Project Dissertation Report on

BENEFITS OF HEALTH-TRACKING APPS: EVIDENCE FROM LONGITUDINAL RANDOMIZED TRIAL

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May 2019

DECLARATION

I Aakriti Srivastava, student of MBA 2017-19 of Delhi School of Management, Delhi Technological University, hereby declare that the Major Research Project report on “Benefits of Health-Tracking Apps: Evidence from a Longitudinal Randomized Control Trial” submitted in partial fulfillment of Degree of Masters of Business Administration is the original work conducted by me.

The information and data given in the report is authentic to the best of my knowledge.

This report is not being submitted to any other University for award of any Degree, Diploma and Fellowship.

(Aakriti Srivastava)

Place:

Date:

CERTIFICATE

This is to certify that the Major Project Dissertation Report on "Benefits of Health-Tracking Apps: Evidence from a Longitudinal Randomized Control Trial" is a work carried out by Aakriti Srivastava who is a student of MBA 2017-19 Batch. The project is submitted to Delhi School of Management, Delhi Technological University in partial fulfillment of the requirement for the award of degree of Masters of Business Administration.

Signature of Guide　　　　　　　　　　　　Signature of Head (DSM)

Place:　　　　　　　　　　　　Seal of Head

Date:

ACKNOWLEDGEMENT

Due to the fact that all the knowledge required was not in the literature, it was imperative that the people who guide be very resourceful and knowledgeable. A deep sense of gratitude for the above reason is thus owed to Dr. Rajan Yadav (HOD and Associate Professor at DSM,DTU) for his continuous guidance and motivation and for helping in whatever capacity he could at various stages in the project. I would also like to thank Ms. Deep Shree (Assistant Professor, DSM) for her guidance and help in all the matters, whenever required. I really appreciate their involvement in the project and their regular advices that helped me refine the project as I went along and also inculcate all the points that help significantly with the growth in my learning.

I extend a vote of thanks to Research Scholar Ms. Meena Chopra for her guidance and valuable suggestions on completing this project.

I would also like to thank all the faculty members of Delhi School of Management for helping me throughout with their critical advice and guidance.

Finally a note of thanks is due to all those, too many to single out by names, who have helped in no small measure by cooperating during the project.

Aakriti Srivastava

EXECUTIVE SUMMARY

Usage of Health-tracking apps to track wellness metrics of day to day life is on the rise but there is a lack of scientific evidence on its benefits for the users.

The objective of this study is to analyze the benefits of using Health-tracking apps on first time users over a trial period of 15 days. It is a randomized longitudinal study conducted from T1: 16th April 2019 to T2: 30th April 2019.

Current application markets are flooded with numerous apps like Runtastic, HealthifyMe, Health Tracker, etc. One such app is Google Fit that was primarily used in this study. It is a simple app by Google which measures metrics like Steps, Calories and Distance travelled using GPS and AI technology. It uses these metrics to give Move per Minute and Heart Points to its users.

In the present study, participants were asked to fill a pre-trial questionnaire which measured their Health Consciousness, Overall Psychological Well-Being and Perceived Physical Health before the start of the experiment. Standard questionnaire items of Health Consciousness by Dutta-Bergman and PERMA-Profiler by Butler & Kern were used for this initial stage.

The respondents of the pre-questionnaire (T1) were asked to download Google Fit app on their mobile devices. They were also given the liberty to choose any other app of their choice as long as it measured the basic metrics of Steps, Calories and Distance.

The respondents were asked to track their health using this app and were informed that they were now the part of the experimental trial. Respondents could also voluntarily record the daily data of the same in an excel sheet to help with the second objective of the study to see trend in the usage of the app.

After 15 days, the post-trial questionnaire (T2) was floated to the respondents with the same items as first questionnaire along with a section of their tracking experience.

This data was then analyzed by studying the descriptive means of the parameters and difference in the means was calculated to determine percentage increase in health-related behavior of the users.

It was found that there was significant increase in means of parameters defining well-being and usage of health-tracking apps had a positive effect on a user's health parameters. It was also found that the motivation to use the app declined overtime and it needed stimulations to keep the user engaged.

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1. INTRODUCTION

1.1 Overview

The poor general state of health of the world population will have dramatic effects on our healthcare system in future. A preventive measure against such a development can be by enforcing a permanent change in the lifestyle and health-awareness of adolescents by the use of wellness management and self-observation. Such measures fit well into the description of the health continuum by Saranummi, who emphasizes the advantage of proactive management of health and illness compared to reactive action.

Saranummi also states that the provision of knowledge and tools for self-management is another important part of the health continuum. This can be achieved through the use of wellness applications that offer their end users assistance in performing self-observation and motivate them to improve their lifestyle over a long-term period. Mobile applications offer some important advantages for this task such as pervasive and permanent availability.

The new possibilities offered by technological advances in sensors and portable devices open new opportunities for Personal Informatics (PI) systems, “those that help people collect personally relevant information for the purpose of self-reflection and gaining self-knowledge” (Li et al., 2010).

Nowadays, a large variety of data can be gathered by means of ubiquitous and wearable technologies: from internal states (as mood or glucose level in the blood) to performance values (as pace or kilometers run), from habits (as food, sleep) to actions (as visited places). PI tools allow users to self-monitor their behaviors in a variety of contexts simplifying data collection, management and visualization.

Activity-tracking devices are argued to provide greater awareness about one’s activity and motivate engagement in specific healthy behaviors. They have the potential to support health self-management by tracking, storing, compiling, and providing feedback about an individual’s engagement in movement activities. Users have ready access to comprehensive data, which provides them with more insight into how their body performs and reacts to certain habits on a daily basis.

The primary benefits of these technologies can be interpreted as bringing physical activity to the forefront of users ’ attention, making health-monitoring part of one ’ s lifestyle. However, despite the passion around the use and benefits of these devices, anecdotal evidence and recent studies indicate that users may stop using their device once they have gained sufficient information about their routine activities.

1.2 Market Overview

The market for wearable technologies and self-tracking applications is growing rapidly. Health and fitness apps usage grew by more 330% in the last three years according to research by Flurry Analytics. Forecasts predict that up to 245 million units will be sold in 2019, compared to the 84 million devices sold in 2015 (CCS Insight, 2016). Wearable devices and self-tracking applications allow people to monitor their health (e.g., diet, fitness, mood, sleep) work-related performance (e.g., productivity, creativity) and even leisure activities (e.g., travel, music) (Li, Dey & Forlizzi, 2011; Marcengo & Rapp, 2014; Silverman & Barasch, 2016).

Among the devices available on the market today are wearable cameras that record films based on what individuals see during the day, some wearable augmented-reality headsets that adapt sound to someone's bodily needs and environmental noise, and even certain mobile applications that allow users to record information about sexual activities and to compare their performance to the global average. These examples demonstrate the ease of obtaining rich data about individuals' performance, of examining these data, and of acting on them. This process is referred to as self-quantification (Li, Dey, & Forlizzi, 2010; Lupton, 2013a).

In a technological environment characterized by the ubiquity of mobile devices and wearable electronics, use of activity-tracking devices has gained rapid momentum as more curious users acquire them to monitor and record their health-related activities. Market analysts suggest that unit sales of these devices grew dramatically over the past few years. In 2014 alone, 90 million devices were sold, and demand is expected to remain strong, and predictions indicate that market volume for smart wearables will grow from $2 billion in 2014 to $41billion by 2020, an annual growth rate of 65%. In the USA, Fitbit is considered the dominant player, accounting for 67%of sales for the period.

The global mHealth apps market is segmented based on type and region. Based on the type, the market is segmented into healthcare apps and medical apps. Healthcare apps segment held the largest market share in 2017. Healthcare applications include chronic care management apps, medication management apps, general health and fitness applications, personal health record (PHR) apps, women's health apps, and others (dermatological treatment, sleep monitoring, and emergency response (vital tracking)). General health and fitness apps include weight and obesity management apps, health-tracking apps, and fitness and nutrition apps. Chronic care management apps include diabetes management apps, behavioral disorder, and mental health management apps, cancer therapy management apps, blood pressure & ECG monitoring apps, and others (kidney disorders, respiratory diseases, and infections management apps). Women's health apps are further classified into fertility apps, breastfeeding apps, pregnancy apps, and others (apps for sleep, activity, and stress level tracking). Medical apps are made for medical professionals and are classified into continuing medical education apps, consulting and communication apps, medical reference apps, and patient management & monitoring apps.

1.3 Health-Tracking Apps

Emerging health and fitness tracking technologies such as Fitbit, Jawbone, Nike + FuelBand, or Samsung Gear Fit, Google Fit offer much promise for improving health and fitness practices. These devices do not offer identical functionalities, but common features allow users to track and monitor fitness-related metrics, such as distance walked and calories burned. They also provide means to gamify activities, work towards personal goals, and interact with other users through social features. It is important to note that the terms B activity tracking and B fitness-tracking device are now primarily used to refer to dedicated electronic monitoring devices, which can be synced (in most cases wirelessly) to transmit activity/fitness data to the user ' s computer, smartphone, and to a server. Unlike smartphone-embedded functionality, or applications, activity-tracking devices are mostly wearableand primarily serve a fitness monitoring purpose.

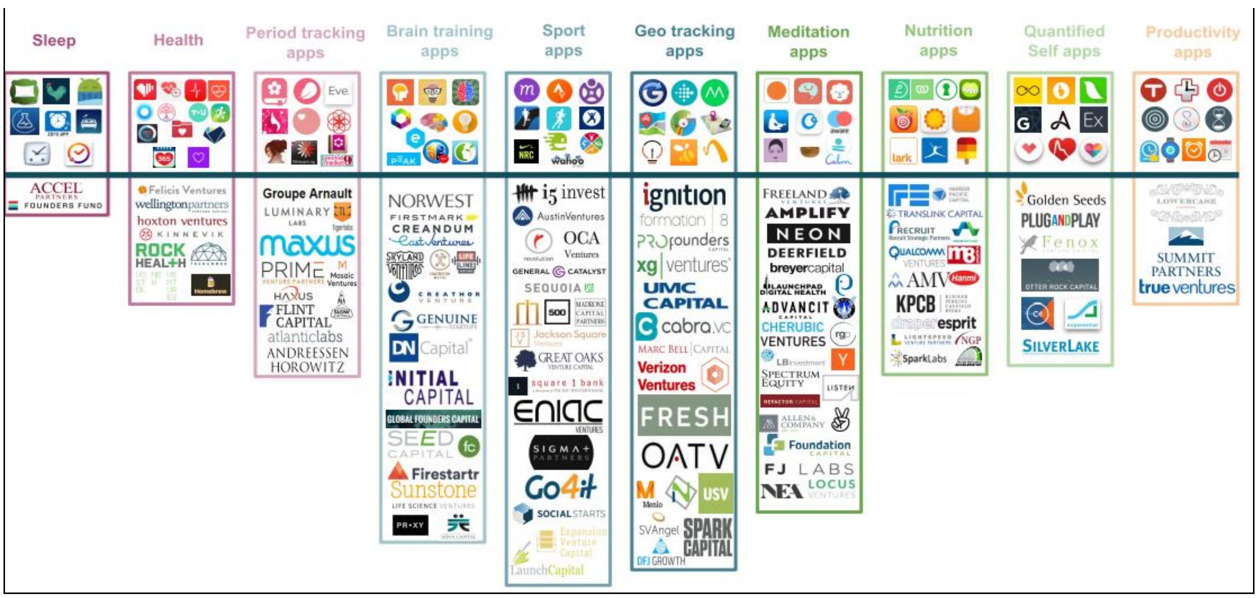

Figure 1. 1 Health-tracking apps in various categories

1.3.1 Google Fit

Google Fit is a health-tracking platform developed by Google for the Android operating system, Wear oS and Apple Inc.'s IoS. It is a single set of APIs that blends data from multiple apps and devices. Google Fit uses sensors in a user's activity tracker or mobile device to record physical fitness activities (such as walking or cycling), which are measured against the user's fitness goals to provide a comprehensive view of their fitness. It measures metrics like Step count, Calories, Distance travelled. These are used to calculation move per minute and heart points. A participant can set goals for himself.

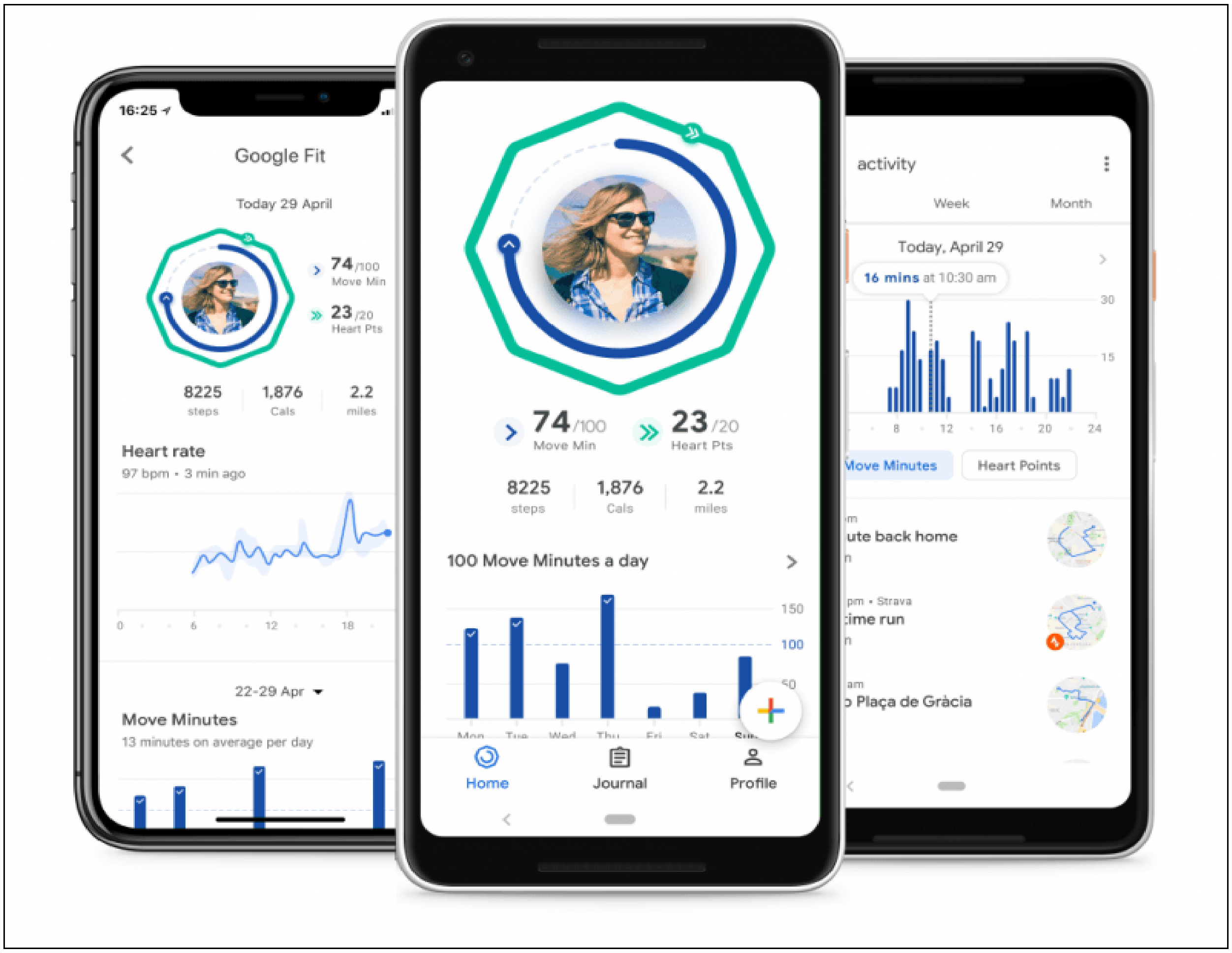

Figure 1. 2 Google-Fit App

1.4 Empirical Research of Health Tracking Apps

Health and well-being related self-tracking is not a new phenomenon, but its practice has changed considerably due to the advent of wearable tracking technologies. online and mobile applications, activity trackers, or smart-watches have simplified almost all stages of the self-quantification process (Kersten-van Dijk et al., 2017; Li, Dey, & Forlizzi, 2010; Matselva & Lutz, 2018). Consumers can collect data about themselves automatically or with minimal effort, and their collected data is automatically integrated and processed into customized and visualized feedback (displayed in an online or mobile application and/or on a screen on the wearable device itself), which facilitates the interpretation of and reflection on the data, ultimately (supposedly) leading to behavior change (i.e., action).

However, QS technologies face the challenge of sustained user engagement. A commercial survey conducted in 2014 (Ledger, 2014) revealed that one third of the users abandoned their activity tracker within the first three months, and more than half of the users had stopped wearing the tracker after one and a half year.

Taken together, these empirical findings may serve as initial reliable evidence that QS technologies can support healthy behaviors such as physical activity and may thereby improve health and well-being (e.g., Fanning, Mullen, & McAuley, 2012; Penedo & Dahn, 2005; Warburton, Nicol, & Bredin, 2006).

1.5 Objectives of the Study

The objective of the study is to analyse the benefits of using health tracking apps on health consciousness, overall health and psychological well-being of an individual.

1.3.1. To study the difference in means of parameters in the trial period.

1.3.2 To study the user behaviour overtime using daily data metrics.

2. LITERATURE REVIEW

2.1 Self-monitoring

Self-monitoring, the activity of observing and recording one's own behavior (i.e., actions, thoughts and emotions), is a well-known technique in cognitive and behavioral psychology (Foster et al., 1999, Korotitisch and Nelson-Gray, 1999). Conceived as a clinical assessment method for collecting data on behaviors that only the patient could observe and record (e.g. eating, smoking), self-monitoring has become a standalone intervention technique, because of its reactive effects. Reactivity refers to the phenomenon in which the process of recording behavior causes the behavior to change (Nelson and Hayes 1981): self-monitoring often changes behavior, and this change is typically in the desired direction (Miltenberger, 2007). Personal Informatics technologies enhance the self-monitoring process, allowing people to track their behaviors outside the clinical setting.

2.2 Self-Evaluation

The feedback consumers receive from Health-tracking apps also helps them to satisfy self-evaluation motives (Gregg, Hepper, & Sedikides, 2001). Overall, most individuals desire to have an accurate and positive view of themselves (self-assessment and self-enhancement motives), to confirm their pre-existing view of themselves (self-verification motive), or to even improve the self (self-improvement motive). Thus, it is likely that consumers will engage in more healthy behaviors, as they want to receive positive feedback from the QS technology (to ensure need satisfaction). However, it may also happen that consumers score below expectations (e.g., the QS technology revealing that they were not as active as they thought they would be), and this could cause cognitive dissonance (Festinger, 1957). On the one hand, the resulting state of psychological discomfort may have negative consequences. For example, consumers may experience a decrease in their self-esteem and/or abandon the tracking device (Almaki et al., 2016; Diefenbach, 2018; Lee & Drake, 2013). On the other hand, however, cognitive dissonance may encourage consumers even more to engage in healthy behaviors to resolve the discomfort and to ensure that future feedback from the QS technology will again confirm the positive self-view. Furthermore, QS technologies are fashion products and similar to other visible products serve a symbolic function (Belk, 1988; Hui-Wen Chuah et al., 2016; Rauschnabel, 2018). Wearing an activity tracker could signalize that technology and health is an important part of the person's identity. Thus, QS technology usage may make up the extended self of being a person with a healthy lifestyle, which "forces" the person to actually engage in a healthier lifestyle in order to maintain self-congruence. In sum, QS technologies may act as a congruence or dissonance-based intervention. Previous research has shown that such interventions are effective in changing health behavior (Freijy & Kothe, 2013).

2.3 Personal informatics for activity tracking

Interactions with technologies that keep track of and reflectone’ s behavior can arise from a variety of behavioral nudges. In recent years, the possibility of keeping records of dailyactivities, exercises, vital parameters, disease symptoms, nutrition, and much more has increased remarkably. This has been driven by the advent of ubiquitous personal information technologies, decreasing sensor sizes, and increasingly seam-less Internet connections. An ever-growing community ofusers has consequently become attracted to the idea of garner-ing knowledge about themselves, by quantifying and analyzing self-related data.

Activity-tracking devices are argued to provide greater awareness about one ’ s activity and motivate engagement in specific healthy behaviors. They have the potential to support health self-management by tracking, storing, compiling, and providing feedback about an individual ’ s engagement in movement activities [18, 31]. Users have ready access to comprehensive data, which provides them with more insight into how their body performs and reacts to certain habits on a daily basis [46]. The primary benefits of these technologies can be interpreted as bringing physical activity to the forefront of users ’ attention, making health-monitoring part of one ’ s lifestyle.

2.4 Health Consciousness

Health consciousness is “the extent to which health concerns are integrated into a person’s daily activities” (Jayanti & Burns, 1998, p. 10). Previous research has shown that health communication in media raises health consciousness (Dutta-Bergman, 2004), and mobile wellness applications have also been found to increase health awareness (Holzinger, Dorner, Födinger, Valdez, & Ziefle, 2010). Thus, by making health-related issues subject of discussion and more salient in people’s everyday lives, their health consciousness should rise (Grifantini, 2014). Similarly, we expect health consciousness to increase in response to QS technology usage, as these technologies support health self-regulation, such as the monitoring of health-related parameters throughout the day.

2.5 Physical Health

As outlined above, there are many theoretical accounts in support of the assumption that QS technology usage drives health behavior change, such as physical activity (Etkin, 2016; Harris et al., 2015), which in turn has beneficial effects on people's health (e.g., Warburton et al., 2006). Accordingly, we expect perceived physical health to increase in response to QS technology usage.

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2.6 Psychological Well-Being

We also expected positive effects of QS technology usage on psychological well-being, for several reasons. First of all, there is substantial evidence that physical activity is not only beneficial for physical health, but also for psychological well-being (e.g., Penedo & Dahn, 2005). And second, health and well-being are highly valued goals in people's lives (e.g., Boumphrey & Brehmer, 2017; oECD, 2017). According to the PERMA-model (Seligman, 2001) and empirical evidence thereof (e.g., Deci & Ryan, 2008; Diener, Suh, Lucas, & Smith, 1999; Hooker, Masters, & Park, 2018; Klug & Maier, 2015; Sheldon & Elliot, 1999), these five elements are important building blocks of psychological well-being.

3. RESEARCH METHODOLOGY

3.1 Participants

Participants were N = 76 (T1) from various backgrounds and age groups. The post experiment questionnaire was filled by N = 72(T2) participants.

Hence the effective sample size is *n = 72* (52% male) aged above 18.

3.2 Procedure

The first questionnaire was shared via Google Forms to over 250 participants from diverse backgrounds and was filled by 76 respondents.

The respondents of the pre-questionnaire T1) were asked to download Google Fit app on their mobile devices. They were also given the liberty to choose any other app of their choice as long as it measured the basic metrics of Steps, Calories and Distance.

The respondents were asked to track their health using this app and were informed that they were now the part of the experimental trial. Respondents could also voluntarily record the daily data of the same in an excel sheet to help with the second objective of the study to see difference in usage of the app.

After 15 days, the post-trial questionnaire (T2) was floated to the respondents with the same items as first questionnaire along with a section of their tracking experience.

Post-Experiment Questionnaire was sent only to these 76 respondents, out of which 72 responded who had downloaded and used the app.

3.3 Measures

The questionnaire was administered via Google Forms through online medium of mail and relevant social media sites. The questionnaire included health consciousness, physical health and psychological well-being related questions. Both the questionnaires can be found in Appendix.

3.3.1 Health Consciousness

Health Consciouness was assessed with the help of 5-item health consciousness subscale developed by Dutta-Bergman (2004). The response format was a 5-point scale from 1 indicating strongly disagree to 5 indicating strongly agree. To ease interpretation, the responses were re-scaled to a scale from 0 to 10, which was the response format of the health and well-being measure.

3.3.2 Perceived Physical Health and Psychological Well-Being

Perceived Physical Health and Psychological Well-Being were measured with the German version (Wammerl et al., 2015) of the PERMA-Profiler (Butler & Kern, 2016). It is a short self-report instrument to assess well-being in terms of Seligman's (2011) PERMA model. It includes three items for each of the five well-being components: positive emotions, engagement, relationships, meaning, and accomplishment It further includes eight filler items that measure overall happiness (1 item), loneliness (1 item), negative emotions (3 items), and physical health (3 items). Together, the average of the 15 PERMA items plus the overall happiness item represent the overall psychological well-being score. The responses are scored on an 11-point scale with the endpoints 0 = never/not at all/terrible and 10 = always/completely/excellent.

3.4 Techniques for Analysis

3.4.1 Descriptive Analysis

The data was analyzed by studying the descriptive means of the parameters and difference in the means was calculated to determine percentage increase in health related behavior of the users.
Respective means of every item were calculated in both time periods (T1 and T2). The means of these were calculated to determine the parameter mean.
The overall mean of the parameters was used as the measure for overall well-being.

3.4.2 Trend Analysis

The movement of daily metric data was studied graphically and was used to determine user's engagement with the app over a period of time.

4. DATA ANALYSIS AND DISCUSSIOn

4.1 Demographic Profile of Respondents

Table 4. 1 Number of respondents in at T1 and T2

Time Period	Number of Respondents
T1	76
T2	72

Interpretation: Out of 76 participants who filled the first pre-questionnaire, 72 participants who actually downloaded and used the app responded to the second post-trial questionnaire. All the data analysis was thus conducted on N=72.

Table 4. 2 Age group of respondents

Age Group	No. of Responses	Percentage
Below 18	0	0
18-24	39	54.2%
25-34	24	33.3%
35-44	6	8.3%
Above 44	3	4.2%
Total	72	100%

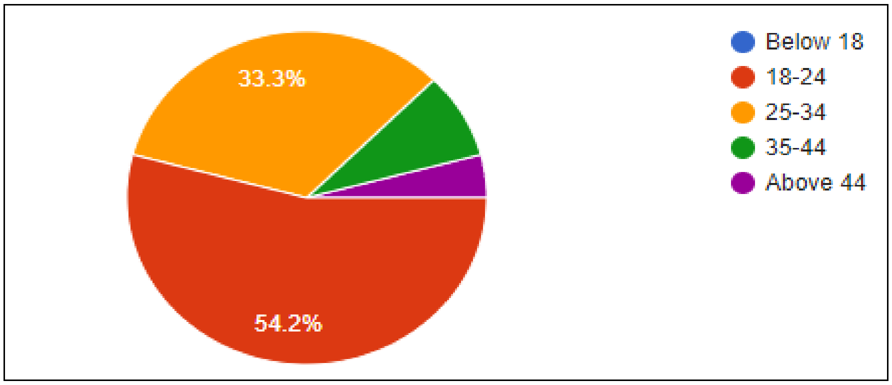

Figure 4. 1 Age of Respondents at T2

Interpretation: Majority of the respondents were in the age group of 18-24 years. Hence it implies that young population is more inclined to use health-tracking applications.

Table 4. 3 Gender of the respondents

Gender	No. Of Respondents	Percentage
Male	38	52.8%
Female	34	47.2%
Total	72	100%

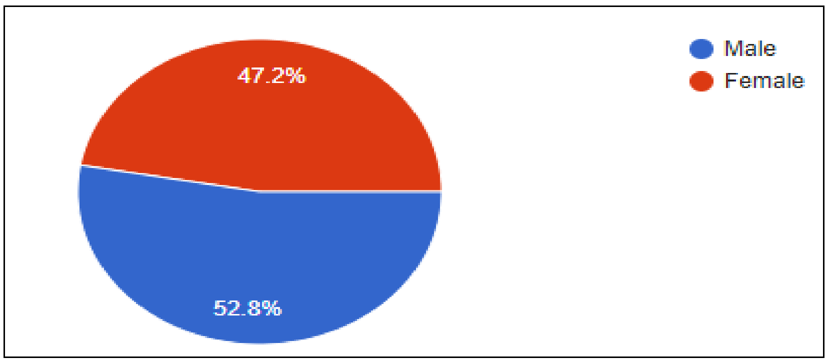

Figure 4. 2 Gender of the respondents at T2

Interpretation: There is only slight difference in number of male and female respondents which implies that both genders are equally likely to adopt usage of health tracking applications.

Table 4. 4 Education level of the respondents

Education	No. of Responses	Percentage
High School/Senior Secondary	4	5.6%
Graduation	18	25%
Post-Graduation	50	69.4%
Doctorate	0	0%
Total	72	100%

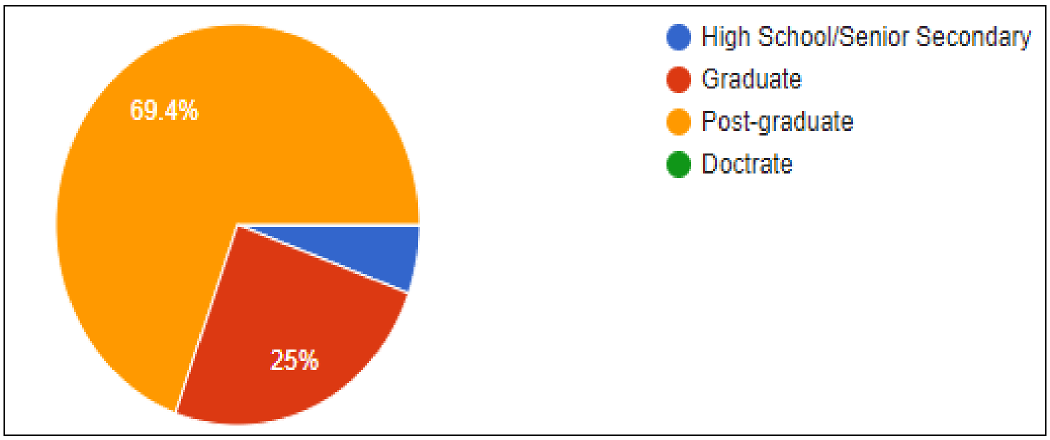

Figure 4. 3 Education level of the respondents

Interpretation: Majority of the respondents are post-graduate which implies they are the majority user of health-tracking apps. But this is most likely a sample error because the study was held in a post-graduate institution hence its students were the first to be administered the questionnaire.

4.2 Analysis of Objective 1: To study the differences in means of parameters in two time periods.

4.2.1 Health Consciousness

Table 4. 5 Descriptive Mean of items of Health Consciousness

Item	T1	T2	Percentage Difference
Living life in the best possible way is very important to me.	9.18	9.19	0.1%
Eating right, exercising and taking preventive measure will keep me healthy for life.	9.17	9.28	1.19%
My health depends on how I take care of myself.	9.08	9.22	1.54%
I actively try to prevent disease and illness.	8.61	9.08	1.54%
I do everything I can to stay healthy.	8.97	9.13	1.78%
Total mean	9.00	9.18	2%

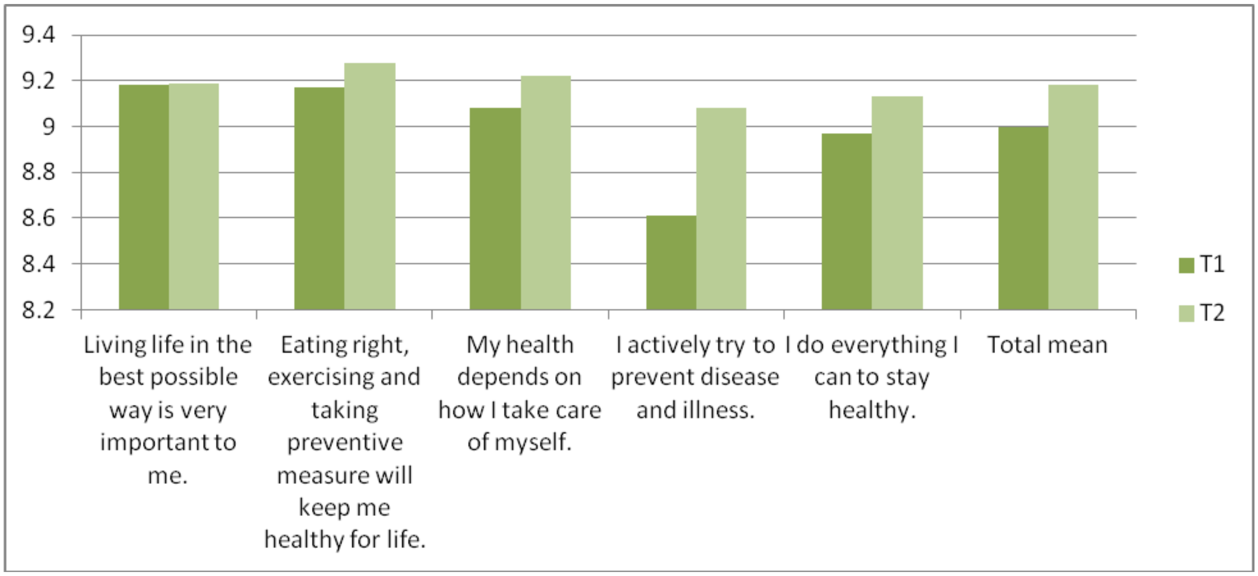

Figure 4. 4 Health Consciousness

Interpretation: As shown in the graph, overall Health Consciousness mean increases by 2% at T2 after the usage of health-tracking app. All the items under the parameters showed a positive increase. It shows the positive effect of usage of health tracking app on health consciousness.

4.2.2 Overall Psychological Well-being

This parameter is divided in two parts. First is the PERMA Profiler containing 15 items (3 each of every sub parameter) plus 5 items containing overall happiness (1 item), negative emotion(3 items) and loneliness (1 item).

Table 4. 6 Descriptive mean of items of Overall Psychological Well-Being

Parameter	Item	T1	T2	Percentage Difference
Positive Emotion	How often do you feel joyful?	6.96	6.97	0.14%
	How often do you feel positive?	7.15	7.18	0.41%
	To what extent do you feel contented?	6.50	7.11	9.38%
Engagement	How often do you become absorbed in	7.31	7.06	-3.41%

	what you are doing?			
	In general, to what extent do you feel excited and interested in things?	7.42	7.38	-0.54%
	How often do you lose track of time while doing something you enjoy?	6.89	6.89	0.00%
Relationship	To what extent do you receive help and support from others when you need it?	7.00	6.94	-0.85
	To what extent do you feel loved?	7.54	7.49	-0.66%
	How satisfied are you with your personal relationships?	6.68	7.08	5.98%
Meaning	In general, to what extent do you lead a purposeful and meaningful life?	7.15	7.33	2.51%
	In general, to what extent do you feel that what you do in your life is valuable and worthwhile?	7.08	7.25	2.40%
	To what extent do you generally feel you have a sense of direction in your life?	6.75	7.10	5.19%
Accomplishment	How much of the time do you feel you are making progress towards accomplishing your goals?	6.29	6.89	9.54%

	How often do you achieve the important goals you have set for yourself?	6.47	6.94	7.26%
	How often are you able to handle your responsibilities?	7.33	7.43	1.36%
Negative Emotion	In general, how often do you feel anxious?	5.81	5.03	-13.43%
	In general, how often do you feel angry?	4.88	4.31	-11.68%
	In general, how often do you feel sad?	4.90	4.46	-8.98%
Loneliness	How lonely do you feel in your daily life?	4.57	4.47	-2.19%
Overall Happiness	Taking all things together, how happy would you say you are?	7.10	7.18	1.13%
Total Mean	Overall Psychological Well-being	6.46	6.59	2.01%

Interpretation: As can be seen in the table, overall psychological well-being mean has increased by 2.01% between two time periods indicating positive effect of usage of Health-tracking app.
But if we look individually, Engagement items show a decrease in their means which implies engagement is not significantly affected by health-tracking apps. Relationship items also show a decrease in their means implying health tracking do not positively affect a user's relationships.
As expected, negative emotion and loneliness items show a huge decrease which is a positive effect of the usage of health tracking app.

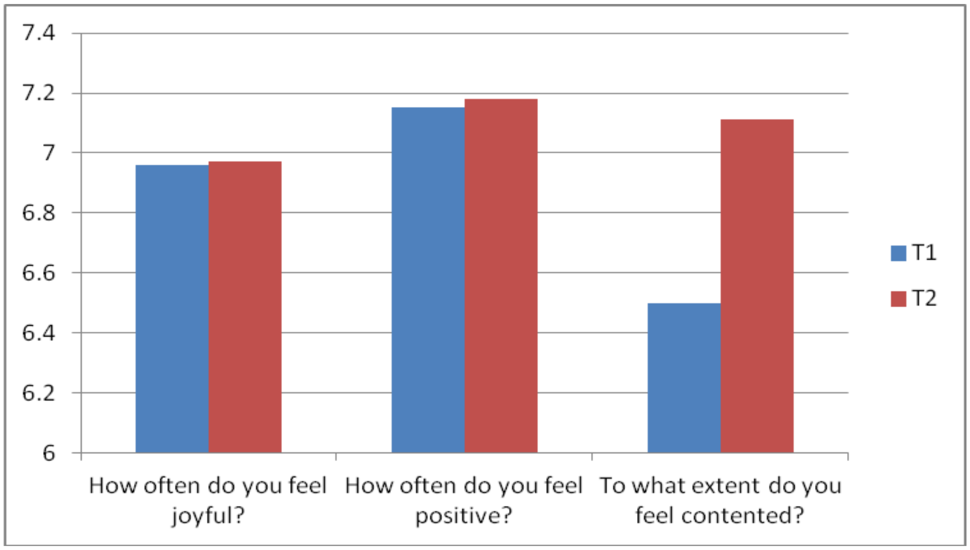

Figure 4.5 Positive Emotion

Interpretation: As shown in the diagram, all items of Positive Emotion show an increase in their descriptive means at T2. The overall increase in this parameter at T2 is by 3.20%. This shows the positive effect of health tracking on Positive Emotions of an individual.

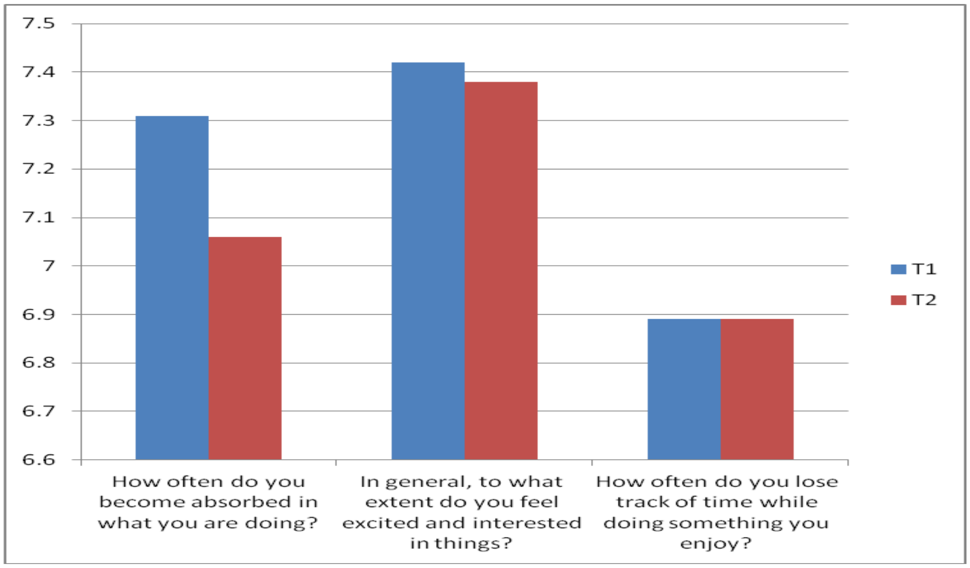

Figure 4.6 Engagement

Interpretation: As shown in the diagram, all items of Engagement show a decrease in their descriptive means at T2. The overall change in this parameter at T2 is 0.14%. This shows that health tracking did not have a substantial positive effect on Engagement of an individual.

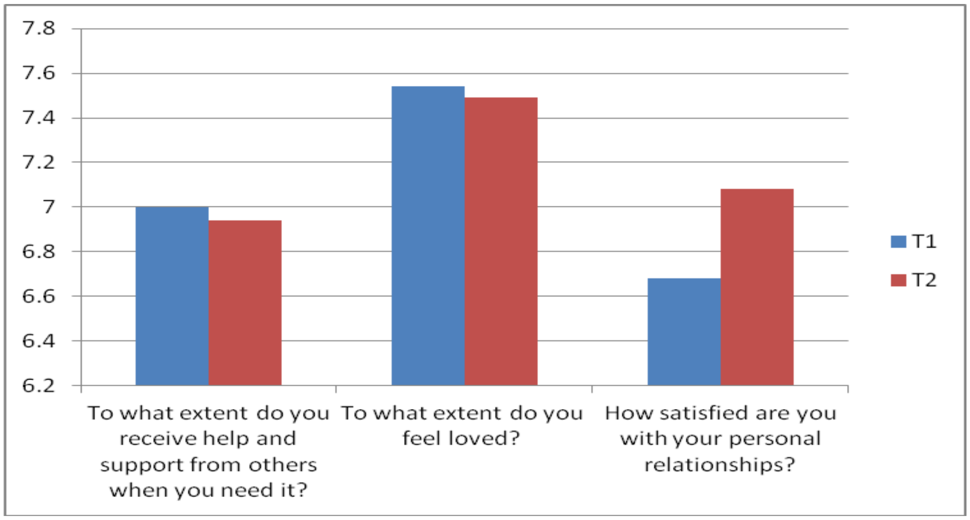

Figure 4.7 Relationship

Interpretation: As shown in the diagram, two items of Relationship show a decrease in their descriptive means and one item shows a substantial increase at T2. The overall change in this parameter at T2 is 1.41%. This shows that positive effect of health tracking does not have a significant effect on an individual.

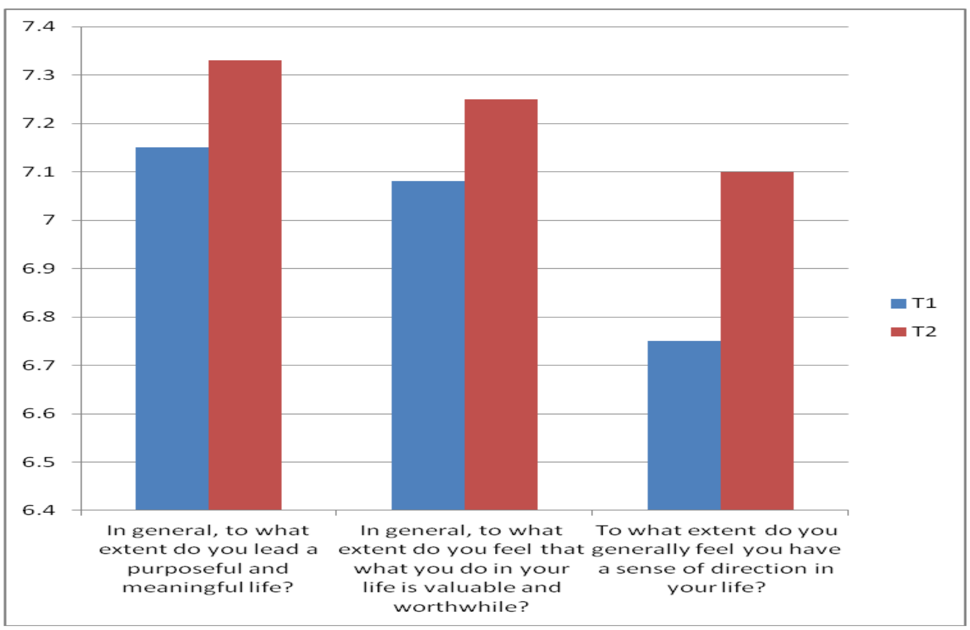

Figure 4. 8 Meaning

Interpretation: As shown in the diagram, all items of Meaning show an increase in their descriptive means at T2. The overall increase in this parameter at T2 is by 3.39%. This shows the positive effect of health tracking on an individual's ability to find meaning in life.

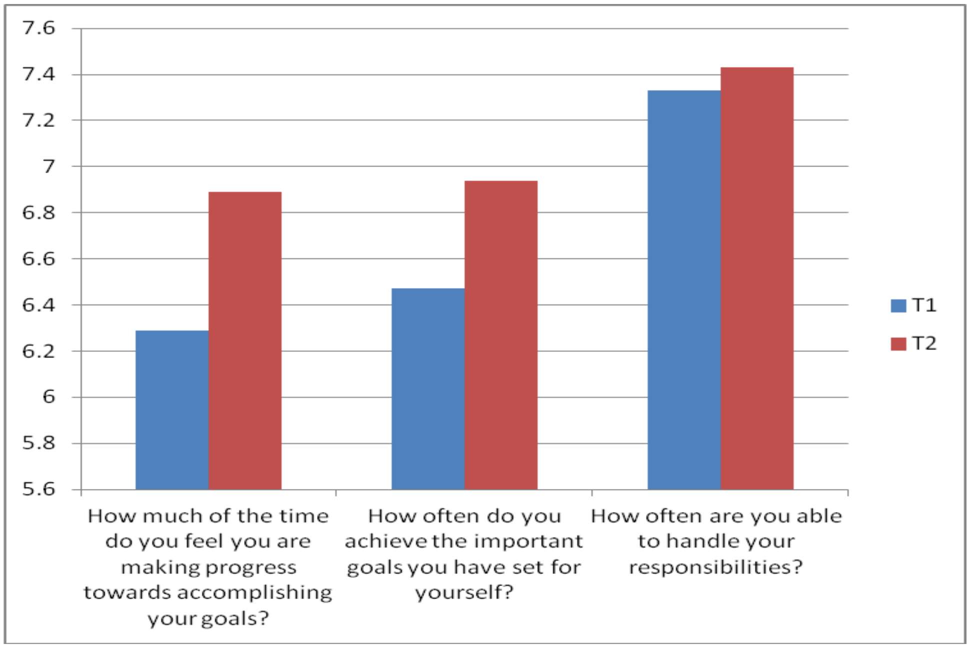

Figure 4. 9 Accomplishment

Interpretation: As shown in the diagram, all items of Accomplishment show an increase in their descriptive means at T2. The overall increase in this parameter at T2 is by 5.82%. This shows the substantial positive effect of health tracking on Accomplishment attitude of an individual.

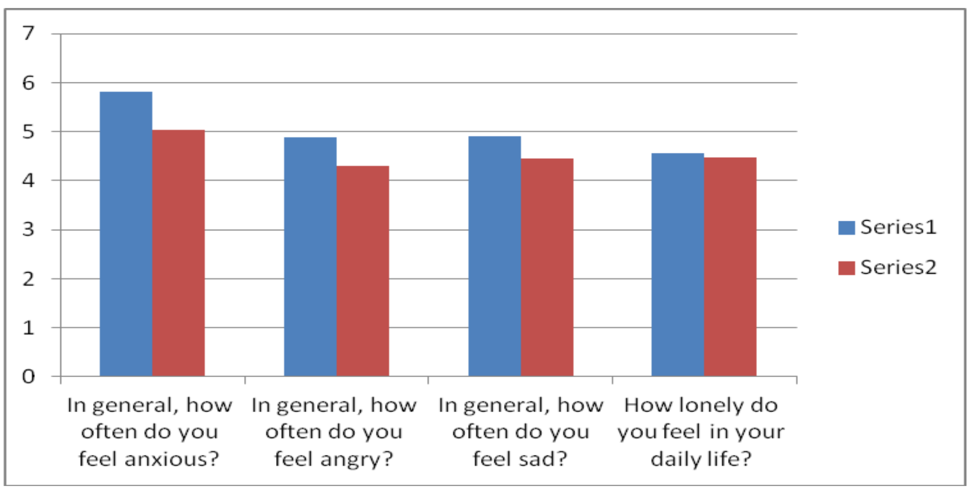

Figure 4. 10 Negative Emotion and Loneliness

Interpretation: As shown in the diagram, all items of Negative Emotion and Loneliness show a decrease in their descriptive means at T2. This is a good thing as it shows decrease of harmful emotions. The overall decrease in these parameters at T2 is -11.37% and -2.19% respectively. This shows the positive effect of health tracking on decreasing negative emotions and loneliness of users.

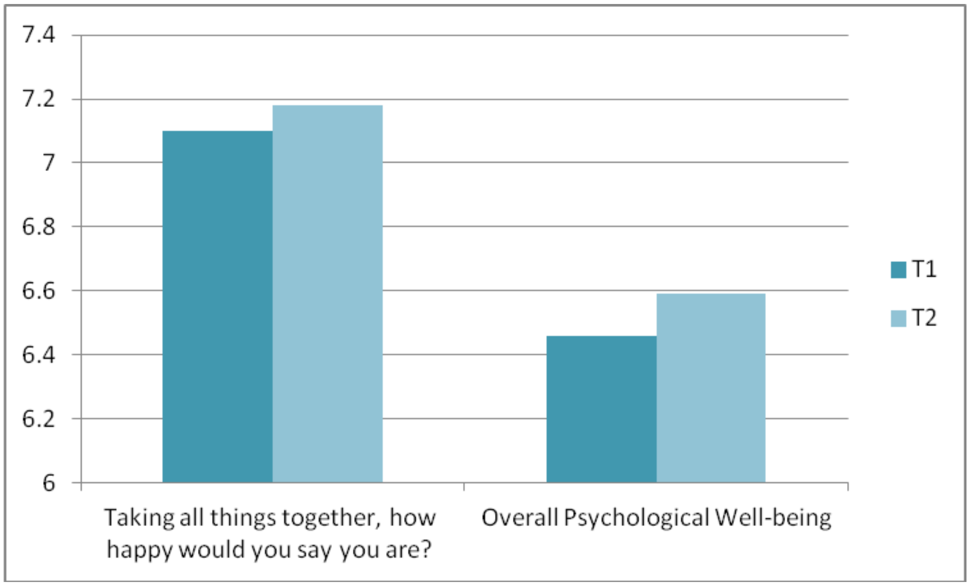

Figure 4. 11 Happiness & Overall Psychological Well-Being

Interpretation: As shown in the diagram, Happiness and Overall Psychological Well-being of the user show an increase in their descriptive means at T2. The overall increase in happiness is by 1.13%.

The overall psychological well being mean was calculated by taking average of means of all the parameters – Positive Emotion, Engagement, Relationship, Meaning, Accomplishment, Loneliness, Negative Emotion and Happiness.

The overall psychological well-being at T2 increases by 1.34%. This establishes the positive effect of usage of health tracking apps on an individual’s psychological well-being.

4.2.3 Perceived Physical Health

Table 4. 7 Descriptive mean of items of Physical Health

Items	T1	T2	Percentage Difference
How satisfied are you with your current physical health?	6.04	6.97	15.40
In general, how would you say your health is?	6.42	6.90	7.48
Compared to others of your same age and sex, how is your health?	6.58	6.69	1.67
Total Mean	6.35	6.86	8.03

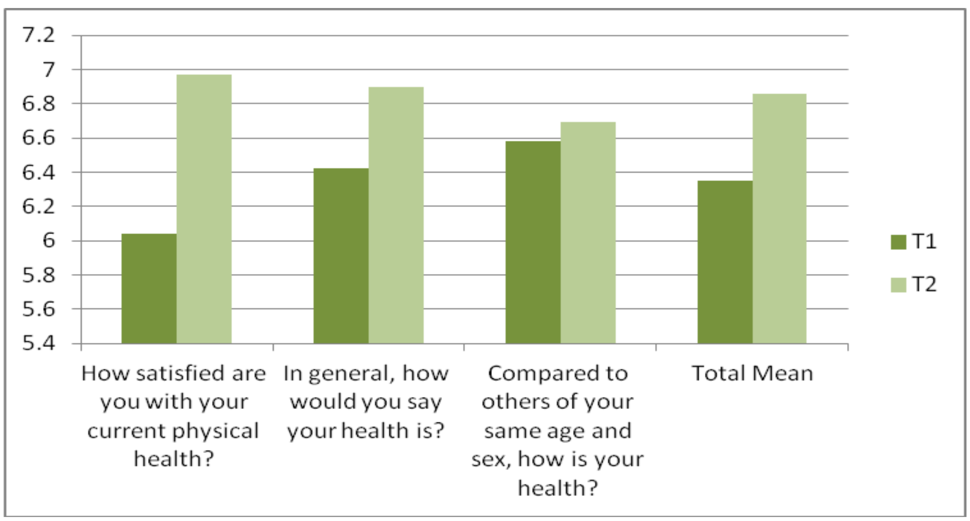

Figure 4. 12 Descriptive mean of items of Physical Health

Interpretation: As shown above, all the items of perceived Physical Health show an increase in their descriptive means at T2. The overall perceived physical health mean increases by 8.03 % in T2 showing a positive effect of health-tracking apps on an individual's perception of physical health.

4.2.4 Overall Review

Table 4. 8 Descriptive means of all parameters of overall well-being

Parameters	T1	T2	Percentage Difference
Health Consciousness	9.00	9.18	2%
Positive Emotion	6.87	7.09	3.20%
Engagement	7.20	7.21	0.14%
Relationship	7.07	7.17	1.41%
Meaning	7.00	7.23	3.39%
Accomplishment	6.70	7.09	5.82%
Negative Emotion	5.19	4.60	-11.37%
Loneliness	4.57	4.47	-2.19%
Overall Happiness	7.1	7.18	1.13%
Physical Health	6.35	6.86	8.03%
Overall Well-Being	**6.71**	**6.80**	**1.34%**

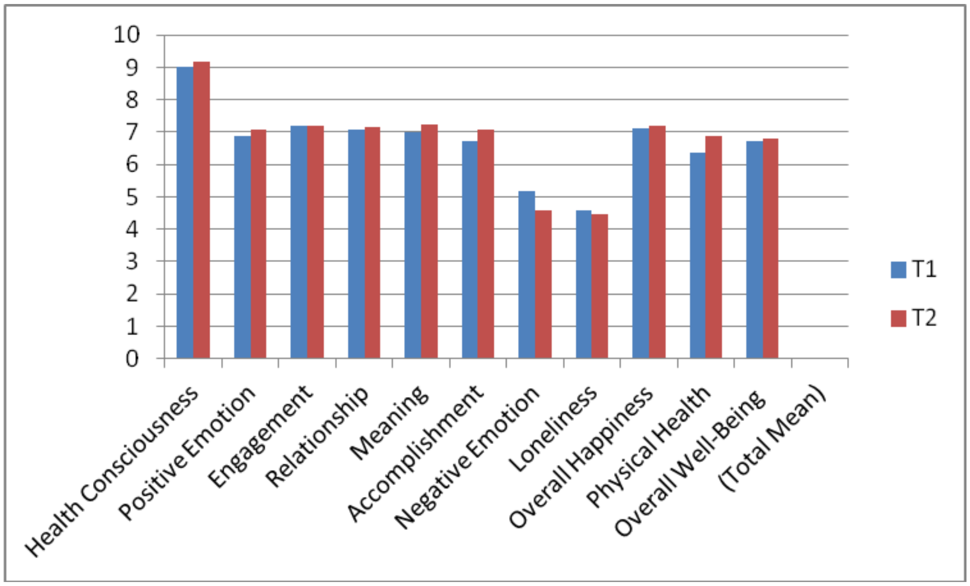

Figure 4. 13 Graphical Representation of mean parameters in T1 and T2

Interpretation: As shown, the overall well-being of the respondents saw an increase of 1.34% during the trial period from T1 to T2. This indicates the overall positive effects of using health-tracking apps on an individual.

4.3 Analysis of Objective 2: To study the trend analysis in measured metrics to determine user behavior.

The respondents were asked to provide their daily metric data (Steps, Calories, Distance) over the 15 days voluntarily.

This data was then converted into a scatter plot to see daily variation in data metrics.

Following is the tabular and graphical representation of two respondents' data:

Table 4. 9 Daily metric data of Respondent 1

Date	Steps	Calories	Distance (Km)
4/16/2019	6316	1816	2.44
4/17/2019	5233	1802	1.32
4/18/2019	10326	2030	5.42
4/19/2019	4014	1759	2.2
4/20/2019	11128	2110	6.31
4/21/2019	9793	2057	5.41
4/22/2019	6039	1924	2.25
4/23/2019	6999	1961	4.83
4/24/2019	7213	1934	3.95
4/25/2019	7199	1914	3.8
4/26/2019	4178	1781	1.77
4/27/2019	4048	1722	1.88
4/28/2019	6696	1873	3.71
4/29/2019	4354	1761	1.75
4/30/2019	4610	1728	2.2

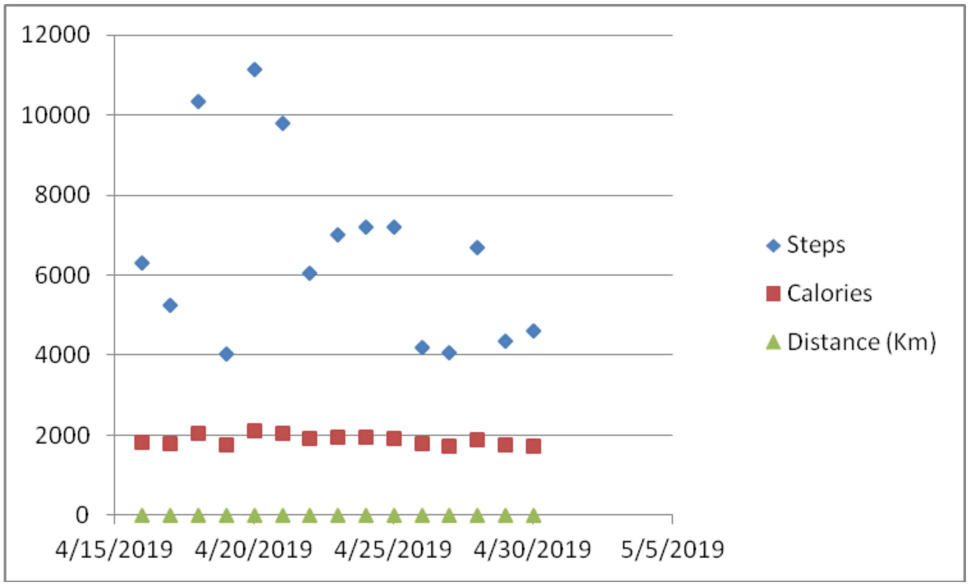

Figure 4. 14 Scatter Plot of daily user metric data of Respondent 1

Interpretation: This is the metric data of a motivated respondent. From the graph we can observe that the number of steps varies highly. Whereas distance covered sees an upward trend. The calories burned have decreased due to lesser number of steps during the end of the trial.

This can be interpreted has falling motivation of a novice user. A respondent is highly motivated in beginning but starts losing interest overtime.

Table 4. 10 Daily metric data of Respondent 2

Date	Steps	Calories	Distance (Km)
4/16/2019	9094	1461	4.18
4/17/2019	1412	1225	0.63
4/18/2019	2300	1275	0.86
4/19/2019	8421	1379	2.85
4/20/2019	8572	1463	3.68
4/21/2019	16412	1565	7.92
4/22/2019	980	1219	0.42
4/23/2019	7960	1382	3.85
4/24/2019	315	1198	0.02
4/25/2019	428	1193	0
4/26/2019	3734	1285	1.41
4/27/2019	1124	1220	0.31
4/28/2019	6794	1296	1.33
4/29/2019	638	1200	0.12
4/30/2019	406	1193	0

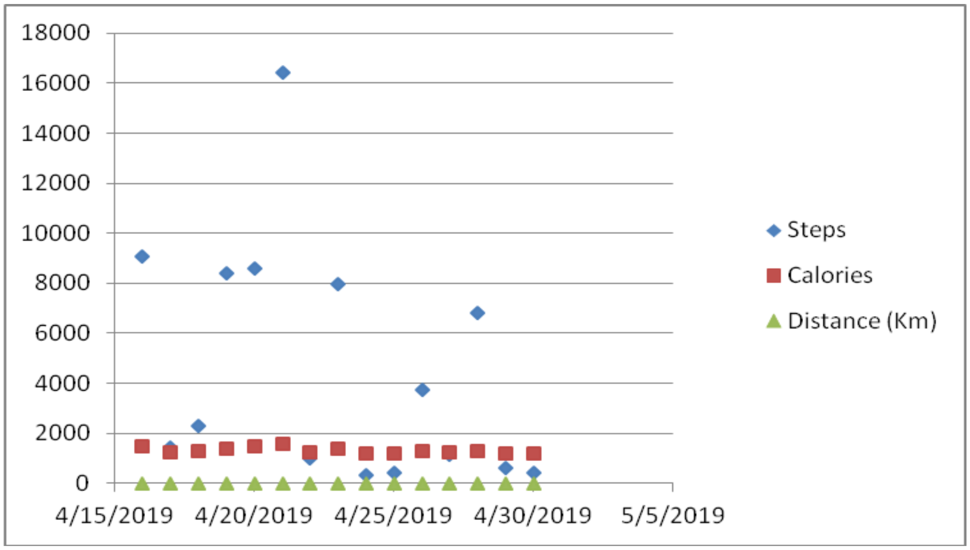

Figure 4. 15 Scatter plot of daily metric data of Respondent 2

Interpretation: For respondent 2, we see an extremely varied step count per day. The distance travelled goes below 1 km on certain days. The motivation is seen falling over the 15 days. Hence users become less interested in using the app overtime unless some engaging methods are deployed.

4.4 Findings and Recommendations

The study of descriptive means of the parameters shows that the total average mean of Overall well-being increases by 1.34% in a period of 15 days of the trial.
This is a significant difference for a short trial period.
Individual parameters of Health consciousness show an increase of 2%, Psychological Well-being increases by 2.01% and Physical Health increases by 8%.

Table 4. 11 Overall percentage increase in Well-Being Parameters

	Percentage increase
Health Consciousness	1.34%
Overall Psychological Well-Being	2.00%
Physical Health	8.03%

The increase in Physical Health is significantly high which implies that usage of Health-tracking apps can have positive intervention in improving user's physical health.

The findings of the second objective are that the motivation to use the app decreases overtime. To avoid that, app makers need to come up with more engaging features.
Features to be able to share results on social communities can also help in increasing usage rate of health-tracking apps.

4.5 Limitations of the Study

a) The sample size is small.
b) Self-reporting metrics have been used primarily to arrive at findings.
c) An even smaller sample could be utilized for daily metric data.
d) Analysis is descriptive in nature.

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6. ANNEXURE