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On computing critical factors based healthy behavior index for behavior assessment

Hafiz Syed Muhammad Bilal[a,b], Muhammad Bilal Amin[d], Jamil Hussain[a], Syed Imran Ali[a], Shujaat Hussain[e], Muhammad Sadiq[a], Muhammad Asif Razzaq[a], Asim Abbas[a], Chunho Choi[c], Sungyoung Lee[a,*]

[a] *Department of Computer Science and Engineering, Kyung Hee University, Seocheon-dong, Giheung-gu, South Korea*
[b] *National University of Sciences and Technology, Pakistan*
[c] *Korea Institute of Industrial Technology, South Korea*
[d] *Department of ICT, University of Tasmania, Australia*
[e] *Department of Computer Science, National University of Computer and Emerging Sciences, Islamabad, Pakistan*

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ABSTRACT

Objective: Ubiquitous computing has supported personalized health through a vast variety of wellness and healthcare self-quantification applications over the last decade. These applications provide insights for daily life activities but unable to portray the comprehensive impact of personal habits on human health. Therefore, in order to facilitate the individuals, we have correlated the lifestyle habits in an appropriate proportion to determine the overall impact of influenced behavior on the well-being of humans.
Materials and methods: To study the combined impact of personal behaviors, we have proposed a methodology to derive the comprehensive Healthy Behavior Index (HBI) consisting of two major processes: (1) Behaviors' Weight-age Identification (BWI), and (2) Healthy Behavior Quantification and Index (HBQI) modeling. The BWI process identifies the high ranked contributing behaviors through life-expectancy based weight-age, whereas HBQI derives a mathematical model based on quantification and indexing of behavior using wellness guidelines.
Results: The contributing behaviors are identified through text mining technique and verified by seven experts with a Kappa agreement level of 0.379. A real-world user-centric statistical evaluation is applied through User Experience Questionnaire (UEQ) method to evaluate the impact of HBI service. This HBI service is developed for the Mining Minds, a wellness management application. This study involves 103 registered participants (curious about the chronic disease) for a Korean wellness management organization. They used the HBI service over 12 weeks, the results for which were evaluated through UEQ and user feedback. The service reliability for the Cronbach's alpha coefficient greater than 0.7 was achieved using HBI service whereas the stimulation coefficient of the value 0.86 revealed significant effect. We observed an overall novelty of the value 0.88 showing the potential interest of participants.
Conclusions: The comprehensive HBI has demonstrated positive user experience concerning the stimulation for adapting the healthy behaviors. The HBI service is designed independently to work as a service, so any other wellness management service-enabled platform can consume it to evaluate the healthy behavior index of the person for recommendation generation, behavior indication, and behavior adaptation.

1. Introduction

Over the last few decades due to the affluent environment, people's physical activity have become sedentary, their diets malnutrition, and their smoking and alcohol consumption increases. Lifestyle-habits impact the well-being, health, and socio-economical condition of individuals [1]. These lifestyle-habits have a significant role in spreading the non-communicable diseases (NCDs). These NCDs are the major cause of premature mortality, disability, and continuous burden on the economy [2,3].

* Corresponding author at: Department of Computer Science and Engineering, Kyung Hee University, Seocheon-dong, Giheung-gu, South Korea.
E-mail addresses: bilalrizvi@oslab.khu.ac.kr, bilal.ali@seecs.edu.pk (H.S.M. Bilal), bilal.amin@utas.edu.au (M.B. Amin), jamil@oslab.khu.ac.kr (J. Hussain), imran.ali@oslab.khu.ac.kr (S.I. Ali), shujaat.hussain@nu.edu.pk (S. Hussain), sadiq@oslab.khu.ac.kr (M. Sadiq), asif.razzaq@oslab.khu.ac.kr (M.A. Razzaq), asimabbasturi@oslab.khu.ac.kr (A. Abbas), cchoi@kitech.re.kr (C. Choi), sylee@oslab.khu.ac.kr (S. Lee).

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Table 1
Summary of the related work.

Sr. #	Behavior	Domain	Assessment process	Reference
1	TV viewing	Physical activity	Self report, questionnaire	[20–23]
2	Total inactivity	Physical activity	Self report, IPAQ: International Physical Activity Questionnaire	[23,24]
3	Leisure time active sports	Physical activity	Self report	[25–27]
4	Bicycle/walking for commuting	Physical activity	Self report	[28–30]
5	Fruit	Diet	Self report, parent report, FFQ: Food Frequency Questionnaire	[31,32]
6	Vegetables	Diet	Self report, other questionnaire, FFQ: Food Frequency Questionnaire	[33,34]
7	Soft/energy drinks	Diet	24-hour recall, other questionnaire, Self report	[35,36]
8	Energy-dense / healthy snacks	Diet	24-hour recall, other questionnaire, self report, FFQ: Food Frequency Questionnaire	[37,38]
9	Sweets, chocolates, candies	Diet	Self report, FFQ: Food Frequency Questionnaire	[39,40]
10	Total fat, saturated fat, red meat	Diet	24-hour recall, other questionnaire, self report, FFQ: Food Frequency Questionnaire	[41–43]
11	Carbohydrate, fiber, grains	Diet	Self Report, 24-hour recall, FFQ: Food Frequency Questionnaire	[34,42,44]
12	Fish, protein	Diet	24-hour recall, Self report, FFQ: Food Frequency Questionnaire	[42,43]
13	Dietary pattern	Diet	Self report, FFQ: Food Frequency Questionnaire	[22,45–47]
14	Nicotine patch / spray	Smoking	Self report, Questionnaire of Smoking Urges	[48,49]
15	Cigarettes	Smoking	Self report, Questionnaire of Smoking Urges	[5,50]
16	Oral alcohol	Drinking	Self report, Alcohol Urges Questionnaire	[5,51,52]

Studies in the literature have highlighted the four important healthy behaviors i.e. balanced diet, physical activity, nonsmoking and non-alcohol consumption [4,5]. Most epidemiological researches have designed a lifestyle index through the accumulation of risky or non-risky behavioral indicators' level. These mono-dimensional approaches arbitrarily assign behaviors into the 'risky' category and overlook the impact of multi-dimensional behaviors on health [6]. However, in few studies prediction models were used to derive risk indexes for targeted assessment of multiple risk factors on health with specific profiles over a certain period of time [7] and few mortality prediction models for elderly have been developed. These approaches failed to provide information for risk intervention. The prevention of chronic diseases is better achieved through adopting healthy lifestyle habits [6]. Therefore, we aimed to develop healthy behavior index based on modifiable lifestyle factors to prevent or delay in the occurrence of non-communicable chronic diseases.

In the paper, we have addressed the index identification challenge to cover the health-behavior status comprehensively. Quantification provides the foundation for the identification of the behavior condition. The behavior condition is mapped to appropriate status through indexing as per guidelines provided by the healthcare and lifestyle experts. So quantification and indexing support to represent the behavior and without indication, the change in behavior cannot be tracked and evaluated. The impact of unhealthy habits is non-linear, so we have adopted the life expectancy based weight-age for each habit. Hence our proposed methodology is divided into two major processes of Behavior Weight-age Identification (BWI) and Healthy Behavior Quantification and Index (HBQI) modeling. The BWI process mining the health-related concepts through text mining, expert-based filtration of identified concepts for ranking and, life-expectancy based behavior weight-age derivation. Where HBQI, is a mathematical model, derived based on wellness guidelines for quantification and indexing of behavior. The evaluation of the methodology is done through real-world user-centric statistical User Experience Questionnaire (UEQ) method.

The main contribution of the study is three-fold as follows: Firstly, we have applied dictionary-based text mining to extract contributing factors which is verified by experts with agreement value of 0.379. Secondly, we have established the weight-age of the lifestyle behaviors based on life expectancy studies. Lastly, a comprehensive healthy behavior index is derived to depict the status of lifestyle behavior for representing the respected unhealthy, normal, and healthy scale. This is a comprehensive scale with ICT based implementation to enhance the applicability of wellness application through quantification and indexing service.

The remainder of the paper is organized as follows: Section 2 covers the existing studies of indexing and gathering various behavior information; the mapping of HBI with behavior understanding, and change related theories in Section 3. Section 4 discusses the proposed methodology of HBI, and Section 5 covers the details of evaluations along with results as well as discusses the significance of the proposed system. Section 6 concludes the paper with a summary of the research findings.

2. Related work

The wellness management organizations focus on behavior adaptation to improve quality of human health, increase the life span and reduce the burden on society [8]. In [9] authors evaluated the efficacy of sequential and simultaneous intervention for physical activity (PA), diet, and sleep to improve the behaviors. Similarly in [10] authors consider the status of PA, diet, and sleep for generating the intervention and personal motivation messages for behavior improvement.

Generally, health behavior models don't consider the habitual actions, so Self-Report Habit Index (SRHI) synthesis the influence of consistent actions on behavior [11]. Habitual behavior is one that someone usually does or has, especially one that is considered to be a characteristic of the person [12]. In the wellness domain, the behavior related to the activity is defined on the basis of different time duration. Nutrition and smoking behavior are considered on a daily basis, where physical activity and alcohol are considered on a weekly basis. So we consider the habitual on the basis of quantity in specified time duration. The diverse nature of habits makes them difficult to accurately assess them in a rigorous manner. Therefore, habit reports may be biased due to recall inaccuracies and human memory, which is catered in HBI. The SRHI is related to a specific behavior at a time such as smoking, junk food, and energy drinks, while HBI is based on the multiple behaviors, which are in tern composed of micro factors. In HBI, the index is calculated through the weighted contributing factors based on the life expectancy impact. The SRHI considers the intention and attention of a behavior, ignoring the chance of biasness.

In literature, studies focused on the dietary patterns and assessed dietary behavior through self-report questions of food frequency questionnaire (FFQ) [4,11,13,14] as summarized in Table 1 under the section of diet to index the eating habits. Multiple studies summaries in Table 1 reflect which identify that most preventable cause of death are tobacco and alcohol which lead to thousands of deaths yearly [15]. 20% adults [16] consumed tobacco and alcohol together [17], which has been associated with fetal diseases [17,18] are assessed through self-report questionnaires to get related urges index. The discussed literature under the purview of this research, focus on only some specific behaviors related to lifestyle instead of considering an array of pertinent behaviors, holistically. Furthermore, the quantification process depends on gathering explicit feedback in terms of self-reported health related questionnaires ignoring the chance of biasness due to human

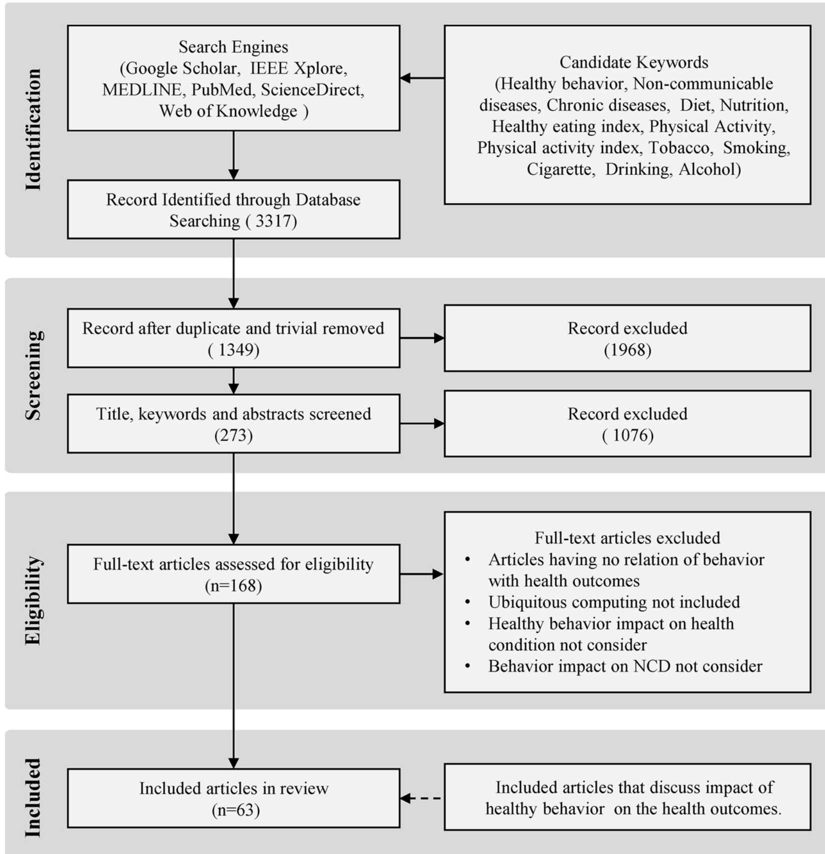

Fig. 1. A survey analysis for document selection.

memory error and some social norm.

The domain analysis literature was performed on Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines followed in [19] with nontrivial alteration such as article types, keywords, duration and search engine. Two reviewers cross-checked these studies through a systematic search of the PubMed, MEDLINE, Web of Knowledge, Google Scholar, IEEE Xplore, and ScienceDirect databases. The following potential keywords of *healthy behavior, diet, nutrition, sedentary behavior, healthy food, chronic diseases, noncommunicable diseases, alcohol consumption, drinking, smoking, and tobacco* were applied for exhaustive search in the operational definition of healthy behavior i.e. *physical activity, diet, smoking, alcohol, stress, and sleepingas shown in* Fig. 1 .

The inclusion criteria were research studies that focused healthy behavior in adult members as a dominant variable to at least one health outcome. To consider, research studies were required to (1) comprise adults aged > 35 years as subjects of study at baseline; (2) have a mean of at least one facet of healthy behavior (Diet, physical activity, smoking, drinking, stress, sleeping); (3) have observation and assessment of association between healthy behavior components; (4) have published in the English language in peer-reviewed journals; and (5) have published up to and including May 2018. We have selected the potentially relevant articles by (1) titles screening; (2) filtering the abstracts and conclusions; and (3) if abstracts were not sufficient, the entire document was investigated for inclusion criteria. The analysis of related work depicts that studies have targeted the specific behaviors for respective studies. So we have to develop and verify a comprehensive index to quantify the healthy-behavior status. Our proposed methodology adopt the life expectancy based unhealthy behaviors in appropriate proportion [3].

3. Mapping of HBI with behavior understanding and change related theories

The change in behavior to adopt a healthy lifestyle is the key concern of wellness management organizations to improve life quality and span. The change is controlled and understand through multiple behavior change theories. These theories focus on the behavior and attitude of an individual to support a change in lifestyle for healthy behaviors. The HBI service supports multiple theories at different stages as discussed in Table 2 . The theory of planned behavior determines an individual's intention of behavior through attitude and subjective norms [53]. The action of a person represents the attitude and change in actions may represents the change in attitude either it is positive or negative. So, if the HBI increases, it reflects the positive change in attitude. While, social cognitive theory deals with personal factors, individual ability, and environmental factors [54]. The Transtheoretical model emphasizes multiple stages of behavior change: (1) precontemplation, (2) contemplation, (3) preparation, (4) action, and (5) maintenance [55]. The Fogg Behavior Model focuses on three basic ingredients of behavior occurs: (1) motivation, (2) ability, and (3) trigger [56]. The theory of reasoned action explains that individuals consider the consequences before performing a particular behavior. As a result, attitude and intention are enforcing factors for behavioral change [57].

4. Proposed methodology for healthy behavior index derivation

The proposed methodology consists of three main processes: (1) Factors' Weight-age Identification (FWI), (2) Healthy Behavior Quantification and Index (HBQI) modeling, and (3) Realization and Evaluation as shown in Fig. 2 . The FWI process further consists of three sub-processes: (i) mining of the health-related concepts through text

Table 2
HBI service mapping to behavior change theories.

Sr. #	Theory	Non-mapping concepts	Mapping concepts	HBI support
1	Theory of planned behavior	Subjective norm	Attitude	Change in HBI score indicate about the attitude
2	Theory of reasoned action	Subjective norm, important norm	Attitude towards factors	Change in level score of factors indicate attitude towards factors
3	Social cognitive theory	Environmental factors	Personal factors, ability	HBI's factors values, level of factors
4	Transtheoretical model	Precontemplation	Contemplation, preparation, action, maintenance	HBI score indicate the status and condition of the ingredient factors
5	Fogg behavior model	Trigger	Motivation, ability	HBI's sub factor score change indicate the level of motivation and ability to perform

mining, (ii) expert based filtration of identified concepts for ranking and (iii) life-expectancy based factor weight-age derivation.

4.1. Factors' weight-age identification

The FWI process identifies and verifies the most contributing high-ranked factors of health-related behavior. Besides, it derives the weight-age of the identified factors with the help of guidelines.

4.1.1. Text mining for candidate factors identification

We have adopted the dictionary-based methodology to scrutinies the documents using synonyms, hyponyms, hypernyms, and other contextual texts, which increases the success rate of documents categorization [58]. The concept mining approach identifies the frequency of multiple health-related behaviors discussed in the literature. In this way, we are able to obtain the behaviors which are highly studied. It supports us in finding out their importance, which lays the foundation for our baseline concept list. The obtained list is further finalized with the agreement of experts. The workflow of the knowledge extraction methodology is shown in Fig. 3 , which consists of four modules, namely *document database*, *text preprocessing*, *dictionary based analytics*, and *visualization*.

The *Text Preprocessing* performs *Preliminary Transformation*: identification and marking of sentences, *Tokenization*: dividing the given text into pieces (tokens) and tag them as a parts-of-speech, *Filtration and Stopword Removal*: excluding the non informative words, stopwords and connecting words, and *Stemming*: for identifying the root of the word. The dictionary consists of terms related to habits and behavior obtained from the National Diet and Nutrition Survey (NDNS nutrient Databank), Composition of Foods Integrated Dataset (CoFID-Version 2015), 2018 Physical Activity Guidelines (PAG) Advisory Committee Scientific Report, the lexical database WordNet, and A guide to smoking cessation in Scotland 2010-updated 2017. It performs (1–3)-gram based filtration on the bag of words (document) and the term frequency is calculated to determine the critical factors from literature as shown in Fig. 4 .

4.1.2. Expert based health behavior candidate factors evaluation

The Experts Based Evaluation (EBE) of the identified factors is quite necessary to verify the key impact factors and their sub-factors. Seven experts from the wellness domain have registered their agreement or disagreement intensity through a psychometric scale "Likert" questionnaire [59] to grade 20 identified attributes. The experimentation was performed with the collaboration of wellness support organization. The organization has experts who are supporting elderly people and persons with lifestyle-based chronic diseases. These experts have atleast more than three years of experience and education of post-graduation level in the human health and wellness domain. The mean of assigned grades has been utilized to map the factors' importance level as shown in Table 3 .

Kappa is a statistical measure for estimating the agreement reliability between a fixed numbers of raters when using categorical ratings to a number of classifying items [60]. Fliess's kappa is a particular type, which contrasts with other kappas. Such as Cohen's kappa, which only works when estimating the agreement between not more than two raters. Kendall coefficient and cohesion kappa are related to measuring the inter-rater agreement reliability. Still, the issue is that these are specific to two raters if the number of raters increases, then Fliess' Kappa supports well.

The Fliess' Kappa is a ratio of the actual degree of agreement achieved above chance, over the attainable degree of agreement above chance. Kappa value equal to 1 represents complete agreement among the raters otherwise its value is less than or equal to 0. The Kappa value shown in Eq. (4) is fair enough to accept the agreement level with multiple categories and among multiple raters as shown in Table 4 .

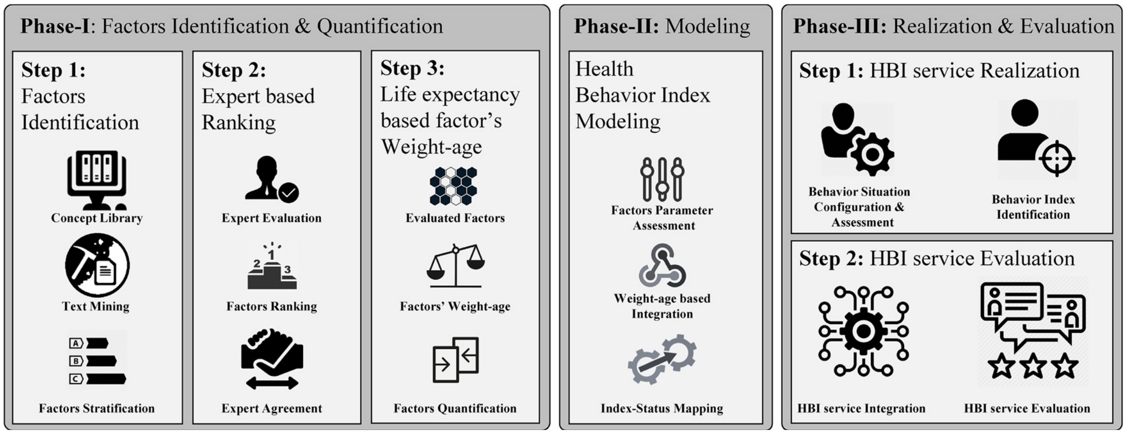

Fig. 2. Healthy behavior index derivation and evaluation process.

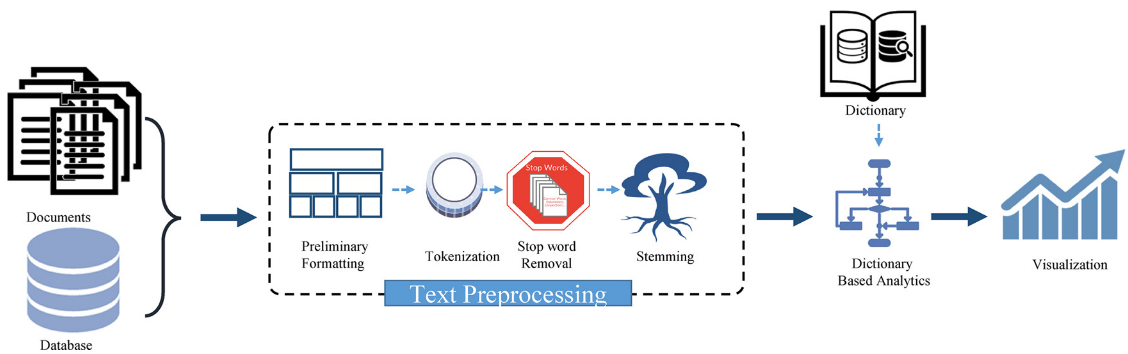

Fig. 3. Work-flow of text mining methodology for concept identification.

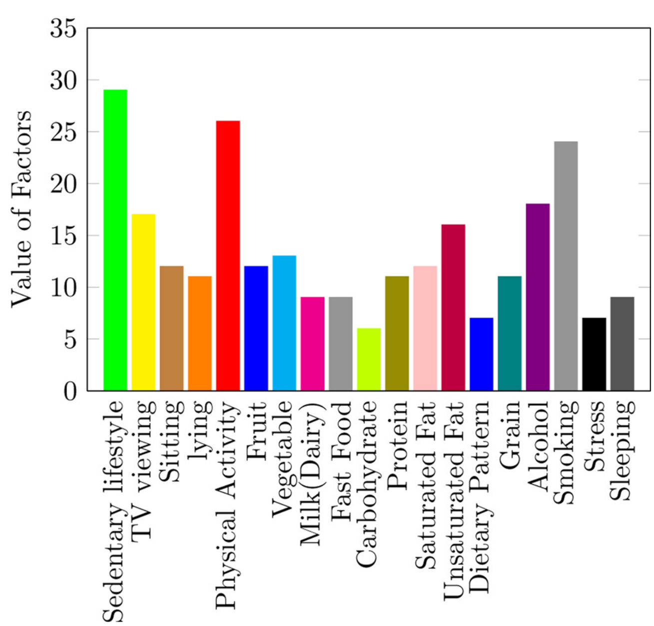

Fig. 4. Frequency of the targeted term.

$$k = \frac{\bar{P} - \bar{P}_e}{1 - \bar{P}_e}, \quad (1)$$

$$\bar{P} = 0.537, \quad (2)$$

$$\bar{P}_e = 0.254, \quad (3)$$

$$k = 0.379. \quad (4)$$

The value of Kappa will be higher when there are fewer categories and inter-raters have few options to register their agreement [61]. When we have transformed the responses of the inter-rater into three categories of agree, neutral and disagree the value of Kappa is 0.52 while when the responses are categorized into agree and disagree the value of kappa is 0.91 which is reasonably acceptable.

4.1.3. *Life-expectancy based factors' weight-age derivation*

The expert's evaluation finalizes the assessment of user's healthy behavior status as shown in Table 5 along with the definition.

The focus of the assessment criteria is only on the behavior risk factors rather than intermediate or proximal risk factors as shown in Table 6 .

In study [3,97] authors had introduced the concept of life expectancy and prediction for future mortality. According to the studies, life expectancy based on recommended healthy behavior was 17.9 years more for people with the most favorable risk-profile compared to the least favorable one as shown in Table 7 . In study [3], authors have developed a Mortality Population Risk Tool (MPoRT) risk algorithm based on the Cox proportional hazards model to estimate the time to death by the primary risk factors. We have utilized the same technique to identify the weight-age of risk factors through proportion from a difference of life gain and life loss because of a particular risk factor.

The HBI is categorized into three levels such as healthy, unhealthy and normal against four primary factors for behavior quantification. So, we have 3^4 total possible cases with a mean value of 23.25 index as shown in Table 8 . The HBI in the least favorable conditions is 7.75 index while in most favorable conditions is 38.75 index. The standard deviation is about ± 6.75, so the range of regular HBI lies between 16.0 and 29.0 which is the significant portion of the range, where unhealthy HBI lies between 7.75 and 15.99 index and similarly healthy HBI lies between 29.01 and 38.75 index.

As there are multiple contributing factors to decide the appropriate

Table 3
Evaluation of key factors from experts.

Key factors	Exp 1	Exp 2	Exp 3	Exp 4	Exp 5	Exp 6	Exp 7	Average
	Likert scale: Min 1 2 3 4 5 Max							
Physical activity	5	5	5	5	5	5	5	5.00
Sedentary activity	4	4	4	4	5	4	4	4.14
Sleeping	1	3	3	1	3	4	1	2.29
Regularly eating	5	5	4	5	4	5	5	4.71
Sugar amount	5	5	5	5	4	5	5	4.86
Dietary fiber	2	2	3	3	3	2	3	2.57
Carbohydrate amount	3	1	2	1	3	1	2	1.86
Grain	4	4	3	4	4	4	3	3.71
Fats (cholesterol)	4	4	4	4	5	4	4	4.14
Saturated fat	2	2	3	3	2	2	2	2.29
Unsaturated fat	2	2	2	2	3	2	2	2.14
Protein (fish, poultry)	4	3	2	2	3	4	4	3.14
Milk	3	3	4	3	4	4	4	3.57
Vegetables	4	4	4	4	5	4	4	4.14
Fruits	5	5	4	3	5	5	5	4.57
Salt amount	5	3	5	4	4	5	5	4.43
Balance diet (5 groups)	3	5	4	4	3	5	5	4.14
Smoking	5	5	5	4	5	5	5	4.86
Alcohol	5	5	4	5	4	5	4	4.57
Stress	1	2	2	1	1	2	2	1.57

range we get the values of HBI with all combination of factors while keeping one factor either worst, best, and medium respectively. Initially, we have kept the value of smoking worst and read all possible values of diet, physical activity and alcohol and get average. In this way we draw the values of HBI to get the appropriate values of worst, medium, and best.

4.2. System architecture: healthy behavior quantification and index (HBQI) modeling

The proposed architecture consists of two major components *Behavior Situation Assessment (BSA)* and *Behavior Index Identifier (BII)*. The BSA manages the rules for quantification and assessment of multiple activities. In BSA, *Assessment Rule Manager (ARM)* manages the flow from rule creation to rule orchestration through categorization of rules with the help of *Rule Authoring Interface (RAI)*, *Rule Categories Identifier (RCI)*, and *Rule Orchestrator (RO)*. The RAI is the convenient access point between the expert and the system to transfer their knowledge in the form of rules for assessment and quantification. The RCI categorizes the rules into monitorable parameters and assessment parameter where the RO is responsible for managing the inter-process communication for assessment and monitoring of the behavior for final behavior index identification. The *Rule Configurator (RF)* configures the rules into two different kinds of knowledge-bases to handle the assessment criteria and monitor-able parameter separately with the help of *Assessment Parameter Configurator (APC)* and *Monitor-able Parameter Configurator (MPC)*. The *Behavior Monitor (BM)* analyzes the behavior and its related situation according to the assessment criteria, if the rule is not matched then there is no need to monitor the behavior parameter through *Assessment Parameter Analyzer (APA)* and *Monitor-able Parameter Analyzer (MPA)*.

The APA manipulates the situation data of the behavior from the user's lifelog and profile which is collected by Lifelog Collector. For a success full behavior assessment, the assessment parameters must

Table 4
Evaluation of Kappa for expert agreement.

Sr. #	Key factors	Evaluation categories for inter-related agreement					Agree item
		Strongly disagree	Disagree	Neutral	Agree	Strongly agree	
1	Physical activity	0	0	0	0	7	1.00
2	Sedentary activity	0	0	0	6	1	0.71
3	Sleeping	3	0	3	1	0	0.29
4	Regularly eating	0	0	0	2	5	0.52
5	Sugar amount	0	0	0	1	6	0.71
6	Dietary fiber	0	3	4	0	0	0.43
7	Carbohydrate Amount	3	2	2	0	0	0.24
8	Grain	0	0	2	5	0	0.52
9	Fats (cholesterol)	0	0	0	6	1	0.71
10	Saturated fat	0	5	2	0	0	0.52
11	Unsaturated fat	0	6	1	0	0	0.71
12	Protein (fish, poultry)	0	2	2	3	0	0.24
13	Milk	0	0	3	4	0	0.43
14	Vegetables	0	0	0	6	1	0.71
15	Fruits	0	0	1	1	5	0.48
16	Salt amount	0	0	0	6	1	0.71
17	Balance diet (5 groups)	0	0	2	2	3	0.24
18	Smoking	0	0	0	1	6	0.71
19	Alcohol	0	0	0	3	4	0.43
20	Stress	3	4	0	0	0	0.43
	Aggregate	0.06	0.16	0.16	0.34	0.29	

Table 5
Key factors definition along with expert agreement status.

Sr. #	Key factors	Importance level of factors	Definition	References
1	Physical activity	5.00	Moderate to vigorous physical activity for at-least 150 min in a week	[62,63]
2	Sedentary activity	4.14	Spending more waking time in activity with MET < 1.5	[64–66]
3	Sleeping	2.29	Activity with MET value < 1.0	[67,68]
4	Regularly eating	4.71	3–5 time with proper duration delay	[69–71]
5	Sugar amount	4.86	Less than 10% of calories per day from added sugar	[72,73]
6	Dietary fiber	2.57	25–30 g of food must be dietary fiber (adults) (unabsorbable plant part)	[74,75]
7	Carbohydrate amount	1.86	Major source of energy and 4-5 g/kg/day carbohydrate are recommended	[76,77]
8	Whole Grain	3.71	3 serving or about 84 g per day of whole grains are recommended to maintain a long-term health	[78]
9	Fats (cholesterol)	4.14	The diet should not contain more than 78 g of fat	[79,80]
10	Saturated fat	2.29	Unhealthy fats from animals (solid at room temperature) and body requires about 13 g per day	[81,82]
11	Unsaturated fat	2.14	Healthy fats from plants and fish (liquid at room temperature) and replace saturated fats with unsaturated one	[83,84]
12	Protein (fish, poultry)	3.14	Consumption of poultry, fish, egg to fulfill about 56 g of protein requirements	[85,86]
13	Milk (dairy)	3.57	Rich source of calcium, vitamin D and essential minerals and recommended 3 servings per day	[87,88]
14	Vegetables	4.14	2–3 servings of vegetables (preferably green color vegetables) per day	[88,89]
15	Fruits	4.57	1.5–2 servings of fruit (preferably fresh fruits and juice) per day	[88,89]
16	Salt (sodium) amount	4.43	2.5–5.0 g of salt is recommended per day	[90,91]
17	Balance diet (5 groups)	4.14	Combination of grains, fruits, vegetables, dairy, and proteins in appropriate proportion	[78,86,92]
18	Smoking	4.86	Cigarettes, pipe, and cigar all are injurious to health and major preventable risk factor of non-communicable diseases	[92,93]
19	Alcohol	4.57	Less than 14 units per week keep health and premature mortality risks to a low level	[94,95]
20	Stress	1.57	Mental or emotional pressure threats the quality of working life and can cause aggression, absenteeism and reduced productivity	[96]

match the criteria defined by the Expert. The parameter assessment is modeled as shown below:

Consider,

$$M = \{m_1, m_2, \ldots, m_j\}, \tag{5}$$

where M = {set of monitorable Parameter}, and

j is the number of monitorable parameter.

Now,

m_j has related subset of assessment parameter which is denoted by S:

$$S = \{s_1, s_2, \ldots, s_n\}, \tag{6}$$

where n is the total number of assessment parameter.

The assessment parameter of a monitor-able parameter A_M is defined as:

$$A_M = \{A_{MS_1}, A_{MS_2}, \ldots, A_{MS_K}\}, \tag{7}$$

where $S_K \in S$.

The indication of assessment parameter related to monitorable parameter is as follows:

$$I_{\mathrm{MA}_j} = \begin{cases} 1, & \text{if } \bigcap_{i=1}^{K} A_{\mathrm{MS}_i} = 1,\ i \in A_{\mathrm{Mj}} \\ 0, & \text{Otherwiseignore} \end{cases}$$

The MPA extracts the parameter values from the lifelog activities to represent the behavior atomically or part of composite behavior. The difference between atomically or part of composite behavior can be distinguished by example. Smoking is a behavior, which can be understood and quantified atomically. However, the nutritional behavior is not quantified atomically; we have to consider the subparts like regularity, the quantity of salt, sugar, fruits, vegetables, etc. For example, smoking is a parameter which represents a single behavior atomically, whereas, the physical activity status is obtained through processing of the multiple physical activities' duration. The assessment of parameters is expressed mathematically as shown below:

Pre-Condition

$$I_{\mathrm{AM}_j} = 1. \tag{8}$$

Then

Table 7
Health behavior risk factors' weight-age.

Behavior	Average life (in years)	Life loss (in years)	Life gain (in years)	Loss and gain (in years)	Weight-age
Smoking	82	73	85	12 years	3.00
Poor diet	82	78	86	8 years	2.00
Alcohol	82	80	86	6 years	1.50
Physical inactivity	82	81	86	5 years	1.25
Stress	82	79	83	4 years	1.00

Table 6
Categories of health behavior risks factors.

Behavior	Category	Description	Score
Smoking	Heavy smoker	Daily current smoker (≥1 pack/day)	1
	Light smoker	Daily current smoker (< 1 pack/day)	3
	Non smoker	Former occasional smoker or never smoker	5
Diet	Poor diet	Irregular, imbalanced 5 groups food, high sugar and salt	1
	Fair diet	Partial regularity, partial balanced 5 groups food	3
	Adequate diet	Regular, balanced 5 groups food, low sugar and salt	5
Alcohol	Heavy drinker	10–24 (men) or 6–17 (women) drinks/week	1
	Moderate drinker	5–9 (men) or 3–5 (women) drinks/week	3
	Light/no drinker	0–4 (men) or 0–2 (women) drinks/week	5
Physical activity	Sedentary	0 to < 1.5 METs/day	1
	Moderately active	1.5–3 METs/day (for 20–25 min)	3
	Active	> =3 METs/day (for 20–25 min)	5

Table 8
Health behavior risk factors' average in multiple combination.

Fixed factor	Combinational factors	Average HBI			
		Worst	Medium	Best	Average
Smoking	Diet	17.25	23.25	29.25	23.25
	Alcohol				
	Physical activity				
Diet	Smoking	19.25	22.80	27.25	23.10
	Alcohol				
	Physical activity				
Alcohol	Smoking	20.25	23.25	26.25	23.25
	Diet				
	Physical activity				
Physical activity	Smoking	20.75	23.25	25.75	23.25
	Diet				
	Alcohol				
Average		19.38	23.14	27.12	*23.21*

$$M = \sum_{i=1}^{n} \{M_{i\text{SCORE}}\}/\text{time}, \tag{9}$$

where

$$\text{time} = \{\text{Day, Week, Month}\}, \tag{10}$$

but:

$$n = \begin{cases} 1, & \text{forsimplemonitorableparameter} \\ 2 - \infty, & \text{forcomplexmonitorableparameter}. \end{cases}$$

The BII manages the aggregate and interprets the behavior index level. It consists of the *Behavior Index Compiler (BIC)*, *Behavior Interpreter (BI)* and *Visualization Enabler (VE)*.

The BIC drives the comprehensive index and ingredient level index. The comprehensive index presents an overall state of smoking, drinking, diet, and physical activity behaviors while ingredient level index represents individual behavior index. According to the guidelines, there are different criteria to evaluate the behaviors based on time duration. Consider the example of nutrition; it consists of further sub ingredients like regular eating, balanced diet, fats consumption, sugar intake, salt status, and vegetable intake. So in the compiler, consider the nutrition data of at least seven consecutive days as given below:

Consider,

$$B = \{\text{Set of Behavior}|\text{Smoking, Diet, Alcohol, PhyAct}\}, \tag{11}$$

where

Table 9
Participants demographic information.

	No. of users	% of users
Age (year)		
35–40	25	24.27%
41–50	52	50.48%
50 and above	26	25.24%
Gender		
Male	65	63.10%
Female	38	36.89%
Health issues		
Obesity	33	37.86%
Hyperlipidemia	25	24.27%
Hypertension	21	20.39%
Diabetes	24	20.30%
Course completion		
Complete	99	96.12%
left	4	3.89%
Smart devices expertise		
Expert	20	19.42%
Intermediate	76	73.79%
Novice	7	6.80%

$$\begin{aligned} B_{\text{Smoking}} &= \text{no. of Packs/Day}, \\ B_{\text{Diet}} &= (\text{DietaryHabit}_{\text{SCORE}} + \text{DietaryNutrient}_{\text{SCORE}}), \\ B_{\text{Alcohol}} &= \text{no. of Drinks/Week}, \\ B_{\text{PhyAct}} &= \frac{\sum (\text{time}_{\text{PhyAct}}|\text{MET}_{\text{PhyAct}} \geq 3)}{\text{Week}}, \end{aligned}$$

$$\text{HBI} = \sum_{i=1}^{n} \{B_i * \text{Wt}_{Bi}\}. \tag{12}$$

The BI maps the behavior-scale to derived-behavior-index, where the VE converts the mapped-behavior into JavaScript Object Notation (JSON) communication format. The values are presented in the form of a key-value pair which is more easily interpretable for the Behavior-Based Wellness Services. The mapping of behavior-scale as per ranges decided in Section 4.1.3 is discussed below:

$$\text{Status}_{\text{HBI}} = \begin{Bmatrix} \text{unhealthy}, & \text{if HBI} \leq 16 \\ \text{moderate}, & \text{if } 16 < \text{HBI} \leq 29 \\ \text{healthy}, & \text{if } 29 < \text{HBI} \leq 40 \end{Bmatrix}$$

4.3. Integration of healthy behavior index with wellness application

The evaluation of HBI requires to link it with the wellness application. We have selected an open-source and sustainable echo wellness application known as Mining Minds (MM), which is adopted by a wellness organization. It was evaluated in two perspectives; the one

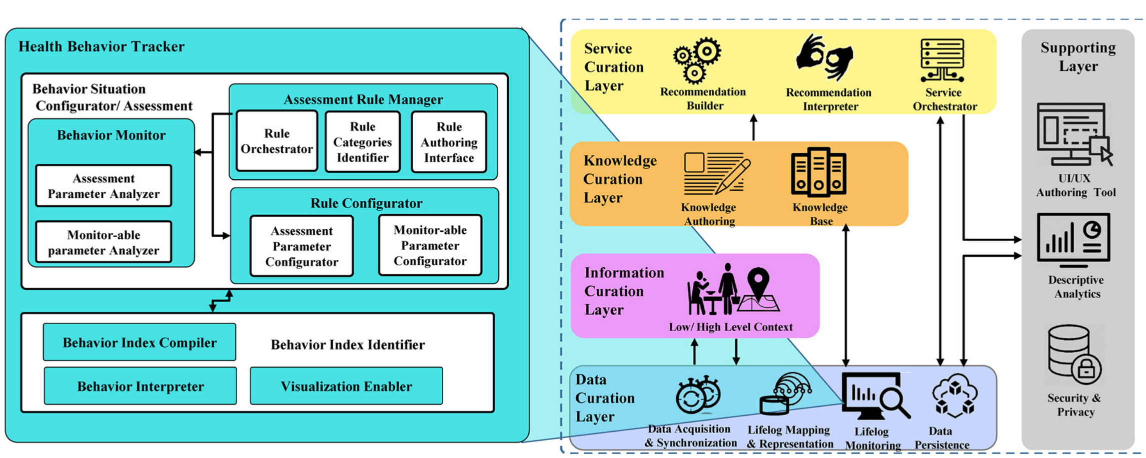

Fig. 5. Integration of mining minds framework with HBI methodology.

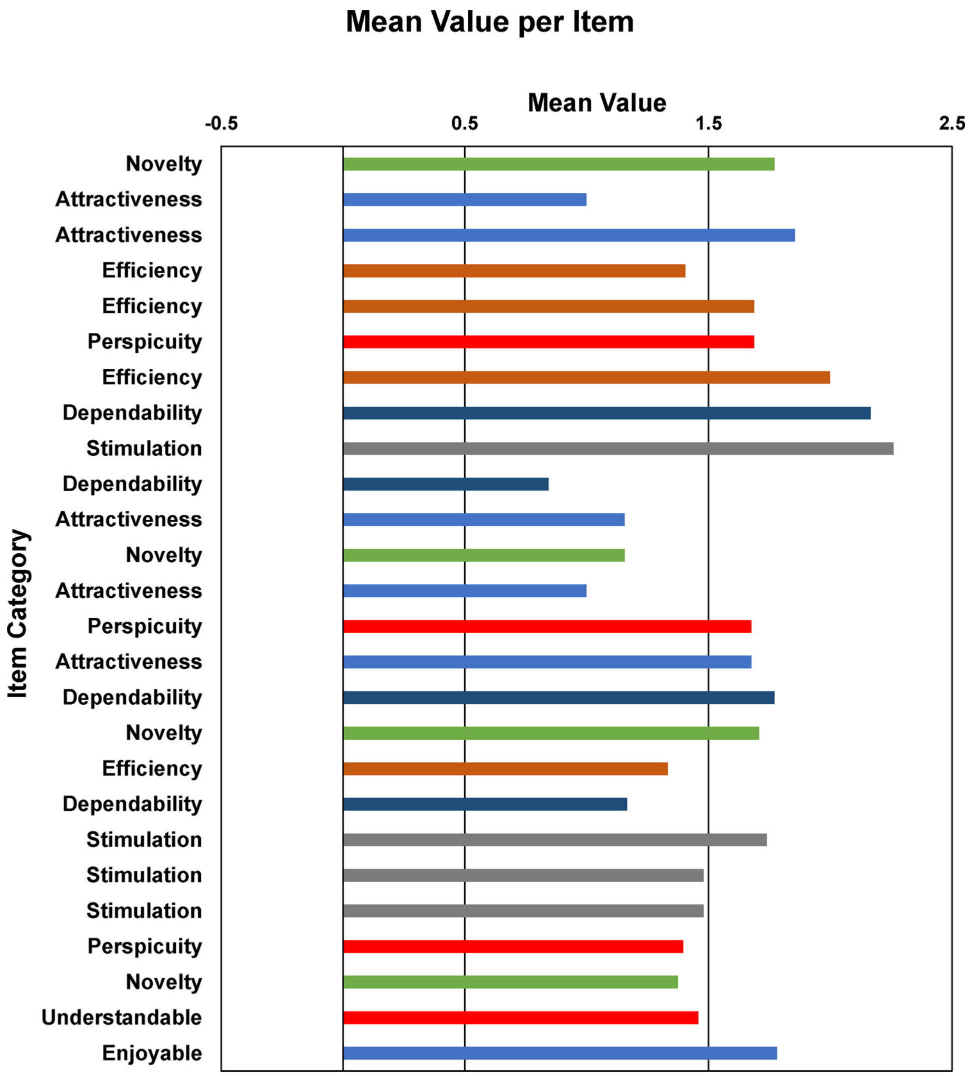

Fig. 6. Scale mean value per item.

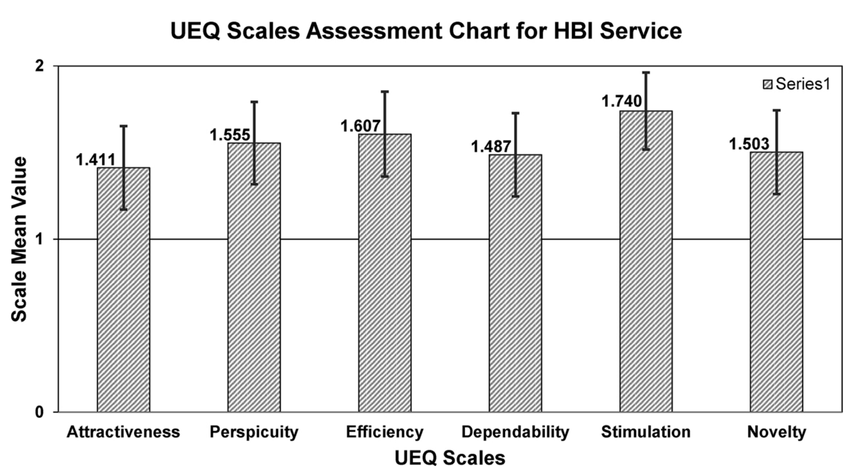

Fig. 7. UEQ scale value.

targets the comparison with state-of-the-art wellness applications. While the other focused on activity recognition and management, specifically targeting the performance measure as published in our previous works [98–100]. It is a user-centric wellness management framework to promote a healthy lifestyle through self quantification [101]. It is using state-of-art technologies like wearable devices, smartphones, big data, and Internet-of-things (IoT) to develop lifelog and provides a personalized recommendation [98], as shown in Fig. 5 . The framework initially obtains the information related to lifestyle behavior through questionnaires to sort out the well-know issue of cold start. After that, it maintains the log related to physical activities, eating, and maintaining the diaries of food, alcohol, and smoking. It

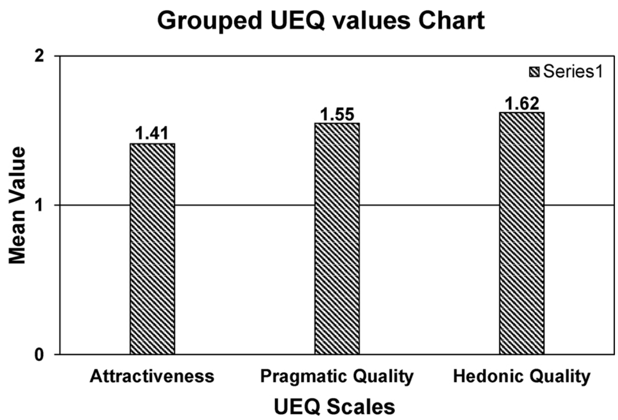

Fig. 8. Grouped UEQ scale values.

consists of *Data Curation Layer (DCL)*, *Information Curation Layer (ICL)*, *Service Curation Layer (SCL)*, *Knowledge Curation Layer (KCL)*, and *Supporting Layer (SL)*. DCL provides the curated data to ICL to determine low-level activities and high-level contexts through two modules Low-Level Context-Awareness (LLCA) and High-Level Context-Awareness (HLCA) [99]. Data generated from multimodal data sources (MDS), is managed, persisted and curated as lifelog by DCL after activity recognition through SCL. The HBI service obtained the activities information from lifelog in the form of temporal, spatial, and responses data to measure the frequency of the activities like physical activities, nutrition, smoking and alcohol based on context. The user's responses and activities log support to identify the status of the behaviors.

The KCL acquires knowledge either through expert-driven or data-driven for recommendation generation. The Behavior Situation Configuration and Assessment module get the rules from the KCL's knowledge base to verify the constraints of the situation for generation of the health behavior index. The hybrid-CBR technique generates personalized recommendations based on activities' status, user location, user preferences, and user profile information [102]. The SL enriches the overall Mining Minds functionalities through adequate privacy and security mechanisms, interactive and adaptive user interface, and implicit and explicit feedback analysis [103].

5. Results and discussion

We have evaluated the user experience and usability of the HBI service that is available to lifestyle curious customers for more than 12 weeks as a part of the MM recommendation and education services. The user experience has been evaluated through validated User Experience Questionnaire (UEQ) which involves pairs of antonyms-adjectives with a seven scale level from −3 to 3 (e.g., annoying vs. enjoyable). The UEQ's 26 pairs are categorized into Attractiveness, Efficiency, Perspicuity, Stimulation, Dependability and Novelty scales. User experience, as well as a change in behavior, is an appropriate way to compare the effectiveness of behavior quantification and adaptation techniques. It is the unique technique that comprehensively covers the essential behavior factors, which are usually not concerned by other applications.

Additionally, the six categorized scales are mapped to the three abstract-level: *Attractiveness*, *Pragmatic quality (Perspicuity, Efficiency, Dependability)* and, *Hedonic quality (novelty, stimulation)* scale.

5.1. Study participants

We have performed the experiments with the collaboration of wellness management organization. There were 103 participants with personal smart devices from wellness management organization, who selected the HBI service voluntarily along with the MM platform as shown in Table 9 .

5.2. Participants experience evaluation

Questionnaires are the most suitable and highly efficient tool of user experience (UX). However, it is not always necessary to benchmark the questionnaires' result to identify the level of effectiveness. The UEQ compares the level of participants' experience, and measured scale means with a benchmark dataset of 4818 persons from 163 studies related to different services. The well-known Cronbach's alpha coefficient guides to evaluate the mean value per item [104]. Fig. 6 shows that the mean values of 50% items are greater than or equal to 1.5, demonstrating the high impact of the HBI service.

The analysis of UEQ support to calculate the means of attractiveness, perspicuity, efficiency, stimulation, dependability, and novelty scales [104,105] in the range of −3 to 3 [106] as shown in Fig. 7 . The stimulation scale has a value close to 2.0, reflecting the higher driving impact of service on the participants [106].

The confidence interval (measure for the precision of the mean estimation) has been evaluated through 95% confidence intervals for UEQ scale mean [107]. The confidence for the HBI service were 0.241 (1.411 to 1.653) for attractiveness, 0.238 (1.555 to 1.793) for perspicuity, 0.246 (1.607 to 1.853) for efficiency, 0.240 (1.487 to 1.727) for dependability, 0.222 (1.740 to 1.962) for stimulation and 0.242 (1.503 to 1.745) for novelty as shown in Fig. 7 .

The consistency of the UEQ scale is based on reliability, measured through the Cronbach's alpha coefficient. The value of Cronbach's alpha was greater than 0.7 for all six scales. Moreover, the UEQ scales are categorized into Attractiveness (ATT), Pragmatic Quality (PQ), and Hedonic Quality (HQ) dimensions [105]. The UEQ evaluation tool analyzed the HQ (1.62) and PQ (1.55) as good with the mean value higher than 0.80 (Fig. 8)[106]. As HBI service has a reasonable high PQ score, so it provides evidence that it is easy to use.

The UEQ tool benchmarks it with other services based on user experience [105]. According to the observation of benchmark comparison, the novelty and stimulation aspects of HBI service lie in an excellent range, whereas the attractiveness aspect is in the above average

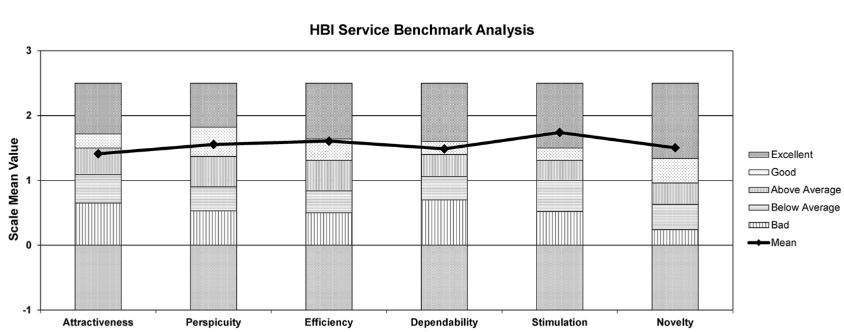

Fig. 9. Benchmark of HBI service.

range, and rest are in the range of good as shown in Fig. 9 .

6. Conclusion

Human behavior quantification for the assessment and adaptation is an active research area in the wellness management community. The root cause analysis of the behavior for the care and cure of the non-communicable diseases depends on identification of the unhealthy daily routine. The derived HBI covers the comprehensive status of four basic habits like smoking, imbalanced diet, alcohol and physical inactivity. It will help the individuals and experts for root cause analysis of disease. The HBI service is designed independently to work as a service so any other service-enabled wellness management platform can utilize it to evaluate the healthy behavior status for behavior indication, recommendation generation, and behavior adaptation. The change in the HBI is a highly useful indicator for behavior adaptation, which motivates the user of wellness application to utilize it for a longer period. In future, the study can be extended to include persons having lifestyle-based chronic diseases such as obesity, diabetes, and hyperlipidemia, where HBI service will support the wellness application to generate intervention based on personalized conditions. Our evaluation showed that hedonic quality was higher than pragmatic quality and attractiveness which depicts that it stimulated the user regarding the behavior status. In future, we want to analyze the impact of HBI service for the healthy behavior adaptation in elderly individuals.

Conflict of interests

The authors have no conflict of interests to disclose and have no objection on any reviewer to review this manuscript.

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