Thesis for the Degree of Doctor of Philosophy

PERSONALIZED COALESCED MODEL BASED ON MULTIDIMENSIONAL HEALTHY BEHAVIOR INDEX FOR LIFESTYLE ADAPTATION

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by

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Submitted to the Department of Computer Science and Engineering and the Faculty of Graduate School of Kyung Hee University in partial fulfilment of the requirements of the degree of Doctor of Philosophy

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Alhamdulillah! by the grace of almighty **Allah**, I am dedicating this achievement to my late ***Father*** (may Allah rest his soul in Jannah), ***Mother***, ***Father-in-Law***, ***Mother-in-Law***, ***Wife***, ***Daughters***, ***Sister***, ***Brothers***, and ***Teachers***, who have strengthened my resolve with their continuous support for facing all hard phases to complete *Ph.D.* degree. I will remain indebted to their patience and support.

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Abstract

Industrial trends in the 21st century have greatly enhanced the positive efficacy and coverage of Healthcare services, to improve worldwide life-expectancy. Consequently in an aging society, the demand for increasing the depth and breadth of the healthcare services has led to unprecedented financial constraints. The enormity of these constraints, necessitate the transformation of current care models from disease-management to disease-avoidance. Preventive personalized healthcare and a proactive approach towards self-managing healthy lifestyle, has evolved the latest trends in societal development. Significant scientific evidence exists; establishing a strong correlation between cognitive lifestyle choices and many disease's triggers. Lifestyle behaviors and habits are the key predictors of illness, morbidity, premature mortality, and fitness. A large part of the healthcare service ecosystem has thus been transformed from cure to care. Optimization of this paradigm shift, in terms of its universal applicability, for various social-economic statuses, necessitates the usage of ubiquitous technologies, such as IoT, Green Computing, Edge Computing, and others. This requirement is favorably aligned with the growth of Smart Devices, in terms of their availability, usability, and unobtrusiveness. Advent of digital technologies in daily life, thus provides various sources of explicit and implicit user feedback data, which can be naively transformed into information and then be used for extracting customized healthcare and wellness knowledge.

However, an integrated and comprehensive approach towards building a multidimensional coalesced model of implicit and explicit knowledge is still lacking. This thesis report, provides a thorough design, implementation, verification, and validation strategy towards the realization of such a customizable, multidimensional, and scalable model, which is of utmost importance towards establishing a ubiquitous and healthy society.

Current state-of-the-art techniques, models, and frameworks, rely on parti pris and intermittent

combination of expert driven approaches with sensory data, which seldom moves beyond the confines of simple gamification strategies. Essentially, several health management applications, in the real world provide limited support for self-quantification based feedback and integration of wellness sensors, for achieving some predetermined and and constricted personalization of wellness goals. For these applications the notion of ubiquity is limited towards the availability and usability of various platforms, such as smartphones, fitness bands, and smart watches. The attraction and novelty of these applications stems from their collections of lifelog data and its visualization to provide goal-driven feedback. However, these applications use a one-size-fit-for-all strategy and are unable to discourage the adaptation of unhealthy and adoption of healthy behaviors, making them ineffective in the long run as their users lose interest. Nevertheless, the existing platforms, provide a stable scaffolding for the creation of the Healthy Behaviour Index, which provides an answer for each of the following three research questions:

(1) How can we provide scalability to quantify the complex behavior of a user for lifestyle assessment?

(2) How can we incorporate the changes in a user's current behavioral stage to form a personalized notion of differences between a healthy and unhealthy lifestyle?

(3) How can we amalgamate a user's implicit and explicit feedback to create a coalesced lifestyle management model?

The main contributions of the work are (1) Leveraging the user profile and the daily lifelog 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.

A real-world user-centric statistical evaluation is applied through the User Experience Questionnaire (UEQ), System Usability Score, and AttrakDiff tools respectively. The study involves 103 registered participants (curious about chronic disease) for a Korean wellness management organization. They used the adaptive intervention service over 12 weeks, the results for which were evaluated through UEQ, SUS, and AttrakDiff. We observed an overall novelty of the value 0.88

showing the potential interest of participants. 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 of the wellness application based on the proposed methodology obtained “Good” and “Desired” status.

Chapter 1

Introduction

Worldwide, non-communicable chronic diseases (NCDs) are the leading cause of morbidity and mortality. These NCDs are largely promoted by unhealthy behaviors. Indeed, malnutrition, alcohol abuse, addictive smoking, sedentariness, and stress are common modifiable risk factors, causing a great financial burden as healthcare costs. Currently, people are more and more suffering from these lifestyle-related NCDs, changing lifestyle behavior and preserving a healthy lifestyle are focusing area of public health sector. So, predictors and pathways of behavior adaptation are main focus of healthcare-industry research. The key concern is about right intervention to the right person at right time. The definition of term right intervention requires understanding of the purpose, consequences, and output of the intervention.

In this information and communication technologies (ICT) era, growing number of consumers and medical devices have shifted the focus of health and wellbeing of individuals and populations, through care coordination, information sharing, and behavior change, ultimately developing the Connected Health (CH) concept. It is a paradigm looks after the community wide health in a "comprehensive" and "linked" manner by leveraging a variety of technologies. The technological shift has a significant impact on conventional healthcare model design. These methods emphasize preventative-personalized health care rather than cure. Consequently, an opportunity for healthcare providers to focus critical person at right time for the appropriate medical cure.

Behavioral Informatics (BI) is a new shinning star of the CH galaxy. Recently, it is emerging as an independent scientific field which tackles the monitoring, assessment, modelling and inference of behavior so as to lead successful interventions that modify unhealthy behavioral patterns with the help of ubiquitous technology. It has the potential to guide individuals in behavior adaptation to improve mental and physical health. In particular, ubiquitous computing has several advantages, including accessibility, personalization, cost-efficiency, and customization. Nowadays, the advancement in mobile computing brings new opportunities to generate health interventions and promote large improvements for behavior adaptation. Thus, the union of informatics and psychology is denoted as persuasive design and refers to all technological intervention.

The opening chapter will contain the main motivations for this process in Section 1.1, the problem statement along with research questions in Section 1.2, key contributions of this research in Section 1.3, and finally, the summary of dissertation is outlined in Section 1.4.

1.1 Motivation

We are living in an era of persuasive technology driven by interactive computing with the design intention of behavior adaptation. A number of research has demonstrated the usage of these technologies in a multiple contexts like advertising, promoting healthy nutrition, active routine, and managing energy consumption. Still, effectively influencing an individual's behavior is a challenging objective. Persuasive systems may be even more convincing than their counterparts since humans respond similarly to computers as they do to humans, whereas computers are more persistent and accessible than humans.

To be receptive intervention, system should intervene the right behavior, with right strategy, at the right time. The emphasized key elements for effective behavior adaptation: First, the objective of intervention attempt needs to be successfully receptive. Here, it refers to the targeted identified behavior that the intervention is intentionally designed to adapt. Second, a large variety of behavior-based strategies are available, in which a context based persuasive intervention can be framed: an intervention can be categorised into authoritative or facilitative. The facilitative intervention supports to fulfil the goal while authoritative indicate the unhealthy situation of the behavior. It is necessary to understand the situation of person with respect to the behavior and then select appropriate way of intervention for fruitful response. Finally, the intervention needs to be delivered at a time that enables the recipient to attend to it, and, if immediate action is required, one that provides the opportunity for the action.

The challenge is to identify the target behavior, appropriate intervention strategy and the right time for a persuasion. It is hard to determine in advance without knowing the person behavior status , context and situation. The limitation of behavior understanding is the qualitative nature of the human behavior. It is observable that other person can see or hear. It is not the feeling but the expression how one should response to the antecedents and the consequences are the result of behaviors. So, it is accompanied by an antecedent (trigger) that initiates the behavior and is followed by a result, or a reaction to the behavior. Events or environments that precipitate a behavior can occur right before an action or as a result of a sequence of previous events. For adults and elderlies, the sequence of events for a particular behavior can be modified to avoid or change the behavior.

The measurement of the behavior drives for the quantification. It is necessary to understand the condition and status of the behavior for modification. The change without understanding may lead to confusion and not able to achieve the desired results. So, self quantification is a continuous process to track all aspects of their daily lives, including physical activities, sedentary hours, number of steps, dinning times, eating foods, amount of sleep, quality of sleep, alcohol consumption, smoking status, heart rate and many others. According to proponents of the campaign, such monitoring not only helps people to learn more about themselves, but it can also enable them to take steps to change unhealthy for their better health and lives. Now, the ambient intelligent world contains distributed smart devices which operate unobtrusively to understand the activity status and its context. In this case, context sensing may assist in deciding effective persuasive ends based on the user's context and activities. Users would be more likely to recognize the message if it is presented in a position that is important to their behavior and context.

The success of behavior adaptation lies in the understanding of behavior-stage-change.Researchers have identified in behavior adaptation, people pass through a series of phases. Every person spend different amount of time in each stage, however the necessary steps to progress the next stage remain same. The efficacy of change processes is uncertain depending on user context to promote improvement, prevent relapse and trigger transformation. So action-oriented interventions ignore the behavior-stage. The quantified behavior is mapped with the behavior-context based stage for the assessment of the behavioral stage. Behavioral stages 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. the stages are *Precontemplation, Contemplation, Preparation,* *Action, Maintenance, and Relapse*.

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, which are further categorized into prescriptive, informative, confronting, supportive, catalytic, and cathartic. The authoritative interventions are suitable at the precontemplation and contemplation stages. When it is necessary to make the person understand through knowledge about the behavior, its pros & cons, challenges, and consequences. The purpose is to comprehend the behaviors and prepare mind for adaptation. The interventions a this stage mainly focused on the education. The educational intervention needs to be modified as per person behavior and context. Once initial stage is obtained then transfer the intervention to achieve the next level. The facilitative interventions support the consumer to achieve the actionable target. Hence improve the receptiveness of the interventions. The intervention guide step by step to achieve the goal towards desired behavior as per the response and feedback.

The feedback driven adaptation of intervention is the orchestrator of intervention management. The feedback is divided into implicit and explicit. The implicit feedback is the representation of the responsiveness of intervention and its impact. The lifelog analytics support to identify and judge the change in behavior after the intervention as an impact. The positive impact represents the attitude and behavior stage. On the basis of positive response, the adaptation in intervention can be to achieve the next level towards complete adoption of new behavior or change the unhealthy one. The explicit feedback is also necessary as there are limitation of the implicit feedback because of lifelog dependency on different devices and environment. The explicit feedback-based evaluation depends on user experience. It is a well-known and widely employed process to estimate the subjective perception of end-users towards the intervention. Generally, end-users have a different experience for the same intervention due to personal abilities, knowledge, liking, and requirements. However, it is necessary to infer the root cause of specific behavior. Sometimes, explicit feedback has some biasness due to human memory involvement, mental status, environmental context and many more. Thus, the mapping of implicit and explicit feedback against the particular intervention or behavior support for the change in intervention content and context.

1.2 Problem Statement

Current state-of-the-art techniques, models, and frameworks, rely on parti pris and intermittent combination of expert driven approaches with sensory data, which seldom moves beyond the confines of simple gamification strategies. Essentially, several health management applications, in the real world provide limited support for self-quantification based feedback and integration of wellness sensors, for achieving some predetermined and and constricted personalization of wellness goals. For these applications the notion of ubiquity is limited towards the availability and usability of various platforms, such as smartphones, fitness bands, and smart watches. The attraction and novelty of these applications stems from their collections of lifelog data and its visualization to provide goal-driven feedback. However, these applications use a one-size-fit-for-all strategy and are unable to discourage the adaptation of unhealthy and adoption of healthy behaviors, making them ineffective in the long run as their users lose interest.

However, an integrated and comprehensive approach towards building a multidimensional coalesced model of implicit and explicit knowledge is still lacking. This thesis report, provides a thorough design, implementation, verification, and validation strategy towards the realization of such a customizable, multidimensional, and scalable model, which is of utmost importance towards establishing a ubiquitous and healthy society.

Nevertheless, the existing platforms, provide a stable scaffolding for the identification of daily life activities, visualization of activities status, goal based indication and support for community competition. The limitations of the existing system lead the following research question to emphasis the problem.

1. How to quantify the complex behavior of a user for lifestyle assessment? The lifestyle consists of multiple physical factors like addictive habits, nutrition habits, physical activities, sleeping routine, and many others. The impacting factors are social, environmental, financial, spiritual, and mental. The physical factors are the modifiable factors and maintaining healthy status support avoiding and prevent the NCDs. The quantified status of these modifiable factors guides the person either to improve or maintain the states. The self-defined and guidelines-based individual factors' quantification processes are well defined. However, to draw a combined impact of these complex behavior is still under investigation.

As a consequence, designing a comprehensive and scalable index to cope overall status of modifiable-lifestyle-factors is the non-trivial target.

2. How to identify the current behavioral stage from a quantified lifestyle? The receptivity of an intervention depends on the behavioral-context. The knowledge and understanding of the consequences of behavior triggers the adaptation. The interventional impact is temporary and chances of relapse of unhealthy behavior are very high with out educating and preparing the person. Currently, state-of-art wellness applications support the short term change in lifestyle behavior through virtualisation and community competition but lacking in developing the healthy behavior. So, the intermediate target is to intervene the unhealthy behaviors driven by behavioral stage to achieve long term impact.

3. How to analyse the user's satisfaction given the behavior stage-based intervention? Behavior adaptation is a slow and steady process that requires continuous monitoring and change in interventions to win the attention and interest of the person. The impact of human memory in explicit responses of the survey are not avoidable, so the hybrid approach of the implicit and explicit feedback is necessary to estimate the behavior status. The ultimate goal of behavior adaptation is to analyse the users' satisfaction through implicit and explicit feedback to maintain the attention and interest.

The main contributions of the work are (1) Leveraging the user profile and the daily lifelog 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, and finally (4) Divert the direction of fitness-oriented applications towards behavior-development applications .

1.3 Key Contributions

Behavior adaptation is complex and slow process requires a strict monitoring and intervention based on context and condition. The goal of this research work is to provide a methodological framework for behavior adaptation to achieve healthy lifestyle. The unhealthy lifestyle is a major factor of the non-communicable chronic diseases in elderlies and adult. While, these lifestyle factors are the modifiable and adaptable. The challenges are to identification, indication and facilitation to adapt these unhealthy behaviors. Thus, the target of this research work is to: identification of the critical factors and behaviors essential for the healthy lifestyle, quantification of these critical factors to understand the stratus and their impact on human life, providing a comprehensive index that can present the current condition of the health related lifestyle behaviors, inferencing of the behavior stage based on the behavior index for the persuasive strategy to support unhealthy behavior, mapping of the behavior stage with type of intervention for personalized adaptive intervention generation, evaluate the response of intervention through implicit feedback for next iteration, and root cause analysis with the help of explicit feedback for intervention adaptation. Fig.1.1 represents the abstract idea of the proposed framework called Healthy Behavior Adaptation Framework with the main focus to achieve the above mentioned targets for lifestyle based behavior adaptation. The main contributions of the thesis in the proposed framework is described as follows in the subsequent sections.

1.3.1 Behavior quantification

Behavior is quantified for the understanding as well as to gain knowledge for an appropriate decision regarding the adaptation. 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 experts based evaluation of the identified factors is performed to verify the key impact factors and their sub-factors. The degree of agreement identified the critical factors which are contextually quantified on the basis of guidelines. The sub-factors are accumulated for a complex factor while simple factors are considered as it is.

1.3.2 Healthy behavior index development

Behavior is a very complex qualitative concept based on multiple micro factors. Therefore, a comprehensive behavior index is composed of multiple ingredient behaviors. The nature and metric of the behavior define its context, which helps to aggregate the behavior in an appropriate proportion. The concept of life expectancy and prediction for future mortality is adopted for the identification of the critical factors' weight-age. The Mortality Population Risk Tool (MPoRT) risk algorithm based on the Cox proportional hazards model is used to estimate weight-age of risk factors through proportion from a difference of life gain and life loss because of a particular risk factor. The individual score, based on the severity mention in the definition, has been utilized to generate the index for healthy behavior.

1.3.3 Behavioral stage identification

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. Similarly, the TTM has identified different stages for behavior change and has become one of the most widely used models of the healthcare domain.

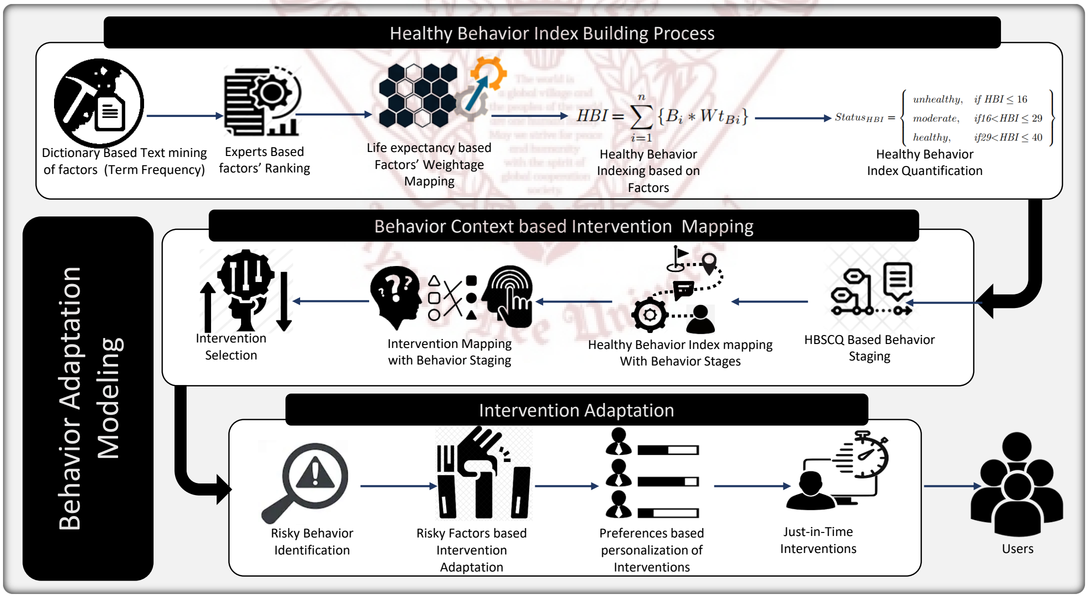


Figure 1.1: Idea diagram of the proposed research studies with chapters mapping.

1.3.4 Bridging behavioral stage and healthy behavior index

In Behavior-Context mapping, we have employed the Transtheoretical Model (TTM) to identify the different stages for behavior change through continuous monitoring of healthy behavior index. Habitual behaviors lay down the foundation of human health. 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. We have shaped the model to represent how individuals perform in adapting various behaviors, including initiating healthy regimens and quitting addictive unhealthy behaviors.

1.3.5 Feedback driven intervention adaptation

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. The implicit feedback obtained from lifelog drives for the assessment and understanding of the attitude towards interventions. It supports the adaptation and analysis of the intervention-strategy selection for the next iterations.

1.4 Thesis Organization

The dissertation aims to investigate a user centric intervention adaptation methodology to adopt healthy behavior based on feedback drive intervention adaptation. Figure 1.1 depicts the dissertation abstract view, and outlines the structural flow.

This dissertation is organized into chapters as following.

- **Chapter 1: Introduction**. Chapter 1 provides the introduction of the research work for behavior quantification to map it with the behavioral stages for an effective intervention to adopt health behavior and adapt unhealthy behavior. It emphasizes on the challenges in particular fields, the goals for solving these issues, the study work's priorities, and finally the dissertation summary.

- **Chapter 2: Related work**. Chapter 2 presents existing research for behavior quantification for healthy behavior adoption. Initially, the identification of critical factors affecting lifestyle based behaviors are discussed. As these behaviors contribute in the development of non-communicable lifestyle based chronic diseases. So, the evaluation and quantification techniques of these unhealthy behaviors are discussed in detail to build a comprehensive idea of the investigated field. The research portion is enriched with the behavior change theories that support the ideology of behavior adaptation. Finally, the state-of-art work of interventions, intervention adaptation, and Just-in-Time interventions is summarized to understand the concept of right intervention for right behavior at the right time.

- **Chapter 3: Quantification of Lifestyle Behavior**. This chapter has discussed that over the last decade, ubiquitous computing revolutionized personalized healthcare through many wellness applications based on self-quantification. These applications analyse routine activities but unable to depict the overall impact of habits on health. As a result, to assist individuals, we have proportionally associated lifestyle behaviors to influence human well-being. The methodology has focused on comprehensive Healthy Behavior Index (HBI) comprises of Behaviors' Weight-age Identification (BWI) process, and Healthy Behavior Quantification and Index (HBQI) modeling. It has demonstrated a positive user experience to stimulate healthy behavior adaptation.

- **Chapter 4: Mapping of Human Behavior** . The chapter has focused digital well-being supported by unobtrusive smart gadgets sources of information acquiring. A variety of personalized wellness applications, however, unable to induce healthy habits as users tend to loose their interest. Thus, User-Centric Adaptive Intervention methodology based on behavior change theory has introduced for enhancing users' interest. It compromises of quantification of behavior based on contributing factors governed by expert-driven rules, behavior-context based mapping for the identification of behavior status of the user, selection of appropriate way of intervention to get fruitful outcomes, and feedback based evaluation on the basis of recorded activities and questionnaires for satisfaction. The HBI supports the machine learning-based prediction model for behavior-context mapping.

- **Chapter 5: Lifestyle Behavior Adaptation**.

  This Chapter has focused to adopt a healthy lifestyle by converging science and technology in this digital world for improving health and quality of life. The challenge of behavior change is not only to indicate the issues but also provides step-by-step coaching and guidance in real-time. The realization of behavior change theories through digital technology has revolutionized lifestyle change systematically and measurably. The methodology understands the behavior for generating just-in-time intervention for adopting a healthy lifestyle through analysis of unbiased lifelog and questionnaires for qualitative assessment of behavior. Behavior stage-wise intervention is provided to adapt behavior for enhancing the quality of life and boost the socio-economic conditions. The healthy behavior index and behavior change theories through smart technologies have enhanced the functionality of wellness management systems and support behavior status sketching to adopt healthy activities for the betterment of long life. The results depict that education and recommendation as per person stage are more responsive and attractive to retain the attention of the users.

- **Chapter 6: Conclusion and future directions**.

  This chapter summarizes the thesis and discussed main contribution in the domain of persuasive computing for behavior adaptation. Furthermore, it highlights the future directions of the proposed methodology and its applications.

Chapter 2

Related Work

According to the latest World Health Organization (WHO) global status report, NCDs associated with lifestyle habits are currently the major causes of worldwide deaths. 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. It has laid forth a clear plan to change the course of the so-called ''slow-moving public health disaster''. The majority of the strategies' measures aim to improve 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. 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.

2.1 Critical Lifestyle Factors

Nowadays, health care focuses proactive approach to avoid and delay the adverse impact of the different non-communicable chronic diseases (NCDs). So, ubiquitous computing supports the community in a very sophisticated manner to guide regarding the adaptation in behavior for quality life to challenge the impact of NCDs. Plethora of wellness applications are available to support for the enhancement of general public fitness-level but lacking in nurturing healthy behavior. Several risk factors contribute to the development and onset of NCDs. The various types of risks can be divided

Table 2.1: Cause of Non-Communicable Diseases

Adaptable Risk Factors	**Non-Adaptable Risk Factors**	**Metabolic Risk Factors**
Tobacco consumption, Physical inactivity, Over weight (Obesity), Unbalanced diet (Salt, Sugar, Fats), Stress and Sleeping issue, Alcohol consumption	Age, Genetic or Family history, Gender, Ethnicity	High blood pressure, High lipids level in blood, Abnormal blood glucose level

into three main categories of risk factors: adaptable behavioral risk factors, non-adaptable risk factors, and metabolic risk factors as discussed in Table 2.1. Usually, the NCDs have a long latency period, non-contagious origin, prolong illness, functional disability, and impairment. These stretch from years to decades as chronic which requires ultimately medical care and makes it difficult for a person to perform duties appropriately.

Wellness management organizations concentrate on behavior modification in order to strengthen human wellbeing, lengthen life spans, and reduce societal burdens [3]. In [4] authors looked at the effectiveness of sequential and overlapping interventions for improving physical activity (PA), diet, and sleep. Similarly in [5] authors consider the status of food, sleep and physical activity for intervene the person with motivation alerts and messages for behavior adaptation.

Lifestyle diseases are primarily affected by the people daily habits. Particularly, the sedentary habits can cause a number of health issues. These issues may lead to non-communicable life-threatening diseases (NCDs) [6]. These NCDs like obesity, diabetes hypertension, cardiovascular, hyperlipidemia are the most challenging issue for the global health organization. It causes an economical burden on developing countries, where 80% of deaths are related to NCDs [7]. Globally, the NCDs epidemic requires effective measures to stifle its emergence, which is a challenge for under developing countries having limited financial, technological and professional human resources [8]. These risk factors are unlikely to appear in isolation, but they will cluster and associate to increase the risk of NCDs exponentially [9]. Although the presence of these risk factors may have a negative impact on morbidity and longevity, adopting healthier lifestyle habits can reduce the risks proportionately .

The adaptable or preventable causes like abuse of alcohol, unhealthy dietary habits, smoking, sedentary lifestyle, abnormal biological clock, restless sleep, and stressful working environment can enhance the probability of NCDs [10]. However, uncontrolled factors like age, race, family history, gender, and genetics cannot be intervened. Similarly, factors like high cholesterol level, blood sugar level, and blood pressure can be controlled and normalized with proper and regular medical intervention to avoid or delay the NCDs.

Latest technologies have been embedded in various smart commercial gadgets to monitor the sound sleeping hours, the intensive activity duration, and prolonged sedentary activities [11, 12]. Activity-based tracking technologies have shifted the phenomenon of "quantified self" from self-reporting to an unobtrusive manner. 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 [13–19].

The diet is a composite concept based on different micro nutrients . Every micronutrient has its importance and criteria for assessment, which are discussed in different literature. The literature is concerned about the dietary pattern, regularity in dinning times, consumption of soft drinks, chocolates, saturated fats, whole grains, dairy products, fruits, vegetable, breakfast, water intake and many more depending on full day consumption [20–32]. The addictive behavior of tobacco consumption, alcohol abuse and urges for these addiction have been discussed in literature for the impact in NCDS [33–38].

2.2 Lifestyle assessment and Indexing

A new paradigm has recently emerged to support healthcare and wellness in this technology era. It refers to a revamped and revised version of what was previously known as Digital Health Care as Digital Health, which encompasses multi-disciplines to empower people to monitor and drive their wellbeing and health. Wellness is a lifelong process of making choices to live a more healthy and fulfilling life, not just the absence of sickness or pain. There are still ways to improve your overall

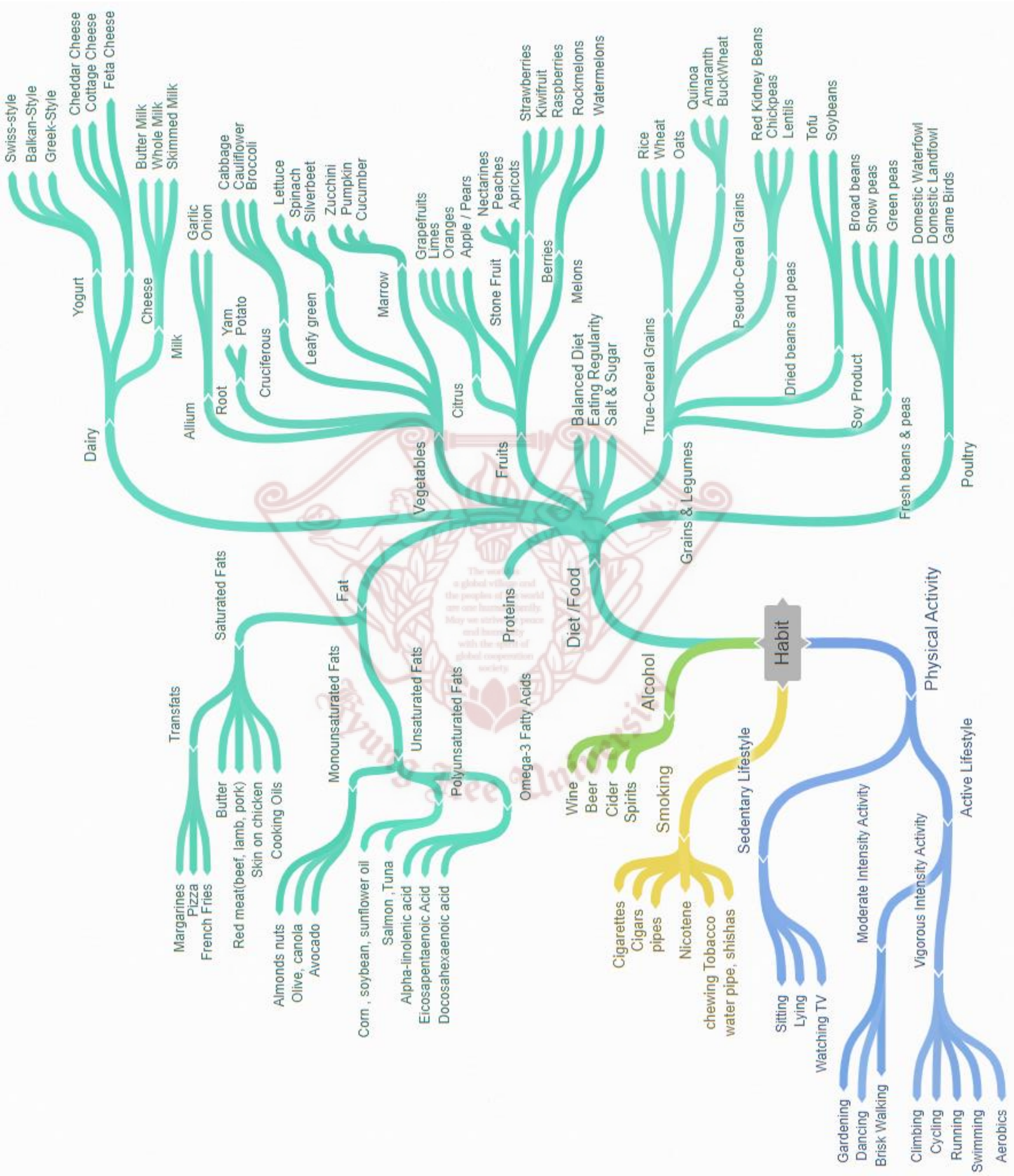


Figure 2.1: The details of contributing lifestyle factors.

health. A good place to start is by assessing your current situation and putting in place processes to help you achieve a greater sense of wellbeing. The Wellness Wheel explains how environmental, emotional, occupational, physical, intellectual, spiritual, and social aspects are intertwined.

The purpose of wellness management organizations is to focus on behavior change to improve health quality, increase the life span and reduce the burden on society [3]. In [4] authors estimated the impact of concurrent and consecutive intervention for physical activity (PA), nutrition, and sleep towards healthy behavior. Although, in [5] authors consider the physical activities status, nutrition condition, and sleeping hours for producing the interventions and modify the messages as per persons'context for the behavior adaptation.

Unfortunately, wellness related models don't consider the recurrent actions, so Self-Report Habit Index (SRHI) deduces the impact of consistent actions on behavior [39]. In the wellness domain, the behavior related to the activity is defined on the basis of time duration spend in performing multiple activities at different intensities. Physical activities and alcohol consumption are assessed on a weekly basis while nutrition and smoking are evaluated on a daily 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.The relationship between health-related behavior and habit strength, as measured by the SRHI, diverts the discussion away from reflective effects on food intake and activity behaviors. However, a continuous behavior is one that someone frequently does or has, especially one that is considered to be a feature of the person [40]. It's important to differentiate between the characteristics of habitual behavior and the factors that influence habit formation and consequences. A history of past enactment in the presence of stable contextual signals is a prerequisite for the development of a habit.

In literature, studies focused on the dietary patterns and assessed dietary behavior through self-

Table 2.2: Assessment of multiple lifestyle behavior in literature.

Sr. #	Behavior	Domain	Assessment Process	Reference
1	Total Inactivity,TV viewing Leisure-Time active sports, Bicycle/ Walking	Physical Activity	Self Report, IPAQ: International Physical Activity Questionnaire,	[14–19, 24, 25, 29, 48–51]
2	Fruit, Vegetables, Soft \Energy Drinks, Energy-dense \Healthy Snacks, Sweets, Chocolates, Candies, Total Fat, Saturated Fat, Red Meat, Carbohydrate, Fiber, Grains, Fish, Protein, Dietary Pattern	Nutrition Food	Self Report,Parent Report, FFQ: Food Frequency Questionnaire, Other Questionnaire, 24-hour recall,	[20, 21, 52–55] [26–28, 30–32, 56, 57]
3	Nicotine Patch\Spray , Cigarettes	Smoking	Self Report, Questionnaire of Smoking Urges	[33, 35, 58, 59]
4	Oral Alcohol	Drinking	Self Report, Alcohol Urges Questionnaire	[35, 36, 38]

report questions of food frequency questionnaire (FFQ) [39, 41–43] as summarized in Table 2.2 under the section of diet to index the eating habits. Multiple studies summaries in Table 2.2 reflect which identify that most preventable cause of death are tobacco and alcohol which lead to thousands of deaths yearly [44]. 20% adults [45] consumed tobacco and alcohol together [46], which has been associated with fetal diseases [46, 47] 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 memory error and some social norm.

2.3 Theories for Behavior Adaptation

The differences in interventions' content have an impact on behavior change.Depending on the context and situation, a strategy based on a single technique or a combination of multiple techniques may improve intervention effectiveness. To increase life quality and span, wellness management companies focus on changing behavior to follow a healthier lifestyle. Multiple behavior change theories are used to monitor and explain the change. These ideas concentrate on an individual's actions and mindset in order to encourage a shift in lifestyle toward healthier habits.

The theories related to behavior change are employed by multiple behavior change techniques (BCTs). Theories that describe the same behavior adaptation method must have the same BCTs. There are few available lists of discrete BCTs used in health behavior strategies. The mind transforming models are based on consciousness raising, counter conditioning, self-reevaluation, self-liberation, stimulus control, helping relationships, dramatic relief, reinforcement, social liberation, and environmental reevaluation. In healthcare the weight management is an important aspect where interventions are designed to lose weight or avoid weight gain through goal setting, contracting, self-monitoring, rewards, stress management, graded tasks, alerts, environment changing, persuasive interaction, peer encouragement, demonstrating a behavior, and experience sharing to motivate. The components of intervention for physical activity are behavioral modification, self-management, social competition, social encouragement, behavioral prescription, rewards, stimulus control, cognitive modification, self-monitoring, thought restructuring, and many others.

In BCTS the methods used to trigger the behavior can be: goal-setting, self-monitoring, contracting, incentives, tasks grading, increasing skills, stress management, planning, environment changing, encouragement, persuasive alerts, behavioral analytics, personalized messages, behavior modeling, and experiential tasks to change motivation. Providing knowledge about the implications of an action, can have an impact on attitudes toward a target behavior. Thus, theories like the theory of rational action, the theory of planned actions, social– cognitive theory, and the information–motivation– behavioral skills model could be used to develop technique.

The identified BCTs to these different theoretical structures, demonstrating how intervention content and efficacy could be used to evaluate a number of behavior change theories are discussed in Table 2.3. If interventions that included techniques like prompt intention forming, and provide outcome-information were found to be noticeably more successful in promoting a specific activity, this would support the theory of reasoned action. However, if interventions involving techniques similar to specific target setting, self-monitoring of actions, and goal review were found to be successful, this would be an affirmation of control theory.

Table 2.3: Behavior change techniques and their related contents.

Sr. #	Behavior Change Technique	Focused Contents
1	Information - Motivation-Behavioral Skills Model (IMB)	Provide information about: a- Behavior health link b- Susceptibility to poor health c- Behavioral risk d- Socail Approval e- To decide to act f- To set a general goal g- Benefits and costs of action
2	Theory of Reasoned Action (TRA)	Provide information about: a- Benefits and costs of action b- Socail approval c- To decide to act d- To set a general goal
3	Theory of Planned Behavior (TPB)	Provide information about: a- Benefits and costs of action b- Socail Approval c- To set a general goal d- To decide to act
4	Social-Cognitive Theory (SCogT)	Provide information about: a- Benefits and costs of action b- Indicate challenges to performing the behavior c- Plan to meet challenges d- To decide to act e- To set a general goal f- Praising for effort g- Rewarding for effort h- Gradually increase the complexity of task to meet target i- Guide to do the task j- Demonstrate the task
5	Control Theory (CT)	Provide information about: a- Planning of goal b- Intensity and Frequency of task c- Reevaluation of goal d- Self-monitoring of a behavior e- Evaluate the performance
6	Operant Conditioning (OC)	Provide information about: a- Praise on target achievement b- Encouragement on gaol meeting c- Environmental cues to perform behavior d- Prompt to do action

2.4 Intervention Types and Impact

Health behaviors have traditionally been described as actions taken by an individual in order to sustain, achieve, or restore good health and avoid illness. Physical activity, such as exercise, diet, alcohol intake, sleeping, socialization, and smoking are all examples of lifestyle and health-related habits. These can be directly and clearly measurable, or indirectly measurable such as physiological responses. Behavioral events are physical events in the body that are regulated by the brain. Unfortunately, unhealthy habits and behaviors tend to be easy to pick up but difficult to quit. Infact, continuous efforts are required to sustain the healthy habits over time, once developed. The expensive approach is Personal face-to-face coaching for addressing these problems. Behavior monitoring, evaluation, statistical modeling, inference, and intervention are all part of behavioral informatics, which is a research and engineering field. This area is poised to advance a range of technologies and computational approaches that will allow scalable, cost-effective, and timely interventions. There is substantial evidence in the healthcare domain that health approaches targeted to individuals are more successful than generalize ones, and that timely input is crucial in improving and maintaining behavior.

The right intervention at the right stage to the right person is the key concerned of the study. However, the personalization of intervention is the target to attain 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 chronic non-communicable diseases.

Health interventions can be synthesized through prescriptive and proscriptive styles. The prescriptive style intervention focuses on what people should do, while proscriptive focuses on what people should not do [60]. Health guidelines usually advise either active participation in wellness activities (e.g., regular exercise; balanced diet having fruits and vegetables) or refraining from engaging in unhealthy activities (e.g., smoking, alcohol). As a result, health recommendations can be organized to support what people should adopt. The advice can evoke different motivational and behavioral outcomes by delivering prescriptive or proscriptive interventions.

The confronting and informative intervention challenge the thinking towards adapting behaviors. Individuals may be more likely to attempt an intrinsically motivating target despite the chal-

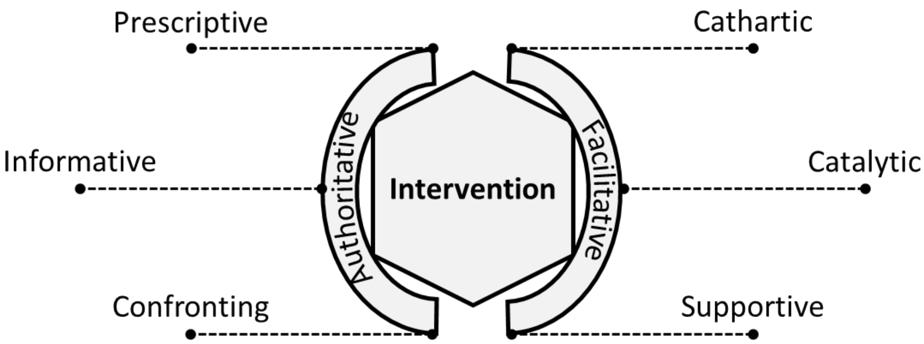


Figure 2.2: Six categories of intervention by John Heron [1].

lenge because intrinsically motivating objectives are ultimately satisfying to them [61]. Furthermore, intrinsic motivation has been linked to better learning and performance, which may help to accomplish the goals. These results indicate that a daunting target that is intrinsically rewarding could be more advantageous than a simple, effortless goal for behavior adaptation.

2.5 Health Behavior Adaptation Interventions - HBAIs

The widespread use of ubiquitous technologies, public health has prompted health professionals to investigate in HBAIs. Social media technologies have enhanced and incorporated social cognitive, social marketing theories, and social support into HBAIs to better understand how user access information through inspiration and social experiences. The major advantage of the technological intervention is the accessibility and greater impact as compared to face-to-face interventions. These interventions have limitation to reach a large population, which subside overall impact of face-to-face counselling despite of big effect size [62]. However, the major challenges of these interventions is to adapt them at real time. Therefore, we are in the need of personalized intervention at right time to change a target behavior.

2.5.1 Adaptive Interventions - AI

An adaptive intervention (AI) is a set of strategies that determines based on metric when, how, which and how much support is provided to achieve the targets. In literature, AIs are referred through “dynamic treatment regimes”, “adaptive treatment strategies”, “stepped-care interven-

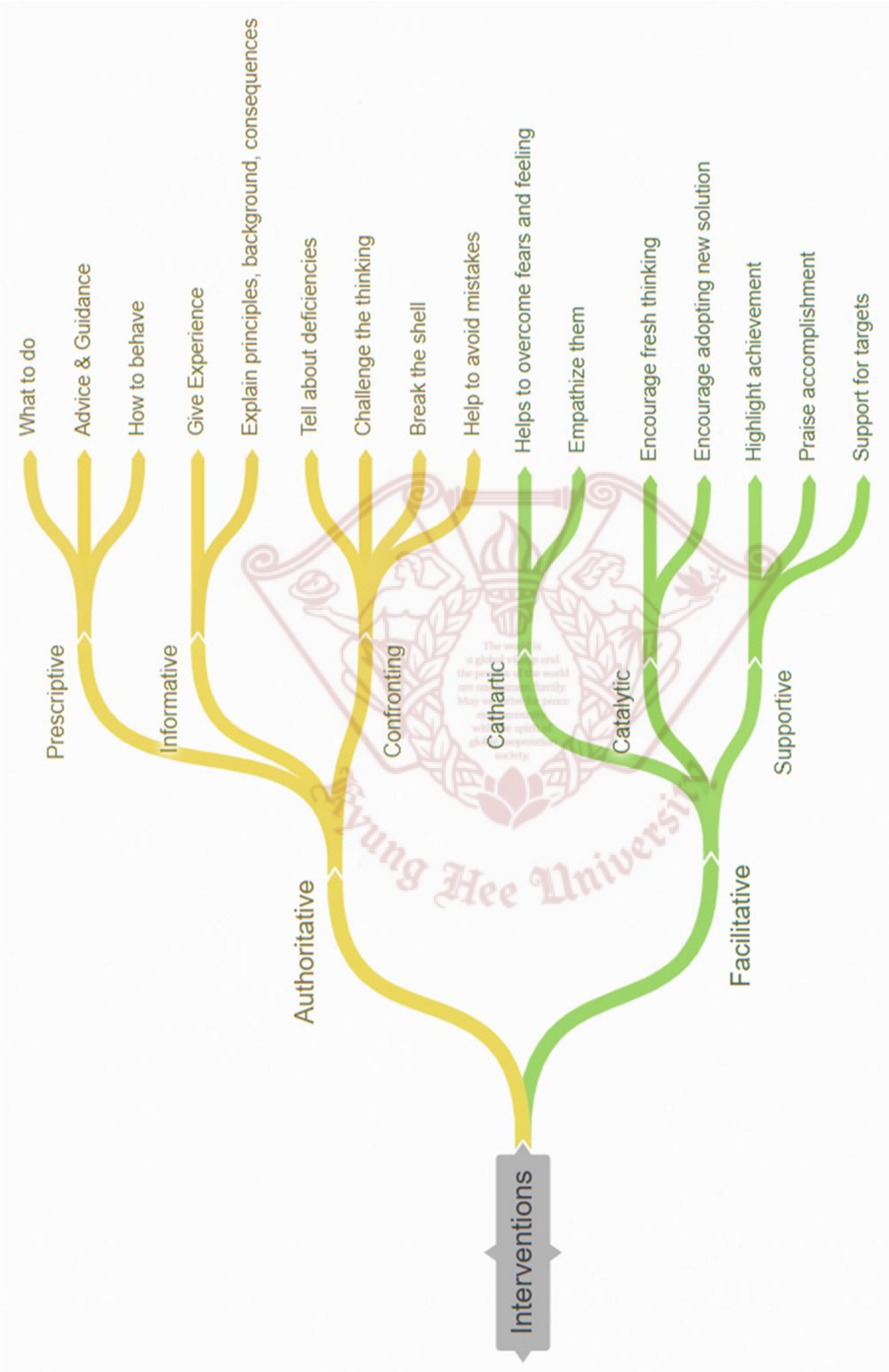


Figure 2.3: Categorical description of interventions.

Table 2.4: Catalogue of intervention type and mode for different lifestyle behaviors in literature.

Sr.#	Target Behavior	Behavior Goal	Intervention	Intervention Frequency	Intervention Mode	Intervention Initiation	Reference
1	Diet (Vegetable intake)	self-select goal from a range of daily vegetable servings (1-10 servings per day)	graphical representation of progress toward goals by day, past 7 days, and past 7 weeks	Daily; immediate upon self-reported data	Mobile phone app	User-initiated	[63]
2	Diet (Fruit and vegetable intake), self-report	weekly goals set by participants and adjusted every other week	intake relative to the self-set weekly goal	Nightly; immediate upon self-reported data entry	SMS text messages	User-initiated	[64]
3	PA:Steps per day, self-reported from a pedometer		social comparison feedback that corresponded their performance relative to a reference population	Daily; immediate upon selfreported data entry and (2) Twice-weekly 3-day summaries	(1) Studyspecific website and (2) Email	User-initiated	[65]
4	PA: Steps per day, activity tracker	Incrementally increase steps per day each week until at least 8500 steps per day for 5+ days per week has been reached	(1) actionable messages aimed at encouraging daily activity, (2) messages regarding progress toward step goals, and (3) graph of the week's daily steps	(1) Daily; within-day action plan in response to answered activity prompts (2) Daily; immediate upon self-reported data entry (3) Weekly; based on self-reported data entry	Mobile phone app	User-initiated	[66]
5	Exercise min and intensity, daily Webbased diary	All groups: 600 activity units per week or 30 min of moderate PA 5 times per week	graphs showing progress toward the weekly goal based on diary entries	Nightly; immediate upon selfreported entry	Website designed specifically for this study	User-initiated	[67]
6	Steps per day, mobile phone app– connected pedometer	30 min of activity or walking daily	steps relative to a goal, as well as distance, time, speed, and calories burned	Continuously available (mobilephone–enabled)	Mobile phone app	Passive	[68]
7	MVPA and dietary intake, Webbased diaries or acceleromter, and accompanying Webbased software (intervention only)	personalized, 1200 to 1800 kcal per day calorie goal; 20 to 30% dietary fat intake; 100 min per week of MVPA that increased every 4 weeks until 300 min per week was achieved	: (1) real-time summary of energy expenditure and total MVPA, (2) MVPA in durations of 10 min or longer, and (3) dietary and PA feedback	(1) Continuously available (via device display), (2) Real-time, continuous (via Web access), and (3) Weekly (months 1-6) and monthly (months 7-12)	(1) FIT core device, (2) FIT core website, and (3) Telephone	Passive and userinitiated	[69]
8	Diet and activity, appbased selfreport	Eat a target ratio of protein to carbohydrates daily and complete three sessions each of core cardiovascular and resistance exercise every 7 to 10 days	(1) Graphical representation of weekly progress toward goal and (2) Motivational messages and advice based on answers to in app questions about diet and exercise behaviors	(1) Daily; immediate upon selfreported data entry and (2) Daily; immediate upon selfreported data entry (diet) or every 7 to 10 days per when an exercise level was completed (exercise)	Mobile phone app	User-initiated	[70]
9	Dietary intake, Webbased selfreport PA, activity monitor Glucosemonitoring, glucometer (selfmonitoring group) or Internet connected glucometer	All groups: static goals of maintaining or increasing daily activity to ¿30 min at least 3 times per week, and measuring blood glucose levels at least 8 times per week	(1) actionable feedback in response to glucometer data aimed to raise glucose levels if ¡50 mg/dl and lower glucose levels if ≥140 mg/dl, (2) average glucose level, (3) time spent being physically active and calorie expenditure, and (4) total caloric intake and carbohydrate, protein, and fat components	(1) Within 1 min upon glucometer use. (2) Weekly at 10 AM on Mondays and monthly at 11 AM on the last day of the month. (3) Upon selfreported data entry, and (4) Automatically displayed upon data entry	(1) SMS text message, (2) SMS text message, (3) Website designed specifically for this study, and (4) SMS Text	Passive and userinitiated	[71]

tion", and many more [72]. The stepped-care intervention is further divided into up and down based on the response of the target behavior. These interventions constitute of trigger condition, target behavior, decision rule and multiple alternative recommendations. The target behavior has multiple attributes that define the situation. The decision rule connects the personalized situation for the appropriate recommendation choice. In literature, there are multiple techniques involved to intervene the unhealthy habits and induce healthy habits as discussed in Table 2.4. In literature, multiple investigations have looked at the effectiveness of emerging fitness technologies in promoting weight loss, physical activity, and healthier eating habits. These studies largely advocate technology usage for intervention generation and self-monitoring, but they also recognize the importance of interventions' content for effectiveness. Mainly works are related to the physical activities, vegetables intake, fruits consumption and chronic disease management.

In [71], an individualized health management system based on ubiquitous technology was discussed for the regulation of blood sugar level of diabetic patients without causing hypoglycemia. It considered modern multidisciplinary techniques to combine physical activity monitoring and food reviews into a robust kit. Similarly, in [70] a coaching platform was discussed where participants took part in a 12-week experiment during which they got wellness interventions via an app on their mobile phones. They were tested every two weeks in physician's office environment regarding the physiological factors and data was compiled on a regular basis for analytics.

The aim of the study [73] was to examine the interest of participants in the SMS-based tracking and feedback system. It also studied that how effective the curriculum was at promoting healthy habits through interventions for greater fruit and vegetable intake, physical exercise, and less screen time. The authors of [68] evaluated the impact of intervention regarding the physical activity in-terms of the number of steps. The participants were assigned a regular walking target of 30 minutes, while the experimental group received intervention from the app that told them the corresponding goal in steps taken. The results demonstrated that an interactive app can significantly increase physical activity through feedback, setting specific goals, and self-monitoring.

The study [69] focused on the impact of wearable sensor devices for the management of obesity through physical exercise and diet control. It highlighted that physical activity monitoring devices not provide benefits over conventional behavioral weight loss methods through visualization and graphical feedback. In [64], authors investigated the effects of an intervention through text messaging for observing adolescents' attitudes, self-efficacy, and outcome perceptions about fruit and vegetables. The participants set weekly fruit and vegetable consumption targets, recorded their intake regularly, and received intervention based on progress via text messaging. According to them the active participation in an intervention was crucial for its success.

2.5.2 Just-in-Time Interventions - JITIs

The just-in-time intervention is a prominent model, has a large potential for changing people's health habits [74]. It focuses adaptable support as per individual's status, context, preference and transforming the intervention most likely to be responsive. These can be described as having the appropriate amount of help at the suitable time. The right moment in just-in-time adaptive approaches might take into account the person's state of insecurity, potential, or receptivity [75]. It is like feedback intervention theory FIT which represents recent actions and gives direction at a crucial moment where a person's mind can need to be redirected back to the goal-directed behavior. The purpose of these interventions is to proactively motivate behavioral changes to minimize or undo the worsening of gaps between actual success and a behavioral goal or aim, allowing the goal or target to be met. As a result, these interventions takes into account the time period in which target success is anticipated. If a person sets a target of physical exercise in a day, intervention guidance will be given till evening of the day to maximize the chances of meeting that goal.

The invention of smart and powerful communication and sensing technologies strengthen the intervention design. It support the quantification and tracking of the individual state and provide real time contextual information in terms of location, and time. These interventions are supporting in adopting healthy behavior such as physical activity, fruit and vegetables intake, obesity control, avoiding addictive use of alcohol and many others. Despite the growing popularity and use of these interventions, research into their production and assessment is still in its early stages. Many interventions have been created without anything in the way of scientific proof, hypothesis, or agreed treatment recommendations.

In [76], authors developed a smartphone based behavioral intervention application (FOCUS) that supported individuals with schizophrenia for illness management. It intervened three times a day for health status assessment through mood regulation, medication adherence, sleep, dealing with hallucinations, and social contact. Individuals might choose to engage or ignore the prompt after it has been signalled. FOCUS proposed self-management techniques to alleviate the types of problems the person endorsed, otherwise, it included guidance and positive reinforcement.

In [77], authors described a supporting application (ACHESS) that helped people recovery from alcohol addiction. It gave users access to a broad range of supportive resources, including computerized cognitive-behavioral counselling, online links to addiction-related websites, and updates about alcohol-free activities in their neighbourhood, 24 hours a day, seven days a week through communicating device. When a person visited a high-risk spot, such as a location that the individual pre-specified as a place where routinely accessed or drank alcohol in the past, GPS technology detected that and application generate intervention.

The interventions in physical activity domain are discussed in [78]. Authors had developed an application (SitCoach) that uses a smartphone to send messages promoting action. The software on the worker's computer kept track of how much time he or she spent on the computer by using the mouse and keyboard. If the user had 30 minutes of screen time, the mobile sent a convincing message to raise awareness of his or her sedentary actions and facilitate walking; otherwise, no messages are sent. In special case, if the person received a message in the past 2 hours and not able to respond properly, the application did not ping again and again to disturb any meeting or special task.

Chapter 3

Quantification of Contributing Behavior Factors

3.1 Overview

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 wellbeing, health, and socio-economical condition of individuals [79].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 [80, 81].

Studies in the literature have highlighted the four important healthy behaviors i.e. balanced diet, physical activity, nonsmoking and non-alcohol consumption [35, 43].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 [82]. 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 [83] 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 [82]. 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 this work, 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 0.397. 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.

3.2 Existing 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 [3]. In [4] authors evaluated the efficacy of sequential and simultaneous intervention for physical activity (PA), diet, and sleep to improve the behaviors. Similarly in [5] 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 [39]. Habitual behavior is one that someone usually does or has, especially one that is considered to be a characteristic of the person [40]. 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) [39, 41–43] as summarized in Table 3.1 under the section of diet to index the eating habits. Multiple studies summaries in Table 3.1 reflect which identify that most preventable cause of death are tobacco and alcohol which lead to thousands of deaths yearly [44]. 20% adults [45] consumed tobacco and alcohol together [46], which has been associated with fetal diseases [46, 47] 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 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 [84] 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 Science Direct 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 sleeping*.

The inclusion criteria were research studies that focused healthy behavior in adult members

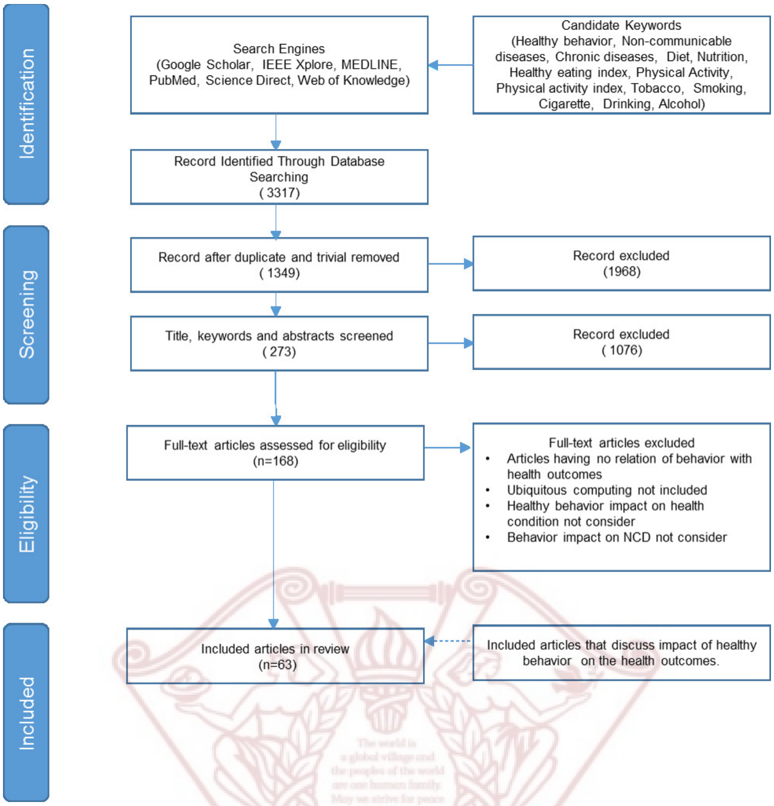


Figure 3.1: A survey analysis for document selection

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 [81].

Table 3.1: Lifestyle factor based assessment process.

Sr. #	Behavior	Domain	Assessment Process	Refernce
1	TV viewing	Physical Activity	Self Report, Questionnaire	[29, 48–50]
2	Total Inactivity	Physical Activity	Self Report, IPAQ: International Physical Activity Questionnaire	[50, 51]
3	Leisure Time active sports	Physical Activity	Self Report	[14–16]
4	Bicycle/ Walking for Commuting	Physical Activity	Self Report	[17–19]
5	Fruit	Diet	Self Report,Parent Report, FFQ: Food Frequency Questionnaire	[20, 21]
6	Vegetables	Diet	Self Report, Other Questionnaire, FFQ: Food Frequency Questionnaire	[24, 25]
7	Soft \Energy Drinks	Diet	24-hour recall, Other Questionnaire, Self Report	[52, 53]
8	Energy-dense \Healthy Snacks	Diet	24-hour recall, Other Questionnaire, Self Report, FFQ: Food Frequency Questionnaire	[54, 55]
9	Sweets, Chocolates, Candies	Diet	Self Report, FFQ: Food Frequency Questionnaire	[56, 57]
10	Total Fat, Saturated Fat, Red Meat	Diet	24-hour recall, Other Questionnaire, Self Report, FFQ: Food Frequency Questionnaire	[23, 26, 28]
11	Carbohydrate, Fiber, Grains	Diet	Self Report, 24-hour recall, FFQ: Food Frequency Questionnaire	[23, 25, 27]
12	Fish, Protein	Diet	24-hour recall, Self Report, FFQ: Food Frequency Questionnaire	[23, 28]
13	Dietary Pattern	Diet	Self Report, FFQ: Food Frequency Questionnaire	[29–32]
14	Nicotine Patch\Spray	Smoking	Self Report, Questionnaire of Smoking Urges	[58, 59]
15	Cigarettes	Smoking	Self Report, Questionnaire of Smoking Urges	[33, 35]
16	Oral Alcohol	Drinking	Self Report, Alcohol Urges Questionnaire	[35, 36, 38]

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 3.2. The theory of planned behavior determines an individual's intention of behavior through attitude and subjective norms [85]. The action of a person represents the attitude and change in actions may represents the change in attitude eithier 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 [86]. The Transtheoretical model emphasizes multiple stages of behavior change: 1) pre-contemplation, 2) contemplation, 3) preparation, 4) action, and 5) maintenance [87]. The Fogg Behavior Model focuses on three basic ingredients of behavior occurs: 1) motivation, 2) ability, and 3) trigger [88]. 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 [89].

Table 3.2: 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 facotrs 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.

3.4 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 Figure 3.2. The FWI process further consists of three sub-processes: (i) mining of the health-related concepts through text mining, (ii) expert based filtration of identified concepts for ranking and (iii) life-expectancy based factor weight-age derivation.

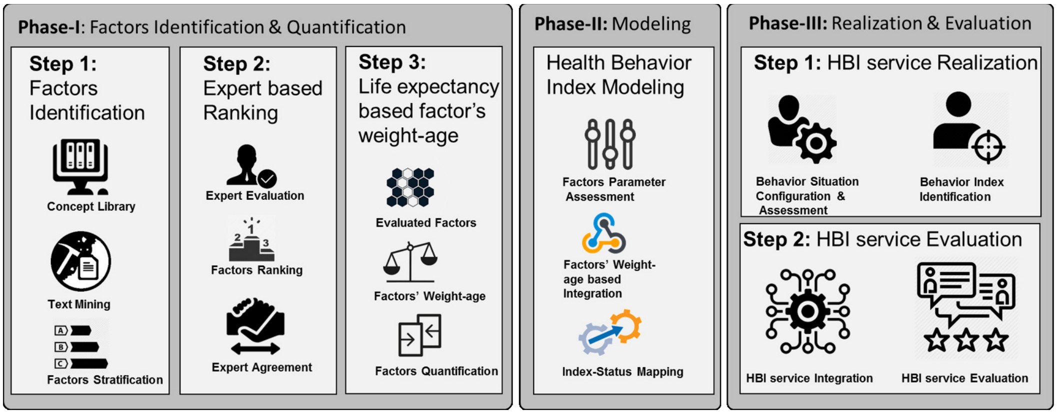


Figure 3.2: Healthy behavior index derivation and evaluation process

3.4.1 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.

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 [90]. 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 Figure 3.3, 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

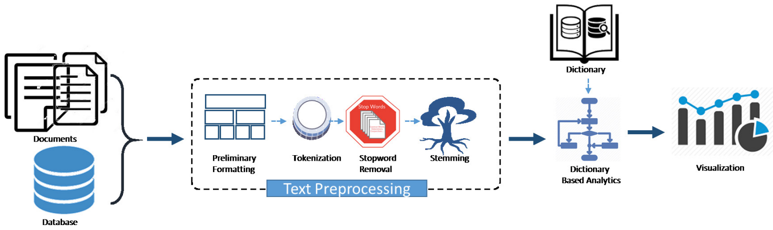


Figure 3.3: Work-flow of text mining methodology for concept identification

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 Figure 3.3.

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 [91] 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 at-least 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 3.3.

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 [92]. 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

Table 3.3: Evaluation of key factors from experts

Key Factors	Exp 1	Exp 2	Exp 3	Exp 4	Exp 5	Exp 6	Exp 7	Avg
	Likert Scale: Min 1 2 3 4 5 Max							
Physical Activity	5	5	5	5	5	5	5	5.00
Sedentary Actvitiy	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 (Cholestrol)	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
Protien (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 (5groups)	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

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 equation 4 is fair enough to accept the agreement level with multiple categories and among multiple raters as shown in Table 3.4.

$$k=\frac{\bar{P}-\bar{P}_e}{1-\bar{P}_e} \tag{3.1}$$

$$\bar{P}=0.537 \tag{3.2}$$

$$\bar{P}_e=0.254 \tag{3.3}$$

$$k=0.379 \tag{3.4}$$

The Value of kappa will be higher when there are fewer categories and inter-raters have few

Table 3.4: Evalution 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 Actvitiy	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 (Cholestrol)	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	Protien (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 (5groups)	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
	AgreeCate	0.06	0.16	0.16	0.34	0.29	

options to register their agreement [93]. 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 as discussed in Table 3.5.

Life-expectancy based factors' weight-age derivation

The expert's evaluation finalizes the assessment of user's healthy behavior status as shown in Table 3.6 along with the definition.

Table 3.5: 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	**Transformation transition**	0	7
10	**Saturated Fat**	5	2	0	(from 3 categories	7	0
11	**Unsaturated Fat**	6	1	0	to 2 categories)	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	

Table 3.6: 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 mins in a week	[94, 95]
2	Sedentary Actvitiy	4.14	Spending more waking time in activity with MET<1.5	[96–98]
3	Sleeping	2.29	Activity with MET value <1.0	[99, 100]
4	Regularly Eating	4.71	3- 5 time with proper duration delay	[101–103]
5	Sugar Amount	4.86	Less then 10 percent of calories per day from added sugar	[104, 105]
6	Dietary Fiber	2.57	25-30 gms of food must be dietary fiber (adults) (unabsorbable plant part)	[106, 107]
7	Carbohydrate Amount	1.86	Major source of energy and 4-5 g/kg/day carbohydrate are recommended	[108, 109]
8	Whole Grain	3.71	3 serving or about 84 gms per day of whole grains are recommended to maintain a long-term health.	[110]
9	Fats (Cholesterol)	4.14	The diet should not contain more then 78 gm of Fat	[111, 112]
10	Saturated Fat	2.29	Unhealthy fats from animals (solid at room temperature) and body requires about 13 gm per day.	[113, 114]
11	Unsaturated Fat	2.14	Healthy fats from plants and fish (liquid at room temperature) and replace saturated fats with unsaturated one.	[115, 116]
12	Protien (Fish, Poultry)	3.14	Consumption of Poultry, Fish, Egg to fulfill about 56 gm of protein requirements.	[117, 118]
13	Milk (Dairy)	3.57	Rich source of calcium, vitamin D and essential minerals and recommended 3 servings per day.	[119, 120]
14	Vegetables	4.14	2-3 servings of vegetables (preferably green color vegetables) per day.	[120, 121]
15	Fruits	4.57	1.5-2 servings of fruit(preferably fresh fruits and juice) per day.	[120, 121]
16	Salt(sodium) Amount	4.43	2.5-5.0 gm of salt is recommended per day.	[122, 123]
17	Balance Diet (5groups)	4.14	Combination of grains, fruits, vegetables, dairy, and proteins in appropriate proportion .	[110, 118, 124]
18	Smoking	4.86	Cigarettes, pipe,and cigar all are injurious to health and major preventable risk factor of non-communicable diseases.	[124, 125]
19	Alcohol	4.57	Less than 14 units per week keep health and premature mortality risks to a low level.	[126, 127]
20	Stress	1.57	Mental or emotional pressure threats the quality of working life and can cause aggression, absenteeism and reduced productivity.	[128]

The focus of the assessment criteria is only on the behavior risk factors rather than intermediate or proximal risk factors as shown in Table 3.7.

In study [81, 129] 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 3.8. In study [81], 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

Table 3.7: Categories of health behavior risks factors

Behavior	Category	Description	Score
Smoking	Heavy smoker	Daily current smoker ($\geq$ 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, Partail Balanced 5 groups food	3
	Adequate Diet	Regular, Balanced 5 groups food, Low Sugar and Salt	5
Alcohol	Heavy drinker	10 to 24 (men) or 6 to 17 (women) drinks/week	1
	Moderate drinker	5 to 9 (men) or 3 to 5 (women) drinks/week	3
	Light/ No drinker	0 to 4 (men) or 0 to 2(women) drinks/week	5
Physical activity	Sedentary	0 to <1.5 METs/day	1
	Moderately active	1.5 to 3 METs/day for 20 to 25 mins)	3
	Active	>=3METs/day (for 20 to 25 mins)	5

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 moderate against four primary factors for behavior quantification. So, we have 3^4 total possible cases with a mean value of 23.21 index as shown in Table 3.9. 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 ± 6.73, so the range of regular HBI lies between 16.50 to 29.95 which is the significant portion of the range, where unhealthy HBI lies between 7.75 to 16.50 index and similarly healthy HBI lies above 29.95 index.

As there are multiple contributing factors to decide the appropriate 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,

Table 3.8: Health behavior risks factors weight-age

Behavior	Average Life (in yrs.)	Life Loss (in yrs.)	Life Gain (in yrs.)	Loss & Gain (in yrs.)	Weight-age
Smoking	82	73	85	12 yrs.	3.00
Poor Diet	82	78	86	8 yrs.	2.00
Alcohol	82	80	86	6 yrs.	1.50
Physical Inactivity	82	81	86	5 yrs.	1.25
Stress	82	79	83	4 yrs.	1.00

Table 3.9: Health Behavior Risks Factors

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

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.

3.4.2 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*

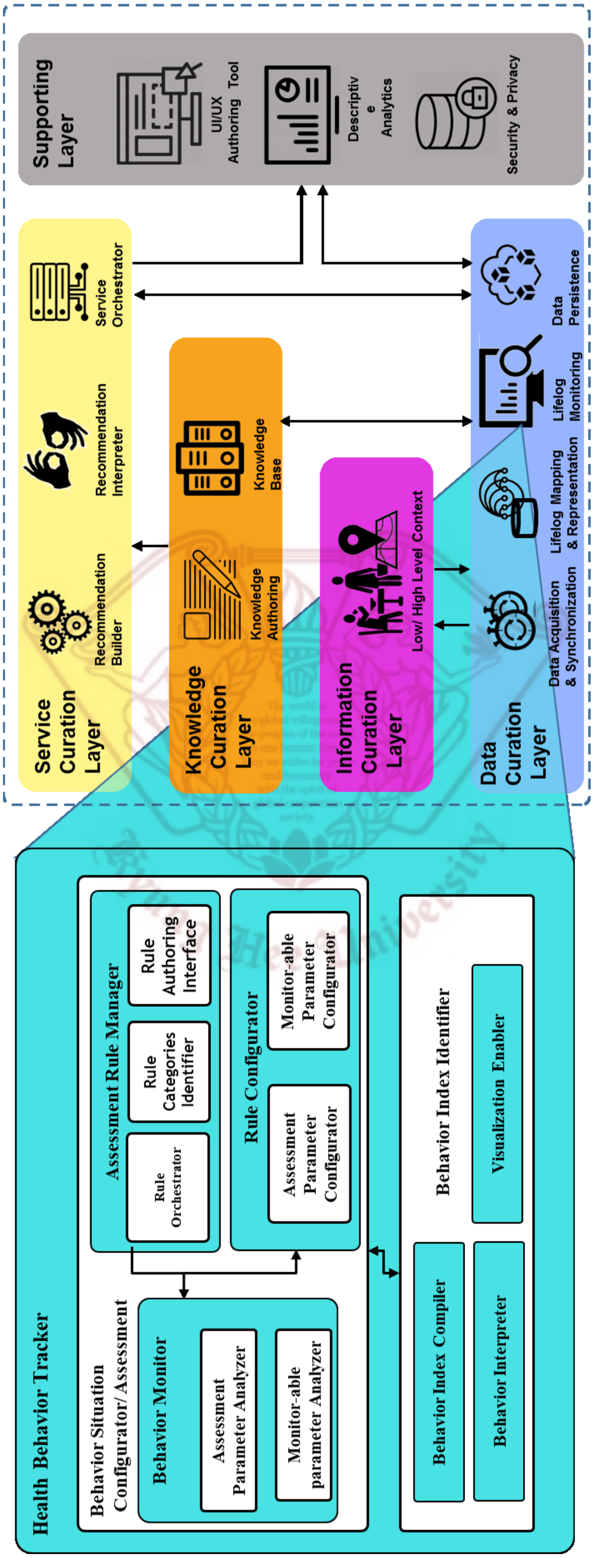


Figure 3.4: Integration Mining Minds framework with HBI methodology

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

Consider,

$$M = \{m_1, m_2, ..., m_j\} \tag{3.5}$$

Where M=$\{$*set of monitor-able Parameter*$\}$
j is the number of monitor-able parameter.
Now,
m_i *has related subset of assessment parameter which is denoted by S:*

$$S = \{s_1, s_2, ..., s_n\} \tag{3.6}$$

n is the total number of assessment parameter.
The assessment parameter of a monitor-able parametr A_M *is defined as:*

$$A_M = \{A_{M_{S_1}}, A_{M_{S_2}}, ..., A_{M_{S_K}}\} \tag{3.7}$$

Where, $S_K \in S$
The indication of assessment parameter related to monitor-able parameter is as follows:

$$I_{MA_j} = \begin{cases} 1, & \text{if } \bigcap_{i=1}^{K} A_{MS_i} = 1, i \in A_{Mj} \\ 0, & \textit{Otherwise ignore} \end{cases}$$

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

$$I_{AM_j} = 1 \tag{3.8}$$

Then

$$M = \sum_{i=1}^{n} \{M_{iSCORE}\} / time \tag{3.9}$$

Where

$$time = \{Day,\ Week,\ Month\} \tag{3.10}$$

But

$$n = \begin{cases} 1, & \textit{for simple monitorable parameter} \\ 2 - \infty, & \textit{for complex monitorable parameter} \end{cases}$$

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,

$$B = \{\textit{Set of Behavior} \mid \textit{Smoking, Diet, Alcohol, PhyAct}\} \tag{3.11}$$

Where

$$\begin{aligned}
&B_{Smoking} = no.of Packs/day \\
&B_{Diet} = (DietryHabit_{SCORE} + DietryNutrient_{SCORE}) \\
&B_{Alcohol} = no.of Drinks/Week \\
&B_{PhyAct} = \frac{\sum(time_{PhyAct} | MET_{PhyAct} \geq 3)}{Week}
\end{aligned}$$

$$HBI = \sum_{i=1}^{n} \{B_i * Wt_{Bi}\} \tag{3.12}$$

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 3.4.1 is discussed below:

$$Status_{HBI} = \left\{ \begin{array}{lll} Unhealthy, & \textit{if HBI} \leq \upsilon - \delta \\ Moderate, & \textit{if} \quad \upsilon - \delta \leq \textit{HBI} < \upsilon + \delta \\ Healthy, & \textit{if} \quad \textit{HBI} > \upsilon + \delta \end{array} \right\}$$

The ranges of HBI in terms of healthy, moderate and unhealthy are verified through six experts from community and general medicine, endocrinology, gynaecology and oncology department dealing with lifestyle based diseases as shown in Table 3.10. These experts evaluate the overall impact based on the individual stage of the behavior. There are total 81 cases with four lifestyle factors having three possible conditions. In the current condition, while considering the marking of the overall behavior conditions is evaluated. The Value of kappa for inter-raters agreement is 0.87 which shows nearly perfect agreement among the raters. Whereas, the $\%$age of matching cases is above 95% with matched cases of 462 out of 486 cases.

Table 3.10: Evaluation of multiple cases from experts

Expert #	Experties	Experience (Years)	Matched Cases	Unmatched Cases	%age of Matching
1	General Physician	17	74	7	**91.36**
2	Endocronologist	13	78	3	**96.30**
3	Family Medicine	25	79	2	**97.53**
4	Gyenacologist	30	78	3	**96.30**
5	Oncologist	20	79	2	**97.53**
6	Community Medicine	15	74	7	**91.36**
	Total		**462**	**24**	**95.06**

3.4.3 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 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 [12, 130, 131]. It is a user-centric wellness management framework to promote a healthy lifestyle through self quantification [132]. 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 [130], as shown in Fig. 3.4. 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 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) [12]. 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 [133]. 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 [134].

3.5 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.

3.5.1 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 3.11.

Table 3.11: Participants demographic Information

Categories	Attributes	No. Of Users	%age of Users
Age(Years)	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	33	37.86%
	Hyperlipidemia	25	24.27%
	Hypertension	21	20.39%
	Diabetes	24	20.30%
Study Completion	Complete	99	96.12%
	Left	04	03.89%
Experties inElectronic Gadgets	Proficient	20	19.42%
	Moderate	76	73.79%
	Newbie	07	06.80%

3.5.2 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 [135]. Figure 3.5 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 [135, 136] in the range of -3 to 3 [137] as shown in Figure 3.6. The stimulation scale has a value close to 2.0, reflecting the higher driving impact of service on the participants [137].

The confidence interval (measure for the precision of the mean estimation) has been evaluated through 95% confidence intervals for UEQ scale mean [138]. 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 Figure 3.6.

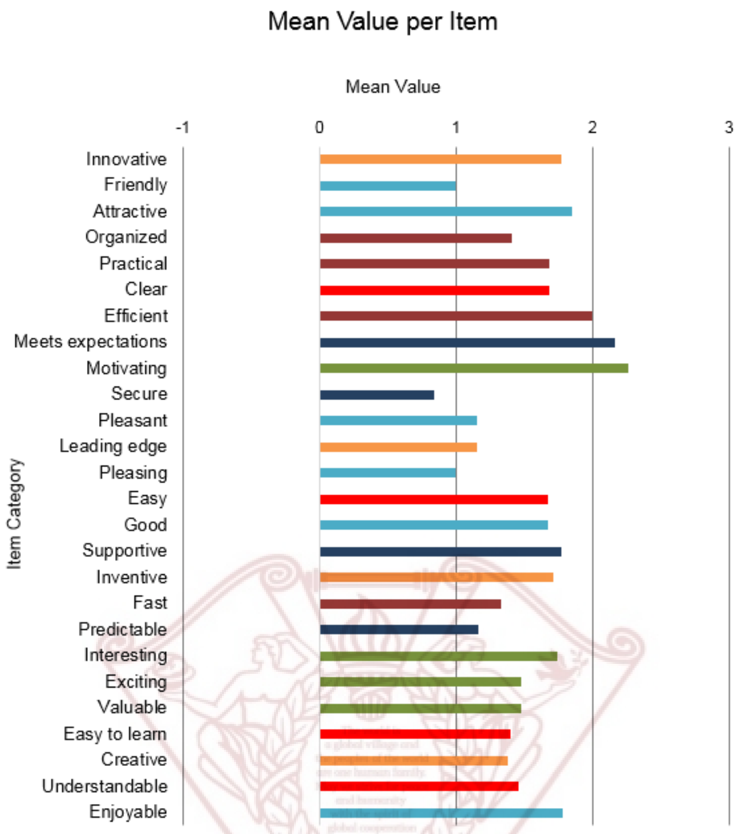


Figure 3.5: Scale mean value per item

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 [136]. The UEQ evaluation tool analyzed the HQ (1.62) and PQ (1.55) as good with the mean value higher than 0.80 (Figure 3.7) [137]. 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 [136]. 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 range, and rest are in the range of good as shown in Figure 3.8.

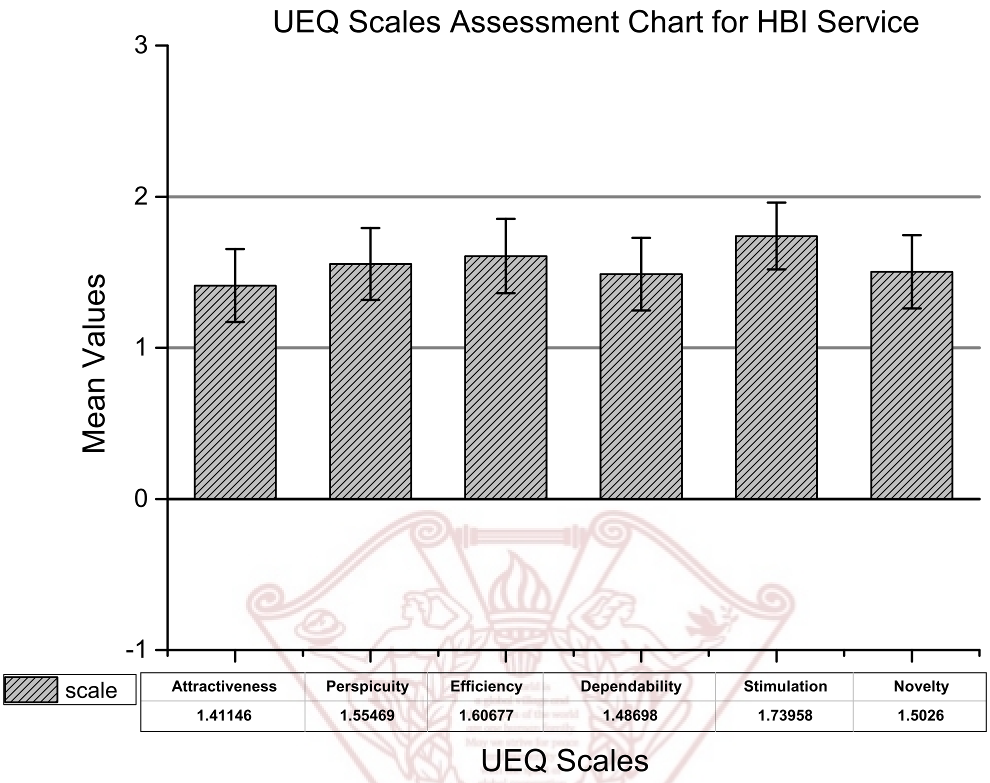


Figure 3.6: UEQ scale value

3.6 Summary

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 noncommunicable 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

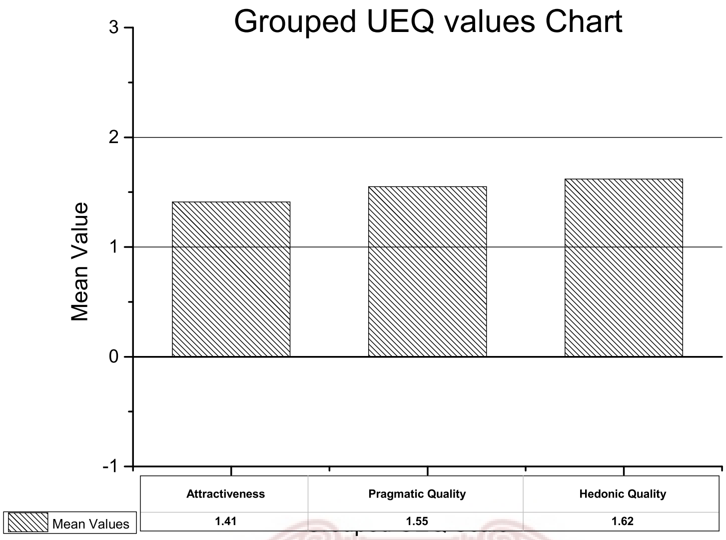


Figure 3.7: Grouped UEQ scale values

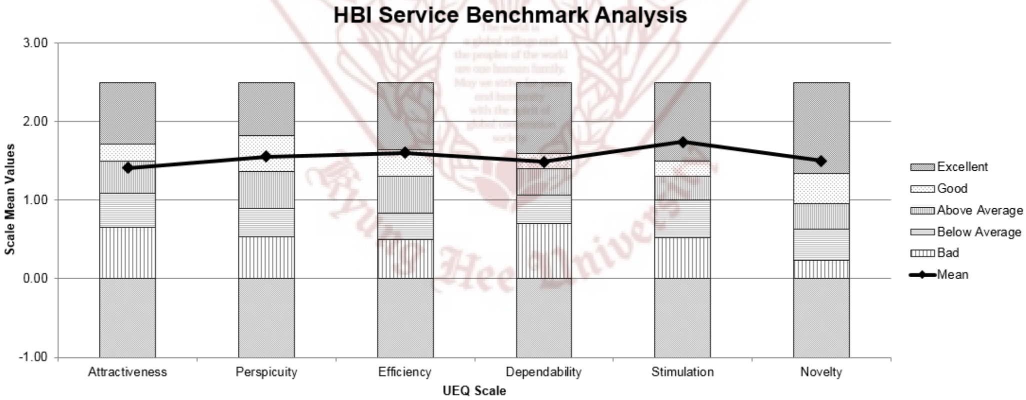


Figure 3.8: Benchmark of HBI service

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.

Chapter 4

Behavior Context based Intervention Mapping

4.1 Overview

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 the society and economy. The personal awareness about lifestyle status has been revolutionized from last decade due to the advancement in information and communication technologies (ICT). Recently, the e-health and wellness applications have changed the trend of healthcare application from responsive to proactive [139] in terms of services and features involving people of all ages with confidence, motivation, and style to adopt a healthier lifestyle. ICT 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 [140]. 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.

4.1.1 Unhealthy Lifestyle Behavior

Multiple lifestyle-related risk factors like unhealthy diet, smoking, physical inactivity, and alcohol consumption have been identified as a cause for the development of Noncommunicable Chronic Diseases (NCD) and the major changeable. 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 [141]. So, an indication of prolonged physical inactivity behavior helps in changing the lifestyle for a long healthy life. Similarly, an imbalanced diet consumed for a long time may increase the probability of chronic disease development. A persuasive health agent and an unhealthy diet pattern are one of the causes of chronic diseases and premature death [142]. 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 dangerous also. 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-severs life-threatening dangers. The only exception is the moderate consumption of alcohol [143]. 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.

4.1.2 Lifestyle impact on Chronic Diseases

Lifestyle patterns such as regular exercise, non-sedentary activities, a balanced diet, not smoking, and controlled alcohol consumption, prevents and manages lifestyle-related NCDs [144], as shown in Table 4.1. The factors that have impact on the diseases are mention through '*' and diseases which are not affected by '-'. The diseases include heart disease, hypertension, stroke, muscles problem, bone disorder, cancer, obstructive lung disease, obesity, diabetes, and chronic back pain. The impact of lifestyle-related factors on the cause of NCDs is significant and by adopting healthy one, a person can enjoy healthy and a long quality life.

Table 4.1: 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

4.1.3 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 [11]. 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 proactively to diagnose the root cause of any undesired chronic health issues. Multiple applications are available like MyFitnessPal, FIIT, Move GB, Sleep++, Headspace, RiseToday, 8Fit, GoogleFit, RunKeeper, and others. These are the current high ranked digital well being applications, which quantify user activities, step counts, calories consumption, and provide visualization of user status to support fulfilling the daily goal and weight management.

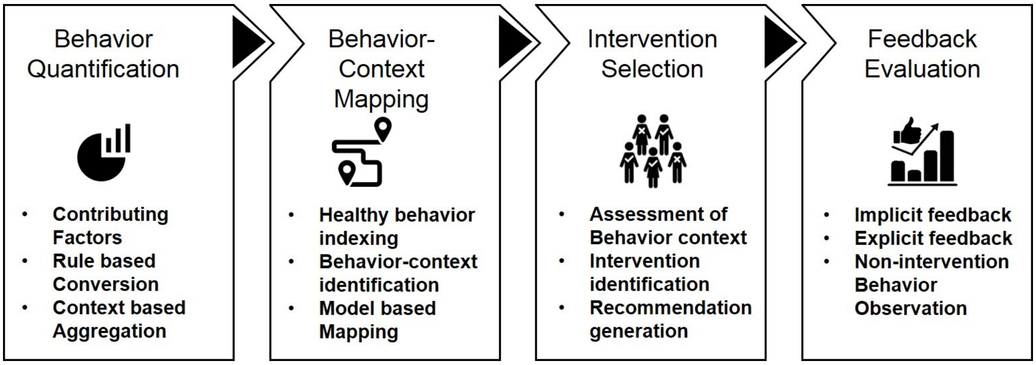


Figure 4.1: Abstract flow of UCAI methodology

The literature has highlighted that self-monitoring the critical concept of well-being apps track activities and record feedback but don't focus in habit formation or social support contents. Habit formation is the most important aspect towards behavior change through the conscious use of technology, which ensures long-term impact [145].

4.2 Background

According to the latest World Health Organization (WHO) global status report, non-communicable diseases (NCD) associated with lifestyle habits are currently the major causes of worldwide deaths [154]. 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 non-communicable diseases and defined a clear strategy to overcome the impact of the catastrophe tie of the scenario. 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 [141]. 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 [142].

Table 4.2: Important factors' definition, expert driven rank along with evaluation process

Sr. #	Important Factors	Expert driven Rank	Definition	Estimation Process	References
1	**Tobacco Consumption (Smoking)**	4.86	Cigar, pipe, and cigarettes all are dangerous and a major preventable risk factor of NCDs.	SR, QSU	[33–35, 124, 125]
2	**Alcohol Consumption**	4.57	A controlled amount per week keep risk of NCDs and premature mortality at low level.	SR, AUQ	[35–38, 126, 127]
3	**Leisure time and daily physical activities**	5.00	Moderate intensity physical activities for at least 150 mins in a week	SR	[13–16, 94, 95]
4	**Dietary Regularity and Pattern**	4.71	Daily 3 to 5 times with at-least 4 to 5 hours delay.	SR, FFQ	[29–32, 101–103]
5	**Sugar, Chocolates, and Sweetened Soft Drinks**	4.86	Added sugar is not good and less then 10% of daily calories obtain through it.	SR, DSQ	[104, 105, 146]
6	**Whole Grains, Fiber, and Carbohydrate**	3.71	Adult food must contain 25 to 30 gms dietary fiber (unabsorbable plant part)	SR, FFQ, 24RC	[23, 25, 27, 106, 107]
7	**Saturated and Unsaturated Fats (Cholesterol)**	4.14	Saturated fat is not good, and diet should contain less then 78 gms of fat	SR, FFQ, 24RC, OQ	[23, 26–28, 111, 112]
8	**Protein (Egg, Fish, Poultry)**	3.14	It is essential nutrient and adult should take about 0.8 gms per kilogram of body weight.	SR, FFQ, 24RC, OQ	[23, 25, 28, 117, 118]
9	**Dairy (Milk, Yogurt, Butter, Cheese)**	3.57	It is source of vitamin D, calcium and essential minerals,at-least daily 3 servings are recommended.	PR, FFQ	[119, 120, 147]
10	**Fruits**	4.57	Daily 1.5 to 2 servings of fresh fruits and juice are preferred	SR, PR, FFQ	[20–22, 120, 121]
11	**Vegetables**	4.14	Daily 2 to 3 servings of preferably green vegetables are recommended.	SR, FFQ, OQ	[23–25, 120, 121]
12	**Dietary / External Salt (sodium) Amount**	4.43	Daily, about 2.5 to5.0 gms of salt is recommended for adult without NCDs.	RES	[122, 123, 148, 149]
13	**Balance Diet (5groups)**	4.14	Multi-nutrient from proteins, dairy, grains, fruits, and vegetables are required in an appropriate proportion .	FFQ	[110, 118, 120, 124, 150]
14	**Mental Stress**	1.57	Mental pressure causes aggression and threats the working quality as well as reduced productivity.	BJSQ, RESTQ	[128, 151–153]

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

The information and communication technologies 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 [155].

The challenge is to engage and maintain the interest for adopting a healthy lifestyle, 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 mechanism 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 [155].

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 [11, 12]. 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 4.2, 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 [13–19]. The diet is a composite concept based on different micro nutrients . Every micronutrient 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 [20–32]. The addictive behavior of smoking and alcohol had been evaluated through self reporting and specific questionnaires related to urges for these addiction [33–38].

Table 4.3: Categories 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

4.3 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 (BCT) in an actionable manner through ICT, as Figure 4.1. 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 4.1. 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 [156], which are further categorized into prescriptive, informative, confronting, supportive, catalytic, and cathartic as discussed in Table 4.7. Finally, the response of the user is evaluated to understand the influence of the intervention on the behavior.

4.3.1 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.

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 had mentioned their agreement or disagreement level through a psychometric scale Likert questionnaire [64] to rank the lifestyle factors with Fliess' Kappa. The Kappa agreement value is 0.379, which is fair enough with multiple categories among multiple raters. The lifestyle factors, along with their definition and ranks, are discussed in the Table 4.3.

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 criteria is only the behavioral risk factors rather than proximal or intermediate risk factors, as discussed in Table 3.8. 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 [157].

LIFE EXPECTANCY BASED WEIGHT-AGE 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 [81, 129]. 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 [158], as shown in Table 3.8. 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' weight-age also depends on the proportion of life loss and life gain because of a specific risk factor. As the focus is not purely related to life expectancy, but to indicate the users about the status of behavior through the health behavior index to take precautionary measures.

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, comprehensive behavior index is composed of multiple ingredient behaviors, which are smoking, drinking, diet, and physical activity [158]. The nature and metric of the behavior define its context, which helps to aggregate the behavior in an appropriate proportion, as shown in Equation 4.1. The dietary behavior is a complex one based on the habit and consumed nutrients. The aggregation based on the weight-age of respective ingredients to compose a Healthy Behavior

Index (HBI), as shown in Equation 4.2:

$$B = \{\textit{Set of Behavior} \mid \textit{Smoking, Diet, Alcohol, PhyAct}\} \tag{4.1}$$

Where

$$B_{Smoking} = No.of Packs/day$$
$$B_{Diet} = (DietHabit_{SCORE} + DietNutrient_{SCORE})$$
$$B_{Alcohol} = No.of Drinks/Week$$
$$B_{PhyAct} = \frac{\sum(time_{PhyAct} | MET_{PhyAct} \geq 3)}{Week}$$

$$HBI = \sum_{i=1}^{n} \{B_i * Wt_{Bi}\} \tag{4.2}$$

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.

4.3.2 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 non-communicable chronic diseases [159]. 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.

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 23.21 index, as shown in Table 3.9. 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 ± 6.73, so the moderate behavior lies in HBI range between 16.50 to 29.95 It is a significantly big portion of the range. The healthy behavior lies in HBI greater than 29.95 whereas the unhealthy lies in HBI range between 7.75 to 16.50 index.

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. Similarly, the Transtheoretical Model (TTM) has identified different stages for behavior change and 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 behavioral 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 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-intervented 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 [160].

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 [160]. 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

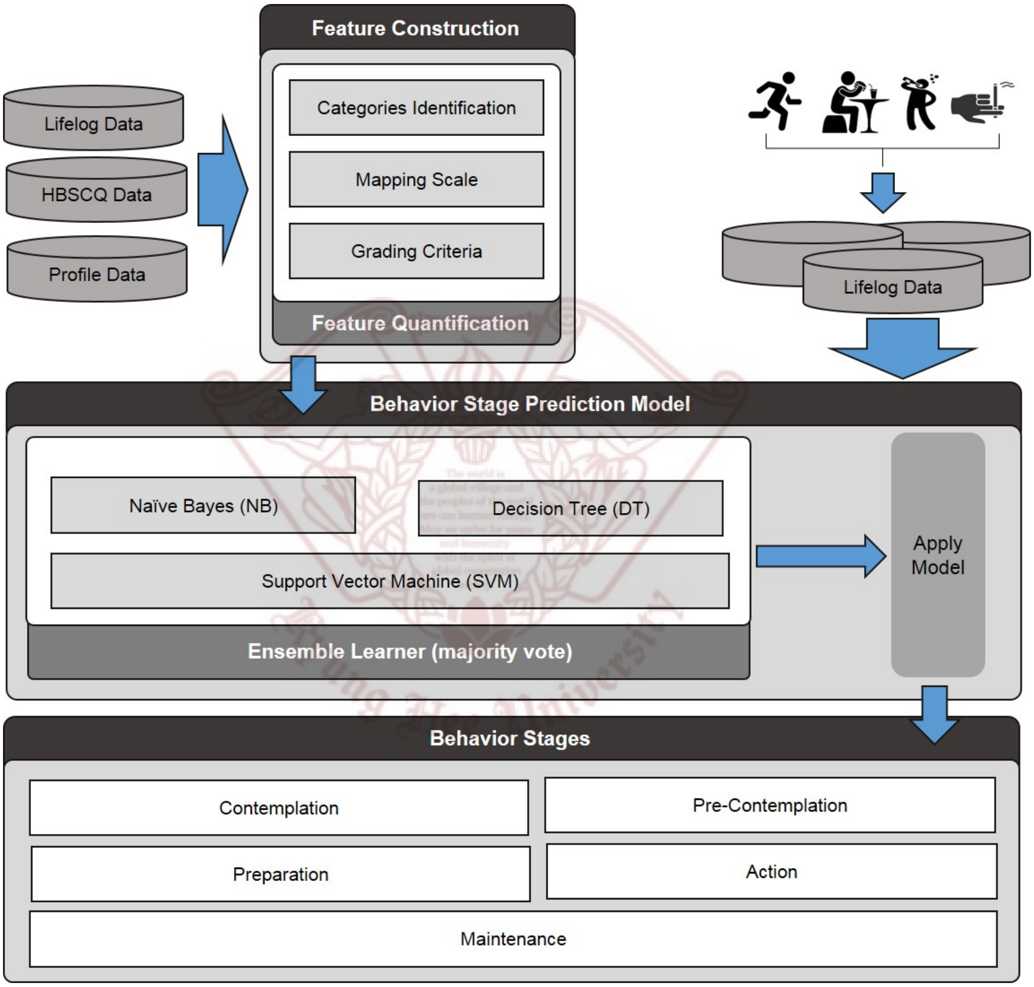


Figure 4.2: Architecture for behavior stage prediction model

through sensors is presented and quantified on the bases of scores, as discussed in Table 3.9. However, the behavior stage data is obtained through the Health Behavior and Stages of Change Questionnaire (HBSCQ) [161]. 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 4.4: 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) [161] 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 FFQ and HBSCQ are used to obtain the responses regarding different lifestyle habits and status of behavior stage. These responses are generally related to 4 main areas of lifestyle habits like physical activity, diet, smoking, and alcohol. The FFQ recorded responses related to the dietary lifestyle behavior of the users. The information related to physical activity, smoking, and alcohol consumption is obtained through different questionnaires, respectively. The HBSCQ consists of multiple questions related to the basic lifestyle habits regarding the level of knowledge,

Table 4.5: Intervention categories to stimulate the user for behavior change

Sr. #	Intervention Style	Intervention Categories	Definition	Example	ICT Based Intervention
1	**Authoritative**	Prescriptive	Explicitly direct the user through advice and direction	1: Guide and advice 2: How to react in a situation 3: What should be the behavior	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
2		Informative	Provide knowledge to guide about the situation	1: Knowledge about the background 2: Explain the experience 3: Make understandable the consequences	
3		Confronting	Challenging the user through pros and cons of identification	1: Support to avoid mistake repeat 2: Challenge the other person thinking 3: Communicate the shortcomings 4: Make users aware of deficiencies	
4	**Facilitative**	Cathartic	Help to overcome the doubts and thoughts	1: Help to understand the feelings and fears 2: Empathize with them	
5		Catalytic	Help to learn through self awareness	1: Encourage for fresh thinking 2: Encourage to adopt new solutions 3: Listen and Summarize	
6		Supportive	Build confidence in the user through qualities and competences	1: Tell the value of achievement 2: Praise on the accomplishment 3: Support to the fulfillment of commitment	

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 user, as discussed in Table 4.4.

The behavior and stage 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 very well known questionnaires related to diet, physical activity, smoking, and alcohol consumption. The responses of the questionnaires are marked through 1-5 Likert scale for the quantification of the contributing features of the lifestyle behavior, as described in Table 3.8.

- 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 base-learners. Based on the majority voting of base learners, the user behavior is classified into 5 basic stages of behavior: pre-contemplation, contemplation, preparation, action, and maintenance, as shown in Figure 4.2.

4.3.3 Personalization of the Intervention: Intervention Selection

The right intervention at the right stage to the right person is the key concerned of the study. However, the personalization of intervention is the target to attain 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 chronic non-communicable diseases. Literature has highlighted that imbalanced diet, physical inactivity, abuse of alcohol, and smoking are the riskiest factors for non-communicable chronic diseases. The impact of these modifiable behaviors on chronic diseases is discussed in Table 4.1. Every person has a different lifestyle behavior status, so it is necessary to generate personalized intervention, as discussed in Table 4.7.

TRANSTHEORETICAL MODEL-BASED BEHAVIOR STAGES

The behavior stats of the user can be categorized according to the Transtheoretical Model (TTM), which divides the For the personalization, the quantification of behaviors, and habits to understand the status and refinement of interventions. The quantification is performed on the basis of 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.

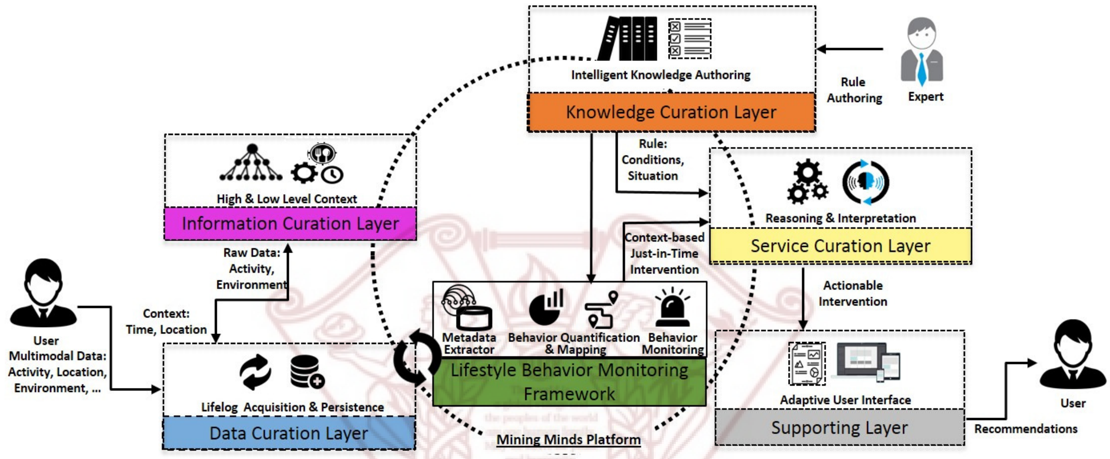


Figure 4.3: The Mining Minds conceptual architecture with integration of lifestyle behavior monitoring framework

4.3.4 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 user satisfaction or through 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 user experience through survey questionnaire discussed in appendix A.

- IMPLICIT FEEDBACK

Implicit feedback data is obtained on the basis of the action performed by the customers maintained in the lifelog. The implicit feedback data is much cheaper and easier to obtain as it requires no extra effort from the customers. 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.

4.4 Realization of Methodology through Wellness Management Platform

The goal of the user-centric behavior context-based intervention methodology is to enhance the efficiency of a wellness platform that can handle the information of user behavior related to lifestyle. This platform has the capability to curate the 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.

4.4.1 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 recommendations for lifestyle adaptation [12], [134]. 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, Internet-of-things (IoT), big data, and ontological inferencing technologies to provide personalized healthcare and wellness services. The smartphone and watch's sensory data

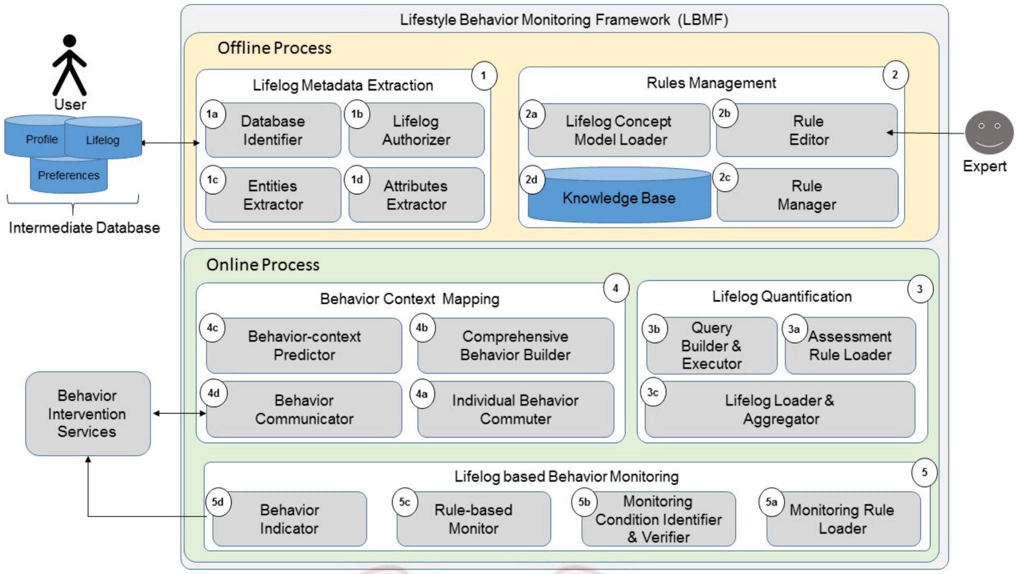


Figure 4.4: Functional diagram of lifestyle behavior monitoring framework

is utilized to recognize activities, emotions, and location, which is persisted into an intermediate database, as shown in Figure 4.3. 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 Service Curation Layer (SCL) orchestrates the personalized requirements of the 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 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 [140]. These rules guide the kind of recommendation provided to the 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

Table 4.6: Classification recall and precision through behavior context prediction model

	True. Contemplation	True. Precontemplation	True. Ready	True. Action	Class Precision
Pred. Contemplation	49	1	0	0	98.00%
Pred. Precontemplation	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%	

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, lifelog representation and mapping, lifelog monitoring and big data storage processes [12]. Information Curation Layer (ICL) identifies user's activities and context from multimodal sensory data managed in hierarchical models. 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.

4.4.2 Lifestyle Behavior Monitoring Framework

The scope of this study is the Lifestyle Behavior Monitoring Framework (LBMF) which enhances the functionality of DCL, as shown in Figure 4.3; the components represented by dotted lines are not covered in detail here. The figure shows a conceptual view of the user-centric behavior context-based intervention process, whose work-flow is explained in the simulation section. The proposed architecture is divided into off-line and on-line processes on the basis of their working situation. The off-line process has two sub-processes known as lifelog metadata extraction and rule management, as shown in Figure 4.4. While the on-line process consists of three sub-processes, know as lifelog quantification, behavior context mapping, and lifelog based behavior monitoring, as shown in Figure 4.4. The functionality of each component under different processes is described as follows:

- META DATA EXTRACTION PROCESS

The metadata extraction is an off-line 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 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 off-line 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 on the basis of 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 on-line 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 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 retrieved data from the lifelog and handover it to the lifelog Loader and Aggregator—the Aggregator than accumulate the activity data according to the requirement defined in the rule.

- BEHAVIOR CONTEXT MAPPING PROCESS

The 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 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 these rules, the monitoring condition is identified, and constraints are verified against the specif 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.

4.5 Experimentation and Results: Evaluation of proposed Methodology

The evaluation of the proposed methodology is performed through two ways for proving the worth of the methodology, along with the evaluation of the behavior context prediction model. 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 healthy behavior index. Additionally, implicit and explicit feedbacks are analyzed from persons who are registered with the wellness management organization.

Table 4.7: 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%

4.5.1 Prediction Model Accuracy and Recall

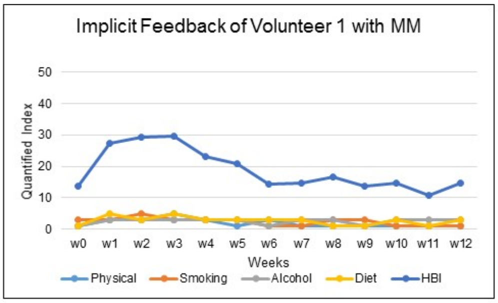
We have utilized set of classifiers to classify the stages of behavior on the basis of the data obtained through questionnaires, as shown in Table 4.6. We obtained the highest accuracy with Ensemble classifier, whereas Naive bayes and Decision trees also had accuracy greater than 90%. The accuracy of the Support Vector Machine was 87%. The precision and recall of the behavior context prediction model are discussed in Table 4.7. The classification precision of the precontemplation, contemplation, and action was more than 98%, whereas for the ready stage was about 96%. Similarly, classification Recall for precontemplation, contemplation, and ready was more than 95%, whereas for action was 80%.

4.5.2 Experimental setup

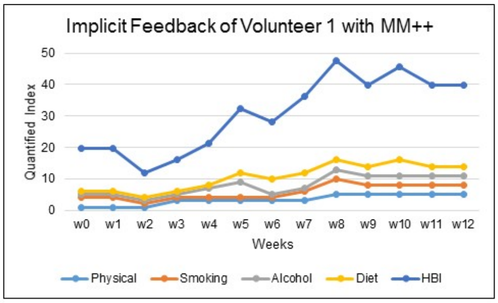
We have evaluated our proposed methodology over the dataset collected from employed volunteers. Initially, we recruited 6 volunteers with an age range between 33 and 41.

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 4.8. 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.

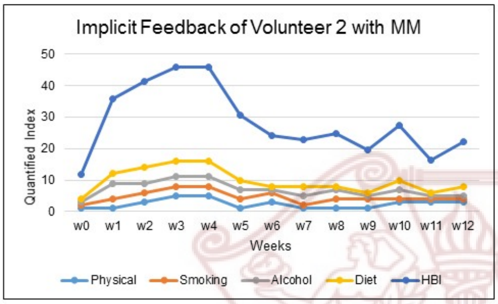


(a)



(a`)

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



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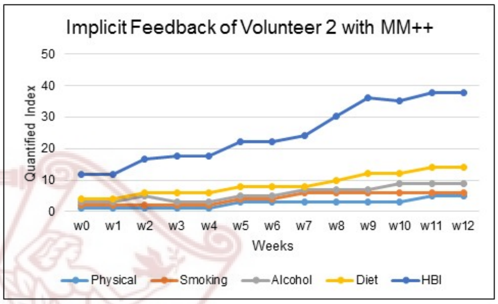
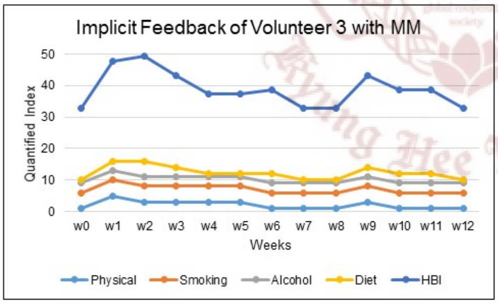
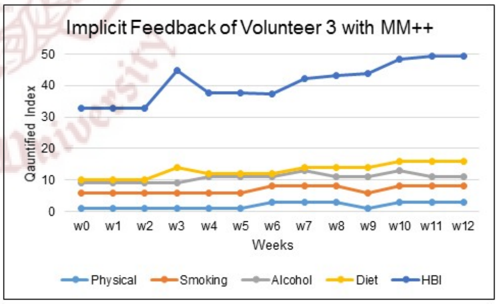


(b`)

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

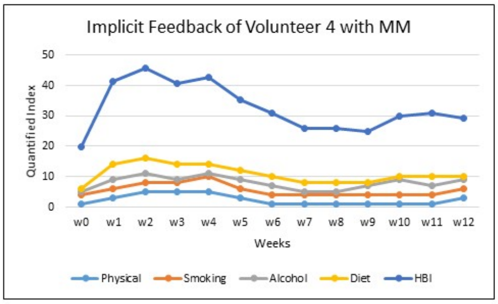


(c)



(c`)

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



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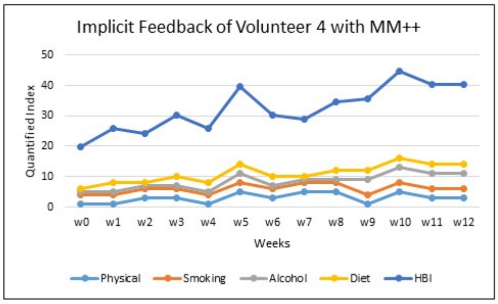


(d`)

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

Figure 4.5: Behavior status of volunteers for comparison

The change in smoking habits and alcohol consumption, however, are the most difficult tasks.

Table 4.8: 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

- IMPLICIT FEEDBACK BASED EVALUATION

We equipped the volunteers with smartphone with pre-installed MM wellness application. We also provided a short training as 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 4.5(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 4.5(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 4.6. 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

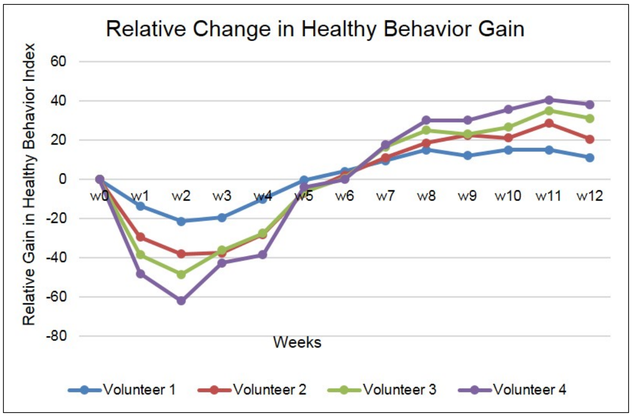


Figure 4.6: Relative change in healthy behavior index gain

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 4.7.

- 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 [134, 162].

The SUS delivers a "quick and dirty", trustworthy tool for assessing the usability of application [163]. 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 [134, 164].

The AttrakDiff is a widely recognized online accessible questionnaire [165] 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) [166]. The AttrakDiff provides a limited free online service (only 20 users) to investigate the pragmatic, hedonic, and attractiveness qualities of applications [167]. It consists of 28 contrasting adjective-pairs, which are clustered into PQ, HQ (Identity, Stimulation), and ATT [165].

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-A and AttrakDiff with the help of eSURVEY Tool[10].

- DEMOGRAPHIC DATA

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 3.11. 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

[10] https://esurvey.uid.com/project!overview

[9] Google Scholar based Citation 9449 (viewed on 15/08/2020)

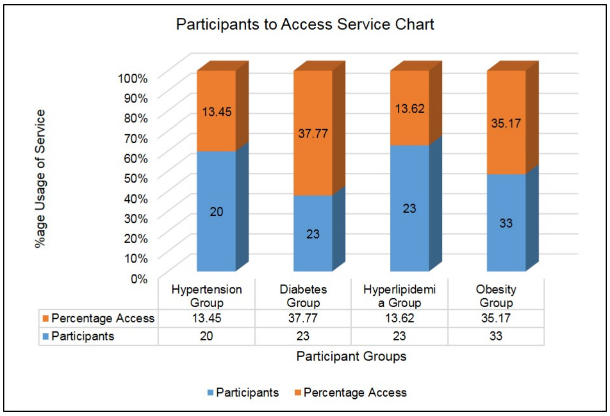


Figure 4.7: Disease wise service utilization comparison

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 volunteers utilized the service 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. For this, we made a questionnaire, related to satisfaction, usefulness, attention, motivation, and knowledge, as shown in appendix A. There are multiple questions related to 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 result of the services are shown in Figure 4.8, which shows that nearly 70% volunteers enjoyed and exhibited their trust on the application where nearly 10% of users somehow are not fully agreed with the support provided by the service. The overall grading of user experience criteria like satisfaction, usefulness, and knowledge lay between 68% to 74% where user psychological experience criteria like attention and motivation lay between 60% to 66% after the usage of 12 weeks. The results show a very comprehensive agreement level of the population, which required a lot of knowledge, and motivation to change lifestyle for the support of medication.

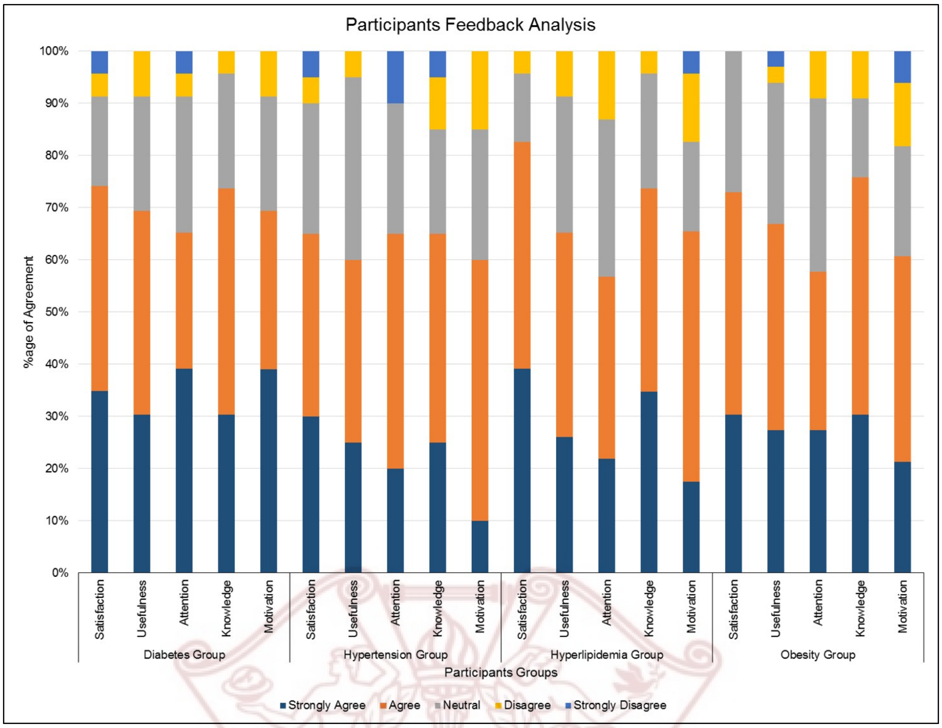


Figure 4.8: Questionnaire based survey result obtained from volunteers

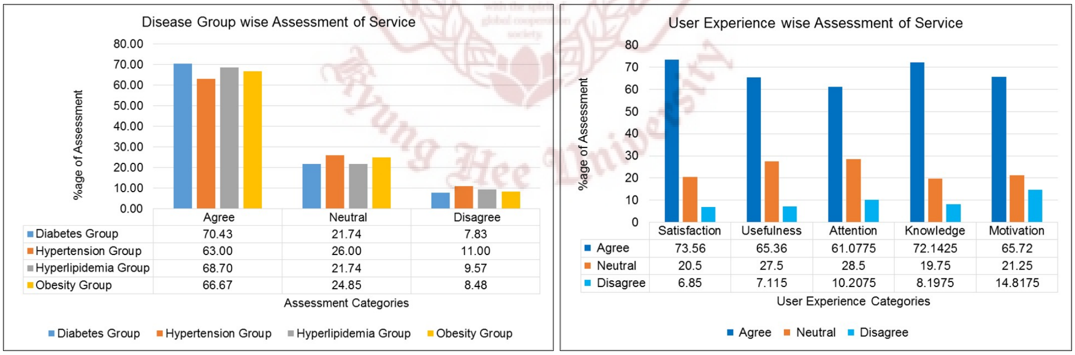


Figure 4.9: Categories wise assessment of the wellness application from volunteers

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.

(i). System Usability Evaluation:- There were 64 end-users who recorded their responses

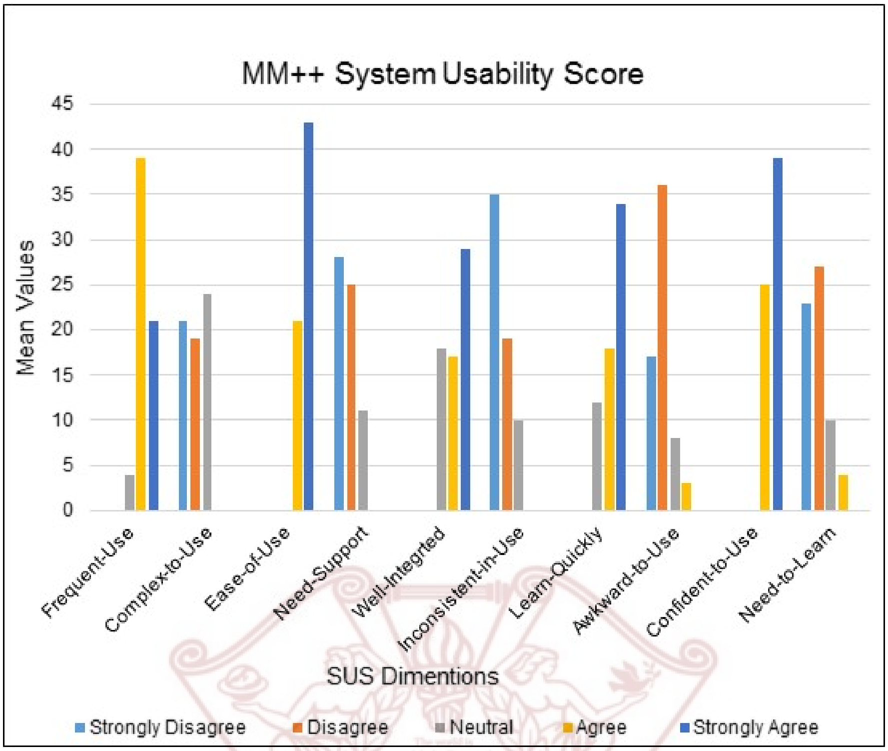


Figure 4.10: The system usability score of MM++.

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 4.10. 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

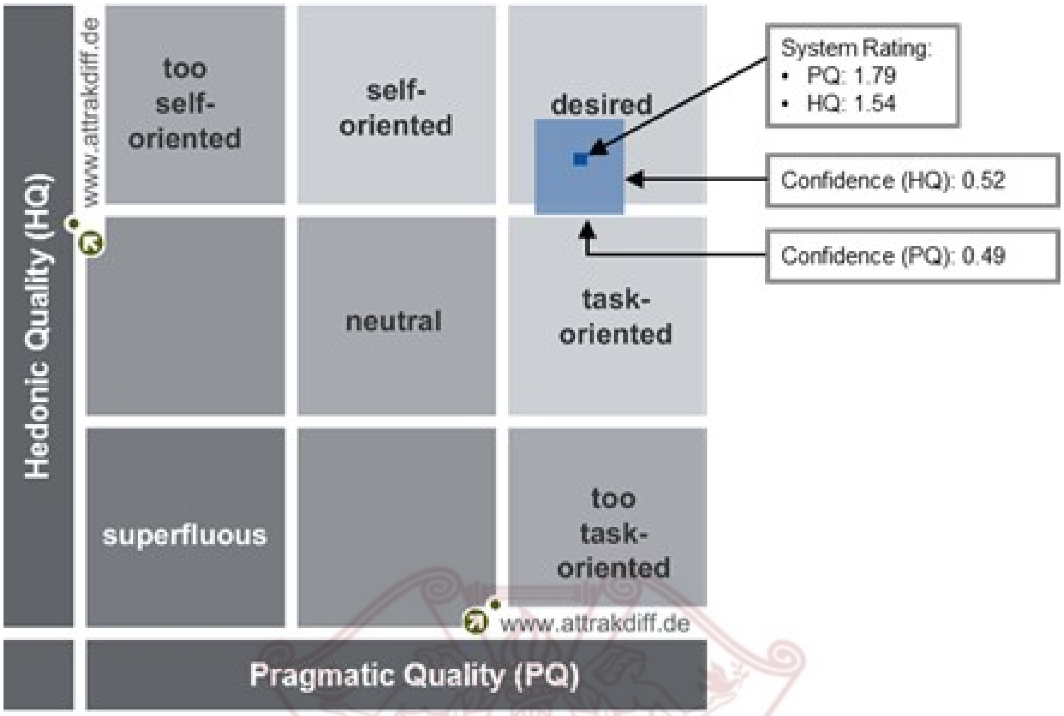


Figure 4.11: MM++ portfolio analysis based on Hedonic and Pragmatic qualities.

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 4.11, 4.12, 4.13. The portfolio diagram summarizes the performance through pragmatic and hedonic qualities of MM++ as shown in Figure 4.11. 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 and HQ take on values 1.79 (with confidence internal 0.49) and 1.54 (with confidence interval 0.52), respectively.

Figure 4.12 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

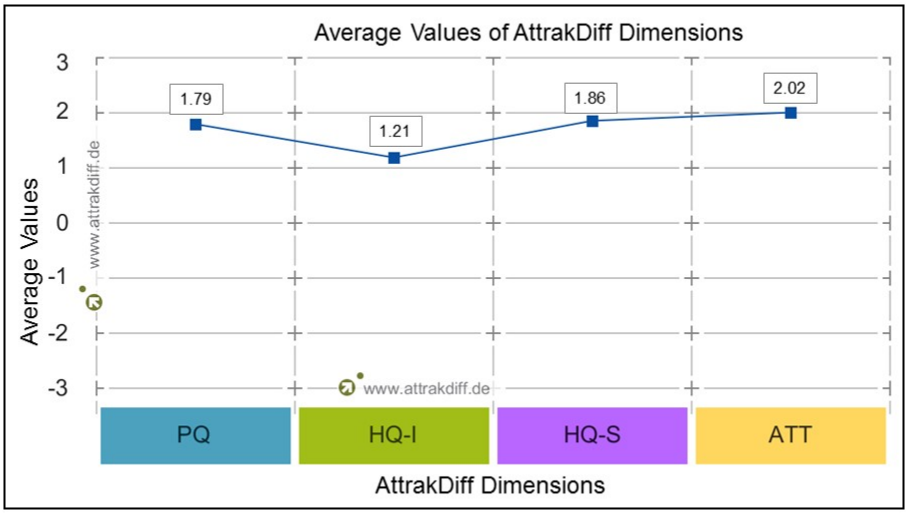


Figure 4.12: AttrakDiff dimensions' average values for the MM++.

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 4.13. 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 A. There are multiple questions related to 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 4.8, 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 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

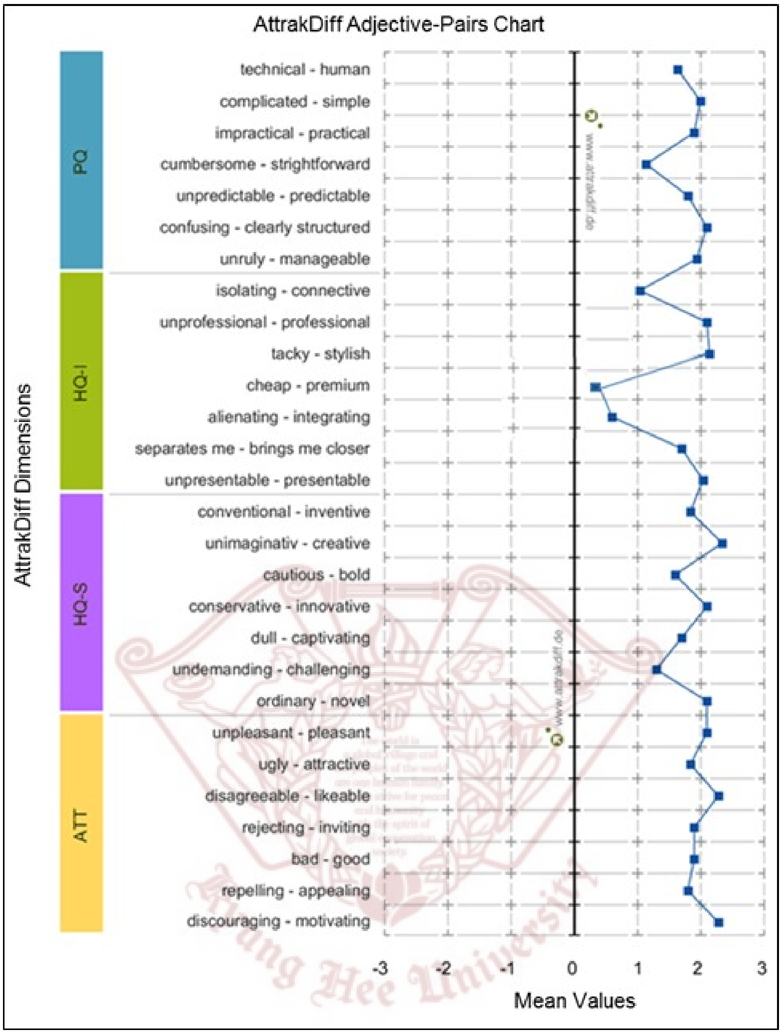


Figure 4.13: AttrakDiff adjective-pairs' mean values for MM++ [2].

medication.

4.5.3 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 4.9(a). The overall service had satisfied the 74% of end-users where 7%of end-users registered unsatisfactory status, as shown in Figure 4.9(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.

4.6 Summary

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.

Chapter 5

Adaptation of Intervention for Behavior Change

5.1 Overview

In recent years, there has been a shift in the way healthcare and its support services are approached. This change has had a significant impact on how traditional models of healthcare delivery are framed - these models emphasize preventative personalized wellbeing rather than tardy disease management and cure. As a result, healthcare providers may focus on ensuring that resources and treatments are delivered to a specific patient or service client. [131, 168]. The cause of this change is the increasing financial pressures that health systems are facing to meet the growing demand for their services. [169]. As a result, service providers are promoting wellness-based models and conducting studies to determine their effectiveness. According to the latest research in biomedical health care, the most common diseases are caused or exacerbated in part by an unhealthy, long-term lifestyle. Unhealthy and junk foods, sedentary lifestyles with little exercise, tobacco addiction and alcohol abuse are all possible factors in the development of disease and limit the effectiveness of medical treatments. [170–172].

With the introduction of personalized smart devices, healthcare professionals and biomedical researchers can make people aware of their health and lifestyle by providing personalized, persistent, and timely help [173]. As a result, the demand for fitness wearables with mobile apps that promote health status and wellness display has exploded [174]. Several wellness platforms and apps such as Withings Activite, Fitbit Surge, Garmin Vivofit, Misfit Shine, Apple Health Kit, Samsung Gear, Google Fit, Microsoft Band and LG smartwatches with Microsoft Health are mainly sensor-based apps that support basic health tips based on tracked step count, calories and sleep hours. Meanwhile, research institutions are focusing on health and wellness programs that can detect physical symptoms and send alerts [175] or detect chronic diseases [176]. Despite immense efforts by industry and researchers, most existing applications are device-specific with limited range [131]. Therefore, these are not able to build a context-rich lifelog to provide a comprehensive picture of daily routine [177] . Lifelog-based self-quantification is an essential and cost-effective way of evolutionary wellness system for successful intervention [178] .

5.2 Existing Work

In the boom of health and wellness services, several systems have been proposed to collect and analyse sensory data for human health and well-being. For research purposes, we categorised these structures into three groups: (i) Mobile Health, where the development of smartphones and their embedded sensors is the subject of implementation; (ii) Wearable Fitness, where wristbands and watches are used in conjunction with smartphones; and (iii) Data Acquisition, where the implementation aims to collect and analyse data from sensors. The following paragraphs elaborate on the different categories.

5.2.1 Mobile Health

The use of smartphones in our daily lives has increased dramatically in the last decade. These smartphones are equipped with a variety of multimodal sensors, such as accelerometers, PPGs, and GPS, which, when used intelligently, can collect real-time activity data from the user for later use. Consequently, the convergence of smartphone devices and online services offers healthcare systems more potential for growth at a lower cost. New criteria and trends, researchers say, are embedded in mobile platforms [179]. In [180], the authors showed the potential of smart devices with a Web service-oriented approach to health service delivery. In addition, mobile phones are now helping in the provision of health services among the elderly [181]. In [182], the authors propose a mobile phone-based portal for mental health research that collects the user's psychological, physiological, and activity data. In [183], they provided a mobile version of a data processing toolbox originally developed for computational architectures and mainly used for human behavior modelling. The [184] proposed a middleware that integrates multiple interfaces for monitoring multi-parameter physiological measurements.

In [185], the authors introduced UbiqLog, a lightweight lifelogging platform. It provided a customizable interface to enable and disable mobile sensors. While more sensors can be added due to the framework's data model compatibility, the sensors need to be integrated into the smartphone device form factor. UbiqLog's lifelog was not shareable or reusable by other systems and did not allow for data tracking. Similarly, in [186] AWARE, the authors presented an open-source toolkit for collecting sensory data via smartphones. AWARE stored all collected data locally on the smartphone when conducting smaller studies; however, when conducting larger studies, the data were uploaded to the cloud. The toolkit included a context plugin that could analyse the accumulated data in the background.

In [187], the DigMem framework was proposed to create rich and interactive HDMs by combining distributed mobile networks, linked data, and machine learning (Human Digital Memory). An HDM generated a complex and data-rich memory when data from ubiquitous devices in the user's environment were used to build it. It was possible to determine details such as how the user felt, where they were, and the context of the environment. It needed a compatible environment to transmit and search information, although it collected data from a variety of sources.

5.2.2 Wearable Health

Wearables have transformed from a medical necessity to an individual accessory in the last decade. Physiological data are collected using galvanic skin resistance, a biaxial accelerometer, heat flow, and body temperature in projects such as SenseWare(SWA). In [188], the authors used SWA compared with healthy adults to estimate energy expenditure and step counts in individuals with fibrosis disease. In [189], the SWA was also used to monitor adherence in women with rheumatoid arthritis. Microsoft's SenseCam [190] was considered a revolutionary pervasive device [191]. It has been used in several studies, for example in [192], the authors used the technology to record daily routines. The images were mapped as a lifelog and presented in a timeline format. In [193], the SenseCam was used to monitor sedentary activity. However, the primary goal of these applications was to capture and monitor activity data.

In [194], InSense scheme was presented by the author to perform real-time context recognition using accelerometer, audio and visual sensing. It collected real-time data from a larger collection of data sources for a context-rich lifelog. Users manually explained and evaluated the data after it was obtained to create an interest operator. This was an offline process that was very time consuming for a consumer who had reported an event for a few hours. Moreover, the lifelog became richer with the declaration, but users could not perform real-time monitoring.

The use of multimodal sensor-based technology has evolved in recent years into customised smartphone-based accessories. The wearable wrist sensor stores and transmits sensory data to a health management system via the smartphone. However, because these devices are focused on a single source of data, such as a wristband sensor, they are unable to infer the proper background of what a consumer is doing. Despite extensive research and development of wellness and health applications, there are few implementations that function as autonomous platforms for dealing with complicated and practical scenarios. Commercial applications such as Apple's HealthKit, Microsoft Health, and Google Fit have transformed the strategy from an application to an ecosystem, but these applications are mostly based on a single device or data integration.

5.3 Wellness Management Platforms

Today's healthcare focuses on prevention rather than cure. To support this theory, healthcare and its support services are undergoing significant changes from their previous implementations [12]. These changes are having a significant impact on the nature of traditional healthcare delivery models. Rather than a late cure for disease, these models are converging toward preventive, personalised healthcare [131, 168]. Moreover, the inability of health systems to cope with unprecedented financial stress at the same time that demand for their services is increasing contributes to this convergence [169]. Recent studies have confirmed that the most common diseases are exacerbated or partially caused by poor lifestyle choices people make in their daily lives. Unhealthy and fast food diets, cigarette consumption, and sedentary lifestyles with little exercise are not only risk factors for disease, but also reduce the effectiveness of medical treatments [170, 171]. As a result, the philosophy of wellness has come to the forefront, prompting researchers to develop wellness models and test their effectiveness.

Productivity in health and wellness today is measured by timeliness and ubiquity as well as knowledge, help, and power [173]. Information and communication technology has collaborated

Table 5.1: Summary of most utilized wellness platforms

Sr.#	Application	Data sources	Domain	Support	Recommendations
1	Google Fit	Sensory, IoT	Wellness	Running, Walking, Cycling, Goal-based weight-loss	Generic & Expert-based
2	Samsung Healthkit	Sensory, User Profile, IoT	Wellness	Running, Nutrition, Indoor & Outdoor activities, Sleep	Personalized
3	Apple Healthkit	Sensory, User Profile, IoT	Wellness & Healthcare	Running, Walking, Nutrition, Exercises, Indoor & Outdoor activities, Sleep, Water intake, Meditation	Personalized & Expert-based
4	Noom Coach	Sensory, User Profile	Wellness	Step counting	Personalized & Expert-based
5	MyFitnessPal	Nutrition and Food Database	Wellness & Healthcare	Calories Intake, Nutrition	Personalized & Goal-based

with biomedical researchers to develop innovative health and wellness solutions. The care industry has recently shown an unusual interest in developing targeted implementations based on individual and community health. As a result, the influx of wearable and mobile technology in the market has grown exponentially [174]. These devices and systems are specifically designed to provide wellness services for overall health management. Moreover, these services complement users' daily routines in the form of exercise and nutritional guidance with personalization as a gateway to chronic disease management [195]. With cutting-edge technology as wearables, researchers have evaluated these devices to alert in case of a physical condition [175], detect chronic diseases [176] and even contact emergency services for assistance.

Traditional healthcare services are evolving alongside wellness, augmented by information technology and connectivity. Intelligent decision-making is being used in modern healthcare systems to supplement physician prognosis. Currently, there is a shortage of about seven million physicians and paramedical professionals worldwide. In terms of health assistants, diagnoses and recommendations for treatment plans, this growing gap can be filled with advanced AI technology to address current and potential challenges. This work aims to examine existing advanced health and wellness platforms and their key offerings and supporting technologies. It also compares the selected implementations to identify their vulnerabilities and potential research areas. We also discussed our contribution to the open source healthcare and wellness program, the Mining Minds platform.

5.4 Mining Minds

This is an innovative health and wellbeing network with a layered architecture as seen in Figure 5.1. Each layer deals with the abstraction of raw sensory data coming from a variety of sources. From top to bottom, Service Curation Layer (SCL) is responsible for curating recommendation-driven services based on user activities and nutrition-related scenarios. Knowledge Curation Layer (KCL) is responsible for curating data- and expert-driven information, which is then extracted and used as rules to track user lives and generate recommendations. The Information Curation Layer (ICL) is responsible for determining the user's meaning based on the raw sensory data. The defined context is then divided into two categories: High-Level and Low-Level Context. The Data Curation Layer (DCL) is the foundation of the platform and is responsible for both real-time data acquisition and non-volatile data persistence. In addition, DCL continuously monitors the user background defined by ICL based on the rules provided by KCL to identify situations where a user may require assistance in the form of recommendations from SCL. To provide cross-platform, usage-based support, the Supporting Layer (SL) is defined to include concepts such as distributed security and privacy, user interface and user experience (UI /UX), visualisation, and analytics. Additional technical information about these layers can be found here and their services are described in [131].

The latest implementation of the Mining Minds platform supports service scenarios based on operations and nutrition. It also integrates a philosophy of consumer education and health awareness into its offerings, such as providing workout guides with digital content for its customers. The current implementation integrates three data sources, i.e. smartwatch, smartphone and a Kinect-based depth camera. The sensors used by these data sources with their respective context are listed in Table 5.2.

Mining Minds components are built according to the software engineering principles of reusability and extensibility to help and contribute to the open source community. To support library and service reusability, each part is designed with two interfaces. Because of its reusability, the Mining Minds platform can be reused not only at the platform level, but also at a finer level of layers and individual components. DCL, for example, is intended to be a standalone application. By using DCL's raw sensory data collection, health and wellness platforms that are user-specific can support a wider variety of multimodal sensory devices. It will be easier for these systems to connect to a range of multimodal sensory data sources that report to a specific user. As a result, these platforms will be able to operate in an IoT-based health and wellness environment. DCL can also curate the raw sensory data as a user's lifelog with continuous monitoring capabilities to detect irregularities that require automated assistance or support from the health and wellness network. KCL, like DCL, is intended as a stand-alone information-gathering tool that can be used to extract expert-driven knowledge through an authoring interface. This expert knowledge has been formalised so that it can be shared across a variety of health and wellness channels. Another important concept promoting open source is the extensibility of the platform by design. Bioinformatics researchers who want to extend the functionality of their current implementation need the components of the platform to be extensible and development friendly. For this reason, industry-proven object-oriented design patterns are used in the implementation of Mining Minds. For example, ICL's low-level context awareness component uses the Strategy pattern to identify different types of context. This architecture allows bioinformaticians to extend the current implementation with additional and customised algorithms to support a broader range of activities based on their service scenarios. The organic growth of any open source platform depends on the reliability of the source code. Mining Minds 2.5 has been evaluated and tested on many levels using software engineering techniques to support this. Black-box and white-box testing methods as well as unit and integration testing are used in all developed components. In addition, the implementation includes exception management to enable graceful recovery in the event of a malfunction. A group of 20 researchers from various fields of computer science, fitness and wellness are working on the Mining Minds network. Following research and software industry standards, the iterative approach to the open source release of this framework is strictly followed. This process is illustrated in Figure 5.2.

The Mining Minds platform consists of 15 components that are loosely coupled but highly coherent. Each component is designed to run as an independent library or service. Components are built under the supervision of a team leader and a build engineer, and are regularly reviewed by experts to ensure high quality source code. A two-stage process was used to develop the platform. In the first stage, the two team build engineers compile layered builds and create a local build with the help of a native-to-local build engineer. The local build is supported by continuous integration

Table 5.2: Data sources and sensors utilized in mining minds.

Data sources	Sensors	Context
Smartphone	Accelerometer, Gyrodscope	Activity(running, walking, climbing, cycling)
Smartwatch	Accelerometer, Gyroscope, GPS	Location(home, office, gym, school, restaurant) Emotion(anger, sadness, happiness)
Depth Camera	Video	Activity(eating, sitting, standing, stretching, sweeping, lying down)

of layers and materials. In the second phase, the local build is replicated via a publicly available open source repository, in our case GitHub. This is a routine phase that occurs when a new platform is built or a major release is marked for researchers and developers. In addition to continuous integration, this two-step construction process supports the platform's large heterogeneous code base Mining Minds. It also helps the Mining Minds research team create a pre-configured virtual test machine for the open source community, saving time on repetitive deployment settings and configurations.

On December 30, 2016, version 2.5 of the Mining Minds platform was released on GitHub under the Apache 2.0 licence. Although the release is still at an early stage, the team has managed to complete 194 successful commits.

5.5 Methodology

The three main phases of our proposed approach are behavioral observation, behavioral assessment, and adaptive approaches. Sedentary, active, and sleeping behaviors can all be categorised as part of daily life. Sleep behaviors are overly influenced by the frequency and intensity of active and sedentary behaviors. It is important to maintain a healthy balance of physical activity throughout life, with adequate breaks from sedentary activities. Similarly, frequent breaks must be taken from sedentary activities to avoid prolonged sitting and lying down.

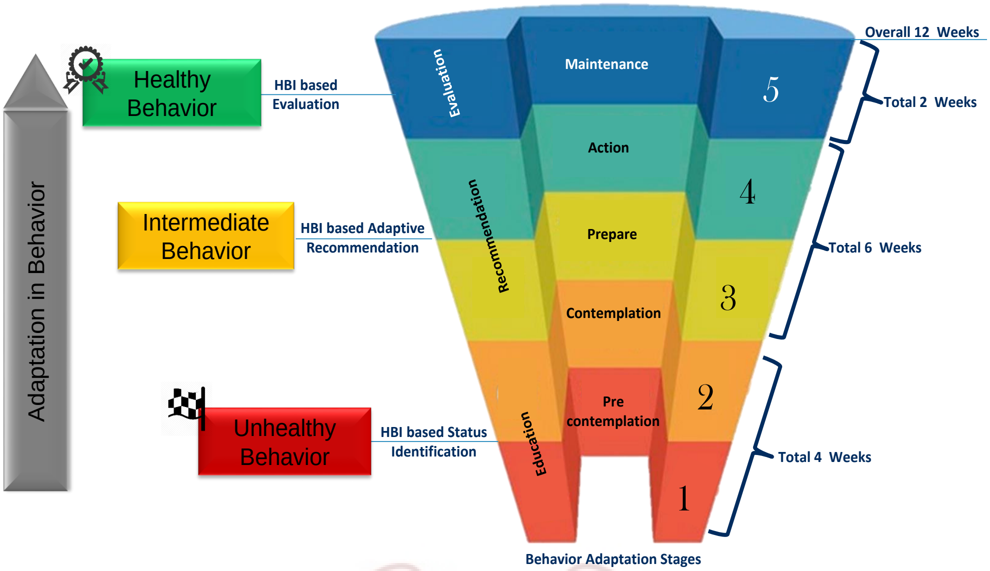


Figure 5.1: Stage wise intervention for adaptation of behavior.

Based on healthcare guidelines, sedentary and active activities can be further characterized into safe and unhealthy activities. These lifestyle activities are associated with physical activity level, activity style, dietary habits and routines, type of nutrients, smoking dependence, and alcohol consumption. Changing these lifestyle behaviors requires an understanding of the actions, identification of the unhealthy habits, and finally, help to adjust the unhealthy behavior. Behavioral adjustment is a step-by-step process in which personalization of the intervention and a thorough understanding of the behavior serve as the foundation for successful efforts.

The process of behavioral adaptation occurs in three steps There are three steps to the behavior adaptation process. During the first process, habits are observed and regular education about unhealthy activity is provided. Most of the education focuses on the negative effects of the unhealthy actions and how to prevent them. In the intermediate process, the consumer is guided step-by-step on how to change their dysfunctional actions to healthy ones. Personalization is done by defining unhealthy and harmful habits. The intervention is adaptive and is created based on the user's current risky actions. The user receives the intervention on a regular basis to change their dysfunctional behavior. In the final process, the behavior is observed at rest to decide whether to repeat the education or recommendation phases based on satisfactory behavioral adaptation.

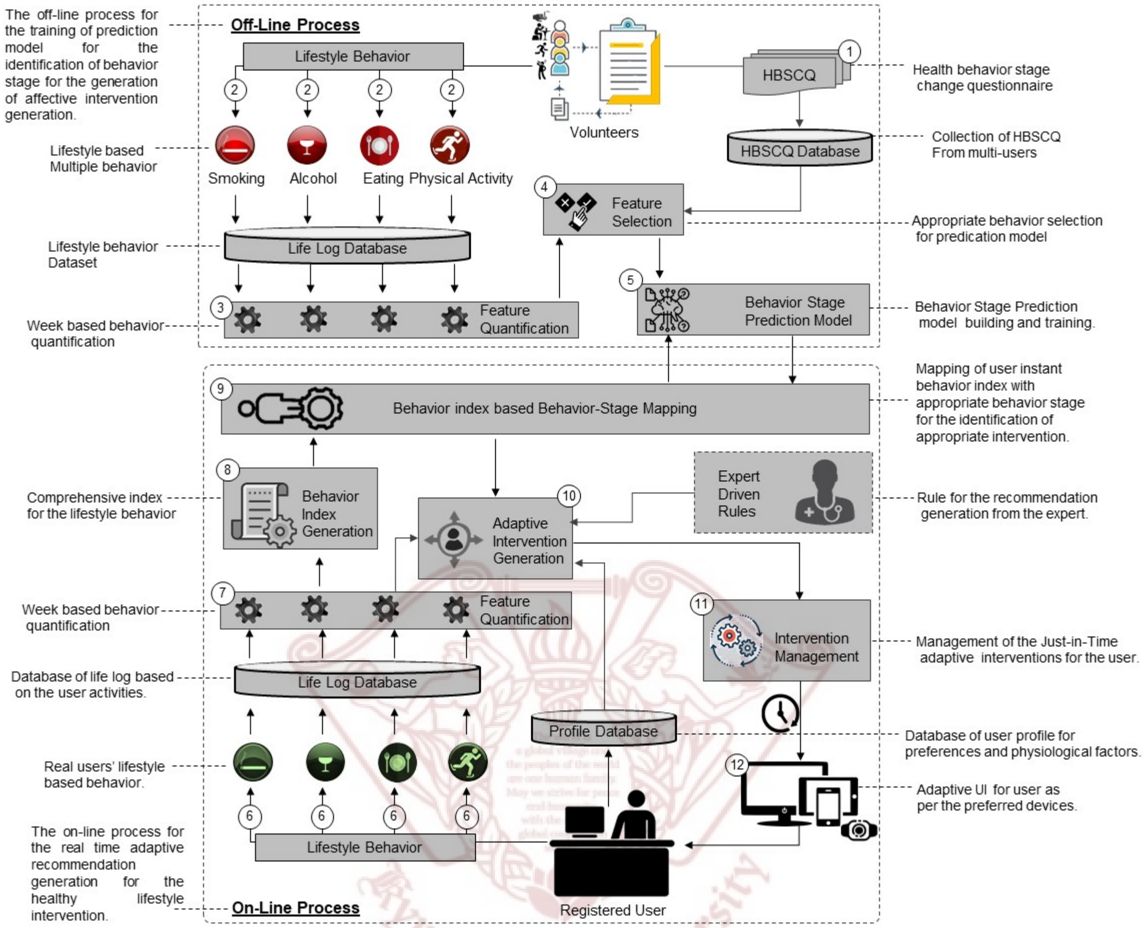


Figure 5.2: Real-life personalized intervention generation steps based on behavior stage.

The key steps of the methodology are as follows:

1. *Step 1:* It is an offline procedure where volunteers had registered their responses against HBSCQ. It is used to obtain the responses related to various lifestyle habits and behavioral stage status. These responses are generally related to 4 main areas of lifestyle habits such as physical activity, diet, smoking, and alcohol. The questionnaire consists of several questions related to the basic lifestyle habits and the level of knowledge, intention to change and current status of the behavior. The HBSCQ responses are quantified to mark the status of a user's behavior change stage.

2. *Step 2:* Users' lifestyle habits such as eating, physical activities, smoking, and alcohol were

recorded for 1 week to understand actual behaviors and to capture users' knowledge level and intention to change. It is an offline process that forms the basis of a predictive model for behavioral assessment and intervention generation.

3. *Step 3:* The log of lifestyle behaviors is quantified to clearly distinguish between multiple levels of behavior with understandable manners. Since the protocol consists of many activities over an extended period of time, the activities are accumulated on a weekly basis to quantify the behavior.

4. *Step 4:* In the feature selection steps, not all behaviors are used to train the model, but only particularly recommended and identified ones. These behaviors are identified based on criticality level. The highly ranked behaviors are selected for model training and use for behavior level assessment.

5. *Step 5:* This is the final step of the off-line process, where the behavioral stage prediction model is trained based on the selected behavior, its stages, and its relationship to the HBSCQ-based behavioral stage.

6. *Step 6:* It is an online process where lifestyle activities are logged in the lifelog of registered users. These activities are logged through the smartphone application which has a dual mode of data entry. Manual entry through a well-defined user interface for smoking, alcohol and eating, with sensor-based recording of activities.

7. *Step 7:* The log of lifestyle behaviors is quantified to clearly distinguish between multiple levels of behavior with understandable manners. Since the protocol consists of many activities over an extended period of time, the activities are accumulated on a weekly basis to quantify the behavior.

8. *Step 8:* In this step, a behavioral index is created from the registered log of lifestyle activities. The index is an accumulation of activities based on their quantification context. Some activities are accumulated on a weekly basis and some on a daily basis.

9. *Step 9:* The behavioral index is then passed to the trained behavioral stage prediction model to identify the stage so that the appropriate intervention style is selected to personalize the

intervention.

10. *Step 10:* In the process of adaptive intervention generation, the behavioral stage, behavioral status, health profile, expert knowledge, and preferences are used to adapt the general intervention to the personal one.

11. *Step 11:* The manager of the intervention is responsible for scheduling the right intervention to right person at right time.

12. *Step 12:* Finally, the adaptive interventions are provided to the user through their communicating devices that support the adaptive user interface.

5.5.1 Realization of Methodology through Wellness Management Platform-Mining Minds

Mining Minds (MM) is an open-source wellness platform that assists in obtaining data from multiple sensors, analyzing it, and generating recommendations [12], [134] . The collected data is related to detected activities, emotions, and locations, which are persisted in an intermediate database and Big Data for immediate recommendations and analysis, as shown in Figure 5.2. It consists of multiple layers to curate data, information, knowledge and services to assist the user with wellness recommendations in real time.

On-Line Process

The Supporting Layer SL interacts with users and provides analytics. Based on access permission, graphical views of lifestyle habits, activity status, and health statistics are provided to the expert and users. The Service Curation Layer (SCL) orchestrates the personalized recommendations based on demographic, contextual, emotional, preference and physiological factors. The recommendations are customizable based on the user's lifestyle status. The orchestrator in the SCL manages the communication of pull- and push-based recommendations for just-in-time interventions, as well as a diet plan based on circadian rhythms. The SCL creates and refines the recommendations using high-level context, SNS data, and expert-provided guidelines to address

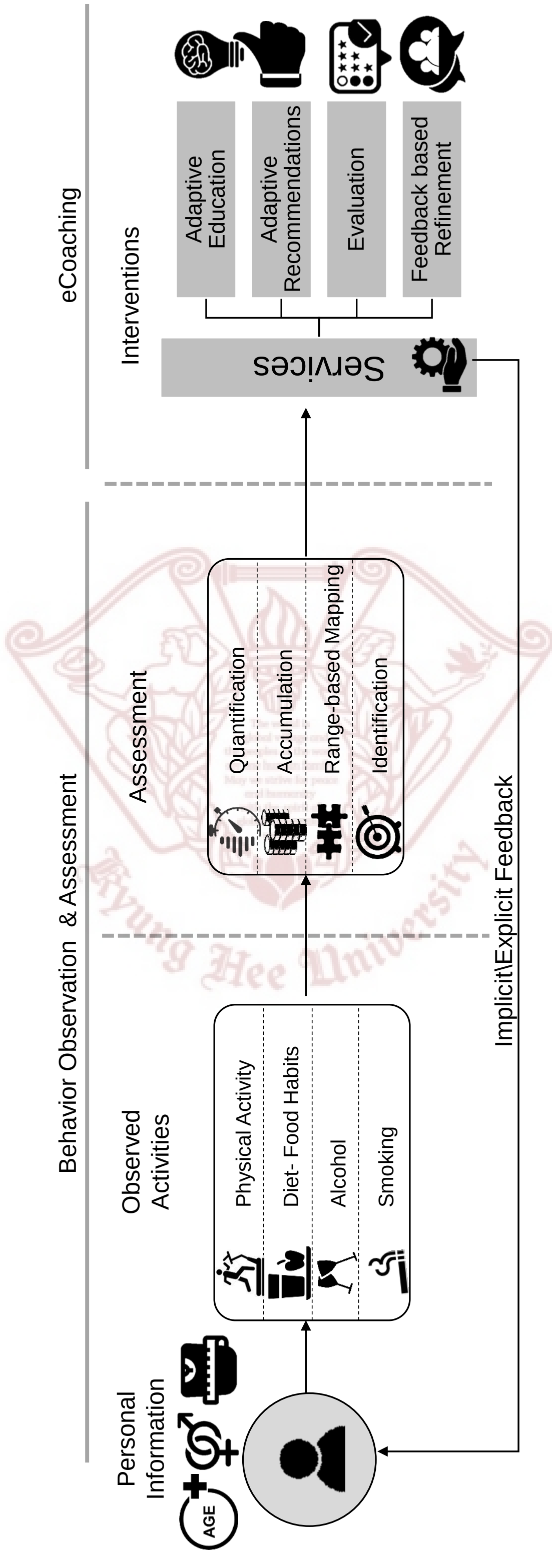


Figure 5.3: Realization of intervention generation through behavior observation and assessment.

each unhealthy habit. It also considers the amount of calories needed and calories consumed based on MET and BMI values.

Off-Line Process

The Knowledge Curation Layer (KCL) helps experts transform their experiences and wellness knowledge into rules via an authoring environment [140]. These rules guide over wellness context-based situational awareness and identification in the lifelog. Furthermore, these rules support the recommendation in a specific unhealthy situation to adapt a healthy lifestyle. The suggestions are the action plan for the targeted risky and unhealthy lifestyle habit, so instead of general recommendations, we have adaptive recommendations based on only harmful habits.

The Information Curation Layer (ICL) identifies user activities and context from multimodal sensory data managed in hierarchical models. It employs emotion, location and multiple activity recognizers. These recognizers generate the low-level context and the fusion of these contexts forms the high-level context curated in Data Curation Layer (DCL). The DCL manages the data in both raw and processed formats through data acquisition and synchronization, lifelog representation and mapping, lifelog monitoring, and Big Data storage processes [12].

The working of MM platform from the application point of view is divided into three execution modules related to education, recommendations and Q&A selection. The execution modules support real-time customization of education, recommendation, and Q&A selection.

5.5.2 Adaptive Education

Education regarding healthy behavior is an important aspect and a necessity for behavior change. There are two ways to do education: 1) Generalized education, 2) Adaptive education. Initially, the system is not able to understand the user's condition. The users's state depends on the lifelog data collected by multiple sensors in the smartwatch, smartphone and Kinect depth camera [12]. Lifelog generation is a time-consuming process, and at least a week's worth of lifelog data is required to understand the consumer's activity status. The challenge of the cold-start-based lifelog data-less condition is overcome by an initial questionnaire survey to obtain the knowledge of users' habits and behaviors.

Adaptive Education Workflow

Wellness users are registered in the application and given a unique identifier for further data processing and indexing. At the time of the educational intervention, the users' profile and lifestyle information is retrieved from the intermediate database, as shown in Figure 5.4. The lifestyle factors are examined and filtered to obtain the MET-based calorie requirement and BMI-based calorie consumption. The status of risk factors in the form of risky, moderate and normal is evaluated and available to retrieve appropriate rules from the expert driven knowledge base.

Since several factors are involved, a set of rules is available to generate the intervention. The maximum specificity technique is used to identify the rule with the highest value over the matching profile, living conditions and constraints as mentioned in Algorithm 1. It supports reasoning about the situation for which a particular intervention is generated based on the focused group of the rule. The identified risk factors based on the matched rule support the interpretation of the context. The index is generated based on the status of the factors, which helps in understanding the content. The interpreted content and context help to retrieve certain data from the knowledge base through the index generated by the content interpretation process. Finally, the adaptation of the intervention is done using risk factors, preferences, context and expert driven rules. The intervention is communicated through an adaptive, user-friendly interface and stored in the user profile for later use.

Algorithm 1: Adaptive education algorithm

Input: $UserId_i, Lifelog_i, Profile_i, KB_{Rule_i}$
`//` $i = \{1, 2, \ldots n\}$
Output: R_{Edu}
Data: *Users, Lifelog, Profile & Knowledgebase*

$UId_i \leftarrow UserId_i$ `//` $UId_i = \{u_1, u_2, \ldots u_n\}$
$X_i \leftarrow Lifelog_i$ `//` $X_i = \{x_1, x_2, \ldots x_n\}$
$Y_i \leftarrow Profile_i$ `//` $Y_i = \{y_1, y_2, \ldots y_n\}$
$R_i \leftarrow KB_{Rule_i}$ `//` $R_i = \{r_1, r_2, \ldots r_n\}$
$R_i \leftarrow RulewithMaxSpecificity\,(UId_i, X_i, Y_i)$
for $j \leftarrow 1$ *to length* (X_i) **do**
  $x_{j_{Status}} \leftarrow QuantifyLifelogFactor\,(x_j)$ `// 1=Risky, 3= Moderate, 5=Healthy`
  if $(x_{j_{Status}} == 1)$ **then**
    $Focused_{Group} \leftarrow Concatenate\,(Focused_{Group}, x_{j_{Status}})$
  end
  else
    Ignore $x_{j_{Status}}$ `// Do not consider normal factors`
  end
end
for $j \leftarrow 1$ *to length* (X_i) **do**
  $x_{j_{Status}} \leftarrow QuantifyLifelogFactor\,(x_j)$
  $Factor_{index} \leftarrow Factor_{index} + x_{j_{Status}}$
end
`/* Refinement of the education matiral as per user context */`
if $Factor_{index} == Recouse_{index}$ **then**
  $Edu_{content} \leftarrow ContentOnIndex(Factor_{index})$ `// this is another comment`
  $R_{Edu} \leftarrow AdaptableEducation(Edu_{content}, Focused_{Group}, Y_i)$
end
else if $Factor_{index} \neq Recouse_{index}$ **then**
  int $n \leftarrow Factor_{index}.length()$
  while $(SubString(Factor_{index}, n)! = SubString(Recouse_{index}, n))$ **do**
    $n \leftarrow n - 1$
  end
  $Edu_{content} \leftarrow ContentOnIndex(subString\,(Factor_{index}, n))$ `// this is another comment`
  $R_{Edu} \leftarrow AdaptableEducation(Edu_{content}, Focused_{Group}, Y_i)$
end

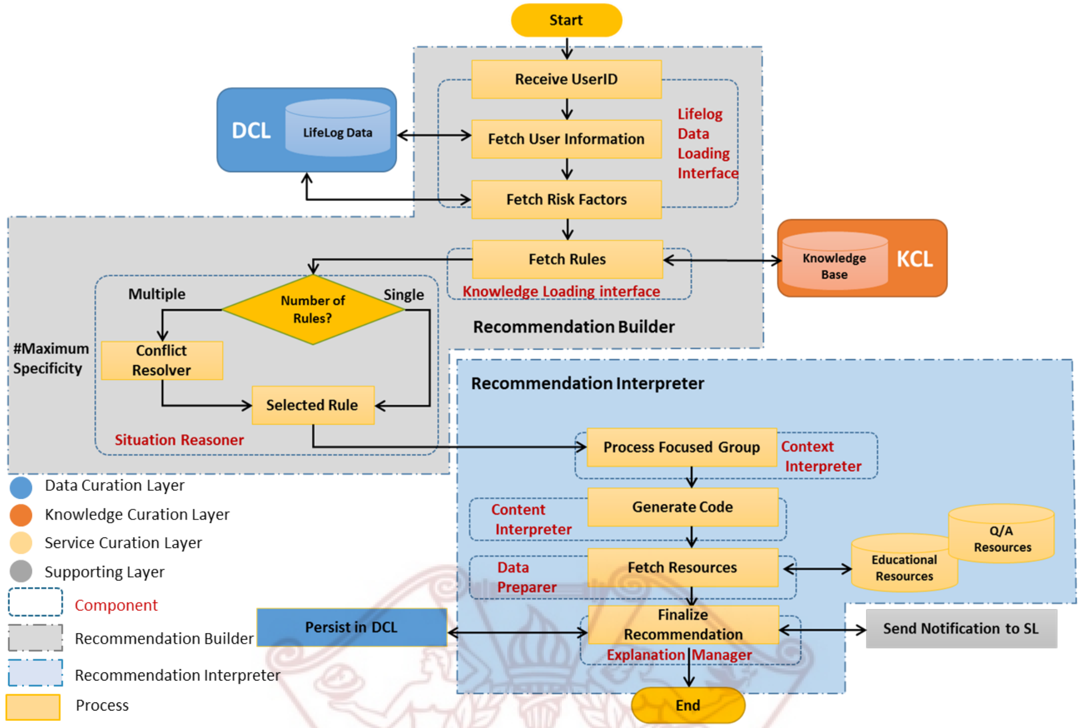


Figure 5.4: Workflow of Adaptive Education and Q&A Selection.

5.5.3 Adaptive Recommendations

The adaptive just-in-time recommendations regarding unhealthy behavior are an important aspect and a necessity for adaptation in behavior. Behavior change is an ongoing process in which the just-in-time recommendations play an important role. The general recommendations affect the human behavior for a few days, but the adaptive recommendations maintain the interest of the customer until it matches with the condition and situation of the customer, with the appropriate tracking capability as shown in Figure 5.5. Recommendation generation is based on the user's lifelog, preferences, environmental context, calorie consumption, calorie requirement, and disease status [133]. The driving information for recommendation generation is obtained from the expert in the form of rules that consider the multiple state of the contributing factors to build a situation for recommendation.

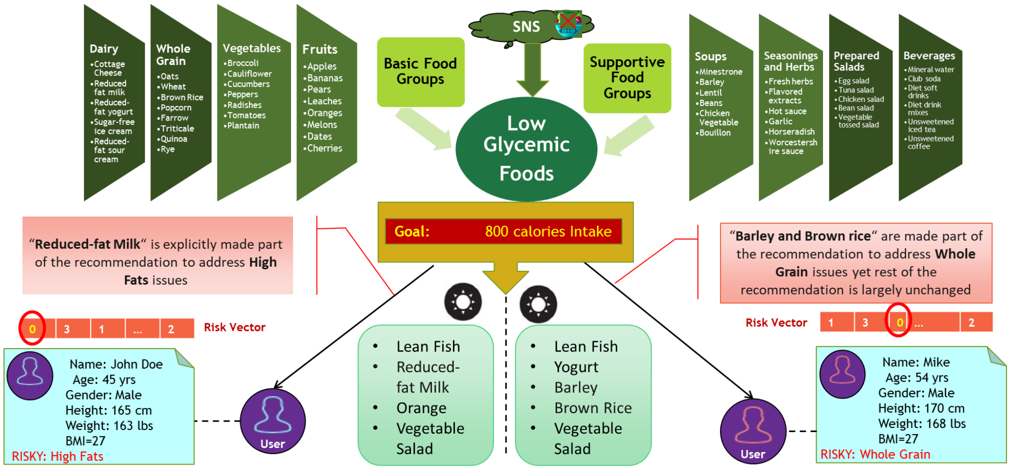


Figure 5.5: Adaptive Recommendation for diet.

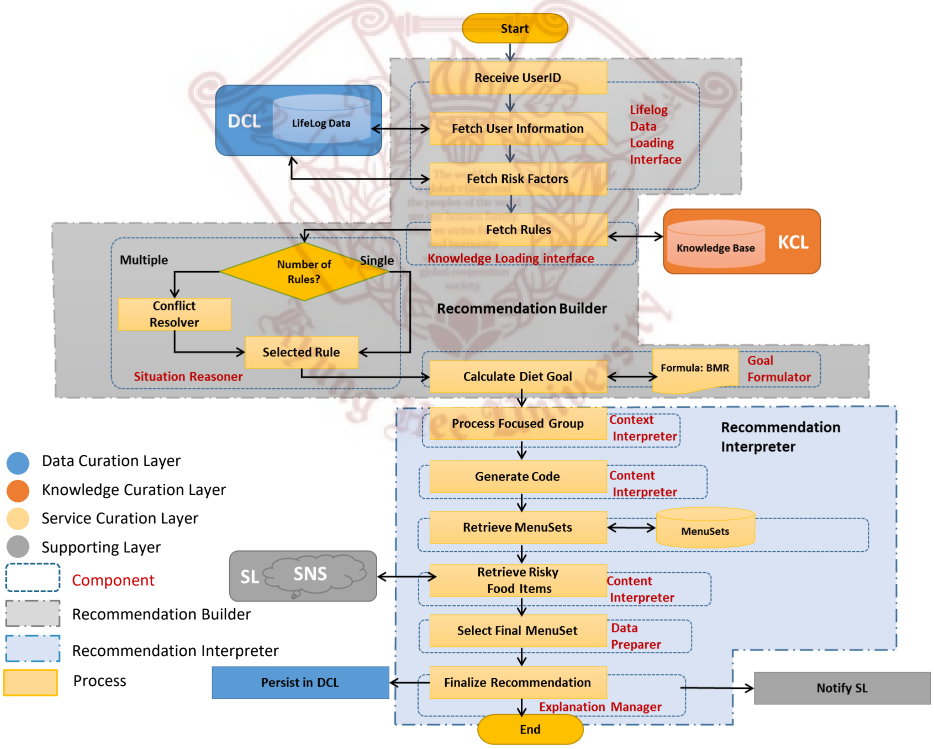


Figure 5.6: Work flow of Adaptation Recommendation for diet.

Adaptive Recommendation Workflow

Wellness users are registered in the application and given a unique identifier for further data processing and indexing. At the time of referral, the users' profile and lifestyle information is retrieved

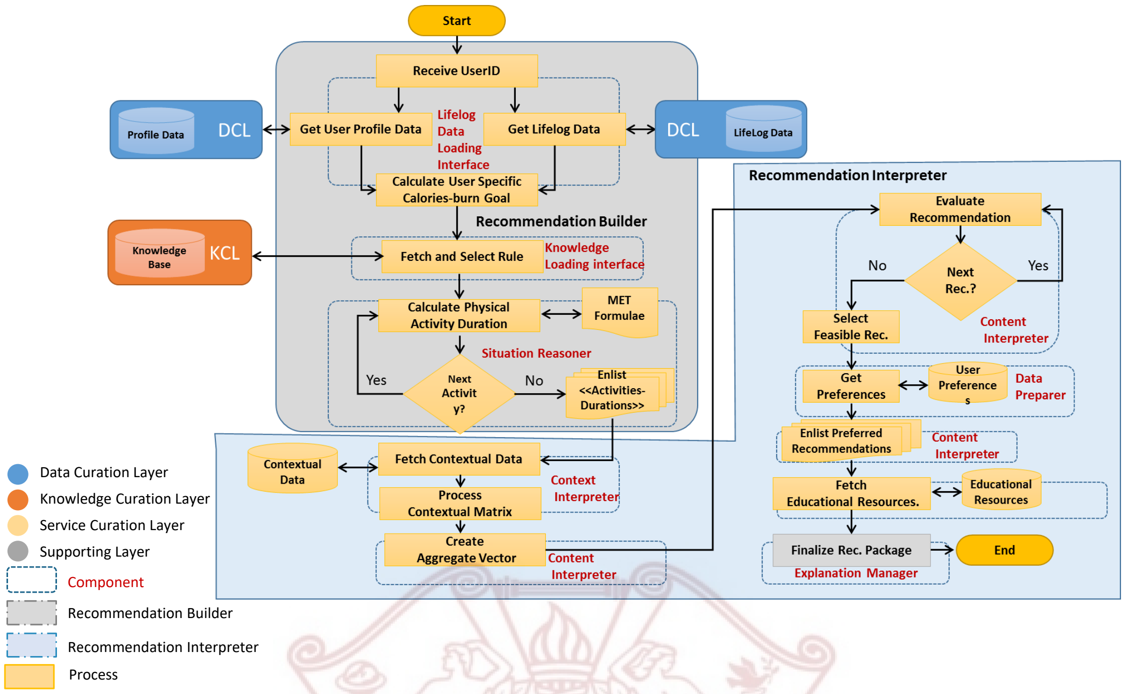


Figure 5.7: Work flow of Adaptive Recommendation for Physical Exercise.

from the intermediate database. The lifestyle factors are examined and filtered to obtain the MET-based calorie requirement and BMI-based calorie consumption. The status of risk factors in the form of risky, moderate and normal is evaluated and used to obtain adjustment rules from the expert driven knowledge base.

1. Diet Recommendation

   Diet is a complex lifestyle factor consisting of type, amount and habits of eating. The regularity of dietary habits is assessed by the weekly state of the user's routine. Whereas the type and quantity of diet is assessed on the basis of daily and time intake of food. It is very important to assess the diet and routine for the appropriate interventions.

   All matching rules are loaded to identify the most appropriate one, as shown in Figure 5.6. The maximum specificity technique is used to identify the rule with the highest value with respect to the matching profile and the conditions and constraints of the dietary protocol. The daily nutritional target is calculated based on BMI, which provides the target calorie requirement based on height and weight. It supports reasoning about the situation for which a particular intervention is generated based on the nutrition focused group of the rule. The identified risky dietary factors based on the matched rule support the interpretation of the context. The index is generated based on the status of the factors that help to understand the content of the behavior. The interpreted content and context help to retrieve appointed data from the knowledge base through the index generated by the process of interpreting the nutritional content.

The generated index helps in finding the food items from the different menu sets. The refinement of the food items takes into account the high-risk and cultural current food trends obtained from recent SNS data. Finally, a menu set for the intervention is organized by calorie needs, risk factors, preferences, SNS trends, disease-friendly and expert-driven rules. The intervention is communicated through a customizable, user-friendly interface and stored in the nutrition profile for future use.

2. Physical Activity Recommendation

   Physical activities can be divided into low, moderate, and vigorous based on their MET values, as described in Table 5.1. The duration of these activities is taken into account when defining body requirements and calorie burning necessities. User information is obtained from life history and profile data. Calorie consumption during a day is measured from the MET values of the activities and their duration, as described in Table 5.3. At the time of intervention creation, a personalized specific target is calculated.

   The goal-based rules are retrieved from the expert-driven knowledge base. The rules provide the specific activities to meet the requirements of the daily goal under certain constraints and conditions, as shown in Figure 5.7. The daily goal for physical activity can be achieved by a multiple combination of activities with different durations, as mentioned in Algorithm 3. The fitted rule based on the constraints and conditions is finalized for calculating the duration. The MET values of the activities are used to evaluate the duration for performing a particular activity as described in Algorithm 3. A few activities require a specific context for their execution. The context is based on the location, time and weather.

   In the interpretation process, the feasibility of the activities is assessed to finalize the phys-

Algorithm 2: Adaptive diet recommendation algorithm

Input: $UserId_i, Lifelog_i, Profile_i, KB_{Rule_i}$

// $i = \{1, 2, \ldots n\}$

Output: R_{Food}

Data: *Users, Lifelog, Profile & Knowledgebase*

$UId_i \leftarrow UserId_i$ // $UId_i = \{u_1, u_2, \ldots u_n\}$

$X_i \leftarrow Lifelog_i$ // $X_i = \{x_1, x_2, \ldots x_n\}$

$Y_i \leftarrow Profile_i$ // $Y_i = \{y_1, y_2, \ldots y_n\}$

$R_i \leftarrow KB_{Rule_i}$ // $R_i = \{r_1, r_2, \ldots r_n\}$

$R_i \leftarrow RulewithMaxSpecificity\,(UId_i, X_i, Y_i)$

$Behavior_{Status}enum \leftarrow \{Risky, Moderate, Healthy\}B_s$

$BMR_{men\|women} 10\times$ weight (kg) $+ 6.25\times$ height (cm) $- 5\times$ age (y) $+ [5\| - 161]$

for $j \leftarrow 1$ *to length* (X_i) **do**

  $x_{j_{Status}} \leftarrow QuantifyNutritionFactor\,(x_j)$

  // 1=Risky, 3= Moderate, 5=Healthy

  if $(x_{j_{Status}} == 1)$ **then**

    $Focused_{Group} \leftarrow Concatenate\,(Focused_{Group}, x_{j_{Status}})$

  end

  else

    $Ignore\ \ x_{j_{Status}}$ // Do not consider normal factors

  end

end

for $j \leftarrow 1$ *to length* (X_i) **do**

  $x_{j_{Status}} \leftarrow QuantifyFoodFactor\,(x_j)$

  $Factor_{index} \leftarrow Factor_{index} + x_{j_{Status}}$

end

/* Refinement of the education matiral as per user context */

$Calories_{Target} \leftarrow \{BMR_{Men|Women} \times Behavior_{PhysicalActivities}\} - \sum_{Cal=1}^{m}$

$int\ \ n \leftarrow Factor_{index}.length()$

while $(SubString(Factor_{index}, n)! = SubString(Recouse_{index}, n))$ **do**

  $n \leftarrow n - 1$

end

$Food_{Menu} \leftarrow FoodMenuOnIndex(subString\,(Factor_{index}, n))$ // this is another comment

$SNS_{Food} \leftarrow SNSBasedFood\,(CurrentTimeStamp)$

$Food_{Menu} := SNS_{Food} \bigcap Food_{Menu}$

$R_{Food} \leftarrow AdaptableNutrition(Food_{Menu}, Focused_{Group}, Y_i, Calories_{Target})$

Table 5.3: Activities with MET values

Sr.#	Activity Name	MET Value
1	Sitting	1.5
2	Standing	3.0
3	Walking	3.5
4	Cycling	6.0
5	Jogging	8.0
6	Running	8.0
7	Dancing	7.0
8	Stretching	2.3
9	Eating	1.5
10	Sleeping	0.9

ical activity intervention. The user preference regarding the physical activity is very important to transform the intervention into an implementable one. Therefore, the activities are filtered based on the user preferences, and then the training material related to these activities is retrieved from the knowledge base. Finally, a complete set of activities along with duration and educational material is communicated as a physical activity intervention. The communication is done through a customizable, user-friendly interface and is logged in the activity profile for performance and feedback analysis.

Algorithm 3: Adaptive physical activity recommendation algorithm

Input: $UserId_i, Lifelog_i, Profile_i, KB_{Rule_i}$

// $i = \{1, 2, \ldots n\}$

Output: R_{PA}

Data: *Users, Lifelog, Profile & Knowledgebase*

$UId_i \leftarrow UserId_i$ // $UId_i = \{u_1, u_2, \ldots u_n\}$

$X_i \leftarrow Lifelog_i$ // $X_i = \{x_1, x_2, \ldots x_n\}$

$Y_i \leftarrow Profile_i$ // $Y_i = \{y_1, y_2, \ldots y_n\}$

= $f_{Cal} := \dfrac{MET_{PA} \times 3.5 \times Weight\,(kg)}{200}$

$Cal_{burned} \leftarrow \sum_{i=1}^{m} t_i \times f_{Cal}\,(MET_{PA_i}, Weight)$

$Cal_{Target} \leftarrow Cal_{Recommended} - Cal_{burned}$

$R_i \leftarrow RulewithMaxSpecificity\,(UId_i, X_i, Y_i)$

for $j \leftarrow 1$ *to length* (R_i) **do**

  $R_i[j] = \dfrac{Cal_{Target}}{f_{Cal}\left(MET_{PA_{R_i}}, Weight\right)}$

end

$ContxtFiltered_{PA} \leftarrow GetContextBasedFilteredPA\,(R_i, CurrentTimeStamp)$

$Feasible_{PA} \leftarrow GetFeasiblePA\,(ContxtFiltered_{PA})$

$R_{PA} := Feasible_{PA} \bigcap PreferredPA\,(Y_i)$

$PA_{Edu} \leftarrow PAContects\,(R_{PA})$

$FinalRec_{PA} \leftarrow PhysicalActivity(R_{PA}, Cal_{Target}, PA_{Edu})$

5.5.4 Adaptive Q&A Selection

An appealing and challenging aspect of behavior management applications is keeping customers interested. Redundancy and irrelevance of information to users are the key issues. To overcome this challenge, the framework must understand the situation and consider the personalization of the customer. Questionnaires are an important way to get the personal details and preferences [134]. The problem is asking the same questions every time to extract the information. Therefore, in

Algorithm 4: Adaptive Q&A selection algorithm

Input: $UserId_i, Lifelog_i, Profile_i, KB_{Rule_i}$
`//` $i = \{1, 2, \ldots n\}$
Output: R_{Que}
Data: *Users, Lifelog, Profile & Knowledgebase*

$UId_i \leftarrow UserId_i$ `//` $UId_i = \{u_1, u_2, \ldots u_n\}$
$X_i \leftarrow Lifelog_i$ `//` $X_i = \{x_1, x_2, \ldots x_n\}$
$Y_i \leftarrow Profile_i$ `//` $Y_i = \{y_1, y_2, \ldots y_n\}$
$R_i \leftarrow KB_{Rule_i}$ `//` $R_i = \{r_1, r_2, \ldots r_n\}$
$R_i \leftarrow RulewithMaxSpecificity\,(UId_i, X_i, Y_i)$
for $j \leftarrow 1$ *to length* (X_i) **do**
    $x_{j_{Status}} \leftarrow QuantifyLifelogFactor\,(x_j)$ `// 1=Risky, 3= Moderate, 5=Healthy`
    if $(x_{j_{Status}} == 1)$ **then**
        $Focused_{Group} \leftarrow Concatenate\,(Focused_{Group}, x_{j_{Status}})$
    end
    else
        $Ignore\ x_{j_{Status}}$ `// Do not consider normal factors`
    end
end
for $j \leftarrow 1$ *to length* (X_i) **do**
    $x_{j_{Status}} \leftarrow QuantifyLifelogFactor\,(x_j)$
    $Factor_{index} \leftarrow Factor_{index} + x_{j_{Status}}$
end
`/* Refinement of the education matiral as per user context */`
int $n \leftarrow Factor_{index}.length()$
while $(SubString(Factor_{index}, n)! = SubString(Recouse_{index}, n))$ **do**
    $n \leftarrow n - 1$
end
$Que_{content} \leftarrow QuestionOnIndex(subString\,(Factor_{index}, n))$ `// this is another comment`
$R_{Que} \leftarrow AdaptableQuestion(Que_{content}, Focused_{Group}, Y_i)$

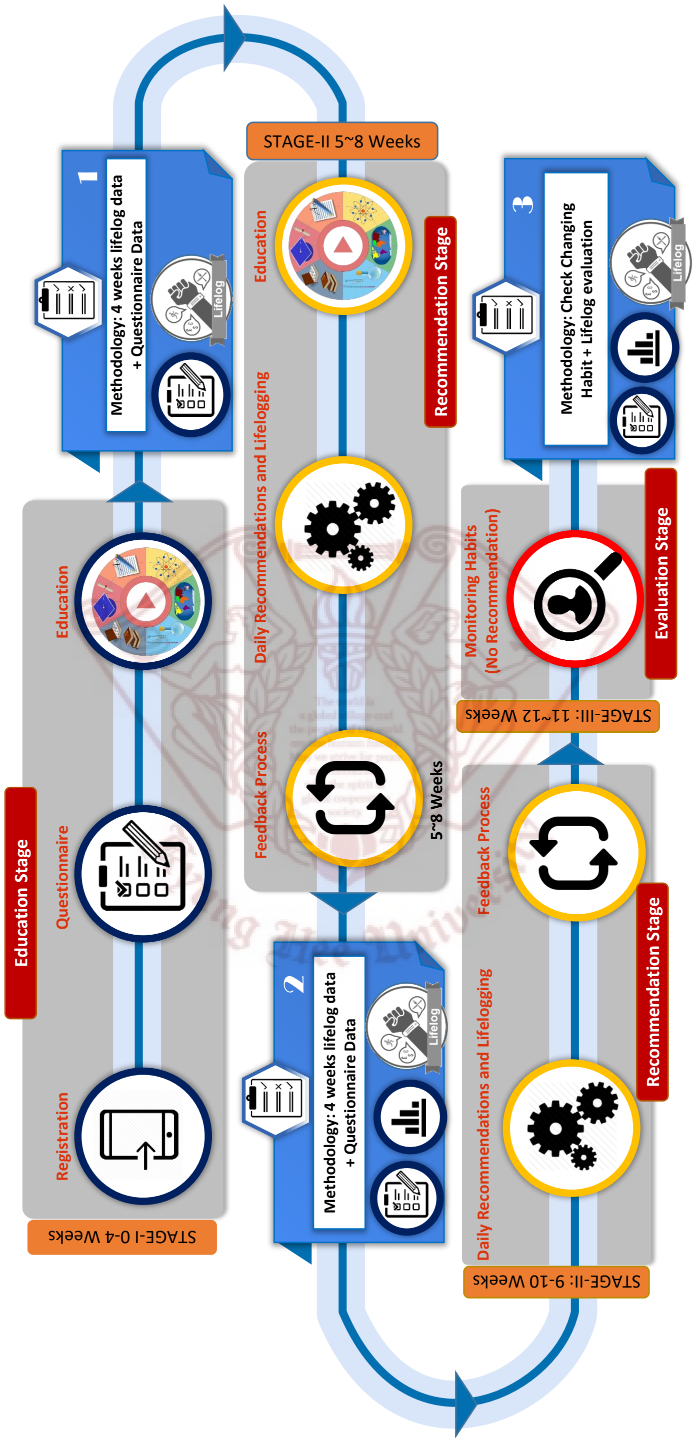


Figure 5.8: Multi-phases adaptive intervention management life cycle.

behavioral adaptation, it is very important that questionnaires are adaptive with respect to user conditions. That is, if a certain behavior corresponds to the recommended status, this behavior does not need to be asked.

Adaptive Q&A Selection Workflow

Wellness users are registered in the application and given a unique identifier for further data processing and indexing. At the time of explicit feedback evaluation, the users' profile and lifestyle information is retrieved from the intermediate database. The lifestyle factors are examined and filtered to get the factors with risky and alarming status. The status of the factors is defined into risky, moderate and normal based on the guidelines and expert driven rules. The factors with risky status are filtered out to target the explicit questionnaires to improve them through root cause analysis.

There are multiple factors are involved, a set of rules is available to evaluate behavior. All the matching rules are loaded to identify the most appropriate one as shown in Figure 5.4.The maximum specificity technique is used to identify the rule with the highest value over the matching profile and lifelog conditions and constraints, as described in Algorithm 4. It supports the conclusion about the behavior for which a particular score is generated based on the focused group of the rule. The identified risk factors based on the matched rule support the interpretation of the context. The index is generated based on the status of the factors, which helps in understanding the content. The interpreted content and context help in selecting appropriate questions from the knowledge base through the index generated by the content interpretation process. Finally, filtering of questions is done using risk factors, preferences, context and expert driven rules. The questionnaire is communicated through an adaptable, user-friendly interface and responses are logged in the user profile for future use.

5.6 Evaluation of methodology

We have several possible scenarios for evaluating the proposed methodology, as there are multiple attributes and multi-phase situation for that of the intervention based on the registered-duration of the user. Each user has different stages of different behaviors, so we have drawn the proposed healthy behavior index to represent the state of the user. The whole intervention period was di-

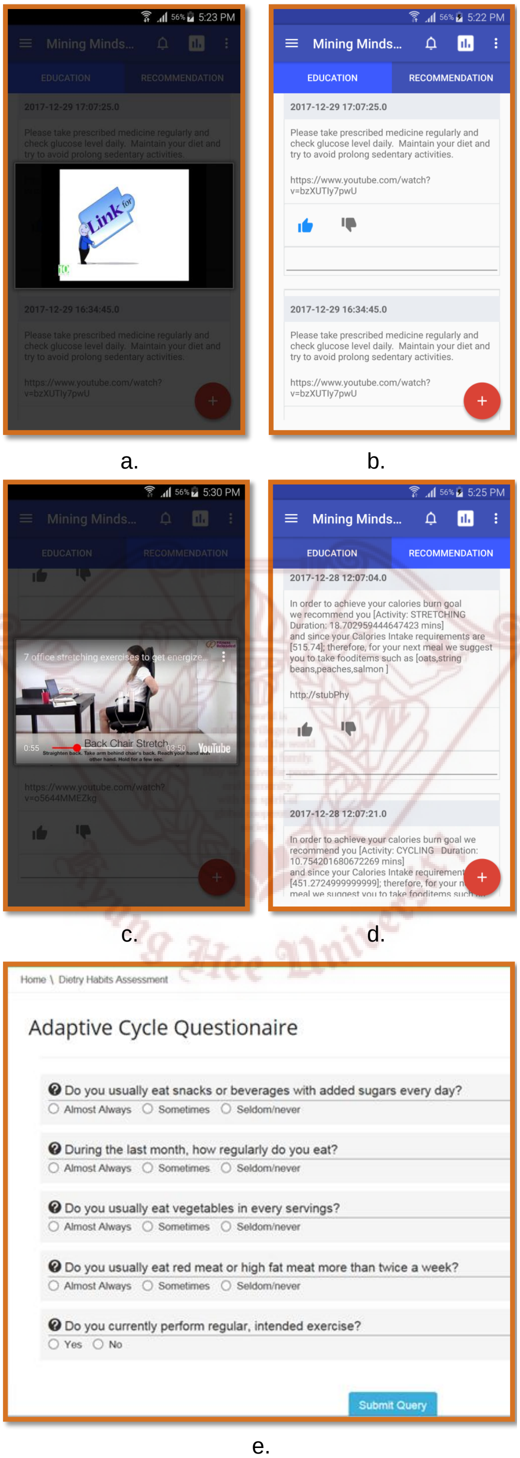


Figure 5.9: User interfaces of designed application.

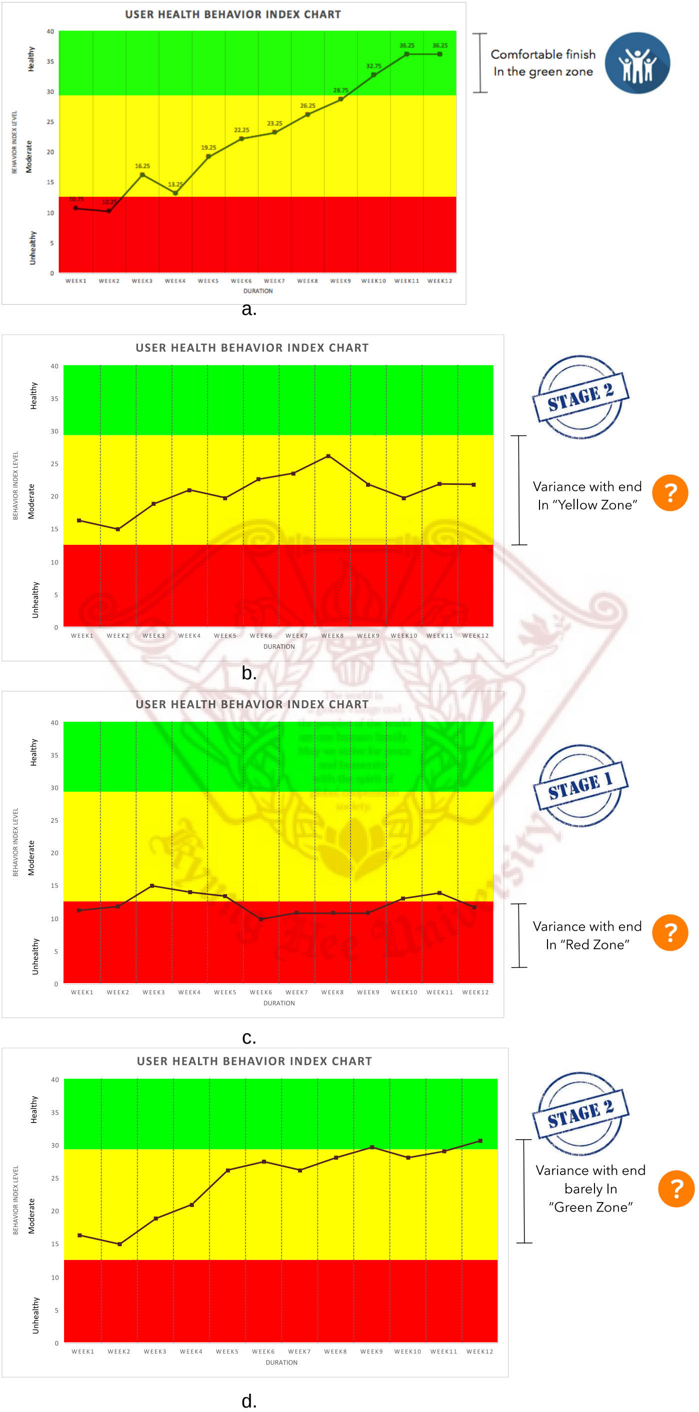


Figure 5.10: HBI results.

Table 5.4: Comparative analysis of the proposed methodology.

Reference	**Goal Oriented**	**Self Monitoring**	**Behavior Adaptation**	**Behavior Education**	**Behavior Formation & Analysis**	**Alert**	**Focus Factors**	**Behavioral Feedback**	**Recommendation & Remarks**
[196] Gonzalez-Sanchez et al.(2019)	User Based	✓	✗	✗	✗	✗	Dietary habits, Physical activity	✓	End of day Report along with full day recommendation
[197] Arrogi et al. (2019)	✗	✓	✗	✓	✗	✓	Sedentary Behavior	✓	No recommendation, visualization of prolonged sitting
[198] Brindal et al.(2019)	✗	✓	✗	✓	✗	✓	Diet & Physical Activity	✓	Feedback driven recommendation on entry data
[199] Dunn et al. (2019)	✗	✓	✗	✓	✗	✗	Dietary habits	✗	Generic podcasts for recommendation twice weekly
[200] Baskerville et al.(2018)	User Based	✓	✗	✓	✗	✗	Smoking cessation	✓	Graphical and tabular report to highlight the status of smoking
[201] Crane et al. (2018)	✗	✓	✗	✓	✗	✓	Alcohol consumption	✓	Daily progress and mission indicator
[202] Kliemann et al. (2019)	User Based	✓	✗	✓	✗	✓	Dietary habits	✓	Promote self-regulatory eating skills through goal diary
Proposed	Expert Based	✓	✓	✓	✓	✓	Diet, Physical activity, Smoking, Alcohol	✓	Personalized context based just-in-time recommendation

vided into education, recommendation and evaluation stages as shown in Figure 5.8. We obtained the information regarding lifestyle through the initial questionnaire at registration, as shown in Figure 5.9, and through the later life log. The status of the contributing factors supports the adaptation of the interventions.

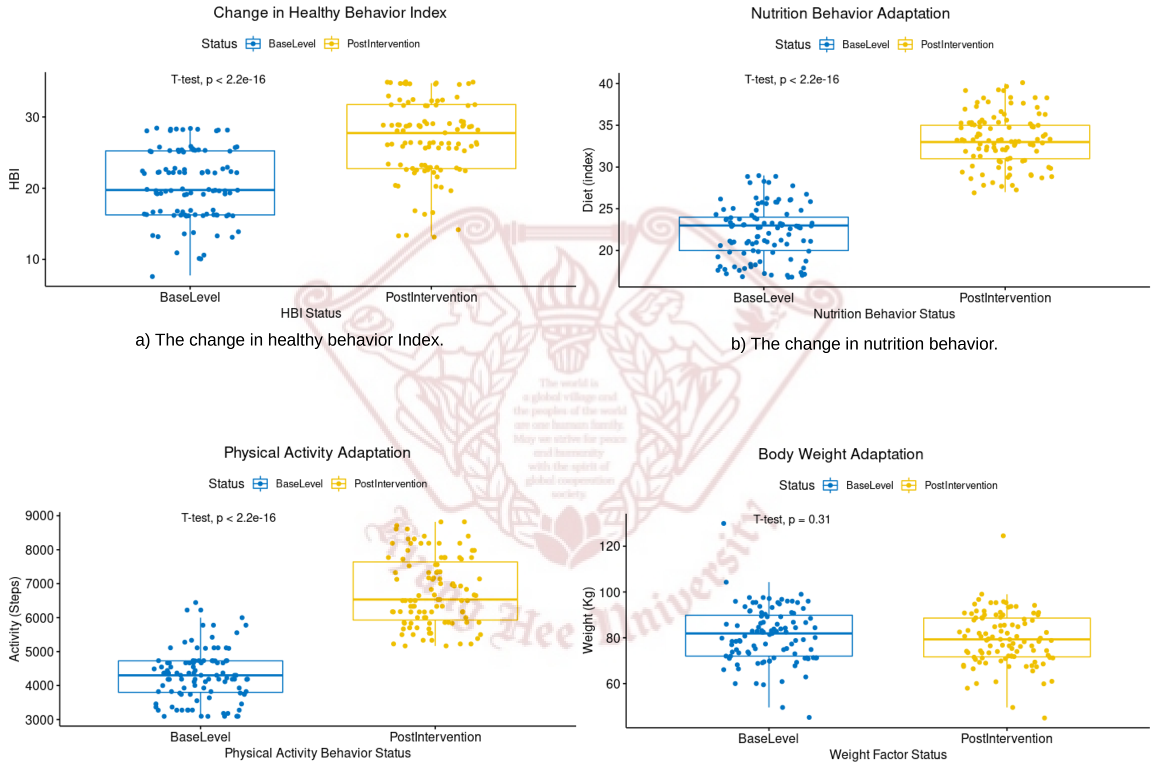
These three stages of behavior change support the slow but steady change in the person's behavioral status, as shown in Figure 5.10. In stage-I, participants have knowledge about the unhealthy behavior obtained after evaluating their lifelog and responses. The frequency of intervention is almost once a day to prepare the mind to understand the impact of these unhealthy behaviors and adopt healthy behaviors for quality living. The lifelog continuously helps to understand the change in behaviors and habits due to the educational interventions.

The adaptive questionnaire is used after every 4 weeks to analyze the causes of the unhealthy behavior and refine the interventions.In the Stage-II, participants receive comprehensive step-by-step support to adopt healthy habits based on context and personal situation. This is the training stage where participants learn the steps for physical activity not only through text messaging but also with supportive videos, as well as identify their foods to meet nutritional requirements.

Multiple wellness applications focus on various techniques to help end users for managing the fitness, but they are not sufficient to promote healthy behaviors throughout life. Several Behavior Change Techniques (BCTs) have been used in the literature to address end-users in terms of self-quantification, education, feedback, interventions, and many more, as shown in Table 5.4. The comparisons of these BCTs along with focused fitness perspectives are elaborated, which mainly lack understanding of end-users' behavioral context and treat them with the same philosophy to improve fitness. In particular, habit formation could play an essential role in digital wellbeing applications by supporting behavior change towards more effective use of technology and ensuring the long-term impact of adapted behavior.

5.6.1 Statistical Analysis of methodology evaluation

The results are evaluated statistically to highlight the effective change in behavior following the delivery of the adaptive interventions over a 12-week period based on behavioral context and preferences. The purpose of conducting this paired t-test is to determine if the values obtained



a) The change in healthy behavior Index.

b) The change in nutrition behavior.

c) The change in physical activity.

d) The change in body weight.

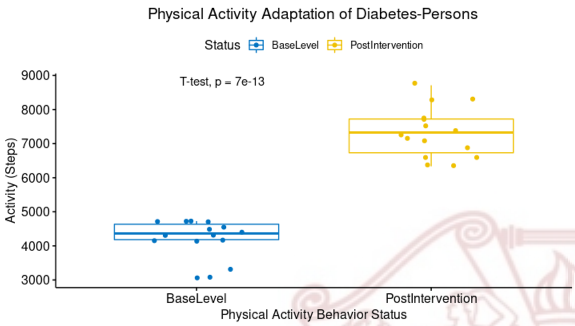
Figure 5.11: Change comparison of behavior and fitness factors.

using the proposed methodology are significantly different from the values obtained without using the methodology. The data is obtained in relation to physical activities, diet and body weight. The population (103 participants) are divided into 4 groups based on non-communicable chronic diseases such as obesity, hypertension, hyperlipidemia and diabetes.

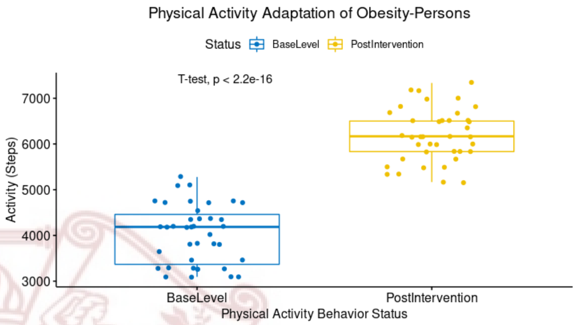
The results of paired-samples t-test of HBI, nutrition, physical activity behaviors and weight fitness factor are discussed in 5.11(a, b, c, d) respectively. The main cause to draw the t-test is to determine the effectiveness of user centric adaptive intervention methodology for nutrition behavior change over a period of three months. In this case, the Before-mean score for the Nutrition behavior (M = 22.22, SD = 3.28) is lower than the After-mean score of Nutrition behavior (M = 33.33, SD = 3.12), with a statistically standard error of difference of 0.435 (95% confidence interval: -11.97 to -10.24 , t(102) = 25.5083, $p < 0.0001$). The Before-mean score for the Physical Activity behavior (M = 4312.88, SD = 767.22) is lower than the After-mean score of Physical Activity behavior (M = 6774.16, SD = 1007.73), with a statistically standard error of difference of91.987 (95% confidence interval: -2643.73 to -2278.82 , t(102) = 26.7568, $p < 0.0001$). The Before-mean score for the Weight fitness factor (M = 81.087, SD = 12.299) is lower than the After-mean score of Weight fitness factor (M = 79.378, SD = 11.615), with a statistically standard error of difference of 0.252 (95% confidence interval: 1.209 to 2.210, t(102) = 6.7756, $p > 0.05$). Since p ¡ .05 which shows that the proposed methodology results are statistically significantly different from the results of existing methodologies.

Disease-wise change comparison of behavior and fitness factor

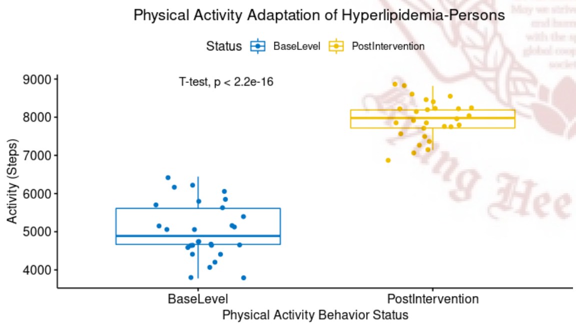
The results of paired-samples t-test of physical activity behaviors with respect to the diabetes, obesity hyperlipidemia and hypertension are discussed in 5.12(a, b, c, d) respectively. The main cause to draw the t-test is to determine the effectiveness of user centric adaptive intervention methodology for physical activity behavior change over a period of three months. The Before-mean score: for the diabetic patient (M = 4206.1, SD = 582.43); for obesity patient (M = 4027.3, SD = 640.32); for hypertension patient (M = 3971.5, SD = 515.2); for hyperlipidemia patient (M = 4027.3, SD = 640.32) are lower than the After-mean score : for the diabetic patient (M = 7326, SD = 740.85) with a statistically standard error of difference of 153.498 (95% confidence interval: -



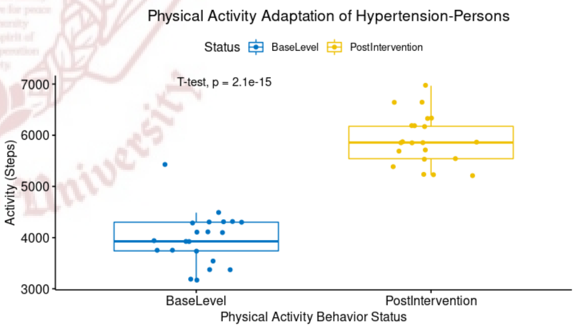
a) The change in physical activity behavior of diabetic patients.



b) The change in physical activity behavior of obesity patients.

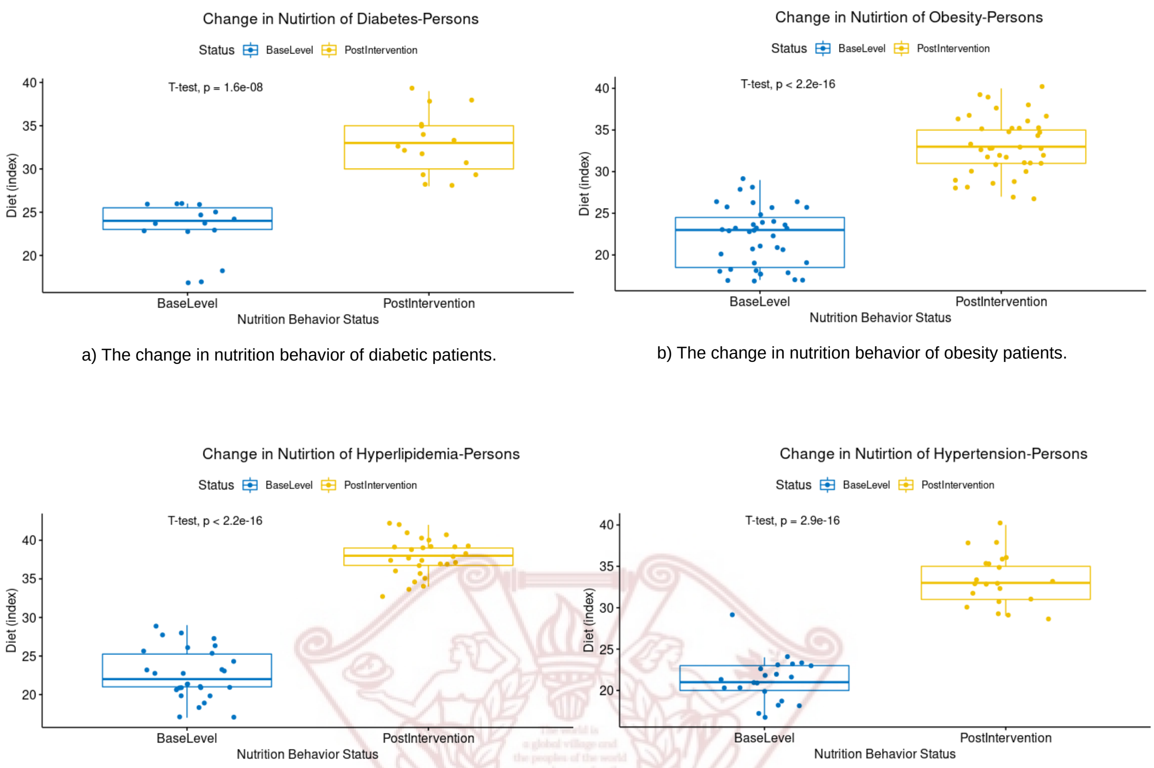


c) The change in physical activity behavior of hyperlipidemia patients.



d) The change in physical activity behavior of hypertension patients.

Figure 5.12: Disease-wise change comparison of physical activity behavior of patients.



a) The change in nutrition behavior of diabetic patients.

b) The change in nutrition behavior of obesity patients.

c) The change in nutrition behavior of hyperlipidemia patients.

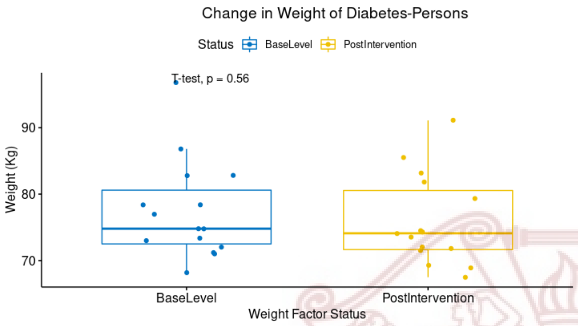
d) The change in nutrition behavior of hypertension patients.

Figure 5.13: Disease-wise change comparison of nutrition behavior of patients.

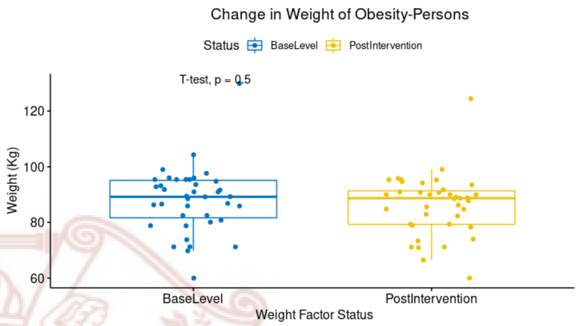
3449.15 to -2790.71 , t(102) = 20.322, $p < 0.0001$); for obesity patient (M = 6183.8, SD = 575.83) with a statistically standard error of difference of 143.923 (95% confidence interval: -2447.82 to -1865.10 , t(102) = 14.983, $p < 0.0001$); for hypertension patient (M = 5918.6, SD = 491.8) with a statistically standard error of difference of 163.353 (95% confidence interval: -2287.80 to -1606.30 , t(102) = 11.919, $p < 0.0001$); for hyperlipidemia patient (M = 7942.5, SD = 498.44) with a statistically standard error of difference of 164.681 (95% confidence interval: -3256.54 to -2580.74 , t(102) = 17.723, $p < 0.0001$) respectively. Since p ¡ .05 which shows that the proposed methodology results are statistically significant.

The results of paired-samples t-test of nutrition behaviors with respect to the diabetes, obesity hyperlipidemia and hypertension are discussed in 5.13(a, b, c, d) respectively. The main cause to draw the t-test is to determine the effectiveness of user centric adaptive intervention methodology for nutrition behavior change over a period of three months. The Before-mean score: for the diabetic patient ($M = 23.13$, $SD = 3.2$); for obesity patient ($M = 22.13$, $SD = 3.52$); for hypertension patient ($M = 21.24$, $SD = 2.76$); for hyperlipidemia patient ($M = 22.61$, $SD = 3.29$) are lower than the After-mean score : for the diabetic patient ($M = 37$, $SD = 3.74$) with a statistically standard error of difference of 0.792 (95% confidence interval: -15.57 to -12.17 , $t(102) = 17.5079$, $p < 0.0001$); for obesity patient ($M = 37.1$, $SD = 3.45$) with a statistically standard error of difference of 0.824 (95% confidence interval: -16.64 to -13.31 , $t(102) = 18.166$, $p < 0.0001$); for hypertension patient ($M = 37.38$, $SD = 3.11$) with a statistically standard error of difference of 0.952 (95% confidence interval: -18.13 to -14.16 , $t(102) = 16.95$, $p < 0.0001$); for hyperlipidemia patient ($M = 37.82$, $SD = 2.37$) with a statistically standard error of difference of 0.755 (95% confidence interval: -16.76 to -13.67 , $t(102) = 20.15$, $p < 0.0001$) respectively. Since $p < .05$ which shows that the proposed methodology results are statistically significant.

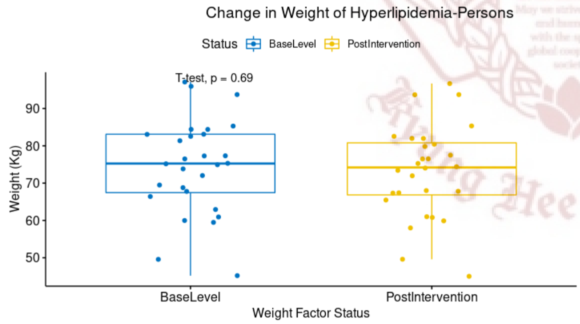
The results of paired-samples t-test of weight fitness factor with respect to the diabetes, obesity hyperlipidemia and hypertension are discussed in 5.14(a, b, c, d) respectively. The main cause to draw the t-test is to determine the effectiveness of user centric adaptive intervention methodology for weight change over a period of three months. The Before-mean score: for the diabetic patient ($M = 77.427$, $SD = 4.403$); for obesity patient ($M = 88.018$, $SD = 11.79$); for hypertension patient ($M = 79.719$, $SD = 9.177$); for hyperlipidemia patient ($M = 74.421$, $SD = 12.676$) are lower than the After-mean score : for the diabetic patient ($M = 75.887$, $SD = 6.818$) with a statistically standard error of difference of 0.467 (95% confidence interval: 0.539 to 2.541 , $t(102) = 3.299$, $p > 0.05$); for obesity patient ($M = 86.259$, $SD = 11.066$) with a statistically standard error of difference of 0.406 (95% confidence interval: 0.938 to 2.580 , $t(102) = 4.3366$, $p > 0.05$); for hypertension patient ($M = 77.5$, $SD = 7.307$) with a statistically standard error of difference of 0.602 (95% confidence interval: 0.963 to 3.475, $t(102) = 3.6851$, $p > 0.05$); for hyperlipidemia patient ($M = 73.071$, $SD = 12.428$) with a statistically standard error of difference of 0.536 (95% confidence interval: 0.249 to 2.451 , $t(102) = 2.517$, $p > 0.05$) respectively. Since $p > 0.05$ which shows that the proposed methodology results are statistically not significant for fitness factor.



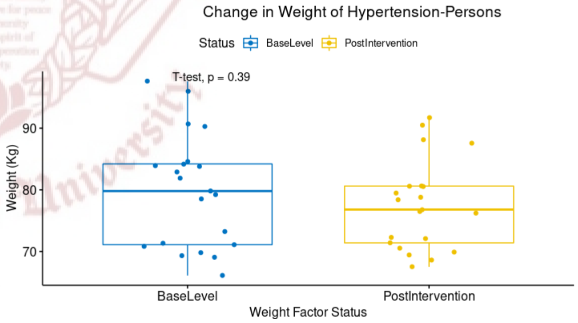
a) The change in weight factor of diabetic patients.



b) The change in weight factor of obesity patients.



c) The change in weight factor of hyperlipidemia patients.



d) The change in weight factor of hypertension patients.

Figure 5.14: Disease-wise change comparison of weight fitness factor of patients.

5.7 Summary

Smart ubiquitous computing plays an important role in preventing and indicating preventable lifestyle-related chronic diseases. It focuses on healthy lifestyle through the convergence of science and technology in this digital world to improve health and quality of life. Since the last decade, the development of wellness applications has supported personalization and self-quantification. These applications facilitate users to adopt healthy behaviors through activity tracking and monitoring based on raw sensory data. The challenge in behavior change is not only to display the problems but also to provide step-by-step coaching and guidance in real time. The implementation of behavior change theories through digital technology has revolutionized lifestyle change in a systematic and measurable way. Our methodology understands behavior to generate just-in-time interventions for healthy lifestyle adoption. The wellness platform-based behavioral analysis is conducted using an unbiased lifelog and a questionnaire to qualitatively assess behavior. Behavioral contextual interventions will be provided to adapt behaviors to improve quality of life and increase socioeconomic conditions. Personalized education is provided to understand the importance of healthy behaviors and motivate users, while just-in-time context-based recommendations have supported the incremental adjustment of unhealthy behaviors. The real focus is to correlate the primary linked habits in an appropriate proportion through the healthy behavior index (HBI) for personalized wellness support services. The healthy behavior index and behavior change theories through smart technologies have improved the functionality of the wellness management system and support the outlining of behavioral status to adopt healthy activities to improve long life. The results show that education and recommendations are appealing and attractive according to the stage of the person to retain the attention of customers.

Chapter 6

Conclusion and Future Direction

Human behaviour is a qualitative in nature depending on several factors to define the context. Quantifying lifestyle behaviour is a challenging task and many efforts are made to transfer behaviour comprehensively. Self-quantification is one of the approaches to register and manage the daily diary of activities performed, visits to places, eating, work schedules and many others. Lifestyle behaviours have an impact on the development of non-communicable diseases and premature mortality and morbidity. So, this chapter concludes the dissertation work and discusses future directions in this research area. Finally, the possible applications of the proposed methodology are listed.

6.1 Conclusion

Quantifying human behavior for assessment and adaptation is an active area of research in the wellness management community. Root cause analysis and prevention of non-communicable diseases depends on early identification and modification of unhealthy daily routines. Fortunately, information and communication technology (ICT) is hailed as a pillar of the modern digital health era that has the potential to empower people to take charge of their health and wellness by providing personalized information, encouragement, and control on a timely and ubiquitous basis. Indeed, the industry has a strong interest in developing specific technologies and systems for health and wellness management, fueled in part by the rise of wearable and mobile technology. Healthy lifestyle services, particularly in the fitness space, are the immediate target of these solutions, which essentially allow users to monitor their daily routines and provide them with feedback. In particular, habit formation could play an essential role in digital wellbeing applications to support behavioral change towards more effective use of technology and ensure the long-term impact of adapted behavior.

Behavioral adaptation requires both identification of unhealthy habits and personalized interventions at the right time with feasible actions. The derived methodology not only identifies behavioral status through the Healthy Behavior Index (HBI), but also uses a behavioral context prediction model for selecting appropriate prescriptive interventions. In this work, we focused on the comprehensive status of four major and basic habits such as smoking, unbalanced diet, alcohol, and physical inactivity. It will help the individuals and experts in root cause analysis of diseases. The HBI service is designed to function independently as a service so that any other service-enabled wellness management platform can use it to evaluate the status of healthy behaviors for behavioral indication, recommendation generation, and behavioral adjustment. The change in HBI is a very useful indicator of behavioral adaptation that motivates the user of the wellness application to use it for a longer period of time.

The dissertation laid a foundation of behavior formation through Behavior Change Techniques under the impact of ubiquitous technologies. To achieve this promising goal, following objectives have been achieved:

1. Contributing Factors Identification: Examining the factors that contribute to lifestyle indication is the basic step of quantification, like refining crude oil. The lifestyle factors are obtained from several wellness guidelines in the field of physical activity, diet, smoking and alcohol. The Kappa agreement value is 0.5282 and 0.9100 respectively, indicating moderate to perfect agreement between the raters.

2. Healthy Behavior Index through Factors Weight-age:

   The impact of the factors is not linear, so we used the life expectancy-based weighting algorithm for each factor by Mortality Population Risk Tool (MPoRT), which is based on the Cox proportional hazards model. The risk factor weighting age is derived by proportion from the difference in life gain and life loss due to a given risk factor.

3. Healthy Behavior Index Mapping with Behavior Stage:

   Ensemble learning is used for classifying behavioral stages. It is based on multiple base learners to improve performance over a single learner for predicting behavior. Thus, we used a majority voting technique in conjunction with Support Vector Machine (SVM), Naïve Bayes (NB) and Decision Tree based learners. We achieved the highest accuracy with the Ensemble classifier, while Naive Bayes and Decision trees also had accuracy greater than 90%. The accuracy of Support Vector Machine was 87.57%.

4. Personalization of Interventions: The behavior-context of the end user is categorized according to the TTM levels to support refinement of interventions depending on behavioral status, disease conditions, and preferences.

A real-world, user-centric statistical evaluation is conducted using the tools User Experience Questionnaire (UEQ), System Usability Score, and AttrakDiff. The gain in behavioral change is inferred from the implicit feedback, which shows that the context-based methods have steadily improved behavioral adaptation in the long run. The explicit feedback from 99 end users of the wellness application based on the proposed methodology resulted in ”Good” and ”Desired” status for the widely used tools System Usability Score and AttrakDiff, respectively. The stimulation coefficient of the value 0.86 showed a significant effect. We observed an overall novelty of value 0.88, showing the potential interest of the participants. The adaptive intervention demonstrated a positive user experience in terms of stimulation to adapt healthy behaviors. The HBI service is designed to function independently as a service so that any other platform that provides wellness management services can use it to evaluate the individual's healthy behavior index for generating recommendations, behavior indication, and behavioral adaptations.

6.2 Future Direction

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.

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Appendix A

List of Acronyms

Acronyms

In alphabetical order:

AI Adaptive Interventions

ATT Attractiveness

AUQ Alcohol Urges Questionnaire

BCT Behavior Change Techniques

BI Behavioral Informatics

BMI Basel Metabolic Index

CH Connected Health

CoFID Composition of Foods Integrated Dataset

CT Control Theory

DCL Data Curation Layer

FFQ Food Frequency Quentionnaire

FIT Feedback Intervention Theory

HBAI Health Behavior Adaptation Intervention

HBI Healthy Behavior Index

HBSCQ Health Behavior Stage Change Questionnaire

HLCA High-Level Context-Awareness

HQ Hedonic Quality

ICL Information Curation Layer

ICT Information And Communication Technologies

IMB Information Motivation Behavioral Skills Model

IoT Internet-of-Thing

IPAQ International Physical Activity Questionnaire

JIT Just-In-Time

JITAI Just-In-Time Adaptive Intervention

JSON JavaScript Object Notation

KCL Knowledge Curation Layer

LLCA Low-Level Context-Awareness

MET Metabolic Equivalent Task

MM Mining Minds

MPoRT Mortality Population Risk Tool

NCDs Non-Communicable Chronic Diseases

NDNS National Diet and Nutrition Survey

OC Operant Conditioning

PA Physiocal Activity

PAG Physical Activity Guidelines

PQ Pragmatic Quality

PRISMA Preferred Reporting Items for Systematic Reviews and Meta-Analyses

SCL Service Curation Layer

SCogT Social-Cognitive Theory

SRHI Self Report Habit Index

TPB Theory of Planned Behavior

TRA Theory of Reasoned Action

TTM Transtheoretical Model

UCAI User Centric Adaptive Intervention

UEQ User Experience Questionnaire

UX User eXperience

WHO World Health Organization

Appendix B

List of Publications

B.1 International Journal Papers [12]

1 **Hafiz Syed Muhammad Bilal**, Muhammad Bilal Amin, Jamil Hussain, Syed Imran Ali, Shujaat Hussain, Muhammad Sadiq, Muhammad Asif Razzaq, Asim Abbas, Chunho Choi and Sungyoung Lee, "On computing critical factors based healthy behavior index for behavior assessment", *International Journal of Medical Informatics*(SCI, IF:2.731), Vol.141, pp.1-13, 2020.

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8 Jamil Hussain, Anees Ul Hassan, **Hafiz Syed Muhammad Bilal**, Muhammad Afzal,Shujaat Hussain, Jaehun Bang,Oresti Banos and Sungyoung Lee, "Model-based adaptive user interface based on context and user experience evaluation", *Journal on Multimodal User Interfaces* (SCIE, IF: 1.031), Vol.12, Issue 1, pp.1-16, 2018.

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14 **Bilal Hafiz Syed Muhammad**, Asad Masood Khattak and Sungyoung Lee, "Sedentary Behavior-Based User Life-Log Monitoring for Wellness Services", *14th International Conference on Smart Homes and Health Telematics (ICOST). Inclusive Smart Cities and Digital Health*, pp.283-292, Wuhan, China, May 25-27, 2016.

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3 **Hafiz Syed Muhammad Bilal**, Sungyoung Lee, “Intimation based Life-log monitoring for unhealthy diet and physical activities” , In *Korea Computer Congress*, 405-407, 2016.

4 **Hafiz Syed Muhammad Bilal**, Sungyoung Lee, “Health Prediction on Sedentary Lifestyle through IoT” , In *Korea Computer Congress*, 523-525, 2015.

5 **Hafiz Syed Muhammad Bilal**, Muhammad Asif Razzaq, Sungyoung Lee, “Election Prediction on Basis of Sentimental Analysis in 3rd World Countries” , In *Proceedings of the Korea Information Processing Society Conference*, 928-931, 2014.

B.5 Patents [6]

1 Sungyoung Lee, **Bilal Hafiz Syed Muhammad**, “ 사용자 건강 상태 제공 방법 및 장치”, *출원인: 경희대학교 산학협력단*, Registration No. 1021666700000, 2020년 10월 12일.

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