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Towards User-Centric Intervention Adaptiveness: Influencing Behavior-Context Based Healthy Lifestyle Interventions

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ABSTRACT In the era of digital well-being, smart gadgets are the unobtrusive sources of acquiring information. A variety of personalized wellness applications support self-quantification based recommendations to provide wellness status for achieving personalized targets. However, these applications are unable to promote the induction of new healthy habits and thus are not too much effective for long term as users tend to loose their interest. Thus, we have proposed a methodology for User-Centric Adaptive Intervention based on behavior change theory for maintaining end-users' interest. The methodology consists of four steps: (1) quantification of behavior based on contributing factors governed by expert-driven rules; (2) behavior-context based mapping for the identification of behavior status of the user; (3) selection of appropriate way of intervention to get fruitful outcomes; and finally (4) feedback based evaluation on the basis of recorded activities and questionnaires for satisfaction. A comprehensive healthy behavior index-based quantification supports the machine learning-based prediction model for behavior-context mapping. Furthermore, the evaluation is performed through implicit and explicit feedback analysis along with the accuracy of the behavior-context prediction model through multiple scenarios to cover comprehensive situations. The ensemble classifier suggests the accuracy of 98.02% for the behavior-context prediction model, which is higher than the other classifiers. The gain in behavior change is drawn from implicit feedback, which depicts that behavior context-based methods have improved the adaptation in behavior at a steady pace for the long term. The explicit feedback from 99 end-users of wellness application based on the proposed methodology obtained *Good* and *Desired* status for widely used System Usability Score and AttrakDiff tools respectively.

INDEX TERMS User behavior, behavior-context, lifestyle, lifelog monitoring, self-quantification, healthy behavior index, adaptive interventions.

I. INTRODUCTION

Behavior related to lifestyle requires continuous guidance to adopt healthy behavior through monitoring and interventions. Unhealthy behavior may cause health complications and consequently, degrade the quality of life hence a burden on society and economy. Personal awareness about lifestyle status has been revolutionized from the last decade due to the advancement in Information and Communication Technologies (ICTs). Recently, the e-health and wellness

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applications have changed the trend of healthcare application from responsive to proactive [1] in terms of services and features involving people of all ages with confidence, motivation, and style to adopt a healthier lifestyle. ICTs and smart gadgetries equipped with wearables have stimulated people to involve such valuable wellness applications. These applications collect a variety of data through built-in sensors seamlessly. It is used to determine the target in the form of steps count, weight loss, women's health during pregnancy, and calorie consumption. Now, it is believed that the future of the health domain lies in big data that is nurtured by the Internet of Things (IoT). Therefore, a variety of digital well-being applications are taking the role of personalized counselors to guide about risky behaviors and adopt healthy ones [2]. The traditional way of behavior adaptation is changing from long interactions of the physician to just-in-time interventions. These overcome the tedious tasks depending on human memory and polluted through some bias. In wellness management, it is essential to understand what are unhealthy behaviors and their consequences.

A. UNHEALTHY LIFESTYLE BEHAVIOR

Multiple lifestyle-related risk factors like unhealthy diet, smoking, physical inactivity, and alcohol consumption have been identified as a preventable cause of Noncommunicable Chronic Diseases (NCDs). The recent emphasis of healthcare has been on promoting a healthy diet, smoking cessation, avoiding alcohol consumption, and regular physical activities. The unhealthy lifestyle not only degrades the quality of life but also increases the economic burden on the community.

Hence, the sedentary living is defined as the waking time spent in such activities whose Metabolic Equivalent Task (MET) value is less than 3. The interrupts at regular intervals in sedentary behavior improve the person's metabolic process [3]. So, an indication of prolonged physical inactivity behavior helps in changing the lifestyle for longer healthy life. Similarly, an imbalanced diet consumed for a long time may increase the probability of chronic disease development and premature death [4]. The balanced diet is a combination of multiple nutrients in different proportions, which is necessary for the nurturing of vital organs, whereas an excess of some nutrients is also dangerous. Similarly, smoking and drinking are two most negatively criticized lifestyle habits. Abuse of alcohol and smoking lay a foundation of multiple and critical health issues that range from mild-to-severe life-threatening dangers. The only exception is the moderate consumption of alcohol [5]. The knowledge about the complications of alcohol consumption and smoking on the body can motivate for their reduction and avoid abuse. Innovative interventions and wellness systems are needed to guide an addicted person effectively and efficiently.

B. LIFESTYLE IMPACT ON CHRONIC DISEASES

Lifestyle patterns such as regular exercise, non-sedentary activities, a balanced diet, not smoking, and controlled alcohol consumption, prevent and manage lifestyle-related NCDs [6], as shown in Table 1. These diseases include heart disease, hypertension, stroke, muscles problem, bone disorder, cancer, obstructive lung disease, obesity, diabetes, and chronic back pain. The lifestyle-related factors impact significantly on the development of NCDs and by adopting a healthy lifestyle, a person can enjoy a quality life for a longer period.

TABLE 1. Contribution of lifestyle factors in chronic diseases.

Sr.#	lifestyle Factors	Diabetes	CVD	Obesity	Metabolic Syndrome	Cancer
1	Physical Exercise	*	*	*	*	*
2	Quite Smoking	*	*	–	–	*
3	Maintain Healthy BMI	*	*	*	*	*
4	Intake Whole Grain	*	*	*	*	–
5	Reduce Sugar	*	*	*	*	–
6	Reduce Salt	*	–	–	–	–
7	Fruits & Vegetables	–	*	*	–	–
8	Low Calories	*	*	*	*	–
9	Low Fats	*	*	–	*	–

- $*$: represents that the lifestyle behavior has an impact in the corresponding disease.
- $-$: represents that the lifestyle behavior has no impact in the corresponding disease

C. WELLNESS MANAGEMENT APPLICATIONS

The design and development of health care and wellness applications are focusing on managing and analyzing the individual's activity log to identify healthy and unhealthy behavior [7]. The recent trend of healthcare for disease management has been shifted from reactive to disease avoidance by identifying a personalized behavior pattern. The behavior patterns support pro-actively to diagnose the root cause of any undesired chronic health issues. Multiple wellness applications focus on different techniques to support the end-users for managing the fitness, however inadequate to nurture healthy behavior for a lifetime. In literature, multiple Behavior Change Techniques (BCTs) were employed to attract the end-users in terms of self-quantification, education, feedback, interventions, and many more as discussed in Table 2 [8]. The comparisons of these BCTs along with focused fitness prospects is elaborated, which lack particularly in understanding the behavior context of the end-users and treat them with the same philosophy to enhance fitness. However, the technical comparison of existing and our proposed system in terms of services, architectural style, design, and state-of-the-art technologies are discussed in our previous published work [7].

Habit formation, in particular, could play an essential role in digital well-being applications, supporting behavior

TABLE 2. A matrix for wellness application and behavior change techniques.

Application		Google Fit[1]	Samsung S Health[2]	Apple Healthkit[3]	NoomCoach [4]	Argus [5]	Mining Minds++ [6]	MyFitnessPal[7]	Fitbit[8]
Behavior Change Techniques	Goal Oriented	User Based	User Based	User Based	Expert Based	User Based	Expert Based	User Based	User Based
	Self Monitoring	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Behavior Adaptation	No	No	No	Yes	No	Yes	No	No
	Behavior Education	Generic	Generic	Generic	Specific	Generic	Specific	Generic	Generic
	Applied Behavior Analysis	No	No	No	No	No	Yes	No	No
	Behavioral Feedback	No	Yes	No	Yes	No	Yes	No	No
	Habit Formation	No	No	No	No	No	Yes	No	No
	Just-in-Time Intervention	No	No	No	No	No	Yes	No	No
	Action Planning	No	No	No	Yes	No	Yes	No	No
	Notification (Alert)	On goal completion	No	No	On goal completion	No	Context based	On goal completion	On goal completion
Focus Activities		Step counter, Calories burn	Step counter, Calories burn	Step counter, Calories burn	Diet management	Step counter, Calories burn	Physical activities, Calories burn, Smoking, and Consume alcohol	Calories intake	Step counter, Calories burn
Recommendation		No	No	No	Expert based	No	Context based personalized	No	No

change towards more effective use of technology and ensuring the long-term effects of the adapted behavior [9]. Hence, our analysis drives the contribution through the following research questions (1) How to quantify the complex behavior of a user for lifestyle assessment? (2) How to identify the current behavioral stage from a quantified lifestyle? (3) How to analyze the user's satisfaction given the behavior stage-based intervention? We have performed a set of experiments in order to gather both implicit and explicit user feedback which in turns fine-tune the methodology. The main motivation of the study is to enhance the quality of life through a number of behavior adaptation strategies along with improving the overall fitness of the user. It leads us to focus on the foundation of behavior formation through BCTs under the impact of new emerging ubiquitous technology. To achieve this promising goal, our research had targeted the following objectives:

- To quantify the behaviors for the understanding as well as to gain knowledge for an appropriate decision regarding the adaptation.
- To identify risky situations of the behavior based on personalized context in-term of physiological and demographic profile.
- To assess the particular behavior stage of the user based on his/her behavior profile obtained through implicit and explicit evaluation.
- To enhance the receptivity of the intervention from a specific intervention style based on the behavior stage.
- To evaluate the methodology through user experience and system usability from the persons who need most to change their behavior in a difficult age range.

The main contributions of our work are (1) Leveraging the user profile and the daily life-log for accurately identifying the risk behavioral patterns, (2) Establishing a one-to-one mapping between a user's behavioral stage and the behavioral condition (3) A methodology for an adaptive recommendation targeting specific behavioral patterns (4) Divert the direction of fitness-oriented applications towards behavior-foundation applications (5) A comprehensive study evaluation based on users comprised of an elderly age group with non-communicable diseases.

The remaining portion of paper is organized into five sections. Background of lifestyle behavior and self-quantification is discussed in section II. User-centric adaptive intervention methodology is elaborated in section III, while section IV overviews the realization of the methodology through a wellness platform. The experimentation and evaluation of methodology are discussed in section V. The final section VI concludes the research work with a summary and future direction.

II. BACKGROUND

According to the latest World Health Organization (WHO) global status report, NCDs associated with lifestyle habits are

[1]https://www.google.com/fit/
[2]https://www.samsung.com/global/galaxy/apps/samsung-health/
[3]https://developer.apple.com/documentation/healthkit
[4]https://www.noom.com
[5]https://www.azumio.com/s/argus/index.html
[6]http://www.miningminds.re.kr/
[7]https://www.myfitnesspal.com/
[8]https://www.fitbit.com/global/us/home

TABLE 3. Definition for important lifestyle effecting factors along with assessment methodology.

Sr. #	Important Factors	Definition	Assessment Methodology	References
1	**Tobacco Consumption (Smoking)**	Cigar, pipe, and cigarettes all are dangerous and a major preventable risk factor of NCDs.	SR, QSU	[10]–[14]
2	**Alcohol Consumption**	A controlled amount per week keep risk of NCDs and premature mortality at low level.	SR, AUQ	[12], [15]–[19]
3	**Leisure time and daily physical activities**	Moderate intensity physical activities for at least 150 mins in a week	SR	[20]–[25]
4	**Dietary Regularity and Pattern**	Daily 3 to 5 times with at-least 4 to 5 hours delay.	SR, FFQ	[26]–[32]
5	**Sugar, Chocolates, and Sweetened Soft Drinks**	Added sugar is not good and less then 10% of daily calories obtain through it.	SR, DSQ	[33]–[35]
6	**Whole Grains, Fiber, and Carbohydrate**	Adult food must contain 25 to 30 gms dietary fiber (unabsorbable plant part)	SR, FFQ, 24RC	[36]–[40]
7	**Saturated and Unsaturated Fats (Cholesterol)**	Saturated fat is not good, and diet should contain less then 78 gms of fat	SR, FFQ, 24RC, OQ	[36], [37], [41]–[44]
8	**Protein (Egg, Fish, Poultry)**	It is essential nutrient and adult should take about 0.8 gms per kilogram of body weight.	SR, FFQ, 24RC, OQ	[37], [38], [42], [45], [46]
9	**Dairy (Milk, Yogurt, Butter, Cheese)**	It is source of vitamin D, calcium and essential minerals,at-least daily 3 servings are recommended.	PR, FFQ	[47]–[49]
10	**Fruits**	Daily 1.5 to 2 servings of fresh fruits and juice are preferred	SR, PR, FFQ	[49]–[53]
11	**Vegetables**	Daily 2 to 3 servings of preferably green vegetables are recommended.	SR, FFQ, OQ	[37], [38], [49], [53], [54]
12	**Dietary / External Salt (sodium) Amount**	Daily, about 2.5 to5.0 gms of salt is recommended for adult without NCDs.	RES	[55]–[58]
13	**Balance Diet (5 groups)**	Multi-nutrient from proteins, dairy, grains, fruits, and vegetables are required in an appropriate proportion .	FFQ	[13], [46], [49], [59], [60]
14	**Mental Stress**	Mental pressure causes aggression and threats the working quality as well as reduced productivity.	BJSQ, RESTQ	[61]–[64]

- SR: Self Report
- PR: Parents Report
- FFQ: Food Frequency Question
- DSQ:Dietary Screener Questionnaire
- RES:Dietary Sodium Restriction
- RESTQ: Recovery Stress Questionnaire
- 24RC: 24 hours Recall
- QSU: Questionnaire of Smoking Urges
- AUQ: Alcohol Urges Questionnaire
- OQ: Other Questionnaire
- BJSQ: Brief Job Stress Questionnaire

currently the major causes of worldwide deaths [65]. In reality, NCDs are responsible for more than 66% of the world's deaths, out of which 40% represents premature deaths under the age of 70. The WHO has identified the invisible epidemic of NCDs and defined a clear strategy to overcome the impact of the catastrophe tie of the scenario. The WHO has established a clear road-map to alter the course of the so-called ''slow-moving public health disaster''. Most of the measures outlined in these strategies seek change to an unhealthy lifestyle and adverse behaviors, such as alcohol and tobacco use, excessive salt and sugar intake, and poor physical activity, among others, by applying systematic methods of prevention and control. Traditional behavioral change approaches require users to engage in self-monitoring regularly. Notwithstanding the theoretically well-founded self-monitoring systems, many of them have proven to be unsuccessful in practice [3]. The main reason for the ineffectiveness is the lack of motivation, planning, and diligence shown in these self-tracking systems by frequent users. People regularly encounter discomfort when calculating, analyzing, and annotating information, resulting in a lack of interest in the role of reporting [4].

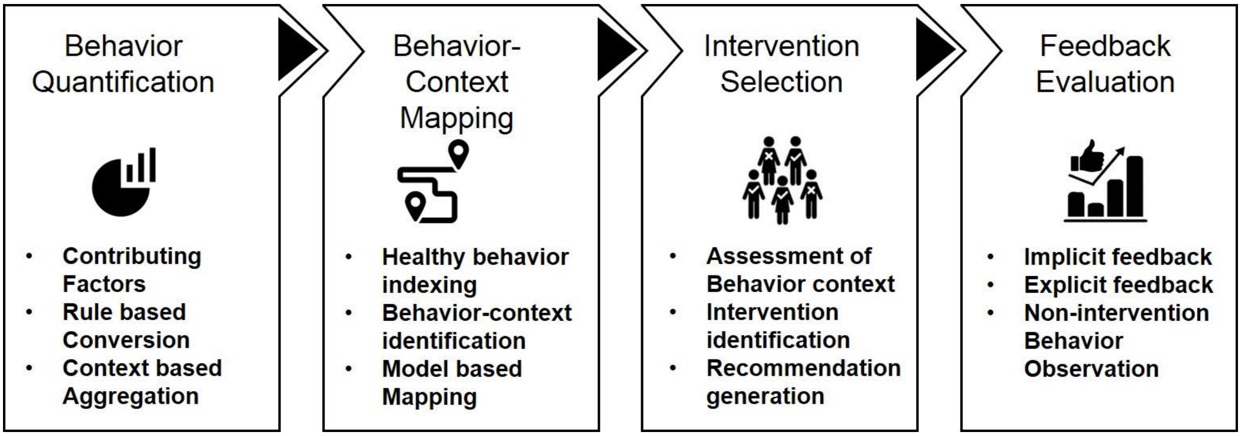


FIGURE 1. Abstract flow of User-Centric Adaptive Intervention methodology.

The ICTs have shifted the focus of healthcare and wellness applications to facilitate the seamless and automatic monitoring of user's behavior. User-centric Personalized Interventions (UCPI) can be sufficient to persuade, learn, adapt, and adopt practice towards a healthy lifestyle. The user-centric interventions should be developed by analyzing the user's lifelog data, preferences, context, and health constraints. Notably, in the health and well-being domain, the consideration of user-centric information can be valuable for attaining the user's attention in adopting and maintaining healthy behaviors for a quality and long life [66].

The challenge is to engage and maintain an interest in adopting a healthy lifestyle so that it becomes the behavior of the user. The generation of effective user-centric intervention implies, the justification of given recommendation and the adaptation of intervention in response to the modification of users' status and environment. Thus, instead of generalized persuasive features, systems should have adaptive capabilities to provide flexible persuasive interventions to teach a healthy lifestyle in an actionable and feasible manner. The modeling of persuasive mechanisms for adoptable and context-dependent intervention is more ambitious than most current approaches on persuasive technologies. The design of a persuasive system for behavior adaptation must ensure the consideration of user behavior status, knowledge, context, preferences, and health conditions [66].

Diverse commonplace technologies, such as GPS or accelerometers sensors, have been embedded in various smart commercial products to assess the most trouble sleeping, the total number of steps taken at a reasonable speed, and prolonged sedentary activities [7], [67]. Activity-based tracking technologies have shifted the phenomenon of ''quantified self'' from self-reporting to an unobtrusive manner. In literature, multiple studies are found related to self-quantification, as discussed in Table 3, depending on different techniques. In self-reporting studies, surveys were conducted related to physical activities, leisure time sports, walking for commuting, and daily habits related to performing different tasks [20]–[23], [68]–[70]. The diet is a composite concept based on different micro-nutrients. Every micro-nutrient has its importance and criteria for assessment, which are discussed in different literature. The evaluation is based on parents and self reported Food Frequency Questionnaire (FFQ) depending on 24-hour recall [26]–[29], [36]–[38], [41], [42], [50]–[52], [54]. The addictive behavior of smoking and alcohol had been evaluated through self reporting and specific questionnaires related to urges for these addiction [10]–[12], [15]–[17].

III. USER-CENTRIC ADAPTIVE INTERVENTION (UCAI) METHODOLOGY FOR BEHAVIOR CHANGE

We have proposed a conceptual framework based on the User-Centric Adaptive Intervention (UCAI) for behavior change, which has engaged behavior change theory in an actionable manner through ICTs. This framework consists of four steps a) Behavior quantification, b) Behavior-context mapping, c) Intervention selection, and d) Feedback evaluation.

The behavior change requires continuous monitoring and guidance according to the user context and preferences. However, the understanding of users' context and the condition is the foundation for generating fruitful interventions. The intervention is adapted concerning the context, preferences, abilities, knowledge, behavior status, and health conditions. The involvement of the user with a little effort to map with the intervention aggravate the behavior successfully by adapting the process. The philosophy of the UCAI is based on multi-steps from expert-based knowledge to personalized, just-in-time intervention, as shown in Figure 1. Initially, the quantification of user lifelog to estimate the condition of users' behavior status. The quantified behavior is mapped with the behavior-context based stage for the assessment of the behavioral stage. Once a behavioral stage is identified, then appropriate intervention is selected based on the expert-defined rule. According to Heron's intervention model, there are two styles of interventions authoritative and facilitative [71], which are further categorized into prescriptive,

TABLE 4. Category-wise description and score of health behavior risk factors.

Behavior	Category	Description	Score
Tobacco Consumption (smoking)	Low	No. of Packs $\geq$ 1 pack/day	1
	Medium	No. of Packs <1 pack/day	3
	High	No smoking or occasional smoker	5
Alcohol Consumption	Low	10-24 drinks/week (men) or 6-17 drinks/week (women)	1
	Medium	5-9 drinks/week (men) or 3-5 drinks/week (women)	3
	High	0-4 drinks/week (men) or 0-2 drinks/week (women)	5
Physical Exercise (Waking time activities)	Low	Activities with 0-1.5 METs/day	1
	Medium	Activities with 1.5-3 METs/day (for at-least 20 mins)	3
	High	Activities with >=3 METs/day (for at-least 20 mins)	5
Dietary Habits (Food)	Low	Imbalanced , Irregular, Unhealthy Fat, Sugar and Salt	1
	Medium	Partial Balanced and Regular multiple food	3
	High	Regular, Balanced food, Low Fat, Sugar and Salt	5

- High: The quantified value is marked high when it is best for life and assign maximum (5) score.
- Medium: The quantified value is marked medium when it is normal for life and assign medium (3) score.
- Low: The quantified value is marked low when it is worst for life and assign low (1) score.

informative, confronting, supportive, catalytic, and cathartic. Finally, the response of the user is evaluated to understand the influence of the intervention on the behavior.

A. LIFESTYLE BEHAVIOR QUANTIFICATION (LBQ)

Recently, our lives are over-saturated with data, but we are lacking from exploiting its full potential. Mainly, wellness is one area where this issue is very prevalent. Digital well-being technologies have produced a plethora of data for individuals who want to abandon, adapt, and adopt habits to improve health. Therefore, the selection and quantification of appropriate habits are most non-trivial. We have identified most discussed lifestyle factors from the various guidelines based on the term related to behavior discussed in *2018 Physical Activity Guidelines (PAG) Advisory Committee Scientific Report, A guide to smoking cessation in Scotland 2010-updated 2017, Composition of Foods Integrated Dataset (CoFID- Version 2015),* and *National Diet and Nutrition Survey (NDNS nutrient Databank)*. The process of LBQ is discussed in subsequent sections from factors selection to aggregation for behavior quantification.

1) EXPERT DRIVEN LIFESTYLE FACTORS SELECTION

The scrutiny of contributing factors for the indication of lifestyle is the fundamental step of quantification, as a refinement of crude oil. The lifestyle factors are obtained from multiple wellness guidelines in the domain of physical activity, nutrition, smoking, and alcohol. Experts have graded the identified factors to define the contributing factors and sub-factors. Seven professionals from the wellness domain with an experience of at-least 3 years after post-graduation had mentioned their agreement or disagreement level through a psychometric scale Likert questionnaire [72] to rank the lifestyle factors with Fliess' Kappa. The Kappa agreement value obtained from Equation 1 was 0.5282 when agreement categories were *agree*, *neutral* and *disagree*. However, when we mapped the *neutral* to either *agree* or *disagree* on the basis of majority consensus the Kappa value became 0.9100 which was very much acceptable as shown in Table 5.

$$k=\frac{\bar{P}-P_e}{1-P_e}. \tag{1}$$

where $\bar{P}$ is like the accuracy of agreement among raters known as relative observed agreement and its value is 0.7445 and 0.9615 for 3 and 2 categories respectively. Similarly, P_e is the probability of change agreement and its value is 0.4584 and 0.5722 calculated for 3 and 2 categories respectively. The value of k (Kappa) is 0.5282 and 0.9100 respectively, which shows moderate-to-perfect level agreement among raters.

2) CATEGORIZATION OF CONTRIBUTING FACTORS

The categorization of factors into different levels is necessary to estimate their impact. It is also essential to distinguish between the different levels of multiple factors that are included in each assessment for the proper quantification of the behavior. The main concern of the evaluation

TABLE 5. Kappa-based evaluation of inter-rater agreement.

Sr.#	Attributes	Disagree	Neutral	Agree		Disagree	Agree
1	**Physical Activity**	0	0	7		0	7
2	**Sedentary Activity**	0	0	7		0	7
3	**Sleeping**	3	3	1		6	1
4	**Regularly Eating**	0	0	7		0	7
5	**Sugar Amount**	0	0	7		0	7
6	**Dietary Fiber**	3	4	0		7	0
7	**Carbohydrate Amount**	5	2	0		7	0
8	**Grain**	0	2	5		0	7
9	**Fats and Cholesterol Amount**	0	0	7		0	7
10	**Saturated Fat**	5	2	0	**Transformation transition** (from 3 categories to 2 categories)	7	0
11	**Unsaturated Fat**	6	1	0		7	0
12	**Protein(Fish, poultry**	2	2	3		2	5
13	**Milk**	0	3	4		0	7
14	**Vegetables**	0	0	7		0	7
15	**Fruits**	0	1	6		0	7
16	**Salt Amount**	0	0	7		0	7
17	**Balance Diet (5 groups)**	0	2	5		0	7
18	**Smoking**	0	0	7		0	7
19	**Alcohol**	0	0	7		0	7
20	**Stress**	7	0	0		7	0
$\bar{P}$ **(relative observed agreement)**		0.7445				0.9615	
P_e **(probability of chance agreement)**		0.4584				0.5722	
k-(kappa)		0.5282				0.9100	

criteria is only the behavioral risk factors rather than proximal or intermediate-risk factors, as discussed in Table 4. The individual score, based on the severity mention in the definition, has been utilized to generate the index for healthy behavior. Improving health behaviors would result in adding years to life and could reduce the financial burden on the health care system as well as family caregivers [73].

3) LIFE EXPECTANCY BASED WEIGHTAGE OF FACTORS

The concept of life expectancy and prediction of mortality drives us to deduce the weight-age of each factor discussed in the study [74], [75]. The life expectancy of people with the most favorable risk-profile based on recommended behavior was about 18 years more than the least favorable one [76]. The *Mortality Population Risk Tool* (MPoRT), based on the Cox proportional hazards model, was adopted to estimate expected time to death based on the primary risk factors. The proposed technique of risk factors' weightage also depends on the proportion of life loss and life gain because of a specific risk factor as shown in Table 6. As the focus is not purely related to life expectancy, but to indicate the users about the status of behavior through the behavior index to take precautionary measures.

$$Weightage = \frac{\Delta_{factor}}{\Delta_{min}} \tag{2}$$

where Δ_{factor} is sum of the $Gain_{factor}$ and $Loss_{factor}$. The $Gain_{factor}$ and $Loss_{factor}$ represent the life expectancy in years. The Δ_{min} is the minimum value of Δ of all factors to get the *Weightage* of the respective factor using Equation 2.

4) CONTEXT-BASED AGGREGATION

The essence of behavior quantification is to get the value which can easily represent the status of the behavior. Behavior is a very complex qualitative concept based on multiple micro factors. Therefore, a comprehensive behavior index is composed of multiple ingredient behaviors, which are smoking, drinking, diet, and physical activity [76]. The nature and metric of the behavior define its context, which helps to aggregate the behavior in an appropriate proportion, as shown in Equation 3. The dietary behavior is a complex one based on the habit and consumed nutrients. The aggregation is based on the weightage of respective ingredients to compose a Healthy Behavior Index (HBI), as shown in Equation 4.

$$B = \{SetofBehavior \mid Smoking, Diet, Alcohol, PhyAct\} \tag{3}$$

where

$$\begin{aligned} B_{Smoking} &= No.ofPacks/day \\ B_{Diet} &= (DietHabit_{SCORE} + DietNutrient_{SCORE}) \\ B_{Alcohol} &= No.ofDrinks/Week \\ B_{PhyAct} &= \frac{\sum(time_{PhyAct} \mid MET_{PhyAct} \geq 3)}{Week} \end{aligned}$$

$$HBI = \sum_{i=1}^{n} \{B_i * Wt_{Bi}\} \tag{4}$$

TABLE 6. Weightage of health behavior risk factors.

Behavior	Approximate Life (years)	Loss in Life (years)	Gain in Life (years)	$\triangle$: Total Loss & Gain (years)	Weightage
Tobacco Consumption	82	9	3	12	3.00
Alcohol Consumption	82	2	4	6	1.50
Sedentary	82	1	4	5	1.25
Unhealthy Diet	82	4	4	8	2.00
Mental Stress	82	3	1	4	1.00

The behaviors are evaluated based on habit frequency: the smoking habit is quantified through the daily number of packs; the alcohol consumption and performing physical activities are assessed weekly; the diet behavior is a composite-behavior and is assessed based on individual nutrients quantity.

B. BEHAVIOR-CONTEXT MAPPING

In Behavior-Context Mapping (BCM), we have employed the Transtheoretical Model (TTM) to identify the different stages for behavior change through continuous monitoring of HBI. Habitual behaviors lay down the foundation of human health, which impacts the cause of multiple NCDs [77]. Some behaviors require some instantaneous attention to achieve recommended health outcomes like vaccination, while many behaviors require continuous and repeated efforts and knowledge to attain the recommended outcomes related to routine habits like eating, drinking, exercising, and smoking. For such a condition, behavior change must be considered as a long-term and continuous process, which can be strategically staged from initiation to maintenance. In BCM process HBI is categorized and mapped with users' behavior-context.

1) HEALTHY BEHAVIOR INDEX CATEGORIZATION

The comprehensive HBI is quantified into low, medium, and high at a scale of 1, 3, and 5, respectively, for four primary factors. So, there are 3^4 total possible cases with a mean value of 23.25 index obtained through Equation 5, as shown in Table 7. The least favorable condition of HBI is 7.75 when all factors have the lowest values. However, HBI is in the most favorable value of 38.75 when all factors are at the highest. The ranges for the healthy, moderate, and unhealthy status for behavior are set through the standard deviation. The standard deviation is about ± 6.75, so the moderate behavior lies in HBI range between 16.0 to 29.0 index, which is a significantly a major portion of the range. The healthy behavior lies in HBI range between 29.01 to 38.75 whereas the unhealthy lies in HBI range between 7.75 to 15.99 index.

$$f^{i} = \frac{1}{(N-1)\,M+1}\left(w_k x_i^k + \sum_{j\neq k}\sum_{i} w_j x_j^i\right). \qquad (5)$$

where $i = \{Lowest, Medium, Highest\}$ represents the states of the behavior, k is index of fixed variable, j is a variable index, N represents the total number of factors, M represents the total number of values obtained, x is a fixed factor index value, and y is the variable-factor index value.

2) MAPPING HEALTHY BEHAVIOR INDEX WITH USER CATEGORIES

Behavior status can be categorized into multiple levels depending on the user's knowledge, mindset, and actions. According to Bloom's taxonomy, which is related to learning, the behavior can be classified into six different levels based on knowledge and comprehension [78]. Similarly, the TTM has identified different stages for behavior change and has become one of the most widely used models of the healthcare domain. The model is based on multiple strategies used by individuals to adapt unhealthy habits and behaviors. The TTM stages are described as follows:

- PRE-CONTEMPLATION
  Pre-contemplators don't understand the necessity of behavior change. They can be distinguished into those who are aware of it but have not decided to pursue it and those who don't know the possibilities and benefits of behavior change.
- CONTEMPLATION
  Contemplatists consider adaptation in behavior, weighing the pros and cons, or advantages and disadvantages of behavior changing. Ambivalence, the mixed feeling of confusion regarding the change, is the foundation of the contemplation stage. It is essential to overcome the confusion before initiating any successful adaptive therapy.
- PREPARATION
  Individuals who have resolved the confusion and are about to pursue the change are now in the preparation stage. At this stage, the verbal commitment of change reflects the readiness state of the individual. Even setting up a goal for changing the behavior is possible, because the person is ready to take action.
- ACTION
  In this stage, individuals are actively engaged in modifying their respective behavior. It has adopted healthy lifestyle behavior and followed appropriate one form the

TABLE 7. Combinational factors based average of Healthy Behavior Index.

Fixed Factor	Combinational Factors	Average HBI			
		Lowest	Medium	Highest	Average
Tobacco Consumption (Smoking)	Diet Alcohol Physical Activity	17.25	23.25	29.25	23.25
Alcohol Consumption	Diet Smoking Physical Activity	20.25	23.25	26.25	23.25
Physical Activity	Alcohol Smoking Diet	20.75	23.25	25.75	23.25
Nutrition (Diet)	Alcohol Smoking Physical Activity	19.25	22.80	27.25	23.10
Average		19.38	23.14	27.12	23.21

- Lowest: Keep the fixed factor at lowest value while use all combination of rest of the factors and then drive the average value.
- Medium: Keep the fixed factor at medium value while use all combination of rest of the factors and then drive the average value.
- Highest: Keep the fixed factor at highest value while use all combination of rest of the factors and then drive the average value.

recent past. The strategy for observing healthy actions is based on the quantification of the behavior nature i.e. the amount of alcohol consumed in a week.

- MAINTENANCE

The behavior-maintenance stage is the practice of newly adopted un-intervened behavior in daily routine. The confidence level increases gradually as the adopted behavior is exercised continuously. The permanent habitual change process requires a lot of user's determination and patience [79].

Advanced researches have shaped the model to represent how individuals perform in adapting various behaviors, including initiating healthy regimens and quitting addictive unhealthy behaviors. It has been largely applied across multiple health-related behaviors, including physical activities, diet, smoking, and alcohol consumption. It provides an organizing framework to facilitate the adaptation of behavior [79]. The framework identified five stages of users concerning their condition and situations.

- DATA PREPARATION

The mode of data acquisition for health behavior stage prediction is a questionnaire-based and lifelog. The lifelog data contains multiple attributes related to nutrition, smoking, alcohol consumption, and physical activities and maintained by Mining Minds (MM) platform. The behavior stage-wise information is obtained through survey questionnaires. The lifestyle data collected through sensors is presented and quantified on the bases of scores. However, the behavior stage data is obtained through the Health Behavior and Stages of Change Questionnaire (HBSCQ) [80]. In the data acquisition process, nearly 87 people used MM for seven days, but the seven persons' responses were not completed. Finally, the individuals are surveyed to provide lifestyle-related stage-wise behavior information through HBSCQ. Since the focus is on the generalized behavior stage prediction model, so we tried to get information from random people, irrespective of ethnicity, gender, culture, environment, education, income, and location. Though few of the elements have impacts on the behavior, our focus is towards basic lifestyle behaviors (diet, physical activity, smoking, alcohol).

TABLE 8. HBSCQ questions related to TTM stages.

Smoking	Physical activity	Nutrition consultation	Alcohol consumption	TTM Stages
QueID	QueID	QueID	QueID	
a	c	b	a	**Pre-contemplation**
b	d	c, g	b, c	**Contemplation**
c	b, e	d	d	**Ready**
d, e	a, f, g	e, f	e	**Action**
f, g, h	h, i	a, g	f, g	**Maintenance**

- The Health Behavior and Stages of Change Questionnaire (HBSCQ) [80] is used.
- The HBSCQ is mapped with different stages of Trans-theoretical Model TTM. It reflects that responses guide us to identity the behavior wise stage of the user.

- FEATURE CONSTRUCTION

The HBSCQ is used to obtain responses regarding different behavior-context. These responses are generally related to 4 main areas of lifestyle habits like physical activity, diet, smoking, and alcohol. The information related to physical activity, smoking, diet, and alcohol consumption is obtained through lifelog. The HBSCQ consists of multiple questions

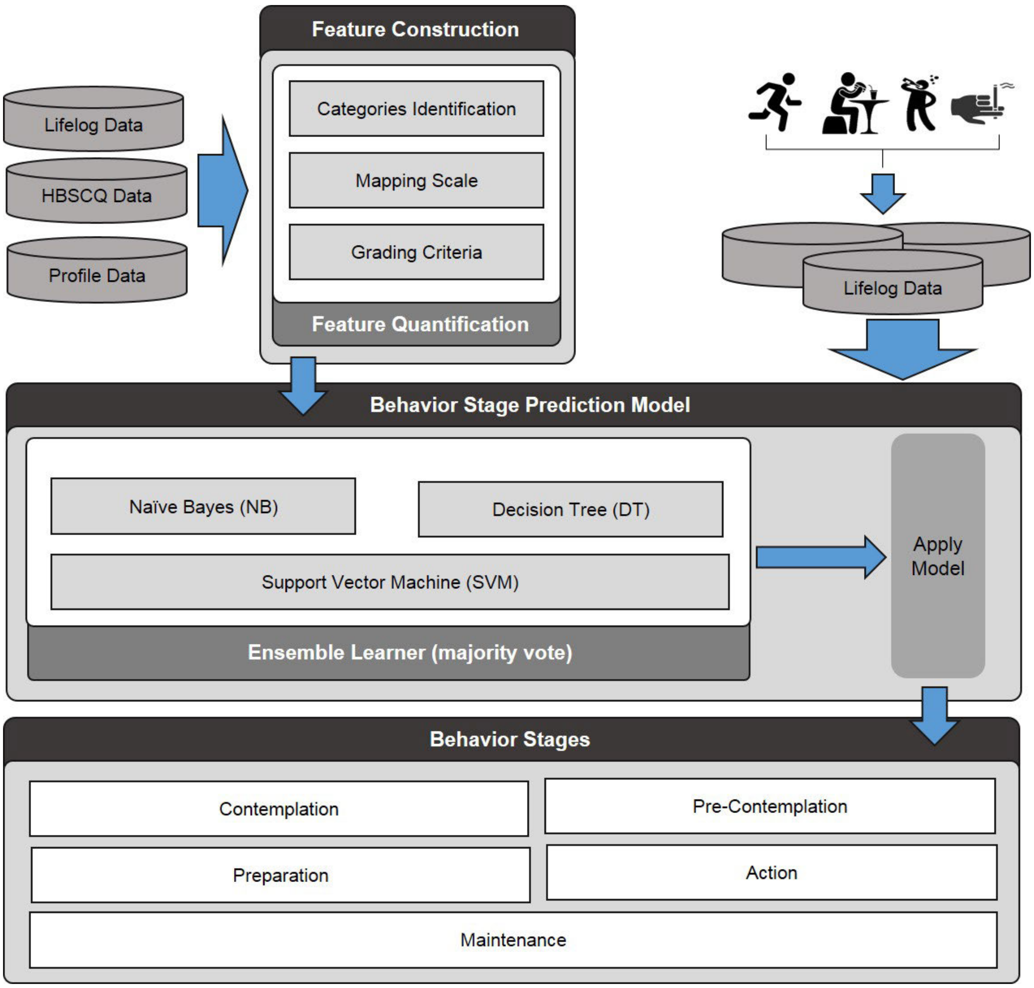


FIGURE 2. **An architectural view of Behavior Stage Prediction Model.**

related to the basic lifestyle habits regarding the level of knowledge, intention to change, and current status of behavior. The responses of the HBSCQ is quantified to mark the status of the behavior change stage of a end-user, as discussed in Table 8.

The behavior and context of behavior are two different prospects to understand and correlate with each other. We have collected the lifestyle behavior data of the same volunteers based on the week experience. The lifestyle behavior data is collected through lifelogging of MM application related to diet, physical activity, smoking, and alcohol consumption. The status of behaviors is scaled for the quantification of the contributing features of the lifestyle behavior.

- BEHAVIOR STAGE PREDICTION MODEL

The ensemble learning method is applied for behavior stage classification. It is based on multiple base learners to improve performance over a single learner for the prediction of behavior. So we have used a majority voting technique in conjunction with Support Vector Machine (SVM), Naïve Bayes (NB), and Decision Tree based-learners as shown in Figure 2. Based on the majority voting of base learners, the end-user behavior is classified into 5 basic stages of behavior: pre-contemplation, contemplation, preparation, action, and maintenance.

C. PERSONALIZATION OF THE INTERVENTION: INTERVENTION SELECTION

The right intervention at the right stage to the right person is the key concern of the study. However, the personalization of intervention is the target to attain end-user attention so that it becomes actionable and enhances the chances of behavior adaptation. The adaptation of modifiable behaviors related to diet, physical activity, alcohol, smoking, stress, and sleeping is necessary to avoid the probability of NCDs. Literature has highlighted that imbalanced diet, physical inactivity, abuse of alcohol, and smoking are the riskiest factors for NCDs. Every person has a different lifestyle behavior status, so it is necessary to generate personalized intervention, as discussed in Table 9.

1) TRANSTHEORETICAL MODEL-BASED BEHAVIOR STAGES

The behavior-context of the end-user can be categorized according to the TTM. The stages of TTM support the refinement of interventions depending on preferences,

TABLE 9. Intervention categories to stimulate the user for behavior change.

<table>
<tr><th>Sr. #</th><th>Intervention Style</th><th>Intervention Categories</th><th>Definition</th><th>Example</th><th>ICT Based Intervention</th></tr>
<tr><td>1</td><td rowspan="3">Authoritative</td><td>Prescriptive</td><td>Explicitly direct the user through advice and direction</td><td>1: Guide and advice
2: How to react in a situation
3: What should be the behavior</td><td rowspan="6">1: Virtual assistance based reminders
2: Smart Environments
3: Educational Text Messages
4: Video Link
5: Recommendations on instant messages
6: Internet-based Program
7: Emails
8: Just-in-Time Alarm & Alert
9: SMS Reminder</td></tr>
<tr><td>2</td><td>Informative</td><td>Provide knowledge to guide about the situation</td><td>1: Knowledge about the background
2: Explain the experience
3: Make understandable the consequences</td></tr>
<tr><td>3</td><td>Confronting</td><td>Challenging the user through pros and cons of identification</td><td>1: Support to avoid mistake repeat
2: Challenge the other person thinking
3: Communicate the shortcomings
4: Make users aware of deficiencies</td></tr>
<tr><td>4</td><td rowspan="3">Facilitative</td><td>Cathartic</td><td>Help to overcome the doubts and thoughts</td><td>1: Help to understand the feelings and fears
2: Empathize with them</td></tr>
<tr><td>5</td><td>Catalytic</td><td>Help to learn through self awareness</td><td>1: Encourage for fresh thinking
2: Encourage to adopt new solutions
3: Listen and Summarize</td></tr>
<tr><td>6</td><td>Supportive</td><td>Build confidence in the user through qualities and competences</td><td>1: Tell the value of achievement
2: Praise on the accomplishment
3: Support to the fulfillment of commitment</td></tr>
</table>

behavior-status, and disease conditions. It requires quantification, which is performed based on health standards set by different organizations. The quantification needs the targeted behavior and then converted into an appropriate scale as per the standard way or through expert-defined guidelines.

D. FEEDBACK EVALUATION

The response evaluation of the intervention is a very non-trivial task to improve the content as well as understand the context of the situation. There are two possibilities to record the responses either through end-user satisfaction or through end-user actions. The direction of the latest research is shifting towards implicit feedback from explicit feedback.

- EXPLICIT FEEDBACK

The level of satisfaction against the intervention from the system is obtained after an appropriate time. The satisfaction level is graded based on the Likert scale from 1-5, representing strongly disagree to strongly agree regarding the different kinds of interventions. The challenge is to obtain feedback from elderly people in a regular manner and avoid memory and emotion-based bias. Finally, we have obtained the end-user experience through a survey questionnaire discussed in appendix.

- IMPLICIT FEEDBACK

Implicit feedback data is obtained on the basis of the action performed by the end-users maintained in the lifelog. The implicit feedback data is much cheaper and easier to obtain as it requires no extra effort from the end-users. The challenge is to map the response actions with the interventions for effectiveness measurement. So our methodology has utilized the change in comprehensive HBI over time with respect to the behavior context for the evaluation of interventions' effectiveness. The computation of HBI is totally dependent on lifelog and the responses of the behavior-evaluation questionnaire.

IV. REALIZATION OF METHODOLOGY THROUGH WELLNESS MANAGEMENT PLATFORM

The goal of the UCAI methodology is to enhance the efficiency of a wellness platform that can handle the information of end-user behavior related to lifestyle. This platform has the capability to curate the end-user information and generate the appropriate recommendation. For the evaluation of the methodology, we have selected our ongoing wellness management project. It has the capability to obtain raw data from multi-modal sensors and process the data to build context for recommendation generation.

A. MINING MINDS IN A NUT SHELL

Mining Minds (MM) is an open-source and person-centric wellness platform that is designed to gather lifestyle data through multi-modal sensors and build context to generate

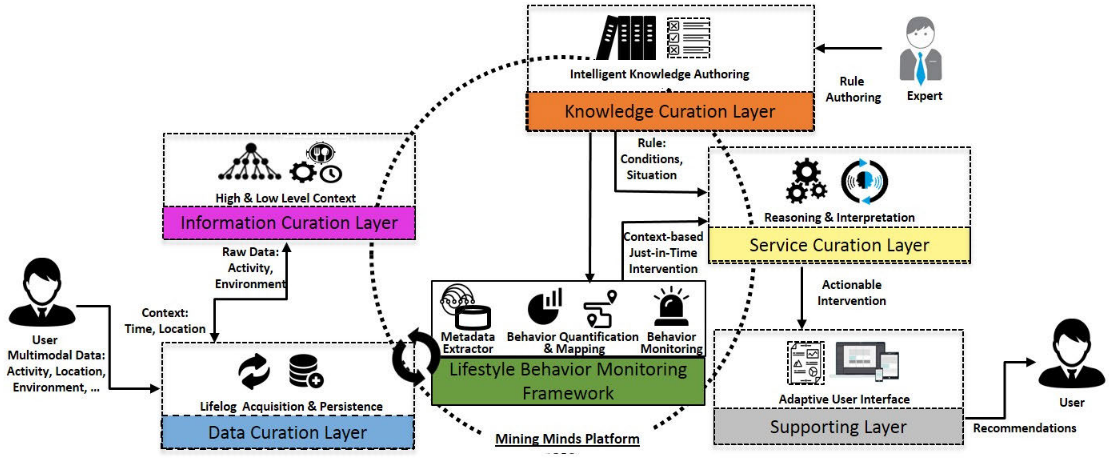


FIGURE 3. The Mining Minds conceptual architecture with integration of lifestyle behavior monitoring framework.

recommendations for lifestyle adaptation [67], [81], [82]. The primary focus of the framework is digital health and well-being through daily activities based on recommendations and educational facts. It comprises state-of-the-art wearables, IoT, big data, and ontological inferencing technologies to provide personalized healthcare and wellness services. The smart-phone and smart-watch's sensory data is utilized to recognize activities, emotions, and location, which is persisted into an intermediate database, as shown in Figure 3. Where information for the diet, alcohol consumption and smoking is obtained through a questionnaire. The platform manages the complete life cycle from raw data to personalized recommendations through data curation, information curation, knowledge curation, service curation, and supporting layers.

The Supporting Layer (SL) is responsible for managing the access of the application for end-users as well as experts. It provides interactive interfaces for analytics, recommendations, and feedback. The safety and security is maintained through standard cryptosystems under the provisioning of Homomorphic encryption [7]. The Service Curation Layer (SCL) orchestrates the personalized requirements of the end-user through context, emotion, preferences, demographics, and physiological factors based recommendations. It manages the pull and push-based recommendations' communication for just-in-time interventions as well as circadian rhythm-based diet plan. It also considers the goal-based calorie requirement through personalized MET and Body Mass Index (BMI) values.

The Knowledge Curation Layer (KCL) provides intelligent rule authoring toolkit to support expert for transforming their experiences and wellness knowledge in the form of recommendations rules [2]. These rules guide the kind of recommendation provided to the end-user based on the situation context identified from the lifelog. These rules consider the list of unhealthy and risky habits at a particular time to target specialized recommendations as compare to general recommendations for change in lifestyle.

The data curation and information curation layers play a vital role in providing the foundation of activity recognition, context building, emotion identification, and lifelogging. The Data Curation Layer (DCL) manages the data in raw as well as processed format through data acquisition and synchronization, life-log representation and mapping, lifelog monitoring and big data storage processes [67]. Information Curation Layer (ICL) identifies end-user's activities and context from multimodal sensory data managed in hierarchical models [83]. It employs emotion, location, and multiple activity recognizers, respectively. These recognizers generate the low-level context, and the fusion of this context builds a high-level context that is curated in DCL. The developed Lifestyle Behavior Monitoring Framework (LBMF) is integrated with DCL to obtained data from intermediate databased. The intermediate database comprises of lifelog, and profile information.

B. LIFESTYLE BEHAVIOR MONITORING FRAMEWORK (LBMF)

The scope of this study is the lifestyle behavior monitoring which enhances the functionality of DCL. The proposed architecture of LBMF is divided into Offline and Online processes on the basis of their working situation. The Offline process has two sub-processes known as Lifelog Metadata Extraction and Rules Management, as shown in Figure 4. While the Online process consists of three sub-processes, know as Lifelog Quantification, Behavior Context Mapping, and Lifelog based Behavior Monitoring. The functionality of each component under different processes is described as follows:

- METADATA EXTRACTION PROCESS

The Metadata Extraction is an Offline process and provides the foundation for understanding the nature of the data available for behavior processing. Lifelog and activities data is too much based on the requirements, so it is necessary

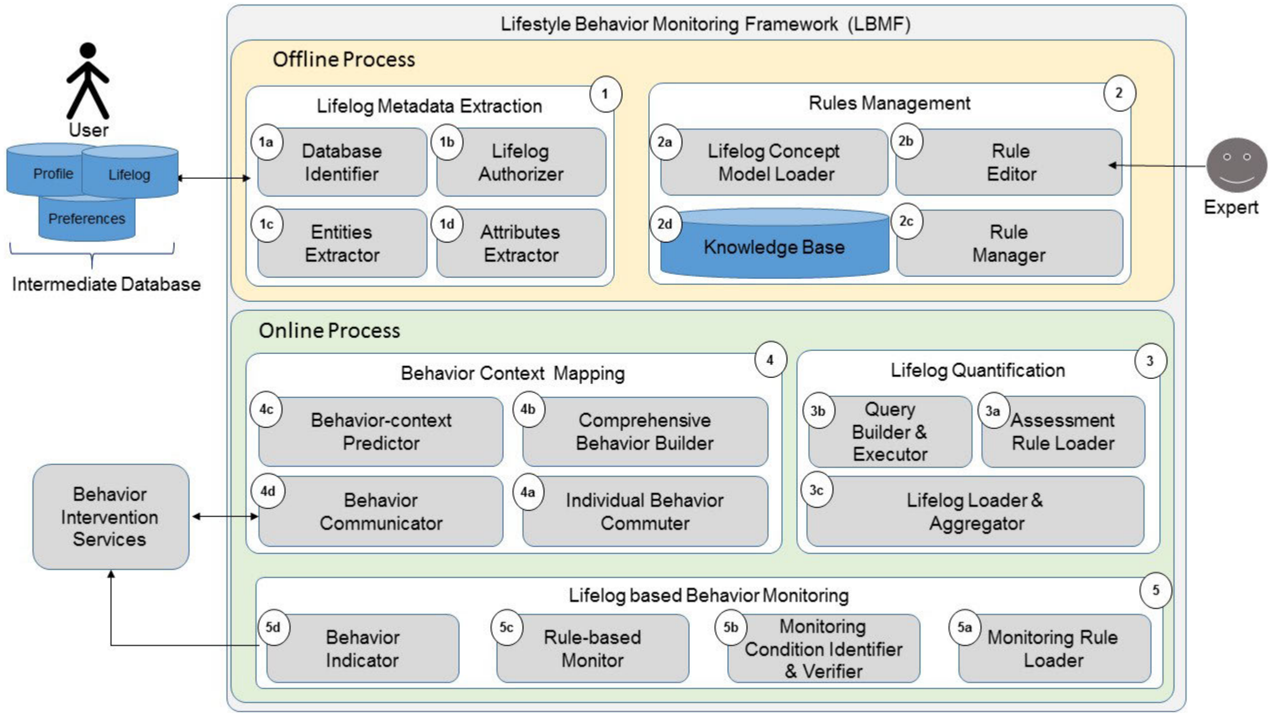


FIGURE 4. **Functional diagram of lifestyle behavior monitoring framework.**

to understand the structure of the existing database. At the initial stage, the database identifier fetches all the available databases, and then the lifelog authorizer access the specific lifelog data through valid credentials. Moreover, the entities and attributes extractors retrieve the tables and corresponding attributes, including data types, respectively.

- BEHAVIOR-ASSESSMENT RULE MANAGEMENT PROCESS

The behavior-assessment rule management is an offline process that supports the experts to define the rule for the assessment of behavior conditions. Every behavior has independent criteria for assessment based on the nature of behavior. The lifelog concept model loader loads the schema obtained from the metadata extraction, which is available for selecting the behavior for rule definition. The expert selects the domain and attributes which indicate the behavior. After that, the expert defines the assessment criteria by expressing multiple conditions based on the metadata analysis of the attribute. Finally, the conclusion against the behavior is defined as the assessment status of the behavior. The Rule Manager is responsible for persisting and retrieving the specific assessment rule from the knowledge base. In the knowledge base, rules are stored in the form of a key-value pair with a specific identifier. The rule is communicated in the JSON format.

- LIFELOG BASED BEHAVIOR QUANTIFICATION PROCESS

The behavior quantification is an online process that utilized the assessment rule to convert the activities' data to quantify the behavior. The Assessment Rule Loader fetches the rule of the appropriate behavior through the rule manager from the knowledge base. The query builder and executor then convert the rule into an executable query through a dynamic query structure. The query retrieves data from the lifelog and gives it to the Lifelog Loader and Aggregator—the Aggregator than accumulates the activity data according to the requirement defines in the rule.

- BEHAVIOR-CONTEXT MAPPING PROCESS

Individual behavior commuter uses the aggregated data of specific activity to map the behavior status based on the quantified value of that behavior. The Comprehensive Behavior Builder uses individual behavior to build the HBI to present the overall behavior status of the person at a specific time. The HBI is mapped with the behavior context, which is responsible for the status of the end-user behavior. The context helps the wellness services to personalized the interventions for effective feedback. The behavior communicator is responsible for the communication of the behavior-index, ingredient behavior-status, and behavior-context in a common communication format.

- LIFELOG BASED BEHAVIOR MONITORING

The just-in-time interventions are managed through Lifelog-based Behavior Monitoring, which identifies the unhealthy behavior in the lifestyle and generates intervention so that behavior can be avoided. These interventions are for short term behavior like sedentary behavior and the total quantity of fats consumed. The Monitoring Rule Loader fetches the rule related to the current ongoing activity; from

TABLE 10. Classification recall and precision through behavior context prediction model.

	True. Contemplation	True. Pre-contemplation	True. Ready	True. Action	Class Precision
Pred. Contemplation	49	1	0	0	98.00%
Pred. Pre-contemplation	0	20	0	0	100.00%
Pred. Ready	0	0	26	1	96.30%
Pred. Action	0	0	0	4	100.00%
Class Recall	100.00%	95.24%	100.00%	80.00%	

these rules, the monitoring condition is identified, and constraints are verified against the specif end-user. After verification, the Rule-based Monitor continuously monitors the activity status to generate intervention in a specific situation. These interventions, along with the situation, are handover to Behavior Indicator, which communicates the information of intervention to wellness services in the form of a common communicator format.

V. EXPERIMENTATION AND RESULTS: EVALUATION OF PROPOSED METHODOLOGY

The assessment stage is essential for trust development on the maturity and reliability of the proposed methodology. It requires a qualitative and quantitative measurement of the methodology. The evaluation of the proposed methodology is performed through two ways for proving it's worth along with the evaluation of the behavior context prediction model. We have adopted implicit feedback-based evaluation for quantitative assessment while explicit feedback-based evaluation for qualitative assessment. In this section, we will describe the experimental setup as well as the execution of the application in a real environment. The focus is to evaluate the impact of behavior-context based intervention over simple interventions for behavior change through HBI. The implicit and explicit feedbacks are analyzed from persons who are registered with the wellness management organization.

A. PREDICTION MODEL ACCURACY AND RECALL

We have utilized a set of classifiers to classify the stages of behavior on the basis of the data obtained through questionnaires, as shown in Table 11. We obtained the highest accuracy with the Ensemble classifier, whereas Naive Bayes and Decision trees also had accuracy greater than 90%. The accuracy of the Support Vector Machine was 87.57%. The precision and recall of the behavior-context prediction model are discussed in Table 10. The classification precision of the pre-contemplation, contemplation, and action was more than 98%, whereas for the ready stage was about 96.30%. Similarly, classification Recall for pre-contemplation, contemplation, and ready was more than 95%, whereas for action was 80.00%.

B. EXPERIMENTAL SETUP

We have evaluated our proposed methodology over the dataset collected from employed volunteers. Initially,

TABLE 11. Accuracy of multiple classifier to predict behavior context.

Sr. #	Classifier	Accuracy
1	Support Vector Machine	87.57%
2	Naive Bayes	93.63%
3	Decision Trees	96.74%
4	Ensemble	98.02%

TABLE 12. Multiple scenarios for the evaluation.

Scenario #	Physical Activity	Smoking	Alcohol	Diet
S1	Unhealthy	Unhealthy	Unhealthy	Unhealthy
S2	Normal	Normal	Normal	Unhealthy
S3	Unhealthy	Normal	Unhealthy	Normal
S4	Normal	Healthy	Healthy	Normal

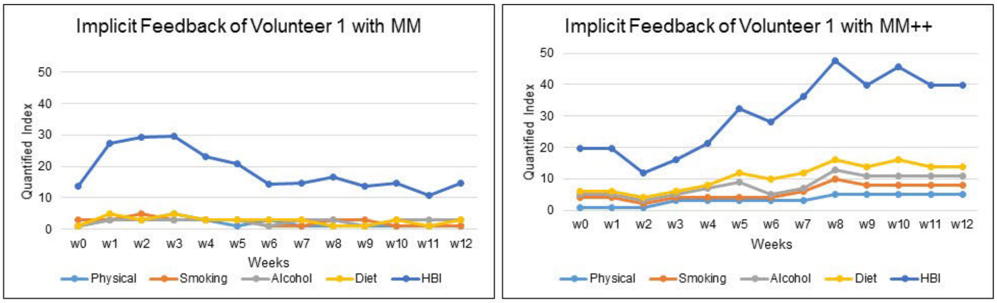
we recruited 6 volunteers with an age range between 33 and 41.

The 4 volunteers completed a lifestyle-adaptation cycle of 24 weeks in such a manner that for the first 12 weeks they got simple interventions and for next 12 weeks they obtained behavior-context based interventions. The purpose of the pilot study was to estimate the usage and effectiveness of the wellness application without and with the proposed methodology.

These volunteers had a different status of multiple lifestyle habits, which helped us to cover comprehensive scenarios as mentioned in Table 12. The few habits are unhealthy, but a certain level of the habits may be considered as an addiction. Addiction to everything is bad and very difficult to overcome. A total of 4 scenarios were covered from the lifestyle of the volunteers. The physical activity and diet habits are complex, and no volunteer had a healthy one, while alcohol consumption and smoking have all three possibilities of normal, healthy, and unhealthy. The change in smoking habits and alcohol consumption, however, are the most difficult tasks.

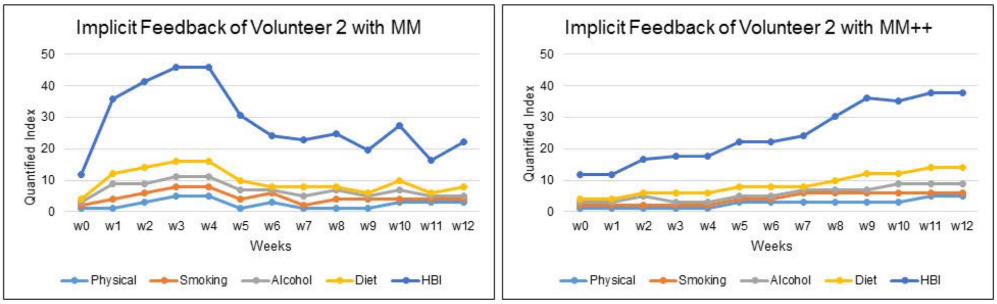
- IMPLICIT FEEDBACK BASED EVALUATION

Implicit feedback captures salient information about the user's behavior in a tacit manner without drawing attention towards it. This approach invariably results in an unbiased and accurate estimation of the user's actions. As this study



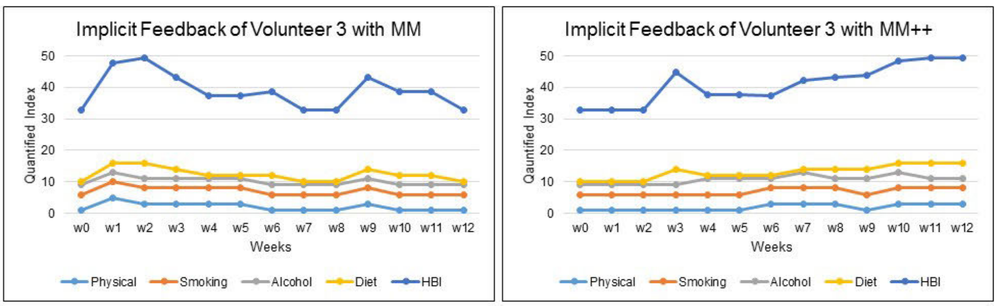
(a) (a`)

Volunteer 1:
Physical activity status: Sedentary; Smoking status: Normal;
Alcohol consumption: Unhealthy; Diet status: Unhealthy



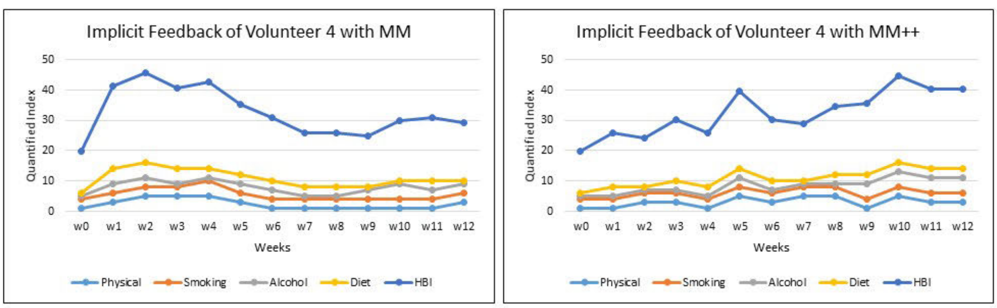
(b) (b`)

Volunteer 2:
Physical activity status: Sedentary; Smoking status: Unhealthy;
Alcohol consumption: Unhealthy; Diet status: Unhealthy



(c) (c`)

Volunteer 3:
Physical activity status: Normal; Smoking status: Normal;
Alcohol consumption: Unhealthy; Diet status: Unhealthy



(d) (d`)

Volunteer 4:
Physical activity status: Sedentary; Smoking status: Healthy;
Alcohol consumption: Normal; Diet status: Unhealthy

FIGURE 5. The comparison of health behavior status of volunteers in MM and MM++.

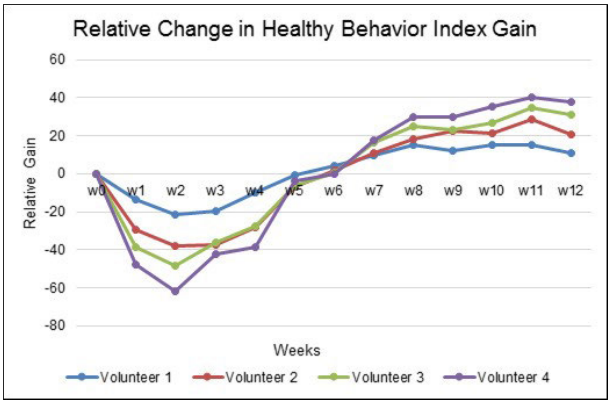


FIGURE 6. **Week-wise Healthy Behavior Index gain.**

require an objective and impartial measure of human behavior, therefore, hereby the implicit method of feedback collection is favored. So, we installed the MM wellness application to volunteers' smart-phone. We also provided short training on how to use this application. It provided time to time intervention to avoid unhealthy habits and communicated the personalized recommendations. The system provided the interventions over 12 weeks and recorded the activities in lifelog, as shown in Figure 5(a,b,c,d). The lifelog supported to track back and mapping the effectiveness of interventions.

In the 2nd phase, the same persons were provided with the extended MM application MM++, where interventions are based on the proposed methodology. The comparison of implicit feedback obtained from the recorded activities and the quantified index was drawn to obtain the view of behaviors as shown in Figure 5(a',b',c',d').

The HBI not only supports to represent the status of the behavior but also helps the experts to understand the change in behavior. From the initial pilot study results, we obtained the change in HBI over a period of time, as shown in Figure 6. The change in healthy behavior index gain is obtained through the difference of the base healthy behavior index to the current healthy behavior index of a respective period. We consider the base HBI when the system is providing services to the volunteers without behavior-context and current HBI when the system is considering the interventions based on personalized behavior-context.

- UTILIZATION OF EXTENDED WELLNESS MANAGEMENT SERVICE

The volunteers had access to the wellness management service 24/7, where they could visualize their behavior status as well as crawl time-based recommendations. The availability of information avoids the mental stress of memorizing the pattern for the whole week as well give freedom to access the education material whenever and where ever they want to access. After 12 weeks of study, we found that volunteers with obesity and diabetes accessed the service about double the time of the volunteers with hypertension and hyperlipidemia, as shown in Figure 11.

- EXPLICIT FEEDBACK BASED EVALUATION

The explicit feedback-based evaluation depends on user experience (UX). It is a well-known and widely employed process to estimate the subjective perception of end-users towards the application. Generally, end-users have a different experience for the same application due to personal abilities, knowledge, liking, and requirements. So, in order to estimate the UX, questionnaire-based surveys are the most appropriate tool. In the literature, multiple state-of-art UX research frameworks like Questionnaire for User Interaction Satisfaction (QUIS), System Usability Scale (SUS), Post Study System Usability Questionnaire (PSSUQ), Computer System Usability Questionnaire (CSUQ), Standardized User Experience Percentile Rank Questionnaire (SUEPRQ), Software Usability Measurement Inventory (SUMI), AttrakDiff, and User Experience Questionnaire (UEQ) are utilized for UX estimation [82], [84].

The SUS delivers a ''quick and dirty'', trustworthy tool for assessing the usability of application [85]. It has become a highly cited industry standard[9] that consists of a 10 five-items (from the Strongly agree to Strongly disagree) questionnaire. The benefits of using SUS are that (1) It is a simple scale to manage participants' responses (2) It can support small sample sizes with trustworthy results (3) It can successfully distinguish between practical and non-practical applications, (4) it can evaluate wide variety (hardware and software) of applications, products, and services. The constituent's questionnaire evaluates more precisely as compared to PSSUQ and CSUQ when participants are more than 8 [82], [86].

The AttrakDiff is a widely recognized online accessible questionnaire [87] to estimate UX, which is based on the UEQ research framework. The pragmatic qualities (PQ) of AttrakDiff correlate with the dependability, efficiency, and perspicuity scale of UEQ while hedonic-stimulation quality (HQ-S) has a correlation with novelty and stimulation scales of UEQ. Whereas, both have identical adjective-pairs in attraction quality (ATT) [88]. The AttrakDiff provides a limited free online service (only 20 users) to investigate the pragmatic, hedonic, and attractiveness qualities of applications [89]. It consists of 28 contrasting adjective-pairs, which are clustered into PQ, HQ (Identity, Stimulation), and ATT [87].

Thus, we have adopted multiple procedures to evaluate the application MM++ for its effectiveness and usability. For effectiveness, we have studied the change in lifestyle pattern covering multiple scenarios based on lifestyle factors. The change in lifestyle is observed through implicit feedback recorded in the lifelog for an appropriate duration. The UX and usability assessment is performed through SUS, organization-defined questionnaire as discussed in appendix and AttrakDiff with the help of eSURVEY Tool[10].

- DEMOGRAPHIC DATA

[10]https://esurvey.uid.com/project!overview
[9]Google Scholar based Citation 9449 (viewed on 15/08/2020)

TABLE 13. Demographic information of volunteers.

	No. of Participants	%age of Participants
Age (Year)		
35 to 40	25	24.27%
41 to 50	52	50.48%
Above 50	26	25.24%
Gender		
Male	65	63.10%
Female	38	36.89%
Chronic Diseases		
Obesity (Over weight)	33	37.86%
Hyperlipidemia (High cholesterol)	25	24.27%
Hypertension (High blood pressure)	21	20.39%
Diabetes (High blood glucose)	24	20.30%
Study Completion Status		
Complete	99	96.12%
Left	4	3.89%
Expertise in Electronic Gadgets		
Proficient	20	19.42%
Moderate	76	73.79%
Newbie	7	6.80%

For this study, we have collaborated with wellness management organization, which provides lifestyle based support to registered persons. The organization recruited 103 volunteers for evaluation. These were divided based on gender, age group, electronic gadgets expertise, medical ailment and study completion. These volunteers consisted of 37% of females and 63% of males who suffered with medical issues like obesity, diabetes, hypertension, and hyperlipidemia (lifestyle-based chronic diseases) as shown in Table 13. There were 99 volunteers who completed the course and 4 volunteers left the study in middle due to some unavoidable circumstances. Along with medication, these persons wanted to get recommendations from professional lifestyle experts. In general, the wellness-management experts are contacted through a phone call to get feedback on their weekly activities to get recommendations. So we had provided the wellness management application to these volunteers, which recorded their activities and gave knowledge, personalized recommendations, support through educational videos and questionnaires for explicit feedback in order to evaluate the services.

- PARTICIPANTS EXPERIENCE TO WELLNESS SERVICE

The MM++ application was installed on mobile phone of the volunteers for evaluation purpose. The volunteers utilized the application for 12 weeks, where they got interventions according to their behavior status and personalized context. It is very necessary to evaluate the service through volunteers' explicit feedback. The end-users' experience and system usability along with organizational questionnaire are used to evaluate the system efficiency and usability.

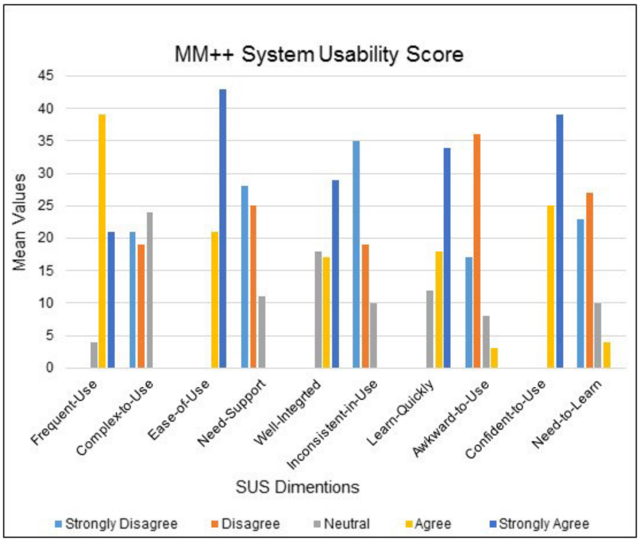


FIGURE 7. The system usability score of MM++.

(i). System Usability Evaluation:- There were 64 end-users who recorded their responses against the SUS 10 questions in a range from 1 to 5 presenting *strongly disagree* to *strongly agree* respectively. The SUS items perceive the efficiency of the MM++ functionality through complexity, ease-of-use, consistency, learnability, and confidence-in-use as shown in Figure 7. The overall score for SUS based evaluation is 81.95%, which is marked as *B* and ranked as *Good*. It depicts that end-users' efficiency increased with the behavior adaptation support of the MM++. Thus, the usability-level of MM++ has significant impact on end-users behavior adaptation. The behavior analysis according to the end-users' context support the enhancement of behavior adaptation.

(ii). User Experience Evaluation:- The AttrakDiff provides the anonymous evaluation of the product and gauges it based on usability, appearance, and attractiveness from experienced end-users. We had created an assessment project with the name MM++ using the eSURVEY tool to measure the end-user's experience. After creating the project, the URL was shared to the wellness organization, which sent an invitation email to the wellness end-users and asked them to evaluate the MM++ directly based on their judgments. The organization had selected only those end-users who had experienced it for at least 10 weeks. After receiving the responses of maximum allowed participants, the results were compiled using the eSURVEY tool as shown in Figures 8, 9, 10. The portfolio diagram summarizes the performance through pragmatic and hedonic qualities of MM++ as shown in Figure 8. It highlights task-oriented, too task-oriented, superfluous, too self-oriented, self-oriented, desired, and neutral confidence regions. HQ's top values are regarded higher than the bottom ones, and PQ's right values are marked as higher than the left ones. Based on the aforementioned categorization of UX, the "Desired" category is assigned to MM++ when both PQ

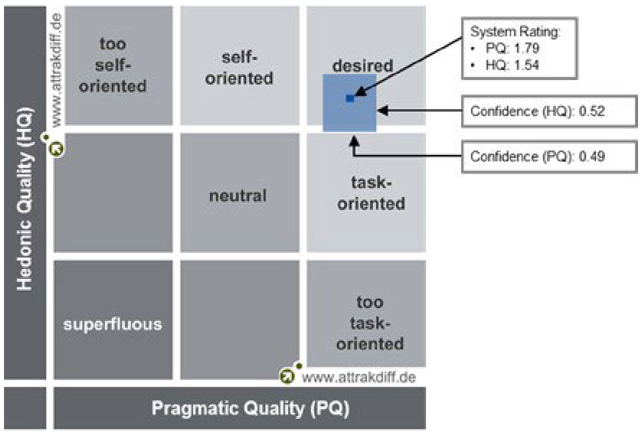


FIGURE 8. **MM++ portfolio analysis based on Hedonic and Pragmatic qualities.**

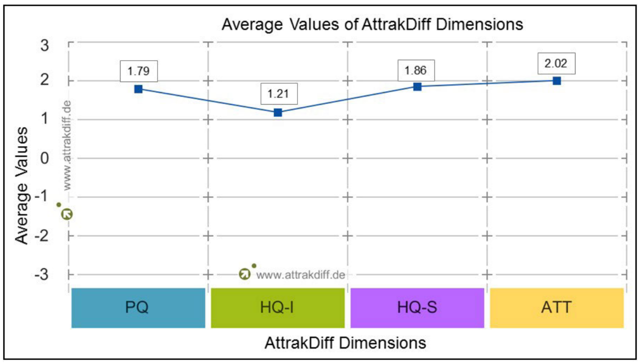


FIGURE 9. **AttrakDiff dimensions' average values for the MM++.**

and HQ take on values 1.79 (with confidence internal 0.49) and 1.54 (with confidence interval 0.52), respectively.

Figure 9 represents the average scores of PQ, HQ-I, HQ-S, and ATT. The PQ reflects the product's usability and demonstrates how well end-users achieve their goals; HQ-S deals innovation, interesting and relaxing functions, content, and styles of presentation like supporting features; HQ-I demonstrates end-users' expertise to communicate the system; and ATT reflects the perceived system performance as a whole. The MM++ is in the "over-average" zone, where end-user measurements of all four dimensions lie between 1 and 2. The attractiveness aspect of the MM++ is more appreciated than the other three and it lies in *Good* category.

The comprehensive rating view of the four dimensions through the *Adjective-Pair* questions of AttrakDiff is presented in Figure 10. The average score of four measurements of all *Adjective-Pairs* are between 5 and 7 except "*Premium Cheap*". The end-users may misinterpret it based on the cost, otherwise, end-users' experience overall has been rated as good.

(iii). Organizational Questionnaire-based Evaluation:- The organization-defined questionnaire is related to satisfaction, usefulness, attention, motivation, and knowledge, as shown in appendix. There are multiple questions related to

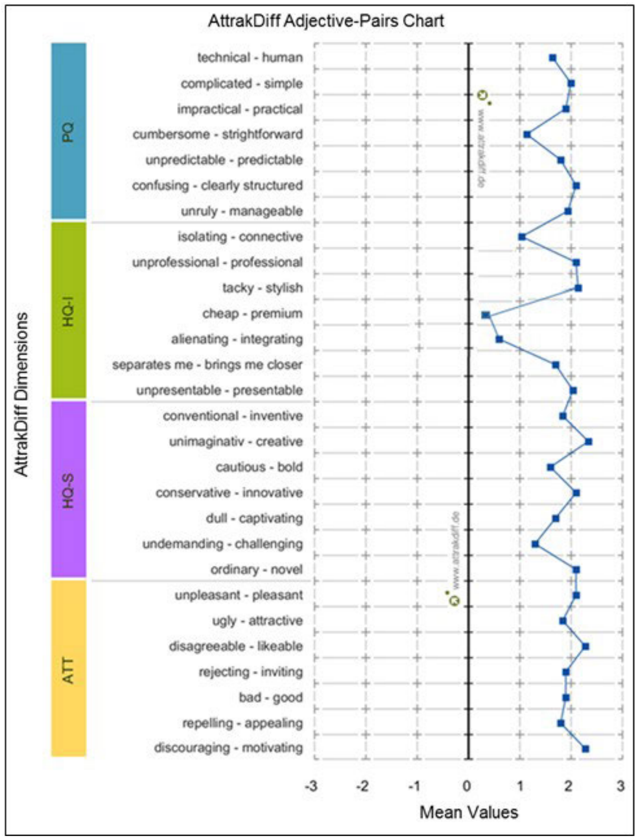


FIGURE 10. **AttrakDiff adjective-pairs' mean values for MM++ [90].**

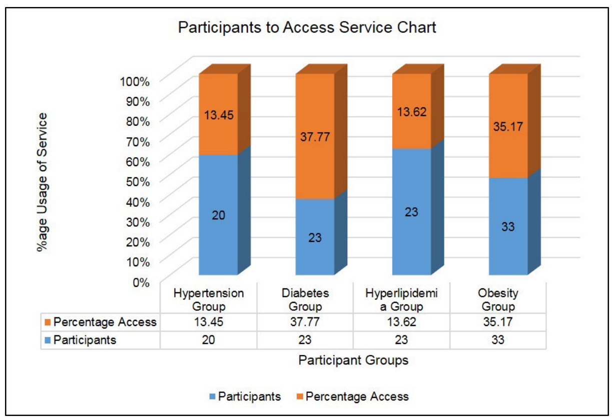


FIGURE 11. **Disease-wise service utilization comparison.**

the different categories and are marked on the Likert scale, where 1 means least agree and 5 means most agree. The disease ailment wise evaluation results of the services are shown in Figure 12, which shows that nearly 70% volunteers enjoyed and exhibited their trust on the application whereas nearly 10% of end-users somehow are not fully agreed with the support provided by the service. The overall grading of end-user experience criteria like satisfaction, usefulness, and knowledge lie between 68% and 74% where end-user psychological experience criteria like attention and motivation

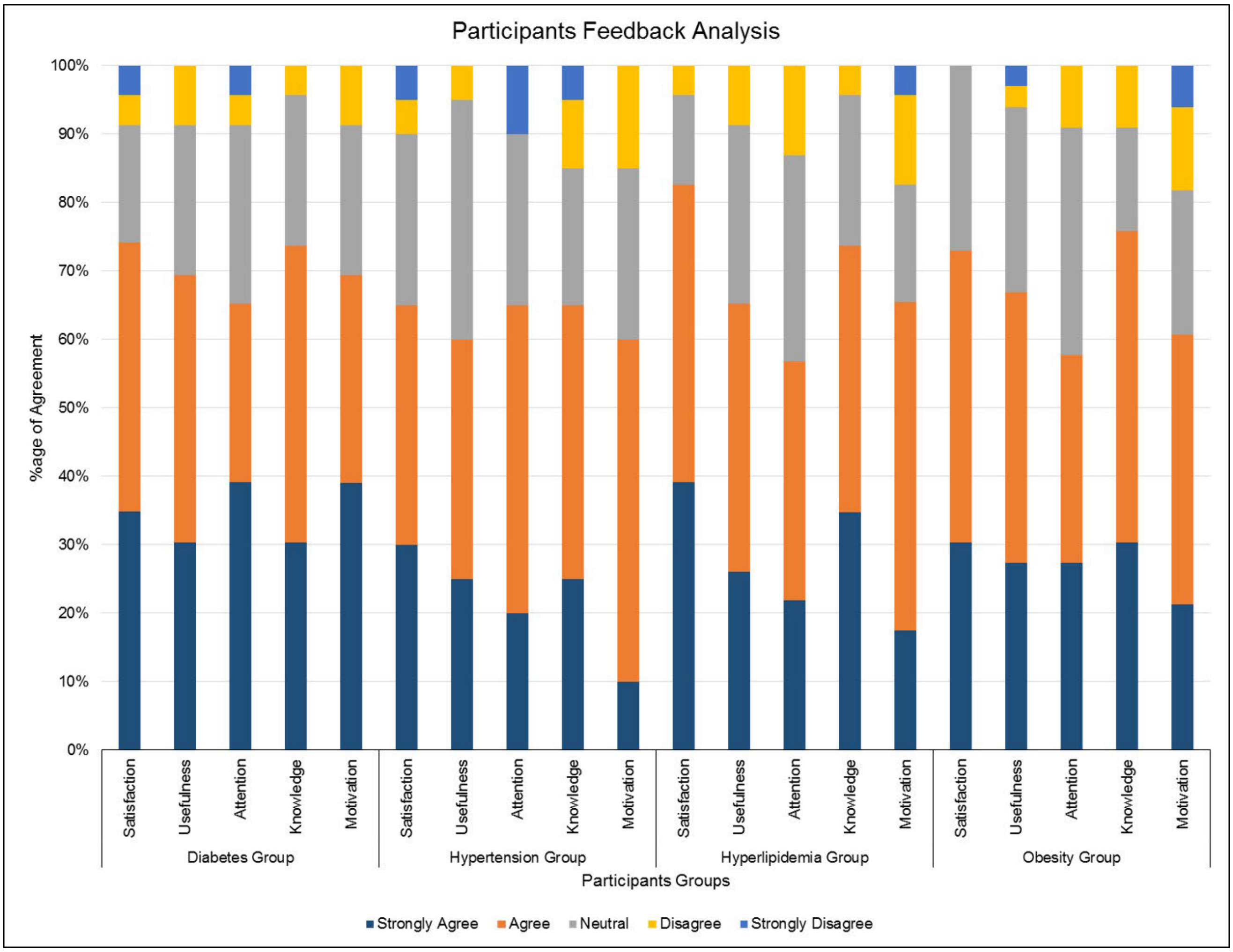


FIGURE 12. **Questionnaire-based survey result obtained from volunteers.**

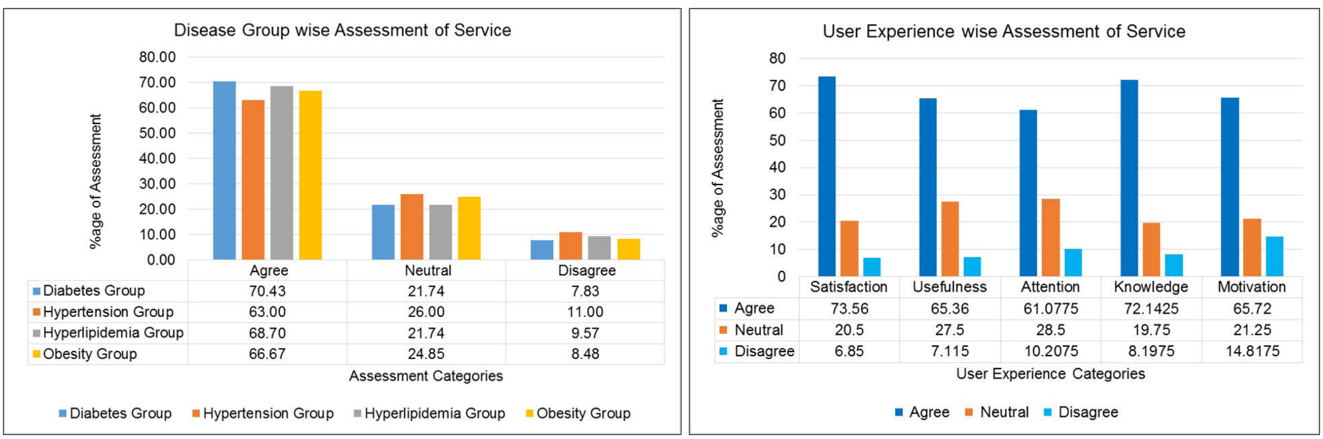


FIGURE 13. **Category-wise assessment of the wellness application from volunteers.**

lie between 60% and 66% after the usage of 12 weeks. The results show a very comprehensive agreement level of the population, which require a lot of knowledge, and motivation to change lifestyle for the support of medication.

TABLE 14. Organization-defined survey questionnaire.

Survey Question for Multi-dimensional Evaluation	
Matters concerning the usefulness of services-(Usefulness)	
Q1.	Did the chronic disease management program help you improve your healthy lifestyle
Q2.	Please indicate how helpful it has been. [(1) It improved my health.]
Q3.	Please indicate how helpful it has been. [(2) It was effective in promoting my health.]
Q4.	Please indicate how helpful it has been. [(3) It was useful in managing my illness.]
Matters concerning the use of services / interests -(Attention)	
Please indicate if it is difficult to ensure your overall involvement with this service.	
Q1.	It could easily and clearly make understand how to participate in the service.
Q2.	Using the service apps was not too difficult.
Q3.	For 12 weeks, could you participate with interest and attention.
Matters concerning the Expertise of Service-(Knowledge)	
Please check the reliability levels of the service.	
Q1.	I think it provides exact information about health, and it is a service that has lots of experience in this field.
Q2.	The service has helped to resolve question related to health / diet / Physical Activity
Q3.	The expertise of the service has raised my health knowledge level, so it will likely help me to practice my healthy lifestyle.
Q4.	There was a high level of trust in service expertise.
Matters concerning the abundance of service media-(Satisfaction)	
Question on content and configuration provided by Service App. Please check the pertinent information.	
Q1.	It has helped to manage health by providing easy understanding and use of the functions. (Function : Activity measurement, diet input, etc.)
Q2.	It has helped to practice healthy lifestyle in real life.
Q3.	The contents provided enabled us to accumulate necessary health knowledge.
Q4.	The services offered in the " Services App " are similar to the actual offline health care services.
Matters concerning the incentive by the service-(Motivation)	
Please check the pertinent information	
Q1.	Feedback, Reward, has been properly motivated to improve lifestyle.
Q2.	Feedback has been given at the right time.
Q3.	Would you recommend this service to an acquaintance or colleague?
Q4.	Do you plan to maintain / practice a healthy lifestyle after service is terminated?
Q5.	Do you think it would be beneficial for our future members to choose that service over the current comprehensive examination?

C. DISCUSSION

Lifestyle adaptation is a very challenging task, especially when concerned with elderly people. Multiple triggers, motivational booster, and context-based interventions are required to achieve desired targets. The chronic diseases, which are too much affected through lifestyle are the main concern of the wellness organizations and nations. The population affected by these diseases are the major burden on the economy of the country and required special attention to overcome, or at least reduces the impact of these preventable lifestyle-based diseases. The challenge is that the population usually leave the wellness applications after approximately 4 weeks due to a lack of interest and generalized recommendation.

In this study, the focus is on the identification of the behavior state of our participants that can be dealt with appropriate interventions. At the initial phase, the behavior context prediction model supports identifying the behavior status of the participants through lifestyle data obtained from an initial questionnaire, which helps to overcome the issue of cold start. According to the behavior status, specific intervention not only reduces the number of interventions but also increases the effectiveness of the interventions. The personalization through behavior context support steady learning, based on BCTs, and induce adaptive behavior strategically. The extended methodology of MM++ has a slow impact at the initial stage, whereas the respective intervention style tries to enhance the knowledge about unhealthy behaviors. This is the reason that the proposed methodology did not performed well in the initial weeks, but with the passage of time and with the improvement of the behavior status, the intervention style change from *prescriptive and informative* to *cathartic and catalytic*. As a result of just-in-time interventions after education, the response of behavior improves a lot lead to change in behavior, which is expressed through HBI. The relative gain in HBI, depicts that usually wellness applications have exponential impact, but with the passage of time, the change in behavior reduces due to lack of interest and personalization. However, the proposed methodology has a little steady impact, which not only increases the end-users' knowledge but also supports to handle the unhealthy behavior in an appropriate way based on behavior context. As a result, the end-users gradually adapt the harmful behavior, and hence the HBI improves with the passage of time and retains even without catalytic interventions due to knowledge and routine induction. This is the reason that the change in HBI gain becomes steady with in the last few weeks.

Multiple surveys were conducted related to the usability, satisfaction, attention, motivation, attraction, knowledge, hedonic and pragmatic qualities through SUS, AttrakDiff, and organization-defined questionnaire. The SUS and AttrakDiff results showed that proposed methodology had enhanced the attractiveness and adaptability. In the organization-oriented evaluation, on average, 67% of end-users registered their responses as agreeing, whereas only 9% of end-users showed disagreement with the service provided by an extended application, as shown in Figure 13(a). The overall service had satisfied the 74% of end-users where 7%of end-users registered unsatisfactory status, as shown in Figure 13(b). Considering the knowledge related to behavior and action plan, 72% of end-users registered their consensus in its favor whereas 8% of end-users were not convinced with the provided knowledge. The perceived usefulness affected the motivation of the end-users, and hence the level was about 65%, where the registered attention level was about 61% that is quite reasonable for the engagement with wellness applications in a long duration.

It can be depicted that persons with diabetes recorded the highest agreement level, which is more than 70% whereas persons with hyperlipidemia, obesity, and hypertension registered their agreement level 68%, 66%, and 63% respectively. On the other hand, nearly about 24% of end-users remain neutral regarding the application, while about 9% of end-users were unconvinced with the application. There may be multiple reasons like financial constraints, social, environmental, emotion, and age, which affected these 9% end-users to get the full benefit from the application to adapt unhealthy behavior.

VI. CONCLUSION

Human behavior quantification for the assessment and adaptation is the targeted research area in the wellness domain due to its complex nature. The adaptation requires identification of unhealthy behavior as well as personalized interventions at the right time with feasible action. The derived methodology not only identifies the behavior status through HBI but also uses a behavior-context prediction model for the selection of appropriate prescriptive intervention. In this work, we have focused on the comprehensive status of the four most important and fundamental habits like smoking, imbalanced diet, alcohol, and physical inactivity. It has helped the individuals and experts for root cause analysis of noncommunicable lifestyle-based chronic disease. The proposed methodology is designed as a framework to support any other service-enabled wellness management platform for the evaluation of healthy behavior status for behavior indication, behavior-context prediction, recommendation generation, and behavior adaptation. Extensive experimentation is performed that is comprised of a set of factors such as adaptiveness, satisfaction, usability, stimulation, attractiveness, usefulness, and motivation. In experimentation, both implicit and explicit feedback methods are employed. A healthy behavior index gain is observed throughout the evaluation adherence with the proposed methodology. Furthermore, feedback data are also gathered from a large number of registered users through a widely used survey tool such as SUS and AttrakDiff. The evaluation of the wellness application based on the user feedback resulted in encouraging results. It is observed that both the user experience and the usability aspects of the application are highly promising while the reported overall user satisfaction is also favorable. The study can be extended in a number of directions such as it is worthwhile to investigate the impact of financial and emotional distress on behavior adaption. We would also like to extend the scope of the study to include a wider user base such as the younger population having no prior health conditions.

APPENDIX

See Table 14.

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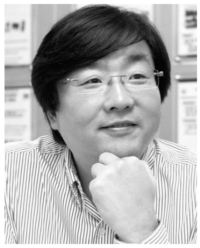

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