P-ISSN: 2618-0723
E-ISSN: 2618-0731

NAAS Rating (2025): 5.04
www.extensionjournal.com

International Journal of Agriculture Extension and Social Development

Volume 8; Issue 8; August 2025; Page No. 92-97

Received: 19-05-2025
Accepted: 21-06-2025

Indexed Journal
Peer Reviewed Journal

# Relationship of mobile health app usage typologies with nutritional and health outcomes: Experience from India

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**DOI:** https://www.doi.org/10.33545/26180723.2025.v8.i8b.2248

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**Abstract**

Mobile health apps are popular, especially among young population, for achieving better nutrition and health behaviour. Despite their popularity, scant information is available regarding their effectiveness particularly in context of an emerging market like India. This paper identifies various user typologies based on health app usage and explores the association of these typologies with various nutrition and health outcomes. Using a novel research approach, we have identified user typologies using cluster analysis and compared these typologies in terms food consumption, nutrient intake, physical activity, physical performance and Body Mass Index. The results reveal significant differences among these typologies on basis of higher consumption of healthy food items such as Cauliflower ($P<.001$), Tomato ($P= 0.01$), Raisins ($P<.001$) and lower consumption of unhealthy food items such as chips ($P<.001$), pizza ($P<.001$), cold drinks ($P<.001$). A significant difference is also observed in time taken for touching toes ($P=.048$) and heart rate after jumping ($P=.02$). BMI measurements differed significantly ($P=.01$) across the user typologies. Long term and frequent use cluster exhibited better nutrition and health outcomes. We have used multivariate probit analysis and marginal effects to examine the influence of health app usage on BMI in presence of various control variables. In multivariate probit model, user typology exhibited a significant association ($P=. 048$) with BMI category even in the presence of control variables. Difference in usage pattern of health apps is significantly associated with different nutrition and health outcomes. Long term and regular use of health apps is recommended for achieving the potential benefits.

**Keywords:** Health app usage, user typology, health behaviour, physical performance, food intake, BMI

## Introduction

Trend of using mobile apps, for achieving health goals, is catching up fast with the users. Currently, health-based apps are recognized as the third fastest growing app category online, subsequent to games and utilities [1]. Health apps are typically used to improve nutritional status, eating habits and overall health and fitness [2-4]. These apps evaluate calorie expenditure, provide benchmarking against nutritional goals, and summarise trends of performance over different time periods [5-7]. Based on monthly usage patterns, Brazil, China and India are the top three users of apps in the world [8]. Deeper market penetration of smart phones and affordable mobile internet coupled with higher concerns for health among individuals are instrumental in spurt of health app usage the emerging market such as India. With 1.156 billion mobile subscriptions, India ranks 2nd in the world for mobile internet traffic [9-10]. In terms of time spent on apps, Indians spend 155 minutes per day on apps and are ranked 5th in the world [8].

Given the emerging nature of the domain, scant information is available regarding the effectiveness and usage of these commercial nutrition and fitness apps [11-12]. The body of knowledge concerning the effects of health app usage on nutritional status, anthropometric and physical characteristics is unsaturated, especially in context of emerging markets. Studies for gathering better evidence of usage pattern of these apps, their associations and benefits with respect to health behaviour and BMI, and their perceived utilities are needed [13-15]. Present study is one of the maiden attempts in exploring the user typologies and their association with afore-mentioned aspects.

In spite of high engagement and user acceptability, the ability of health apps to deliver the desired behaviour outcomes is not proven strongly. Consistency of success, of the health apps, for improving health behaviour has been questioned [16-17]. Concerns regarding lack of correlation between health app generated outcomes and clinical knowledge are also expressed [18]. Purpose of this study is to identify various user typologies based on health app usage and explore the association of these typologies with various nutrition and health outcomes. These outcomes are measured on the basis of nutritional status, physical activity level, physical performance and BMI.

## Materials and Methods

### Sample and Study Design

For achieving the objectives, we conducted a cross-sectional observational study. Population for the study consisted of all

Under Graduate and Post Graduate students pursuing higher education from an Indian university. Based on enrolment, we estimated total number of undergraduate and postgraduate students in the University at 4000. For infinite population size, with 5 percent tolerance of variation at 95 percent confidence level and population proportion of 50 percent, the minimum sample size required is 384 [19]. Using proportionate random sampling, we selected 243 undergraduate and 157 postgraduate students. Overall, the sample size is 400. Therefore, the sample size for the study is statistically adequate. We selected University students as this group is quite familiar with the apps and is one the major app user groups. Previous studies have advocated higher app use by the young population [2, 20-23]. Only the students having a smart phone and current health app use were included in the sample. Health Apps for the purpose of this study included the apps with features related to both fitness and nutritional aspects. The study did not involve any intervention or a control group. Using a pre-structured questionnaire, we collected primary data regarding socio economic profile, level of physical activity, usage of health apps and anthropometric measurements. Using Food Frequency Questionnaire, we collected information regarding consumption pattern of the respondents. We validated the instrument used for data collection by undertaking a pilot survey of 20 respondents and these respondents were excluded from the final sample. Setting up a field experiment, we also measured physical performance of the respondents. Free and informed consent of the respondents was obtained before data collection. The study, on which the current manuscript is based, is approved by a committee formed by Dean, Post Graduate Research of the University. Data collection was done in year 2018-19 and data analysis was done in year 2019.

## Measures

We measured height and weight of the respondents for calculation of BMI [24-25] and used WHO suggested BMI cut off for Asian population [26]. We adapted a Food Frequency Questionnaire (FFQ) to collect data regarding food consumption pattern among the respondents [27]. In all, there were 118 food items included in FFQ. Respondents were asked to indicate the frequency of various food items on a scale of 1 to 7, with '7' representing daily consumption and '1' representing negligible consumption. We used the 24-hour recall method for three successive days for assessing dietary intake of the r66espondents. We calculated average daily intake of nutrients by using Indian Nutrition Software 'Diet Cal' [28]. We used Physical Activity Diary Method (PADM) to determine time consumed to perform various activities for three consecutive days. The Physical Activity Levels of subjects were evaluated using Physical Activity Ratios (PAR) as specified by FAO/ WHO/ UNU [29]. Subsequently, we asked the respondents to perform three physical activities: running for 100 metres, jumping (25 repetitions) and touching the toes (25 repetitions). We measured time taken to complete the activity, heart rate (before and after the activity) and cardiac index (before and after the activity). We measured heart rate using a wireless heart rate monitor. We calculated Cardiac Index using previously suggested methods [30-33]. We used sphygmomanometer to record blood pressure of all the respondents prior to and after each activity. Characteristics used for classification of the respondents are time since starting the usage of health apps, frequency of app use and time spent on the apps. We measured time since starting the usage of apps in weeks. For frequency of app use, daily use is assigned value of 5 and fortnightly use is assigned value of 1. For weekly time spent on apps, more than 5 hours per week is assigned value of 4 and less than one hour per week use is assigned value of 1.

## Statistical Analysis

We used various statistical tools for analyzing the collected data. These tools include Cluster Analysis, Analysis of Variance and Qualitative Limited Dependent Variable Regression. We used SAS 9.4and SPSS for data analysis. Cluster analysis is a multivariate technique with the primary purpose to group the respondents, in form of clusters, on basis of their characteristics. Primarily, Cluster Analysis is used for market segmentation in commercial marketing. Off late, its applications are also available in context of health behaviour as well [34-36]. Resultant clusters exhibit high internal (within-cluster) homogeneity and high external (between-clusters) heterogeneity [37]. For the purpose of dividing the respondents into different clusters, hierarchal cluster analysis is undertaken and agglomeration schedule is obtained. Agglomeration schedule provides useful information regarding appropriate number of clusters (identified through a sudden jump in error coefficient) using squared Euclidian distance. Subsequently, the respondents are finally divided into different clusters using K-means cluster analysis [38]. We performed cluster analysis by using standardized values (*Z* score) of three input variables.

We used Proc QLIM statement to estimate various categories of BMI (Underweight, Normal, Overweight and above). Marginal effects were also calculated. Interpretation of the marginal effects is similar to the interpretation of partial coefficients with Ordinary Least Squares (OLS) regression in that each effect represents the change in the dependent variable caused by the effect of the independent variable while controlling for the effects of the remaining independent variables. Before estimating BMI category model, we tested for endogeneity. For testing endogeneity, Durbin-Wu-Hausman test is used. Procedure entails estimating endogenous variable with the help of exogenous variables and getting the residuals. Then an augmented regression test is used by including the residual as explanatory variable to check endogeneity.

## Results

Profile of the respondents, in terms of demographic variables and Health App usage is presented as Annexure-1. We used cluster analysis for classifying the respondents into different clusters on basis of their usage of health apps. We used Ward's method of hierarchical clustering for determining the number of clusters. Based on agglomeration schedule, we finalized three clusters for the usage of health apps. Table 1 presents usage characteristics of various clusters obtained from K-means clustering technique. Cluster centroids, in terms of standardized *Z* scores, and cluster means, in terms of raw scores, are presented. Based on cluster centers, Cluster 1 represents the respondents with long term and frequent usage of health apps. Cluster 2 represents the respondents with recent and relatively less frequent usage of health apps and Cluster 3 represents respondents with recent and frequent usage of health apps. Comparison of cluster means indicates a significant difference across all three input variables. We used these identified clusters for further analysis.

Table 2 presents the comparison of the selected variables across the identified clusters. We recorded food frequency for 118 food items from various food groups such as cereals, pulses, milk and milk products, fruits, and vegetables. ANOVA reveals a significant difference across various user typologies (clusters) for 23 food items. Table 2 shows that cluster 1 respondents have significantly higher consumption of various food items such as fruits, vegetables, raisins and omega 3 rich food products like flaxseeds and fish.

On the other hand, cluster 1 respondents go for significantly lower consumption of processed food items (chips, nachos, cold drinks), junk food (pizza) and bakery products (pastries, cookies, cakes).Table 2 also presents the comparison of various clusters on basis of Body Mass Index (BMI) and Physical activity level (PAL). Average PAL of cluster 1 members is more as compared to other clusters but calculated *F*-value not significant at 5 percent level. On the other hand, there is a significant difference in BMI across various clusters.

Cross tabulation of identified clusters with BMI categories reveal that 71.43% of cluster 1 members are from normal BMI category, while 52.34%and 50.36% members from cluster 2 and cluster 3 respectively have normal BMI. About 36.60%and 46.72% members from cluster 2 and cluster 3 respectively are from overweight/obese category while the same number for cluster 1 is about 17.86%. Cross tabulation revealed a significant association ($\chi^2_4$:14.85, *P*=.005) between BMI categories (underweight, normal, overweight/obese) and cluster membership Findings pertaining to comparison of user typologies based on physical performance are presented in table 3. Cluster 1 members took lesser time for completing 25 jumps as compared other clusters. In case of jumping, a significant (*P*=0.02) difference in heart rate (after test) is observed. Cluster 1 members performed significantly better as compared to their counter parts on the basis of time taken for touching toes (*P*=0.04).

We run Qualitative limited dependent variable regression to find out the determinants of BMI categories using Proc QLIM. Table 4 presents the results of multivariate probit model. We have used cross-sectional data for estimation of BMI category. Use of cross-sectional data for model estimation raises the issue of causality identification. Presence of bidirectional effects during model estimation can lead to inconsistent estimation. In this case it was difficult to determine whether use of health apps affected BMI category or whether better BMI led to higher health app use. We used Durbin-Wu-Hausman test and non significant value of residual's coefficient ($\chi^2$: 1.15, p=0.2836) indicated consistent estimation of BMI category. Results of multivariate probit model reveal that BMI category is significantly associated with age, gender and cluster membership. BMI is positively associated with age, while it is having negative association with *Cluster*. Significant positive estimates indicate an increased probability of falling in higher BMI category with increase in age and males having higher probability of having better BMI as compared to females. Further, the respondents with long term and frequent health apps use are having better BMI as compared to others. Table 4 also presents marginal effects of significant explanatory variables of multivariate probit model.

**Discussion**

The study classifies actual app usage patterns and compares different health outcomes on basis of the differentiated usage pattern. In contrast to a number of previous research studies, it does not compare Users vs. Non-Users. As the assignment of the respondents to various clusters was not a priori, the present study is free from confounding errors and bias on account of the respondents getting conscious, being part of intervention groups. Findings of the study uncover a number of issues pertaining to the research domain of health app usage. Firstly, out of the identified typologies, the cluster with longer and frequent usage exhibited significantly better nutrition intake, physical performance and BMI. Sustained and longer usage of health apps is associated with significant changes in health behavior and related health outcomes. Previously, studies have focused on shorter intervention periods. There is a possibility of shorter duration randomized control trials not exhibiting the real picture regarding the effectiveness of health apps. Therefore, there is a need to have longer duration studies so as to accurately evaluate the effectiveness of health apps. Previous studies, suggesting longer duration studies to determine the effects of health apps on health outcome, are also available [39-40]. This notion is important in context of user communication as well. There can be a tendency on part of users to have quick outcome expectations. Health app users should be made aware of the fact that longer and sustained use is associated with securing the desired outcomes. Lack of knowledge regarding the sustained use of health apps may lead to users dropping/ interrupting the use of health apps on account of non-availability of desired outcomes in short term.

Secondly, long term and frequent user cluster exhibited better nutrition behavior by significantly higher consumption of healthy foods and significantly lesser consumption of unhealthy foods. These findings of the study are in agreement with a number of previous studies. Significantly higher vegetable consumption on account of health app usage is evident in literature [40, 41]. Apart from this, better eating behavior [13,21,42] and improved food consumption habits, in terms of increased healthy and reduced unhealthy food consumption, for health app users are reported previously.

Similarly, long term and frequent users of health apps recorded higher PAL as compared to other typologies. But, there was no significant difference (*P*>0.05) among various typologies on basis of PAL scores. This finding is in line with the previous studies [41]. Health app usage is associated with significantly higher physical activity for intervention groups [43-44]. Long term and frequent users exhibited better physical performance as compared to their counterparts. For the majority of dimensions related to physical performance, long term and frequent users fared better than others. They had significantly lower heart rate after the jumping activity and completed the activity of touching toes in significantly lesser time as compared to other groups.

In our understanding, this study is also novel in terms of measuring and comparing physical performance across user typologies. Previously, the research studies have been limited only to selected physical activity dimensions such as step counting and time spent on physical activity. Physical activity level may not be the ultimate measure of health outcome as it is merely one component in achieving the desired health outcomes. Physical activity is desirable as it leads to better health outcomes. But the measurement limitations related to physical activity restrict the process only to quantitative aspect. Quality of physical activity is also an important dimension. This dimension is difficult to measure, and therefore, is easily ignored. Given these arguments, physical performance and BMI are better indicators of health outcomes. Interestingly, there is no significant difference in terms of physical activity levels across various typologies but a significant difference is present in terms of BMI and few dimensions of physical performance. There is a possibility that long term and frequent users are able to exercise better quality physical activities on account of knowledge and support available from health apps. Further, better quality physical activity may attribute to better health outcomes in terms of BMI and physical performance.

There is a significant difference in BMI of various typologies. Long term and frequent users have better BMIs as compared to other typologies. This finding is in agreement with previous studies [45-47] reporting a decrease in weight, body fat and BMI. This finding assumes significance in terms of associating effectiveness of health apps with better health outcomes. Cross tabulation analysis also indicates that the highest proportion of normal BMI is from the long term and frequent users. Previously a number of researches have reported a decreased BMI or weight loss [48-51] but the differences were not statistically significant as compared to controls. Further, qualitative limited dependent variable regression indicates significant association of health app usage with BMI even after controlling the other variables such as gender, age, income and background.

Need for exploring frequency of use and use pattern of health apps, [18] especially in context of non-western countries [52] has been expressed in the literature. Further, a gap between app use and health behavior change [16] is also indicated. This study assumes importance as it contributes to address the above-mentioned concerns in the given research domain. To our knowledge, this is first of its kind study that examines the association between health app usage pattern and associated health outcomes such as Body Mass Index and Physical Performance in India. Current study is important as it addresses the next level of research domain pertaining to evaluating health app outcomes rather than comparing users and non users.

As the study is based on the collection of primary data from the respondents, it suffers from the limitations associated with the survey methodology. App use by the respondents is self reported. Further, the study is limited to a specific user group of university students. Therefore, the generalizations of its findings to other user groups may not be appropriate. While comparing user typologies on various dimensions, the present study does not take into consideration the possible qualitative differences across health apps coming from different service providers.

## Conclusion

Findings of the study indicate that long term and frequent use of health app is associated with better health outcomes. User typology with long term and frequent use exhibited better food consumption pattern through relatively higher consumption of healthy foods and relatively lower consumption of unhealthy foods. This user typology also performed better in various physical activities. Further, significantly better BMI is associated with long term and frequent use of health apps. For achieving significant benefits in terms of improved health, nutrition and physical performance, long term consistent and regular use of health apps is recommended.

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