from the usage of a weight management app to understand the role of intervention components in weight loss. We identified a positive correlation between weight loss and the use of the intervention. We also found differences in the app feature use among those who lost weight. To lose weight, users needed to comply with the intervention by completing a combination of tasks. They needed to complete 70% of some tasks and up to a maximum of 30% of other tasks. In the future, we hope to use other types of collected data (logged and survey data) to gain more nuanced insights into how interventions are used. With the help of data analytics, we may find optimal paths of use and determine a satisfactory level of compliance to achieve desired goals. This can deepen our understanding of what works in an intervention.

Keywords: Persuasive Systems, Health Behaviour Change, Weight loss, Self-monitoring

1. Introduction

Accumulated evidence shows that mobile health (mHealth) interventions with appropriate content and features can support effective self-management of health, change risky health behaviors, and prevent chronic diseases (Webb et al., 2010). Obesity is associated with many serious chronic diseases such as type-2 diabetes, cardiovascular disease, cancer, musculoskeletal disorders, and psychological issues which can impair the quality of life of people, and in some cases, mortality regardless of gender, age, or ethnicity (Ross & Bradshaw, 2009). Obesity comes with a huge economic burden born directly by the patient and national health care providers (Dixon, 2010). It also affects society indirectly from costs associated with absenteeism (Cawley et al., 2007), increased sick leaves, workplace injuries (Pollack & Cheskin, 2007), disability payments, and loss of productivity (Schmier et al., 2006). Weight loss has been identified as an effective measure to curb obesity and its related comorbidity (Dixon et al., 2001) and recommended by health authorities (Ross & Bradshaw, 2009). Obesity management via weight loss can be achieved through different strategies such as behavior and lifestyle modification, counseling (Hall & Kahan, 2018), and surgery (Adams et al., 2007). The latter is more invasive (Batchelder et al., 2013).

The impact of clinical lifestyle interventions is promising and employs behavior change theories and

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strategies to support weight loss (Rivera et al., 2016). Such interventions often involve face-to-face contact which can be costly (Rivera et al., 2016). However, mHealth apps are a cost-effective and convenient alternative to delivering face-to-face clinical lifestyle interventions (Khokhar et al., 2014). mHealth is increasingly being used for the management of weight due to its efficacy but more evidence is needed to understand how it works (Hartmann-Boyce et al., 2014). The use of intervention components and the usage threshold required to see a behavior change should be examined (Ainsworth et al., 2017) as user compliance to use is critical to its success.

In this study, we conducted an exploratory data analysis to examine objective data from the usage of an app designed to support users to lose excess weight and prevent chronic diseases associated with obesity. The objective data and their associations with weight loss were investigated using the following questions

1. What is the relationship between intervention usage and the percentage of weight loss?
2. Does compliance to intervention tasks (such as reading content, completing content exercises, self-monitoring weight, food, mood and motivation, physical activity, and self-assessing one's behavior) affect weight loss? We hypothesize that compliance to intervention can lead to weight loss.
3. What relationships exist between patterns of usage and the amount of weight loss? We hypothesize that the frequency of usage of intervention components can support the user to change behavior and lose weight.

2. Persuasive Systems and Behaviour Change

Persuasive systems are information systems designed to induce behavior change without coercion or deception (Oinas-Kukkonen & Harjumaa, 2009). Systems to support behavior modification (known as Behaviour Change Support Systems (BCSS)) are at the heart of persuasive systems and their goals include the types of change and outcomes that can be achieved through persuasion (Lehto & Oinas-Kukkonen, 2014). Behavioral modification can be an act of complying, a change in behavior and/or attitude from three possible voluntary outcomes namely: 1) a forming outcome that describes the formation of a new behavioral pattern, 2) an altering outcome through reshaping existing behavioral patterns to achieve desired behavior, and 3) a reinforcing outcome where an existing behavioral pattern is fortified to make them permanent (Oinas-Kukkonen, 2013). These goals require the use of different strategies and techniques (Oinas-Kukkonen & Harjumaa, 2009).

Onnikka is a digital health intervention designed to facilitate weight management in an ongoing randomized clinical trial (RCT). The app was built using the Persuasive System Design (PSD) model. Self-monitoring, reminders, favorite, etc. were chosen after careful analysis of the persuasion context using the PSD process model. Onnikka translates to "a bus" in a Finnish local dialect (see Figure 1). A bus ride is a journey with stops at specific places. The concept of a journey by bus is used as a metaphor for a behavior change process. Content and self-monitoring tasks are presented to users at the stops in their "bus journey". Users receive content created by health professionals every week. Content exercises and self-monitoring tasks were embedded in the educational content delivered to users. Users could set goals and use self-monitoring features to monitor their weight, meal patterns, mood and motivation, and physical activity. In the first six months of the intervention, users received a total of 53 educational content with reflective exercises based on the content. Two educational content each week except the last week. Users had to submit answers to 51 (out of 53) content exercises. They did not have to provide answers to the two remaining content exercises. Users were expected to make 24 weight notes, eight food notes, eight motivation notes, five sports notes, and complete four self-assessment forms (see Table 1). Successful behavior change with digital interventions may require users to complete tasks: use intervention content and features provided to guide and support them in their behavior change journey (Ainsworth et al., 2017). In this research, completing 70% of the tasks implies that the user is actively using the app.

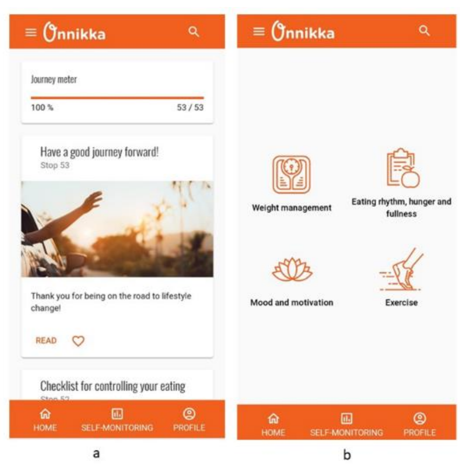

Figure 1 Overview of the Onnikka intervention

Table 1: Intervention components and minimum tasks to complete

Intervention components	Intervention tasks	70th percentile
Educational Content	53	37
Content Exercises	51	36
Weight Notes	24	17
Food Notes	8	6
Motivation Notes	8	5
Sport Notes	5	4
Tool Forms	4	3

3. Research method

The study design of the trial was approved by the Ethics committee of the Northern Ostrobothnia Hospital District with approval number 138/2020. The trial was registered at ClinicalTrials.gov (Identifier: NCT04558801). In this study, we used a subset of the data that was collected in the larger RCT study. We were interested in the usage of the content and persuasive features for self-monitoring and their impact on weight loss. The data were collected by automatically logging the actions of each user of Onnikka. From this data, the number of specific actions (i.e., educational content read, completed reflective content exercises, notes recorded for weight, food, mood, and motivation, and tool forms completed for self-assessment purposes) was computed.

To answer the research questions posed, a descriptive analysis, correlation analysis, independent median test, and association mining data analysis methods will be used. The descriptive analysis will reveal insights into the frequency of the use of intervention features. Correlation analysis will examine the relationship between intervention features and the percentage of weight loss. The usage patterns of the intervention will be investigated to determine if there are any differences among the weight loss groups using the independent median test. Lastly, association mining will be used to investigate how the completion of recommended intervention tasks influenced the percentage of weight loss. Association mining may reveal features that are common among users and can tell which intervention features when used together, can lead to behavior change and improve health (Turkington et al., 2018). To prepare the data for association mining, the dataset was labeled using compliance criteria. Currently, a validated compliance criteria have not been established. Intervention compliance was defined using the 70th percentile. A minimum of 70% compliance (i.e., complete) was desired and used for labeling the data. Data below this threshold was labeled as incomplete. The chosen percentile for compliance is based on ongoing research and feedback from clinicians in this research.

5. Results

Users were grouped by the percentage of body weight lost. See Table *2*. About 69% of users lost weight

Table 2: Use of intervention components and the amount of weight loss

Groups	Number of users	Percentage	Statistics	Educational content	Content Exercise	Weight Notes	Food notes	Mood and Motivation notes	Sport Notes	Tool Forms
Weight loss <0%	56	30.6%	Number	56	56	56	56	56	56	56
			Median	46.5	31.5	16.5	42	5.5	9	2
			Minimum	2	1	0	0	0	0	0
			Maximum	53	48	51	542	72	209	4
Weight loss 0-2%	47	25.7%	Number	47	47	47	47	47	47	47
			Median	51	40	22	100	7	17	3
			Minimum	2	2	0	0	0	0	0
			Maximum	53	49	138	533	60	202	4
Weight loss 2-5%	43	23.5%	Number	43	43	43	43	43	43	43
			Median	53	42	24	132	11	19	3
			Minimum	9	5	0	0	0	0	0
			Maximum	53	49	59	854	154	244	4
Weight loss >5%	37	20.2	Number	37	37	37	37	37	37	37
			Median	53	45	26	157	22	33	4
			Minimum	17	9	0	0	0	0	1
			Maximum	53	49	147	1141	162	223	4

during the study, while 31% did not. Although users were expected to record 24 weight notes, users used this feature frequently recording a maximum of 147 notes in 6 months. Frequent usage was also observed for food notes (1141), motivation notes (162), sports notes (244), and four tool forms. On the other hand, some users did not record anything for weight notes, food notes, motivation notes, sports notes, and tool forms. It was interesting to find out that some users did not use some of the self-monitoring features (weight notes, food notes, motivation notes, and sports notes). While some users opened all 53 educational content delivered, some opened only two. The minimum number of content exercises completed was one and a maximum of 49. Also, some of the users who lost more than 5% of their weight did not record any weight notes, food notes, motivation notes, or sports notes. Appendix 1 shows outliers in the use of intervention features. Users who lost the most amount of weight used the intervention features more frequently. There seem to be variations in the median values for food notes, motivation notes, and sports notes, and hence warrants further investigation to examine the differences between the groups.¨

Further analysis to examine the median differences between the four groups shows a statistically significant difference among the groups for educational content, content exercise, food notes, and tool forms but not weight notes, motivation notes, or sports notes (see Table 3). Beyond statistical significance, the median usage of the intervention features is consistently high for content exercises, weight notes, food notes, motivation notes, sports notes, and tool forms. The median value for the opened educational content is the same for users who lost 2-5% and >5% of their weight. Apart from this similar median value, there is an increase in the usage of intervention features from the users who did not lose weight to users who lost more than 5% of their weight.

Table 3: Differences in the median usage of intervention features in the four weight loss groups

Intervention Components	P value
Educational Content	0.001
Content Exercise	<.001
Weight Notes	0.190
Food Notes	0.033
Motivation Notes	0.168
Sports Notes	0.140
Tool Forms	0.006

Table 4 shows a statistically significant but weak positive correlation between the percentage of weight loss and the use of the features in the intervention. This suggests that by using intervention features users can lose weight.

Table 4: Spearman correlation between usage of intervention components and %weight loss

Intervention components	Correlation coefficient	P value	N
Educational Content	0.342**	<.001	183
Content Exercise	0.350**	<.001	
Weight Notes	0.229**	<.001	
Food Notes	0.276**	<.001	
Motivation Notes	0.286**	0.008	
Sport Notes	0.194**	0.140	
Tool Forms	0.284**	<.001	

5.1. Usage of Intervention Components and %Weight Loss

In this section, we delve into the weekly usage of Onnikka to identify the weight loss patterns during the intervention, we calculated the median from the total number of self-reported entries and visualize the weight loss per week (see Figures 2, 3, 4, 5, and 6).

Figure 2 shows the median reflective exercises completed each week in each weight loss group. Here, we see that majority of the users completed two reflective exercises per week except for weeks 18 and 24 where users who lost 0-2% of their weight did not complete reflective exercises. There was a gradual increase in the number of reflective exercises completed by users who lost more than 5% of their weight from week 7 to week 18.

Figure 3 shows the median self-reported weight per week in each weight loss group. It is interesting to see variations in the weight reported per week for the various groups. Weight notes were recorded at least once every week except for weeks 7 and 23 where there was a steep drop in weight notes made by users who lost more than 5% of their weight in some weeks and less than one weight note for users who lost 2-5% of their weight.

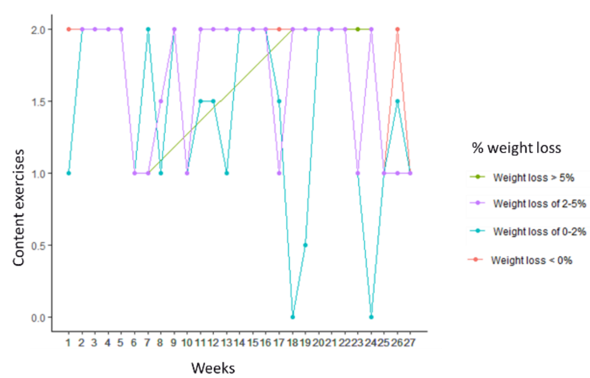

Figure 2 Weekly median content exercises completed per group

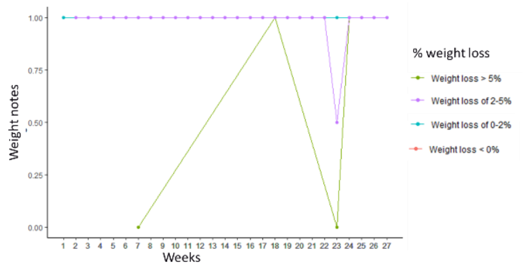

Figure 3 Weekly median weight notes recorded per group

Figure 4 depicts the median food notes of the users per week in each weight loss group. Though the number of food notes was zero for several weeks, users still lost weight. Users who lost more than 5% of their weight started making food notes in week 7. Three food notes were made in that week and gradually decreased every week until the 18th week after which users did not record any food notes. From the figure, users who did not lose weight made food notes often indicating that simply logging food notes does not necessarily lead to weight loss.

Figure 5 shows the median mood and motivation entries reported by users in each weight loss group. Users who lost weight recorded motivation notes for some weeks. For example, users who lost more than 5% of their weight recorded one motivation note in week seven and gradually decreased to zero. Users who lost 0-2% and 2-5% of their weight recorded some mood and motivation notes. In week 15, we see an increase in recordings across all groups with the 0-2% weight loss group recording the highest median number of motivation notes.

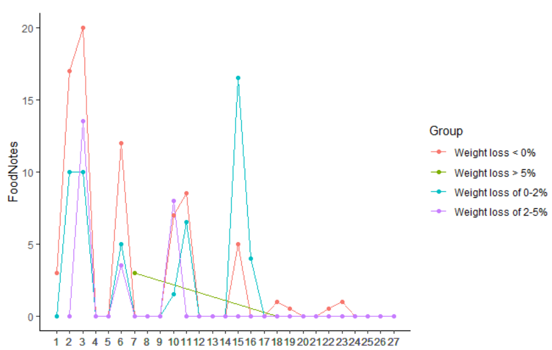

Figure 4 Median food notes recorded per group each week

Figure 6 shows the total number of physical activity entries made by users and how much weight they lost. There were variations in the weight loss per week. Users who did not lose any weight recorded the highest number of sports notes in week four while users who lost more than 5% of their weight recorded one sports note in week seven and gradually decreased to zero. No sports notes were recorded from week 19 till the end of 6 months. Most of the notes were recorded in the early weeks.

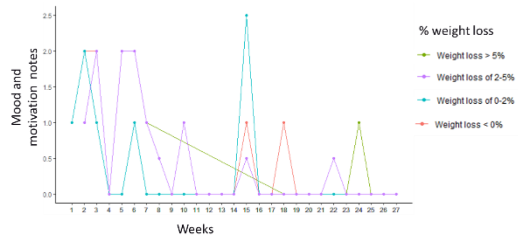

Figure 5 Median mood and motivation notes recorded by users each week

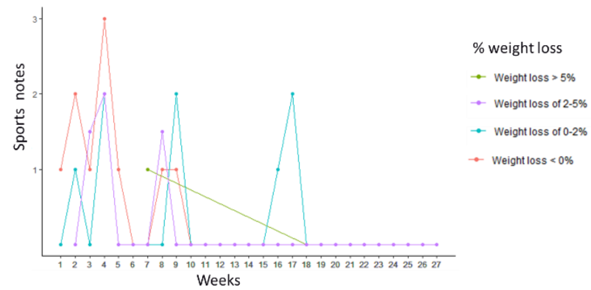

Figure 6 Median sports notes recorded per group per week

Association mining determined the conditional probability of a percentage weight change by comparing relationships among features used in the intervention. The lift values show a strong positive correlation between the user "using" and/or "not using" different features and weight loss as shown in Table 5. In general, the results show that completing a maximum of 30% and a minimum of 70% of the tasks required can lead to a change in weight. Association mining rules show that complete usage (i.e., 70%) of individual features or a combination of certain features is associated with weight change greater than zero.

One rule was discovered for weight loss greater than 5%. The rule specifies that completing 70% of content exercises and food notes and 30% of others (i.e., motivation notes and self-assessment via tool forms) can lead to users losing more than 5% of their weight (see Table 5).

Three interesting rules were uncovered for users who lost 2-5% of their weight:

(1) completing a minimum of 70% content exercises, a maximum of 30% food notes, a maximum of 30% of sports notes, and a minimum of 70% tool forms (for self-assessment),

(2) completing a maximum of 30% weight notes, a minimum of 70% content exercises, a maximum of 30% food notes, and a minimum of 70% tool form self-assessment,

(3) completing a maximum of 30% educational content, a minimum of 70% of food notes, and a

maximum of 30% of motivation notes, sports notes, and tool forms for self-assessment.

For users who lost 0-2% of their weight, two interesting rules were uncovered. The first rule showed that users had to complete a minimum of 70% weight notes and content exercises, a maximum of 30% motivation notes, and a minimum of 70% sports notes and tool forms for self-assessment. This rule occurred five times in the data. The second rule occurred four times in the data. Users had to complete a maximum of 30% weight notes, content exercises, a minimum of 70% food notes, a maximum of 30% motivation notes, a minimum of 70% sports notes, and a maximum of 30% completion rate for tool form self-assessment. Interestingly, no rules were generated for users who did not lose any weight.

6. Discussion

This research demonstrates a positive relationship between intervention components and weight loss.

We noticed (from Table 2) that participants who did not complete all the required tasks also experienced some weight loss. The probability of completing self-monitoring tasks declined in the last few weeks. Interestingly, weekly usage patterns were observed for users who lost more than 5% of their body weight. About 50% of users in this group did not complete any content exercise in the first six weeks. In the 7th week, they completed one of two content exercises which gradually increased to two by week 18 and remained there till the end. These users did not also record any weight notes until week seven, but the frequency of recording weight notes decreased gradually to zero in week 18 after which it remained steady. This trend was also observed in food, motivation, and sports notes respectively. The reason behind the non-use of the self-monitoring features in the >5% weight loss group until week seven warranted further investigations.

Using association mining, we found out that to lose weight, users needed to complete a combination of tasks. They needed to complete 70% of some tasks and up to a maximum of 30% of other tasks. This finding supports our hypothesis that compliance to intervention can lead to weight loss. Although using intervention as intended is desirable, users are unlikely to stick to the predefined paths to success. Interventions must be designed to make room for users to navigate their way to the desired goal. Also, interventions should be able to support users at opportune moments.

The correlation analysis conducted showed a statistically significant but weak relationship between the percentage of weight loss and the use of the features in the intervention (see Table 4). This relationship indicates that an increase in reading content exercises, completing content exercises, recording weight notes, food notes, motivation notes, sports notes, and answering tool forms results in an increase in the amount of weight lost. From Appendix 1, we know that users who lost more than 5% of their weight recorded the highest number of food and motivation notes, and users who lost 2-5% of their weight recorded the highest number of sports notes. While users who did not lose weight also recorded high numbers of food and sports notes, they recorded the least number of weight, food, motivation, and sports notes.

Independent median analysis to assess the differences between weight loss groups shows statistically significant differences in reading educational content ($p = 0.001$), completing reflective content exercises ($p < .001$), making food notes ($p = 0.033$), and completing tool forms for self-assessment ($p = 0.006$) but not for weight notes ($p = 0.190$), motivation notes ($p = 0.168$), and sports notes ($p = 0.140$). This information adds more context to the findings from the correlation analysis revealing further information that can explain this relationship. While our analysis indicates that the non-use, frequent use, and/or decline in the use of the intervention features are associated with some weight loss, the usage patterns of intervention features differ between the groups.

Our hypothesis that the frequency of usage of some intervention components can support the user to change behavior and lose weight is inconclusive. This is because 50% of users who did not lose any weight used the self-monitoring tool to make food notes often in some weeks (e.g., 1, 2, 6, 10, 11, 12; see Figure 4) and sports notes (e.g., 1, 2, 3, 4; see Figure 6) frequently more than the users who lost weight. This result may have been influenced by other factors such as the kind of food they ate or the type of physical activity they engaged in. On the other hand, 50% of users who lost 2-5 percent of their weight did use the self-monitoring feature to record their weight often throughout the 27 weeks except for week one (see Figure 3). We can also observe that this group of users also used the self-monitoring tool to make mood and motivation notes, and sports notes often in some weeks (see Figures 5 and 6). 50% of the users who lost 0-2% of their weight used the self-monitoring tools to make food notes, mood and motivation notes, and sports notes in some weeks (see Figures 4, 5, and 6).

Using the findings from the association mining, we can cautiously say that using intervention features frequently to a certain threshold can lead to weight loss. Association mining of the data did not generate any rules of association for users who did not lose any weight and hence more research is needed to identify such users and support them by for example providing more personalized support. We also need to bear in mind that the life situation of users may change and affect the use of an intervention as well as its expected outcomes.

Prior studies have noted the relevance of educational content (Vlahu-Gjorgievska et al., 2018), and self-monitoring tools, among other features, as important for weight management apps (Burke et al., 2011; Goldstein et al., 2019; Vlahu-Gjorgievska et al., 2018). The effectiveness of such apps in facilitating weight loss lies in the ability of users to use the intervention as recommended. Our findings suggest that satisfactory compliance to intervention content led to weight loss and is consistent with the findings of (Dounavi & Tsoumani, 2019).

Research is needed to define a satisfactory level of compliance required to achieve the desired goals. This satisfactory level of compliance may vary as it will depend on factors such as the context of use, user characteristics, empirical evidence, or experience (Yang et al., 2022).

Table 5: Association rule shows different combinations of intervention components and the amount of weight loss

Antecedent	Consequent	Support	Confidence	Coverage	Lift	Count
CE=Yes, FN=Yes, MN=No, TF=No	Category = >5%	0.016	1	0.016	4.946	3
CE=Yes, FN=No, SN=No, TF=Yes	Category = 2-5%	0.011	1	0.011	4.256	2
WN=No, CE=Yes, FN=No, TF=Yes		0.011	1	0.011	4.256	2
OC=No, FN=Yes, MN=No, SN=No, TF=No		0.011	1	0.011	4.256	2
FN=No, MN=Yes		0.005	1	0.005	4.256	1
WN=Yes, FN=No, SN=No, TF=Yes		0.005	1	0.005	4.256	1
WN=No, FN=No, SN=Yes, TF=Yes		0.005	1	0.005	4.256	1
WN=Yes, FN=No, SN=Yes, TF=No		0.005	1	0.005	4.256	1
WN=Yes, OC=No, MN=No, SN=Yes		0.005	1	0.005	4.256	1
WN=Yes, OC=No, FN=Yes, MN=No		0.005	1	0.005	4.256	1
CE=Yes, MN=Yes, SN=No, TF=No		0.005	1	0.005	4.256	1
CE=Yes, FN=Yes, SN=No, TF=No		0.005	1	0.005	4.256	1
WN=Yes, MN=Yes, SN=No, TF=No		0.005	1	0.005	4.256	1
WN=Yes, FN=Yes, SN=No, TF=No		0.005	1	0.005	4.256	1
OC=Yes, MN=Yes, SN=No, TF=No		0.005	1	0.005	4.256	1
CE=No, MN=Yes, SN=No, TF=Yes		0.005	1	0.005	4.256	1
OC=Yes, CE=No, MN=Yes, SN=No		0.005	1	0.005	4.256	1
OC=Yes, CE=No, FN=No, SN=No, TF=No		0.005	1	0.005	4.256	1
WN=No, CE=Yes, MN=No, SN=No, TF=Yes		0.005	1	0.005	4.256	1
WN=No, CE=No, MN=No, SN=Yes, TF=Yes		0.005	1	0.005	4.256	1
WN=Yes, CE=Yes, MN=No, SN=Yes, TF=Yes	Category = 0-2%	0.027	0.833	0.033	3.245	5
WN=No, CE=No, FN=Yes, MN=No, SN=Yes, TF=No		0.022	0.8	0.027	3.115	4
CE=No, FN=No, TF=Yes		0.005	1	0.005	3.894	1
WN=Yes, FN=No, MN=No, TF=Yes		0.005	1	0.005	3.894	1
WN=Yes, FN=No, SN=Yes, TF=Yes		0.005	1	0.005	3.894	1
WN=No, CE=Yes, MN=Yes, SN=No		0.005	1	0.005	3.894	1
WN=No, CE=Yes, FN=Yes, SN=No		0.005	1	0.005	3.894	1
WN=Yes, CE=No, SN=No, TF=Yes		0.005	1	0.005	3.894	1
WN=Yes, OC=Yes, CE=No, SN=No		0.005	1	0.005	3.894	1
WN=Yes, CE=No, FN=Yes, SN=No		0.005	1	0.005	3.894	1
WN=No, OC=Yes, CE=No, FN=Yes, MN=No, SN=Yes, TF=No		0.005	1	0.005	3.894	1
Abbreviations: CE: content exercise, WN: weight notes, FN: food notes, MN: motivation notes, SN: Sports Notes, TF: Tool Form Yes=a minimum of 70% complete, No=a maximum of 30% incomplete						

Evaluating the impact of intervention usage on health outcomes can deepen our understanding of the factors and usage patterns associated with the effectiveness of an intervention (Leung et al., 2017). Future studies can use machine learning algorithms (see (Turkington et al., 2018)) to identify and predict usage patterns and persuasive features associated with the effectiveness of an intervention (Van Gemert-Pijnen et al., 2014). These insights can be used to tailor the interventions for user groups or personalize them to meet an individual user's need (Oinas-Kukkonen et al., 2022).

7. Conclusion

Objective usage analysis generated insights about how the components of a persuasive health app led to weight loss. Our results show that compliance to the intervention is associated with achieving weight loss and may be highly useful to inform the design of digital interventions. In the future, we hope to use other types of collected data such as logged and survey data to gain much more nuanced insights into how interventions are used. With the help of data analytics, we hope to find optimal paths to weight loss and deepen our understanding of what works in an intervention.

8. Acknowledgements

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9. References

Adams, T. D., Gress, R. E., Smith, S. C., Halverson, R. C., Simper, S. C., Rosamond, W. D., LaMonte, M. J., Stroup, A. M., & Hunt, S. C. (2007). Long-Term Mortality after Gastric Bypass Surgery. *New England Journal of Medicine*, *357*(8), 753–761. https://doi.org/10.1056/NEJMOA066603/SUPPL_FILE/NEJM_ADAMS_753SA1.PDF

Ainsworth, B., Steele, M., Stuart, B., Joseph, J., Miller, S., Morrison, L., Little, P., & Yardley, L. (2017). Using an Analysis of Behavior Change to Inform Effective Digital Intervention Design: How Did the PRIMIT Website Change Hand Hygiene Behavior Across 8993 Users? *Annals of Behavioral Medicine*, *51*(3), 423. https://doi.org/10.1007/S12160-016-9866-9

Batchelder, A. J., Williams, R., Sutton, C., & Khanna, A. (2013). The evolution of minimally invasive bariatric surgery. *Journal of Surgical Research*, *183*(2), 559–566. https://doi.org/10.1016/J.JSS.2013.02.036

Burke, L. E., Wang, J., & Sevick, M. A. (2011). Self-Monitoring in Weight Loss: A Systematic Review of the Literature. *Journal of the American Dietetic Association*, *111*(1), 92–102. https://doi.org/10.1016/J.JADA.2010.10.008

Cawley, J., Rizzo, J., & Haas, K. (2007). Occupation-Specific Absenteeism Costs Associated With Obesity and Morbid Obesity on JSTOR. *Journal of Occupational and Environmental Medicine*, *49*, 1317–1324. https://doi.org/10.1097/JOM.0b013e31815b56a0

Dixon, J. B. (2010). The effect of obesity on health outcomes. *Molecular and Cellular Endocrinology*, *316*(2), 104–108. https://doi.org/10.1016/J.MCE.2009.07.008

Dixon, J. B., Dixon, M. E., & O'Brien, P. E. (2001). Quality of Life after Lap-Band Placement: Influence of Time, Weight Loss, and Comorbidities. *Obesity Research*, *9*(11), 713–721. https://doi.org/10.1038/OBY.2001.96

Dounavi, K., & Tsoumani, O. (2019). Mobile Health Applications in Weight Management: A Systematic Literature Review. *American Journal of Preventive Medicine*, *56*(6), 894–903. https://doi.org/10.1016/J.AMEPRE.2018.12.005

Goldstein, S. P., Goldstein, C. M., Bond, D. S., Raynor, H. A., Wing, R. R., & Thomas, J. G. (2019). Associations Between Self-Monitoring and Weight Change in Behavioral Weight Loss Interventions. *Health Psychology : Official Journal of the Division of Health Psychology, American Psychological Association*, *38*(12), 1128. https://doi.org/10.1037/HEA0000800

Hall, K. D., & Kahan, S. (2018). Maintenance of lost weight and long-term management of obesity. *The Medical Clinics of North America*, *102*(1), 183. https://doi.org/10.1016/J.MCNA.2017.08.012

Hartmann-Boyce, J., Johns, D. J., Jebb, S. A., Aveyard, P., Ogden, J., Onakpoya, I., Summerbell, C., & Phillips, D. (2014). Effect of behavioural techniques and delivery mode on effectiveness of weight management: Systematic review, meta-analysis and meta-regression. *Obesity Reviews*, *15*(7), 598–609. https://doi.org/10.1111/OBR.12165/SUPPINFO

Khokhar, B., Jones, J., Ronksley, P. E., Armstrong, M. J., Caird, J., & Rabi, D. (2014). Effectiveness of mobile electronic devices in weight loss among overweight and obese populations: A systematic review and meta-analysis. *BMC Obesity*, *1*(1), 1–13. https://doi.org/10.1186/S40608-014-0022-4/FIGURES/4

Lehto, T., & Oinas-Kukkonen, H. (2014). Explaining and predicting perceived effectiveness and use continuance intention of a behaviour change support system for weight loss. *Http://Dx.Doi.Org/10.1080/0144929X.2013.866162*, *34*(2), 176–189. https://doi.org/10.1080/0144929X.2013.866162

Leung, A. W. Y., Chan, R. S. M., Sea, M. M. M., & Woo, J. (2017). An Overview of Factors Associated with Adherence to Lifestyle Modification Programs for Weight Management in Adults. *International Journal of Environmental Research and Public Health 2017, Vol. 14, Page 922*, *14*(8), 922. https://doi.org/10.3390/IJERPH14080922

Oinas-Kukkonen, H. (2013). A foundation for the study of behavior change support systems. *Personal and Ubiquitous Computing*, *17(6)*(6), 1223–1235. https://doi.org/10.1007/s00779-012-0591-5

Oinas-Kukkonen, H., & Harjumaa, M. (2009). Persuasive systems design: Key issues, process model, and system features. *Communications of the Association for Information Systems*, *24(1)*(1), 485–500. https://doi.org/10.17705/1cais.02428

Oinas-Kukkonen, H., Pohjolainen, S., & Agyei, E. (2022). Mitigating Issues with/of/for True Personalization. *Frontiers in Artificial Intelligence*, *0*, 67. https://doi.org/10.3389/FRAI.2022.844817

Pollack, K. M., & Cheskin, L. J. (2007). Obesity and workplace traumatic injury: does the science support the link? *Injury Prevention*, *13*(5), 297–302. https://doi.org/10.1136/IP.2006.014787

Rivera, J., McPherson, A., Hamilton, J., Birken, C., Coons, M., Iyer, S., Agarwal, A., Lalloo, C., & Stinson, J. (2016). Mobile Apps for Weight Management: A Scoping Review. *JMIR Mhealth Uhealth 2016;4(3):E87 Https://Mhealth.Jmir.Org/2016/3/E87*, *4*(3), e5115. https://doi.org/10.2196/MHEALTH.5115

Ross, R., & Bradshaw, A. J. (2009). The future of obesity reduction: beyond weight loss. *Nature Reviews Endocrinology 2009 5:6*, *5*(6), 319–325. https://doi.org/10.1038/nrendo.2009.78

Schmier, J. K., Jones, M. L., & Halpern, M. T. (2006). Cost of obesity in the workplace. *Scandinavian Journal of Work, Environment & Health*, *32*(1), 5–11. https://doi.org/10.5271/sjweh.970

Turkington, R., Mulvenna, M., Bond, R., O‟Neill, S., & Armour, C. (2018). The application of user event log data for mental health and wellbeing analysis. *Proceedings of the 32nd International BCS Human Computer Interaction Conference, HCI 2018*. https://doi.org/10.14236/EWIC/HCI2018.4

Van Gemert-Pijnen, J. E. W. C., Kelders, S. M., & Bohlmeijer, E. T. (2014). Understanding the usage of content in a mental health intervention for depression: an analysis of log data. *Journal of Medical Internet Research*, *16*(1). https://doi.org/10.2196/JMIR.2991

Vlahu-Gjorgievska, E., Mulakaparambil Unnikrishnan, S., & Win, K. T. (2018). *mHealth Applications: A Tool for Behaviour Change in Weight Management*. 158–163. https://doi.org/10.3233/978-1-61499-890-7-158

Webb, T. L., Joseph, J., Yardley, L., & Michie, S. (2010). Using the Internet to Promote Health Behavior Change: A Systematic Review and Meta-analysis of the Impact of Theoretical Basis, Use of Behavior Change Techniques, and Mode of Delivery on Efficacy. *J Med Internet Res 2010;12(1):E4 Https://Www.Jmir.Org/2010/1/E4*, *12*(1), e1376. https://doi.org/10.2196/JMIR.1376

Yang, Y., Boulton, E., & Todd, C. (2022). Measurement of Adherence to mHealth Physical Activity Interventions and Exploration of the Factors That Affect the Adherence: Scoping Review and Proposed Framework. *J Med Internet Res 2022;24(6):E30817 Https://Www.Jmir.Org/2022/6/E30817*, *24*(6), e30817. https://doi.org/10.2196/30817

Appendix 1 Outliers (boldened values) in the use of self-monitoring and other intervention features and % weight change

Educational Content	**Content Exercise**	**Weight Notes**	**Food Notes**	**Motivation Notes**	**Sports Notes**	**%Weight Change**
53	48	**16**	**612**	**132**	**83**	**>5%**
53	48	**41**	**521**	**115**	**145**	
53	**49**	26	**748**	**146**	**141**	
53	47	**147**	**649**	**162**	**191**	
53	48	18	**1141**	**51**	19	
41	32	23	**157**	25	**223**	
53	46	29	**588**	40	42	
50	45	**118**	**196**	60	51	
53	47	29	**285**	72	**150**	
53	48	59	148	11	23	2-5%
53	40	27	**854**	**154**	8	
53	49	38	**310**	73	**244**	
53	44	27	**377**	53	68	
48	42	24	**388**	30	31	
53	41	26	**628**	**134**	**113**	
53	47	24	**693**	24	87	
9	5	7	6	2	2	

49	28	138	**445**	5	**134**	0-2%
2	2	0	1	1	0	
29	17	13	37	4	4	
53	48	27	**533**	27	46	
15	9	39	38	8	6	
53	38	26	42	4	**140**	
7	2	**0**	2	1	0	
15	14	3	0	2	2	
20	13	10	6	2	6	
9	8	4	0	2	1	<0%
30	21	29	**131**	7	9	
24	13	43	**217**	18	34	
2	1	0	0	0	0	
7	5	9	0	1	0	
21	16	7	46	10	5	
10	4	11	4	2	0	
47	42	42	**542**	37	**130**	
10	9	7	31	6	2	
53	44	25	**388**	**72**	37	
44	13	51	34	1	23	
8	8	0	0	0	0	