A Framework for AI-enabled Proactive mHealth with Automated Decision-making for a User's Context

Muhammad Sulaiman, Anne Håkansson and Randi Karlsen
Department of Computer Science, UiT The Arctic University of Norway, Tromsø, Norway

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Abstract: Health promotion is to enable people to take control over their health. Digital health with mHealth empowers users to establish proactive health, ubiquitously. The users shall have increased control over their health to improve their life by being proactive. To develop proactive health with the principles of prediction, prevention, and ubiquitous health, artificial intelligence with mHealth can play a pivotal role. There are various challenges for establishing proactive mHealth. For example, the system must be adaptive and provide timely interventions by considering the uniqueness of the user. The context of the user is also highly relevant for proactive mHealth. The context provides parameters as input along with information to formulate the current state of the user. Automated decision-making is significant with user-level decision-making as it enables decisions to promote well-being by technological means without human involvement. This paper presents a design framework of AI-enabled proactive mHealth that includes automated decision-making with predictive analytics, Just-in-time adaptive interventions and a P5 approach to mHealth. The significance of user-level decision-making for automated decision-making is presented. Furthermore, the paper provides a holistic view of the user's context with profile and characteristics. The paper also discusses the need for multiple parameters as inputs, and the identification of sources e.g., wearables, sensors, and other resources, with the challenges in the implementation of the framework. Finally, a proof-of-concept based on the framework provides design and implementation steps, architecture, goals, and feedback process. The framework shall provide the basis for the further development of AI-enabled proactive mHealth.

1 INTRODUCTION

Center for disease control and prevention (CDC) defined public health as "the science and art of preventing disease, prolonging life, and promoting health through the organized efforts and informed choices of society, organizations, public and private communities, and individuals" (Winslow, 1920). This definition likewise emphasizes the need of promoting health and preventing disease providing a holistic solution for the individual. To promote health, people must be enabled to increase control over their health to be able to improve it, World health organization (WHO) (WHOa, 2021).

Health promotion and wellbeing are vital as healthcare globally is dealing with many challenges (Haseltine, 2021). One major challenge is an aging population, life expectancy has increased in the last century or so for instance in Norway it is 84.2 years for women and 80.6 years for men (NIPH, 2018). This increase intensifies the development of multiple chronic diseases like cardiovascular disease, stroke, cancer, osteoarthritis, and dementia (Atella et al., 2018). WHO estimates that about half of the disease burden is from chronic illness (WHOb, 2021). In the US, about 6 out of 10 adults suffer from chronic diseases (CDC, 2021).

The healthcare sector must endure the pressure of dealing with a public health crisis. A recent example is the pandemic (WHOc, 2020) coronavirus (COVID-19) that provides insights on how healthcare has to cope with one of the most contagious diseases that hit mankind in the past decades. COVID-19 is not the first and certainly not the last of these viruses. During a public health crisis, it is important to provide regular care to people at a distance. COVID-19 certainly fueled the need for new tools and practices for healthcare digitalization to provide care to people away from the hospital settings.

Digitalization in healthcare to support self-management is not a new concept. Digital health is playing a pivotal role to support healthcare by

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transforming existing practices (Hermes, Riasanow, Clemons, Böhm & Krcmar, 2020). It contributes to promoting health by providing tools to empower the user (FDA, 2021). Digital health also incorporates mobile health (mHealth) to provide healthcare services using mobile and wireless technology. mHealth combines wearables to render health services to anyone, anywhere at any time (WHOd, 2018). This ubiquitous notion is the key in mHealth to deal with health delivery constraints like location, time, and cost. mHealth and wearables market is growing and is estimated to reach 149.3 billion USD by 2028 (GRAND View Research, 2021).

mHealth facilitates the paradigm shift in self-management by providing tools to the users, so they can become more aware and conscious about their health. The user-centric approach can empower the user by providing new insights into the health information gathered from wearables and mobile devices. These devices that users carry at all times, and the collected health information they generate provide the need for user-level decision-making.

The reactive approach in health is to act when a crisis occurs with damage control (Amir, 2019). It is practical in many circumstances, but it diminishes health promotion and self-management. Proactive health, in contrast, is to act before a crisis to predict and prevent a situation promptly (Sharma, Singh Aujla & Bajaj, 2019). Proactive health promotes wellbeing by empowering the user and making them aware of an anomaly beforehand. The active participation of the user in their health enables more health information. Proactive health can promote wellbeing, so the ultimate goal of proactive health is to be predictive and preventive with personalization. The system should account for the uniqueness of the user. This can enable care for the user ubiquitously but can also save lives and support the healthcare system.

To develop proactive health with the principles of prediction, prevention, and ubiquitous health Artificial Intelligence (AI) with mHealth can play a pivotal role. Many different definitions of AI are available over the decades that serve well for many use cases. IBM defined AI as "artificial intelligence is a field, which combines computer science and robust datasets, to enable problem-solving. It also encompasses sub-fields of machine learning and deep learning, which are frequently mentioned in conjunction with artificial intelligence. These disciplines are comprised of "AI algorithms which seek to create […] systems which make predictions or classifications based on input data (IBMa, 2021). This definition serves well for enabling AI in proactive health.

Wearable and mobile devices which the user carries, have many sensors to collect health data, which can be the key for finding patterns and making accurate predictions for early intervention. AI can apply reasoning and negotiation to the gathered data to automate processes and facilitate decision-making.

This paper explores the fundamentals of AI-enabled proactive mHealth by a comprehensive study for the framework, challenges in design and implementation of a system with automated decision-making. The paper also presents the implementation goals, and a model with an architecture for developing AI-enabled proactive mHealth based on the proposed framework. The result is a proof-of-concept that renders an implementation view of the system with technical aspects of design steps, goals, and a proposed input/output mapping with the architecture. The paper will provide the basis for further development of AI-enabled proactive mHealth.

2 RELATED WORK

Proactive mHealth is to predict and prevent a situation beforehand. A system that can provide proactiveness must have a clear goal to predict and prevent. The level of proactiveness when it comes to proactive mHealth is broad. A basic level of proactiveness provides benefits of being proactive to manage a disease, a medium level corresponds to being predictive, and a high level of proactiveness allows a system to be predictive and preventive. Some studies (McConnell et al., 2018; Aguilera et al., 2020; Korpershoek et al., 2020; Baig, 2017) presented a basic level of proactiveness, and the benefits of being proactive. These are targeted for a specific need to self-manage the disease. Hence, they are not adaptive to new situations which require more level of proactiveness. A few studies (Aguilera et al., 2020; Baig, 2017) focused on managing a chronic disease proactively.

A study (Nag, Pandey & Jain, 2017) presented the importance of proactive health and significance by giving a health map example. The health-map has states of the user drawn in form of a map.

A few research studies (Dijkhuis et al., 2018; Baig, 2017; Rojas & Dey, 2019) used wearables as data sources but with activity data only. Activity data can be useful for promoting health but when it comes to providing prediction activity. A study (Baig, 2017) concludes wearables as a key in providing health for anyone at any time. Another study (Menictas, Rabbi, Klasnja, & Murphy, 2019) highlights the importance of decision-making with mHealth.

2.1 Applications of AI in mHealth

AI is one of the factors driving healthcare towards digitalization. It represents several technologies that enable machines to sense, comprehend, act, and learn (Matthew & Richard, 2021). The booming increase in generated data today (Statista, 2021) has fuelled the need for AI to support and automate healthcare dilemmas. Some examples of domains where AI contributes are administrative workflows, fraud detection, dosage error detection, diagnosis assistance, virtual assistance, decision-support, automated processes, drug discovery, personalized treatment, disease screening and early detection (Matthew & Richard | Accenture, 2021). These application areas provide the basis for the framework of AI-enabled proactive mHealth.

mHealth application and available wearables data have proven another domain where AI is contributing. Many studies have used mHealth with AI, a review (Naseer Qureshi, Din, Jeon & Piccialli, 2020) presented mHealth applications that use machine learning. People are becoming more aware of their health. Statistics show that 62% of smartphone owners search the internet for health-related information (Smith | Pew research, 2015). Estimation indicates that about 80% of mHealth applications will use AI by 2025 (Ghazaryan, 2021). However, not all websites contain the correct information, and an AI system shall be able to filter out the non-correct parts and provide information about the valid and trustworthy websites.

Some use cases (Ghazaryan, 2021) of mHealth with AI are prediction models, personalized treatments, early detection, recommender systems, screening, and triage, and chatbots. For the framework some of these use-cases are included. mHealth with AI can support users in decision-making to promote health. mHealth is beneficial because of the features it provides e.g., personalization and ubiquitousness. It is utterly necessary to account for the uniqueness of the user, handled by user preferences. Table 1 presents some mHealth applications and their features.

Table 1: mHealth applications.

Purpose	Features
Diabetes control (Curran, Nichols, Xie & Harper, 2010)	The paper focuses on adjusting insulin levels using mHealth
Activity (Yom-Tov et al., 2021)	The aim of the study is to promote walking
Blood pressure level (Toro-Ramos et al., 2017)	The aim of the study is BP monitoring

The related work provides the effectiveness of being proactive but in the context of self-managing the disease. There is no prior research that defines proactive mHealth with AI with the capabilities of prediction and prevention. A system to predict and prevent a situation promptly, targeting a user for promoting wellbeing before becoming sick. Such a system can consider multiple parameters of wellbeing i.e., environment or surroundings and current state of the user. The critical analysis determines that AI in mHealth is rapidly growing, but with a focus on monitoring and self-management which depreciates proactiveness.

3 USER-LEVEL DECISION-MAKING FOR SELF-EMPOWERMENT

Decision-making is the process that can have an impact on our lives (Steph | Medium, 2020). Decision-making requires time and effort to comprehend details, make decisions on knowledge at hand, plus decision alternatives to choose from based on the circumstances. Effective decision-making requires a step-by-step approach. One strategy proposes a seven-step model for effective decision-making (Dartmouth, 2021). The steps are as follows: to identify the decision, collect information, identify alternatives, weigh the evidence, choose among alternatives, take action and finally, review the decision.

Decision-making in healthcare often involves several stakeholders in this process, such as doctors, and nurses. Most health-related decisions are said to be in the grey area of decision-making (Abbasgholizadeh Rahimi, Menear, Robitaille & Légaré, 2017). The grey area represents the scenario where there is no right or wrong approach. Health-related decisions can be critical with life-threatening impacts for the users. Thus, there is a need to have more informed choices and insights on the patient to help with effective decision-making. mHealth is contributing to this process by engaging patients in decision-making to support health professionals with new insights.

Most of these mHealth solutions are decision-support systems for clinical decision-making. This is an approach where the system supports evidence-based decision-making. These solutions are crucial, and many healthcare professionals rely on them to provide shared decisions by having a combined opinion between the healthcare professional and the mHealth solution (Abbasgholizadeh et al., 2017).

These shared decisions are indeed beneficial although, this diminishes the fact that many decisions are taken at the user level (Krist, Tong et al., 2017). The health decisions or health choices can have a direct impact on their health, i.e., prevent disease, prolong life, and promote wellbeing. Table 2 presents the types of decisions that can have an impact on the health of a user and the contributors involved in this decision-making. mHealth and wearables are being used by users all the time. There is new health information about the states of the user that is dynamic and can provide health data required for decision-making. The table has two columns, first column provides a case of decision-making. The following column renders detail about contributors in making that decision.

Table 2: User-level decisions with contributors' example.

Cases for decision-making	Contributors involved in decision-making
From Air quality index (AQI = 157), the user profile (asthma), The air quality tomorrow is unhealthy. You are in a risk group, stay home or wear a mask when you go out.	Sensors, mobile and the user
Low activity, the user profile (goals), You are not very active lately. The weather is pleasant today, have a walk for ten minutes.	Wearables, sensors, mobile devices, and the user
The pollen count, User profile (have pollen), The pollen count will be higher tomorrow. You are in a risk group, stay home or wear a mask when you go out.	Meteorological data, user profile, mobile device

These decisions cases are significant for a person since they are not part of the clinical decision-making approach that requires a doctor to examine but must be handled by the user. Let us consider the case of a user called "A" that is wearing a sleep tracker to sleep every day. The information from that tracker can lead to choices that user can take to improve his/her health. These decisions are taken by User-A at the user level and can promote health.

4 THE CONTEXT OF THE USER

The user's context is "the interrelated conditions in which something exists or occurs" (Merriam-Webster, 2021). Context is important when providing proactive mHealth because it consists of parameters that can have a direct impact on the health of the user. Many different circumstances e.g., environment, surroundings, and user-profiling contribute to the context. To emphasize, consider an example of a system that can predict a health issue – atrial fibrillation. Which is a heart condition that causes an irregular heart rate. The system must include every attribute about the user, family history, disease history, current and previous states from the wearables and sensors and user-profiling with user characteristics. A context is anything relevant, can have an adverse impact on health.

A context-aware system must be able to collect information about surroundings and adapt to the environment. Forming a context is vital because it considers the uniqueness of the users and more information on the states of the user. To define the context, it is required to determine the target person by choosing a user or group.

A user's context accounts for user characteristics and profiling. For someone who is suffering from asthma caused by an inflammatory reaction (Djukanović, 2021) the context of air pollution shall be included.

Moreover, for a user in a risk group of infectious disease it is essential to know about an outbreak of flu or the rise of a number of flu cases in the area. In contrast, for a specific group of people in risk groups like the elderly or multi-disease, the context of flu spread can be the same. In addition, a storm warning can have a similar impact on everyone in the area.

The context can be elaborated and defined in many ways, but the limitation comes to what is measurable from the sensors and other sources and what can be predicted and prevented. The context can also include another person in the surroundings, i.e., one infected person can infect another person. In the same way, a driver on the road who suffers from a heart problem or epilepsy can be a threat to the nearby surroundings. But this is not measurable or predictable, in the current systems. With the usage of the Internet of Things, IoT, and autonomous vehicles, it can be a possibility to provide solutions for measuring and predicting failures and epileptic seizures.

Context is dynamic with ever-changing surroundings. A system must be adaptive to cope with the dynamic changes in context. A person suffering from a pollen allergy shall have as context the amount of pollen in the environment, which is fluctuating over time. Everything that can have an impact on one's health, shall be part of the person's /user's context.

With the above-mentioned definition of context, it is assumed to have different attributes e.g., environment, surroundings, user-profile, and characteristics. The table shows several parameters, used for developing the context and how they are related to a user.

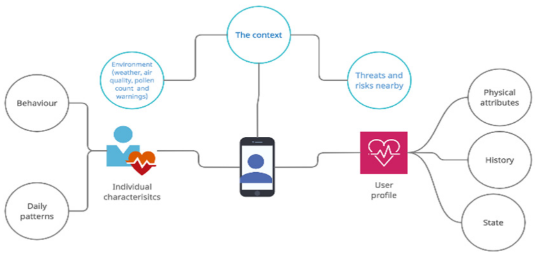

Figure 1: The context of a user.

An example of a user's context is presented with details on what it holds. The figure, Figure 1, shows how a user's context can be and what parameters it includes. The center of the figure displays a user with a user profile. Different parameters that form the context are presented: user's profile, characteristics, environment. Table 3 demonstrates each parameter in detail.

Table 3: Parameters for a user's context

The context	User characteristics		User profiling		
Environment (anything that is around and can have an impact)	Daily patterns	Behaviour	Physical attributes	History	State
Weather, air pollution, threats, and outbreak	Physical activity Screen time	To adapt, actions and behaviour	BMI Allergies Weight	Family, Disease	Location, Health information Activity data, SpO2, and fever

These parameters require multiple data sources as input to the system. In section 5, a comparison of available resources with the parameters of the context is established.

5 THE FRAMEWORK OF PROACTIVE mHealth

A framework provides the supporting structure (Cambridge, 2021) to support building software. The specified framework provides abstraction, which supports the development of systems over it. The framework also defines a set of rules to follow when developing applications.

A conceptual framework defines concepts collected after extensive research into a topic. A definition of the conceptual framework is a "*conceptual framework* as a network, or a plane, of interlinked concepts that together provide a comprehensive understanding of a phenomenon or phenomena" (Jabareen, 2021). It is essential to understand the link between these concepts.

This paper presents, a framework of AI-enabled proactive mHealth. The framework is derived from a systematic literature review of the topic and existing systems. To show proof-of-concept, each part of the framework is defined with examples and use-cases.

Following are the components of the framework:

- Automated decision-making with predictive analytics
- P5 approach to mHealth
- Just-in-time adaptive interventions

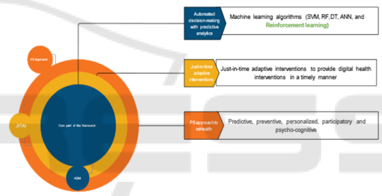

Figure 2: Proactive mHealth framework.

Figure 2 shows the components of the framework: AI with automated decision-making, Just-in-time adaptive intervention, and the P5 approach to mHealth. Each component has variables with relation to other components.

5.1 Automated Decision-making with Predictive Analytics

Automated decision-making (ADM) with predictive analytics is defined as "decisions by technological means without human involvement" (EDPB, 2021) recognizing patterns from extensive information to provide decisions (data-driven). Booming increase in the amount of digital data and ever-growing AI, decision-making is empowered to automated processes (Saha, 2021).

The first step is to process information by applying algorithms and making informed decisions. ADM that is powered with predictive analytics can gather, process, and model health information to render an automated decision (Araujo, Helberger, Kruikemeier & H. de Vreese, 2020).

As presented in section-3, user-level decision-making with multiple use-cases and examples. The emphasis on user-level decision-making proves to be the basis of providing ADM for AI-enabled proactive mHealth. A system must consider multiple factors as input and adapt to sudden changes in the states but eventually, the benefit for the user is to get an automated decision from the system, which is valid for the user. These automated decisions are a part of the prediction and prevention mechanism to promote wellbeing.

Machine learning algorithms such as random forest (RF), decision trees (DT), regression models, artificial neural networks (ANN) can contribute to developing the engine for ADM. Choosing the technique depends on the type of data and decisions to provide to the user.

It is imperative to understand the types of decisions. These automated decisions are for predicting and preventing health issues to promote wellbeing. The system does not provide clinical decision-making and hence, cannot be used as one.

Some examples of automated decisions are:

- The system predicts the air quality to be unhealthy tomorrow, wear a mask.
- High pollen in the area tomorrow you are in the risk group, please use medication.
- There is an outbreak in the area you are in the risk group. Stay home stay safe.

These decisions are based on the parameters (user profiling, context, and characteristics) of the user. The decisions are provided as information to the user to prevent a possible illness or health issue.

5.2 P5 Approach to mHealth

The P5 approach to mHealth is based on the P4 (Sagner et al., 2018) spectrum of medicine presented as an extension to personalized medicine. It proffered new insights into designing health systems to be more vigilant in considering users' uniqueness and timeliness. The spectrum is described as predictive, preventive, personalized and participatory.

There have been many additions to this P4 spectrum. A P5 approach was presented (Gorini et al., 2018) that added a P as Psycho-cognitive to provide more details on the user's decision-making regarding their health. P5 approach to mHealth is relevant because of the capabilities of mHealth to provide more information about the user and a platform to observe timeliness.

Table 4 illustrates the P5 principles for designing health systems in detail. The 5 P's are predictive, preventive, personalized, participatory, and psycho-cognitive.

Table 4: P5 Approach to mHealth (Gorini et al., 2018).

5 Ps	Definition
Predictive	Allowing a precise prediction about the future state
Preventive	Timely preventive interventions
Personalized	The uniqueness of the user
Participatory	Not as passive recipients rather active decision-makers
Psycho-cognitive	Improving the ability to make decisions

AI-enabled proactive mHealth system must adhere to this design principle to be more effective for the users. These design principles are part of our framework of AI-enabled proactive mHealth.

The order of these principles or implementation depends on the use case at hand or the targeted outcome of the application. A motivating factor is the availability of resources and tools to implement that. With AI and the availability of wearable devices, most of the health can be gathered for a more precise targeted outcome. The design implementation can be at different levels as well. Personalization can be achieved for a user by targeting user preferences, but at a community level, it depends on the characteristics of the society.

5.3 Just-in-Time Adaptive Interventions

Just-in-time adaptive interventions (JITAI) are based on health interventions which are a way of providing health services using mobile applications. Digital health intervention aims to deliver information that is useful for the user using digital platforms (Soobiah, Cooper & Kishimoto, 2021).

Interventions are categorized as nudges, boosts and recommendations (Hertwig & D Ryall, 2020). A nudge is defined as "A nudge is an aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives" (Osman, 2016). A boost differs as its objective is to improve someone's ability to make their own decisions (Hertwig & D Ryall, 2020). In this study, the focus is not on the behavioral science aspect of these interventions. The property relevant to the framework is the importance of interventions and their impact.

The focus of the framework is on the architecture of digital interventions that can provide timely interventions to the user but with adaptive behavior. The Just-in-time adaptive intervention (JITAI) is an intervention design that provides the right type of support at the right time, by adapting to one's varying internal and contextual state (Nahum-Shani et al., 2017). JITAI intervention design focuses on 3 principles that are more of a challenge when it comes to implementing JITAI.

- When: When to intervene
- What: What information to provide
- Whom: To whom, the target user receiver of the intervention

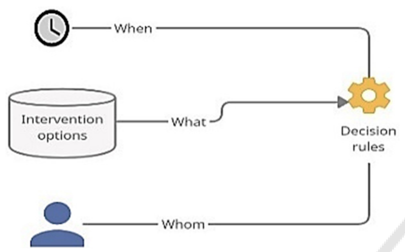

Figure 3: JITAI intervention points (Nahum-Shani et al., 2017).

Figure 3 shows JITAI intervention points: when in time, what intervention options, to whom who is the target user and decision rules. An AI-enabled proactive mHealth system must adhere to these principles to provide timely interventions. That also means it is necessary to understand the current state of the target user before providing interventions. The term internal and contextual state refers to the current state of the user as well as its context.

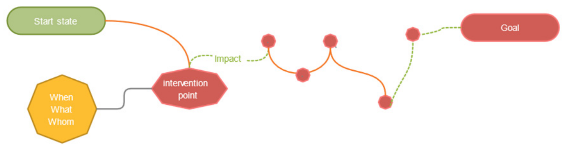

Figure 4: Health map JITAI intervention points.

Figure 4 shows the health map, to highlight the use of JITAI benefits for health promotion. The start state represents the state of the user. The goal state is the state representing goal. The intervention point is a user-level decision required to change the state of the user. The impact after this intervention is displayed with an ascent in green.

6 IDENTIFICATION OF SOURCES: WEARABLES, SENSORS, AND AVAILABLE RESOURCES

Identification of data collecting sources is the first step in developing an AI-enabled proactive mHealth system using the framework. The parameters that provide health information about the user and its context must be gathered as input. Most importantly, information about the current state of the user is crucial when providing JITAI.

Several different resources shall be included for information collection to provide a holistic view of the user's preferences and current health. Table 5 provides some details about the most commonly used sources and features they offer. The first column identifies different sources, the second column features list the detail of each. Finally, the listed factors match what to collect from each source.

Table 5: Sources with features and factors.

Sources	Features	Factors	
Wearables	activity data SpO2 (oxygen saturation), heart rate, body temp, Physical activity and Screen time (inactivity time)	User profile	User characteristics
		Current state	Daily patterns
Sensors	Weather, Air pollution	Context	
		Environment/Surroundings	
Available sources	Outbreaks, Threats, risks in the nearby area. Pollen, Storms, cyclone, and avalanche	Context	
		Environment/Surroundings	

In this paper, sources are categorized as wearables, other sensors, and available resources. Each source is examined with an example to collect data necessary to build a holistic view of the user, but also the challenges it possesses

6.1 Wearable Devices

Wearable devices have sensors that the user wear, are portable, comfortable, and can collect data, which are combined to produce information (Wu & Luo, 2021).

These devices also provide data even when they are not being used (running in the background).

Another definition of wearable technology is "seamlessly embedded portable computers … worn on the body" (Janet, 2016). In health, wearables are adopted as e.g., fitness trackers, biosensors, and smart health watches (Janet, 2016).

Some key features (Bove, 2019) that wearable provides are: Accelerometer, Altimeter, Electrocardiogram, Location GPS, Microphone, Oximeter, Thermometer, Pressure, and Stress.

Table 6 shows common fitness trackers (Fitbit charge 4, Garmin Vivosmart 4, OURA Ring, Polar M430, and Mi band 6) with their features.

Table 6: Wearables with features: a comparison.

Fitbit Charge 4	Garmin Vivosmart 4	OURA Ring	Polar M430	Mi band 6
Activity tracking, GPS, Continuous heart rate, breathing rate, Stress management score, SpO2, Skin temperature, sleep and inactivity	Activity, Sleep, heart rate measurement and inactivity Sensors: accelerometer, pedometer	Activity, Steps, Inactivity time, heart rate, body temperature and sleep Sensors: accelerometer, optical heart rate monitor	Activity, Sleep, heart rate measurement and inactivity Sensors: accelerometer, optical heart rate monitor	Activity tracking, GPS, Continuous heart rate, Stress management score, SpO2, sleep and inactivity time

Data produced by these wearable devices can be collected and used for AI-enabled proactive mHealth. Unfortunately, the interoperability challenges between vendors complicate this data collection process. Most modern wearable sensors provide their software development kit (SDK). An SDK is a set of tools and programs made available by the vendor for developers to work on. It provides several APIs for the developers to use. Although it is a challenge when it comes to data collection and having different sensors connected to a single platform.

Vendors are working on solving the problem with the non-compatibility of wearables, and there have been many recent developments in this. For a clear view of the compatibility problem, a comparison is drawn between two of the vendors and the SDKs they provide. Tables 7 present a comparison between Google Fit and Apple HealthKit in terms of systems and options available and data transfer options.

Table 7: System and options available (De Arriba-Pérez et al., 2016).

Platforms	SDK-Sensors	SDK-Warehouse	REST API
Apple HealthKit	✗	✓	✗
Google Fit	✓	✓	✓

For storage, Google Fit provides warehouse and cloud services with an SDK for developers. It also provides REST API for third-party systems, a very beneficial feature for to getting endpoint access. Another essential feature is access to raw sensor data. It is vital when real-time data from the user is needed. An example of this is to use Sensor API for access to raw sensor data in Google Fit.

The Apple HealthKit does not provide direct data access to the wearable or the warehouse. The only way is to access data by a query. A REST API service is not provided which must be built first to store or retrieve desired data.

Choosing the wearables for AI-enabled proactive mHealth depends on the following factors: what we want to measure, what is essential and what features we can use.

6.2 Other Sensors

To collect real-time information about the context more information from sensors is needed. A proposed project can use the following setup to render information.

- A microcontroller: Arduino Uno Rev3 (Arduino, 2021): It is based on ATmega328P, has 14 digital input/output pins, a 16 MHz ceramic resonator.
- Sensor: MQ-135 (Winsen, 2021): It is a semiconductor sensor to measure air quality, it is widely used as an alarm.
- Sensor: BME 280 (Bosch, 2021): It is an environmental sensor that measures humidity, pressure and temperature.
- Sensor: PM 2.5 (Adafruit, 2021): It is an air quality sensor that measures air quality in real-time.

For AI-enabled proactive mHealth to adapt to real-time context, it is imperative to use these sensors together to aim an overall view of surroundings.

6.3 Other Available Resources

To make accurate predictions, historical data of context is required, i.e., air quality data from previous years can contribute to early detection. These historical data can contribute to an early detection of an outbreak. Cities or communities already provide datasets for their environments. For example, metrological data provide information measured with different parameters regarding the environment, including weather data, warnings data, temperature, outbreaks, and cyclones. The predictions using these resources are possible by training and modelling systems.

This metrological data, combined with other sensors and wearables cover the need for AI-enabled proactive mHealth. A system must consider using multiple parameters as input to provide automated decision-making to the user.

7 CHALLENGES

To establish AI-enabled proactive mHealth many challenges must be tackled.

One challenge is the complexity of being proactive. In terms of implementation or design, it is difficult for defining proactive. As discussed, the system must consider multiple parameters, i.e., environment, surroundings, user profile, and characteristics, but it makes the system more complex when not every parameter is relevant for automated decision-making. Another challenge is the availability of these various parameters. To address this issue a clear target must be considered. For example, if a system is to provide timely intervention to support a user at the right time, the system must alert the user and show if it is safe to go outside or not before the user leaves the house. The goal reduces complexity to exclude data as not relevant for the moment. For example, sleep data is not applicable for air quality. Hence, it is to use the right, proper data at the right time and for the right purpose. In the case of air quality, it is data from the city's sensors that have collected information about the current air quality, the user's existing health information like asthma and user preferences like personal acceptance of the air quality in the surroundings outside the house.

Another challenge is to understand the target of AI-enabled proactive mHealth, that is if the target is for a user or a specific population. The implementation for a user must adhere to the uniqueness of the user, choices, and patterns essential to have an efficient system implementation.

One system challenge is the importance of human behavior as a part when implementing a system. The system must cope with user characteristics and adapt to a healthy lifestyle. The system must adapt to change in lifestyle and the actions that can impact health. This requires the system to constantly get feedback, as a feedback loop from the user to model the behavior and capture user preferences. The feedback shall not require the user to provide information manually. Rather, the systems shall learn from how the user act, in a situation. For example, did the user go out, although the system has alerted the user about the bad air quality.

The timeliness of JITAI is an implementation challenge, as well. A well-directed timely intervention can save lives. Thus, a system must handle precisions, i.e., when is the time for an intervention with what type of information to the user and finally, considering the user preferences when providing this intervention.

Wearables and sensors provide great details into real-time information, such as about the current state of the user. Wearables and sensors indeed support the timeliness principle of these interventions, since real-time data is necessary to provide just-in-time information to the user.

Using this real-time information is beneficial but also a challenge when it comes to implementation. Decision rules that include this information simultaneously with the historical data are tricky to implement because any sudden change must be accepted by the model. Different viewpoints i.e., conditions that can suddenly change are a must for designing decision rules with real-time data. Raw data processing is another complicated process because gathered data from sensors are to be filtered before inclusion.

Sudden change in the context and user characteristics is difficult to include in the system. It produces a challenge of using real-time raw data with historical data. So, the more information sources and resources, the better the adaption mechanisms because raw data must be filtered and processed before inclusion. A system must update itself with the incorporation of new information.

An added challenge is the evaluation of the system and if it works, the accuracy of interventions and their impact on health. It is beneficial to get feedback from the user or a design principle where the system gets a notification from the user, i.e., if they endure a decision or not is beneficial.

Choosing the precise machine learning algorithms depends on the available datasets. Many machine learning techniques i.e., Support-vector machines, SVM, decision trees, DT, and artificial neural networks, ANN, are proven to be accurate. A system must adapt to variations and the accuracy of the predictions and preventions must be evaluated by a defined evaluation mechanism to determine the best model for the dataset.

In decision-making, it is very crucial to interpret and provide transparency. But there is a trade-off between automation and transparency. This opaqueness and black-box system directly impact trustworthiness. eXplainable AI (XAI) (IBMb, 2021) can be applied to making AI techniques more explainable. That is to have a system whose decisions are understandable by humans.

Implementation of the system requires starting from prediction, then moving towards prevention. So, to promote the health of a user the system is built like a stack.

- a prediction that someone can become sick.
- an action, i.e., activity or prevention for the user (a personalized activity)
- Feedback from the user, which becomes a new input for the system.

User participation is a design principle called participatory from the P5 principles of system implementation, which is very complicated when designing the system. The system must handle usability, i.e., to make the system easy to use and acceptable for everyone. The usability of the system is about engaging the user to contribute to the system.

8 PROPOSED DESIGN AND IMPLEMENTATION

The implementation goal is to adopt the framework of AI-enabled proactive mHealth explained in Figure 2. The AI-enabled proactive mHealth system must incorporate automated decision-making with predictive analytics, the P5 approach for design, as well as JITAI for providing interventions to the user.

Implementation of a system using the AI-enabled proactive mHealth framework includes steps, architecture, and processes.

8.1 Building Systems using the Framework

The framework presented above, supports building AI-enabled proactive mHealth systems.

8.1.1 Implementation Steps

The implementation phase starts with identifying sources, then collecting relevant data, preparing data for feature extraction, choosing the algorithms, defining decision rules, training the model, and making a prediction. Also matching the outcome with an automated decision, and finally allowing feedback for evaluation must be taken into account.

- Identification of parameters: This step is necessary when considering what to predict and what attributes to include. For AI-enabled proactive mHealth, the system must recognize parameters of the context, user characteristics, and user profiling.
- Classifying sources: Another step is to look for sources and resources for the parameters. For the AI-enabled proactive mHealth system, these are wearables, other sensors and available resources.
- Collecting data: Data collection is a challenge, considering different heterogeneous sources. In addition, information is required from the user to provide intervention, such as, JITAI. So, this step is significant to collect every possible data from the available sources and then provide a just-in-time module.
- Preparing data: Data preparation is the step where data is processed, to find duplications, noise, distortion, and skewed data. Well-processed and prepared data improves the quality of the system.
- Choosing the algorithm: Choosing the machine learning algorithm is dependent on the type of data that is available at this stage. Several techniques can be adopted, i.e., Deep learning (DL) for image and speech processing, and reinforcement learning (RL) which enables an agent to learn through actions in a specific environment. RL can improve precision by learning optimal decision rules, adapts and adjusts to user preferences to enhance the accuracy of the system.
- Defining decision rules: Decision rules are what make this system operational and reach decisions. A better design is to adapt, though, with more inputs, and the current state of the user.
- Training the model: In this step, algorithms are applied to train the model by loading data and get an outcome from the system.
- Making a prediction: The outcome of the model is the prediction that is interpreted and processed to match a decision based on the user. For example, a prediction that the air quality will be unhealthy tomorrow.
- Matching the prediction with an automated decision: A processed outcome is matched with a decision to provide the user with an

automated decision on time. The prediction that the air quality will be unhealthy tomorrow will follow up with a decision to use an antihistamine.

- Feedback for evaluation: The system must adapt to the user's actions, i.e., behavior, by automatically getting feedback from the user on an intervention. The feedback is the user's action after an intervention. This feedback works as an input to the system.

8.1.2 APIs Endpoints

The system shall have an API for sending requests and receiving a response. Using an application programming interface (APIs) enhances the system effectiveness. The endpoint allows a layer or a system to use this to build the applications. The endpoint provides the following operations.

- Receiving a **request**
- **Loading** the model
- Making the **prediction**
- Sending back the **response**

It allows an application to use the operations where information is added as input and an output is a response from the model.

8.1.3 The Proposed Process with Steps

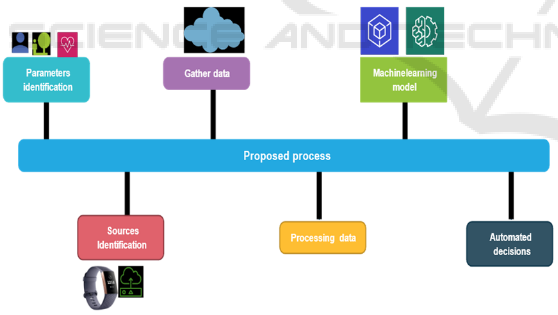

Figure 5: Proposed process with steps.

Figure 5 presents the proposed model with an iterative approach from the parameter's identification on the left to automated decision on the right.

8.1.4 The Feedback Mechanism for Inputs

The outcome of a JITAI is feedback from the user. It is used as an input to the system. This feedback is either explicit or implicit:

- Implicit feedback: This is the feedback is automatically collected from the user based on the decision provided to the user and the action user takes. The health map provides a way to gather implicit feedback.
- Explicit feedback: It is the feedback provided directly by the user of the system. The JITAI must have a mechanism to collect the feedback this. It can be a simple question to the user regarding the intervention.

8.1.5 Features Important for Systems Built on the Framework

Table 8 below presents other features that contribute to the system strength. The features of a system are robust, secure, and private. These features are important for the system that is built on the framework.

Table 8: Features of the system.

Features	Definition
Robust	The system must be robust
Secure	It should account for the CIA principle of security
Private	User data must be private

8.1.6 The Architecture of the System

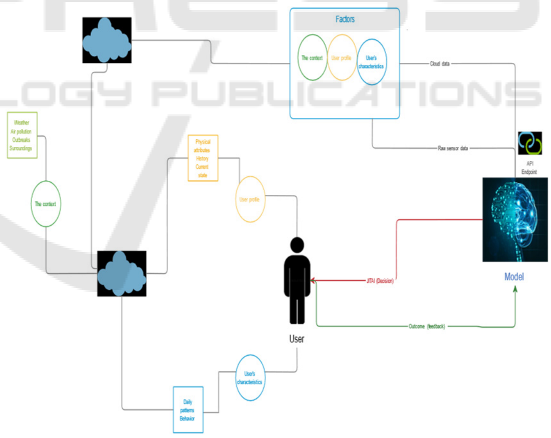

Figure 6: Architecture of the system.

Figure 6 presents the architecture of the system. The figure is drawn in three segments, the user, AI-model and sources with parameters (attributes). Cloud presents storage of data from sources into two sections, raw data, and historical data. This data is an input for the AI model and is provided via an API endpoint. The model then makes a prediction and provides an automated decision in red to the user. The outcome of this is feedback from the system to learn from, presented in green.

8.1.7 Categorization of Interventions

In a proposed model, JITAI or automated decisions can be categorized as Red, yellow, and green. Red-colored intervention is critical and needs urgent attention i.e., a vibration along with the intervention to get the user's attention. Yellow intervention does not have an immediate effect, A green intervention is an acknowledgement.

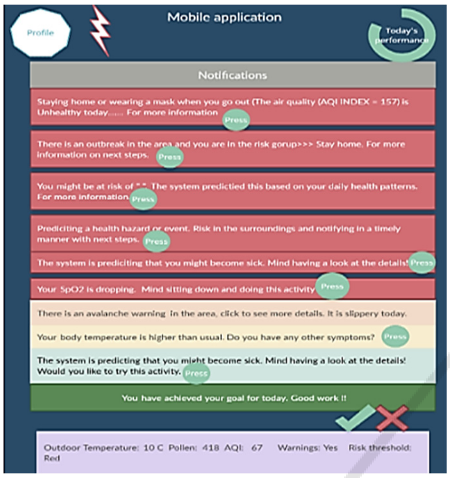

Figure 7: Categorization of interventions with examples.

Figure 7 presents some examples of this approach using a mobile application screen. The colours represent the type of intervention with notifications.

9 CONCLUSIONS AND FUTURE WORK

In this paper, the impact of user-level decision-making for AI-enabled proactive mHealth is presented. The paper reasons the importance of context for establishing proactiveness and provides a framework of AI-enabled proactive mHealth. The framework aims at providing insights into the design and implementation goals of the system. This paper also considers various implementation challenges. The framework identifies the need for multiple attributes as input and sources e.g., wearables, sensors, and other resources. Finally, a system is proposed based on the framework, which is adaptive and provide timely interventions, JITAI architecture with automated decision-making is fundamental for the implementation. To this extent, the proposed system considers multiple sources as input to provide timely intervention to the user. This intervention is an automated decision, which is built on the user's preferences. The outcome of the system is collected implicitly or explicitly as feedback for ensuring adaptiveness.

For future work, the system will be developed using the proposed framework. The system will adhere to the prediction and prevention mechanism to provide timely intervention with personalization. Multiple parameters will provide a holistic view of the user. The implementation will be an AI engine, which depending on the datasets and availability of the features will handle different machine learning algorithms for clustering and classifications. The core part of the system depends on machine learning techniques for providing an automated decision that is beneficial for the user. The proof-of-concept model can then be used for further developing an AI-enabled proactive mHealth system.

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