Fit-Twin: A Digital Twin of a User with Wearables and Context as Input for Health Promotion

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Abstract: Digital health contributes to health promotion by empowering the user with the holistic view of their health. Health promotion is to enable the user to take control over their health. The availability of wearables has contributed to the shift in healthcare, that is more connected, predictive, and proactive. Proactive in healthcare is to predict and prevent a situation, beforehand. This shift in healthcare puts the user in charge of most health-related decisions. Innovative technologies like AI already contribute to the cause by applying reasoning and negotiation to the collected health data to provide timely interventions to the user. The availability of real-time data from sensors that the user wears all the time allows more opportunities with new health insights. One such prospect is the use of digital twins, which provides personalization and precision. Digital twins also allow risk-free modelling for more accurate outcomes. A user digital twin is not just a virtual replica, but it combines all the factors that can impact the user. The context of the user is a prominent factor in healthcare. The paper establishes the need for digital twins in health promotion. In this paper, a Fit-twin is presented that mimics a user with wearables and the user context as input. The Fit-twin is implemented using Azure digital twins, Fitbit charge, and local context API. This allows one-way communication between the user and the Fit-twin. The outcome is a user digital twin that can be used for health promotion by applying predictive capabilities.

1 INTRODUCTION

Well-being is the combination of factors associated with lifestyle, health, living circumstances, and economic situation (CDC, 2018). The increase in well-being will have a positive impact on the health of a user. Boost in well-being directly impact better productivity in individuals (CDC, 2018).

Health promotion is directly associated with well-being of an individual. Health promotion is to enable people to increase control over their health (WHO, *Health promotion*). This increased control leads to user-empowerment which can then improve wellness. Enabling users to take control of their health is the shift in healthcare that gives the user an active role.

The paradigm shift is essential because healthcare is dealing with many obstacles (*CDC - Global Health* 2022), some of these are related to practical issues: the shortage of resources, and the hospital's ability to cope (*CDC - Global Health* 2022). But some challenges are part of the health approach, for example, the reactive approach, which is to wait for something to happen, an example of crisis management. This reactive approach (Alexis Wise, 2020) is useful, but it depreciates user-empowerment. Digital health can contribute to this by supporting and making healthcare more real-time (Argyres et al., 2022), providing the tools that enable the user with the holistic view of their health.

This shift establishes that future healthcare will be more connected, predictive, and proactive (Deloitte, 2021). Proactive in healthcare is to predict and prevent a situation beforehand, before becoming sick (Sulaiman et al., 2021). This enables care that empowers the user to promote health and well-being. A definition of healthcare also emphasizes this shift: "health is the ability to adapt and to self-manage, in the face of social, physical and emotional challenges" (Huber et al., 2016). The goal of this shift is to establish user empowerment to support healthcare.

Digital health can contribute to the cause by providing the tools (Marwaha et al., 2022). Newly available devices that the user can wear furnish new insights into the health information of the user. This information was not part of the traditional health systems. The information can be the bio-signals, and

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patterns of the user, for example, the activity data, heart rate data, sleep data, and change in data after an intervention.

Wearable technology enables the user to continuously monitor activities, behavior, daily patterns, and other parameters. It is a combination of sensors that a user wears on their body. The common features are heart rate, activities, sleep data, SpO2, and body temperature (Loucks et al., 2021). Some advanced sensors also provide blood pressure, electrocardiogram (ECG), and ballistocardiogram (BCG) (Min Wu, 2021). These devices are worn by the user on the wrist, head, finger, or other suitable places. The data from wearables provide the basis for user-empowerment to promote health. Wearables also allow personalization by considering the uniqueness of the user. This continuous abundance of data also fuels the need for innovation with Artificial Intelligence (AI) to analyze and provide support that is tailored to user needs.

We are part of the fourth revolution in the industry, also known as Industry 4.0. This revolutionized most industries by shifting the focus from manual to automation. IBM defines Industry 4.0 as "revolutionizing the way companies manufacture, improve and distribute their products. Manufacturers are integrating new technologies, including Internet of Things (IoT), cloud computing and analytics, and AI and machine learning into their production facilities and throughout their operations." (IBM, 2022). This evolution also affects healthcare that is adapting to the evolution by introducing healthcare 4.0 (Li & Carayon, 2021) which brings in new trends with AI and robotics to provide better and cost-effective healthcare. The goal is to provide healthcare accessible to everyone and to implement automation in clinical decision-making and enable early detection and feedback.

Industry 4.0 also boosts an application area with digital twins. Digital twin is defined as "A virtual model designed to accurately reflect a physical object. The object being studied — for example, an airplane — is outfitted with various sensors related to vital areas of functionality. These sensors produce data about different aspects of the physical object's performance, such as energy output, temperature, weather conditions and more. This data is then relayed to a processing system and applied to the digital copy. " (IBM, *digital twin* 2022). A digital twin is not merely a replica, but it considers the dynamic context and all the factors associated with the object. The digital twin market is growing and is estimated to reach USD 48.2 billion by 2026 (IBM, *digital twin* 2022).

The future of healthcare is also more personalized (Deloitte, 2021), meaning every user is unique when it comes to behavior and internal and contextual states. The digital twin application in healthcare will revolutionize personalization and precision medicine. It will also allow more opportunities for health promotion and well-being. The real-time data will lead to more precise interventions and generate possible improvements in the health of the user.

AI can contribute to this by applying algorithms to the virtual representation, by analysing the data from sensors and other heterogeneous sources. The collected data can be combined to feed an AI model (Agarwal, 2021) for predictive analytics. The model can then provide timely interventions back to the real asset. The data from the real-time object can allow pattern recognition; to early detect and manage health. A challenge would be the heterogenous data streams because of multiple sensors and wearables.

This paper provides insights into innovations in healthcare with digital twins. It also provides fragments on how digital twins can be utilized for health promotion and risk prevention, by understanding the user as a twin, and the significance of the context and states of the user. The later part of the paper furnishes wearables as a source for digital twins. Ultimately, a proof-of-concept implementation of Fit-twin that uses Fitbit and Azure digital twins to implement a digital twin of a user with the context. The outcome is a Fit-twin that mimics the real user, to collect data from wearables and the context in real-time. This allows a one-way communication between the user and the Fit-twin. Fit-twin will combine multiple parameters of the user for predictive analytics with AI to provide timely intervention back to the user for health promotion.

2 RELATED WORK

A digital twin is not a new concept, in 1991, Micheal Grieves (Grieves, 2007) defined the concept of the digital twin in manufacturing: this accentuates it as a process. The idea of a digital twin can even go back to 1960 when NASA (Grieves, 2007) used it for a space mission exploration to simulate.

The current evolution is because of the availability of sensors, that can connect to the real source and the computational power of AI to apply algorithms to the generated data. One such existing research presented, an intelligent personal MINI-Me (Håkansson & Hartung, 2014) that allows contextual-based decision-making for the individual. Personalized data and context data are combined to create a MINI-Me that can interact with other devices within its context. This MINI-Me motivated the formation of Fit-twin, which uses personalized data from wearables and context data to allow better decision-making.

In healthcare, there are many application areas for digital twins - some of these are a work in progress (Hilary, 2021). The implementation of heart twin (Coorey et al., 2022), allows cardiologists to monitor heart performance for early detection. Another study (Dan Bland, 2018) implemented hospital twins that are used for workflow analysis, system redesign, and process improvement methodologies.

Philips used device twins (Philips, 2021) for the complex equipment to ease the maintenance of these devices. A symptom tracker (Babylon, 2020) by Babylon Health introduced the concept of symptom tracking during covid-19 by connecting to the wearables of the user. This is somewhat closer to the concept of the digital twin of the user. The Table 1 shows some examples of digital twins in healthcare.

Table 1: Digital twins in healthcare.

Digital twin	Purpose
Oxygen tank twin	Used in hospital to track real-time availability of tanks.
Precision-medicine	A twin used to see impact of the medicine given to an individual.
Heart-twin	Monitor heart of an individual.

The related work highlights areas of digital twins' implementation, within healthcare, but establishes that no existing research, in particular, creates a digital twin of the user for health promotion and risk prevention. That also considers the states of the user; both internal and contextual. This establishes that digital twins using wearables as a source can provide new insights into user-level decision-making. The goal would be to empower the user with more personalization and timely support.

3 DIGITAL TWIN FOR HEALTH PROMOTION OF A USER

A digital twin is defined as "a digital twin is a virtual model to accurately reflect a physical object" (IBM, *digital twin* 2022). The digital replica is a virtual representation of a physical asset. The virtual copy is a combination of all the elements, associated with that asset. Digital twin connects real and virtual worlds by binding them with real-time data. A change in a physical asset can be seen on the digital twin instantly. The digital twin is not a 3D model of a physical object, but it includes all the parameters where the asset exists and also considers risks. An illustration is a digital twin of a car: that can collect data from sensors attached to the real car. It includes all the information about the car e.g., mechanical, and electric parts. Also, the environment where the car exists, weather, temperature, and traffic.

Information flow from the digital twin is a 2-way process. First, the data is collected continuously from the sensors. This is the real-time data, stored and fed to the virtual twin. This is a one-way flow; the second part is where the collected data models are formed that can be predictive and preventive. These models can then provide useful information back to the real asset.

When it comes to health promotion with digital twins it is noteworthy to consider health promotion as the: "process of health promotion is more than the absence of disease; it is a resource that allows people to realize their aspirations, satisfy their needs and to cope with the environment to live a long, productive, and fruitful life." (CDC, 2018). This establishes that user empowerment can significantly impact health, and digital twins can allow personalization. A user is part of a dynamic environment that is very impressionistic, meaning it affects someone differently, for instance, a higher pollen count can be a bad situation for someone who is allergic to pollen. This information is drawn from the user profile.

A digital twin is usually mixed with simulation, although it allows simulation it is not just a simulation. The difference is that a simulation is just a process that does not need 2-way communication, and does not need real-time data. The digital twin can run multiple simulations but also considers real-time data. The simulation focuses on a process to simulate an outcome, it depreciates the need for states.

Digital twins for the health promotion of a user must include all the parameters that can have an impact on the user. The wearables will be the source of health information in real time. The communication to the user is characterized as 2-way. This will be achieved by an intervention system that allows timely intervention to the user and gets feedback from the user.

To understand the parameters of a user, let us consider the context of the user. The context is: "the interrelated conditions in which something exists or occurs" (Merriam-webster). A study (Sulaiman et al., 2022) explained user context as anything that can impact the user positively or negatively. Table 2 shows the context of the user with some examples. Many different circumstances e.g., environment, and surroundings, can contribute to the context. A user's context is based on the location and conditions where the user exists. Bad air quality can have a bad impact and thus a part of the context of the user. Context is dynamic with ever-changing surroundings. A system must be adaptive to cope with the dynamic changes in context.

Table 2: Context of the user.

Environment/Surroundings
Weather, air pollution, threats, pollen count, and outbreak

Another parameter is the user characteristics which is the combination of behavior and daily patterns. Table 3 shows the parameters of user characteristics. The behaviors and daily patterns are very unique, different users can act and distinctly react to anything. For behavior change, it is important to consider multiple factors considering the user. When it comes to daily patterns, they depend on user preferences, for instance, someone works during the night and sleeps during the day.

Table 3: User characteristics.

Daily patterns	**Behavior**
Step counts, activity, sleep and other	Lifestyle, schedule, and preferences

Finally, the user profile includes the physical and other attributes of the user along with all the vitals. This information is collected from the user explicitly and implicitly. Table 4 presents the user-profile example. The user profile also combines factors that are the core component of the digital twins. The physical and mental states and the current state of the user are also formulated from the profile.

Table 4: User profile.

Vitals	Heart rate, SpO2, temperature, step-count, activity, sleep, and readiness score
Physical attributes	Body mass index (BMI)
Family history	Disease history
Location	Actual location of the user

The next step after the formation of user parameters is to look for sources and resources to collect data from. Table 5 presents the sources available for collecting data. The table also provides extensive information for each of the parameters of the user.

Table 5: User parameters with sources for input to the user-twin.

Sources	Parameters	Actual source
Wearables	Daily patterns, activity data, health information, real-time sudden changes	Wearable devices: Fitbit
APIs	Weather, air quality, Pollen, warning	YR.no or other metrological source
Sensors	Humidity, temperature, noise, rust, air-quality	Netatmo or a user-made project

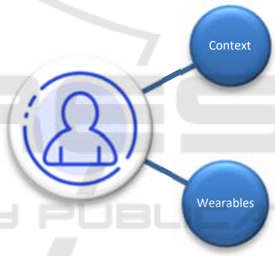

Figure 1: A digital twin of the user with two modules.

Figure 1 presents the digital twin of a user with two modules. The information collected and combined can create a digital twin for the user. The continuous data from the wearables and the context is significantly important to have real-time changes in user internal and contextual states. This information is then used for feeding the digital twin and collecting for modelling.

4 WEARABLES AS A DATA SOURCE FOR INPUT TO THE FIT-TWIN ALONG WITH APIS FOR CONTEXT INPUT

After determining the input of the digital twin, it is specified that it requires continuous data from multiple sources. Wearables are pivotal for integrating user contextual data and personalized data as input. The paper presents a Fit-twin that uses wearables as the input source. Wearables include devices that users can wear, for instance, fitness trackers and smartwatches (Loucks et al., 2021). They are combined with different sensors that are designed to collect data. These devices enable continuous measurement of different body signals and parameters. Wearables are divided into two main types (Min Wu, 2021):

- For health professionals
- For consumers

In our use case of digital twins, the focus will be on consumer-level wearables. These are further divided into three categories.

Wearable Fitness Trackers. These are wrist activity trackers that provide a sensor to collect information. The common activity trackers are Fitbit (Fitbit, 2022), Polar (Polar, 2022), Garmin (Garmin, 2022) and others. They have overlapping features, Table 6 provides a comparison between some fitness trackers available.

Table 6: Wearables fitness trackers.

Fitbit charge 5	Polar	Gramin Vivo	Oura ring	Mi band
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, optical heart rate monitor	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 tracking, GPS, Continuous heart rate, Stress management score, SpO2, sleep and inactivity time

Smart Health Watches. These are smartwatches that are also capable of continuous measurement of body signals and patterns. An example is the Apple Watch, and Samsung watches. The new pixel watch is another new addition to this category.

Wearable Biosensors. Wearable biosensors are used for the continuous monitoring of different parameters more accurately. A common illustration is the continuous glucose monitoring sensor by Abbott. Libre-2 sensors provide continuous monitoring and alarms for blood glucose levels.

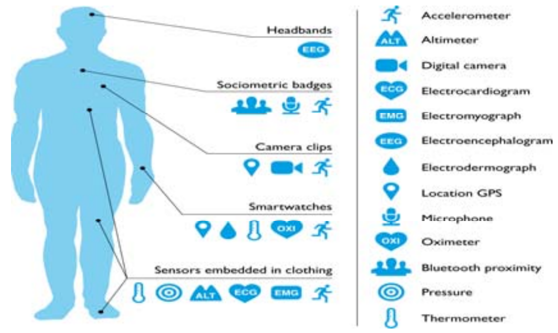

Figure 2: Wearable sensors (Rodrigues et al., 2018).

Figure 2 provides different sensors, their type, and use-case. It also presents details on where the user can wear these devices.

Figure 3: Holistic view of the user.

An example of a holistic view is shown in Figure 3. This holistic view of the user is provided by the wearables. It is the first step towards digital twin formation. The holistic view provides multiple parameters about the user. It includes user daily patterns, current state, data from sensors, and real-time vitals.

A comparison in Table 7 is drawn between two wearable devices for our use case. The first is a Fitbit fitness tracker, and the second is the Oura ring 3. The comparison furnishes details about the parameters and features of both.

The head-to-head comparison shows that both trackers are useful for collecting data from the user. They can provide in-depth real-time data from sensors. The data collected from these can be used as input for our digital twin.

The next step is to compare the APIs of both devices. The Fitbit API (Fitbit-API, 2022) provides endpoints to integrate and collect data. The collected data can be stored and processed to be used for input to the digital twin. Oura ring also provides Oura API V1 (Oura-API). The outcome of this comparison shows that Oura ring is an excellent choice when it comes to sleep tracking, but Fitbit leads the way as a multipurpose tracker. The Fitbit API is well-established and documented.

Table 7: Comparison between Fitbit and Oura ring.

Fitbit features	Oura ring
-Wrist -Continuous heart rate -SpO2 in sleep -Activity tracker -The time, duration, type and intensity -Active minutes -Readiness score -No temperature sensor -Location	-Ring -Continuous heart rate -SpO2 in sleep -Activity tracker -The time, duration, type and intensity -Only with MET for activity tracking -Readiness score -Temperature sensor -Location

Integration to Google Fit is still a work in progress. Although Google acquired Fitbit some time ago. There is no direct official syncing between the platforms. A third-party (HealthSync) application is used for syncing these together.

So, with this extensive comparison between different wearables. It was concluded that Fitbit would be an ideal choice for our use case. The data from Fitbit would be fed to the digital twin. Fitbit profile can also establish the user-profile setting required.

Choosing the wearable is a starting point for our digital twin. The next step would be to collect data from the context. In this use case, YR.no is used as a source. The metrological API provides the following features.

— **YR.no (YR, 2022) as a Context Source.** Weather data, Met warning, Air-quality, Pollen, Storm, Ice mapping, and ocean forecast.

Another choice would be to use indoor-outdoor weather stations. These can be built using a microcontroller and sensors. An example of an indoor context station is given below.

— Sensors with microcontroller:

- Arduino Uno R3 (Arduino): A microcontroller
- MQ-135 (MQ135): A gas sensor
- BME 280 (Bosch): Temperature, humidity, and pressure sensor
- PM2.5 (Adafruit): Dust and particulate matter Sensor

Figure 4: Sources and resources for the user-twin.

After combining the sources and resources, Figure 4 presents sources and resources to input for the digital twin of a user. Fitbit as a wearable can provide real-time data and collect daily patterns. The Fitbit API can also provide user-profile information. The contextual data can be collected from YR.no as a resource. This data is based on the location of the user. Other indoor sensors can be used for collecting indoor contextual data.

5 FIT-TWIN- A DIGITAL TWIN FOR USER (FITBIT + AZURE + CONTEXT)

After the identification of sources for input to the Fit-twin. The next step is to implement each of the components. Implementation components for the Fit-twin are listed and briefly explained.

Fitbit Charge 5. It is a fitness tracker that is worn on the wrist. It provides continuous measurement of activity, heart rate, calories burned, active minutes, breathing rate, and sleep. The collected information is displayed on-screen or can be synced to the mobile device. Fitbit charge 5 possesses multiple sensors like an optical heart rate monitor, a 3-axis accelerometer, built-in GPS + GLONASS, and red and infrared sensors.

Fitbit Web API. Fitbit provides a public API for the integration and collection of data. The data collected is stored and then retrieved using the Web API. The endpoints are accessible for the retrieval of data. Examples of some end-point scopes are activity, sleep, heart rate, location, and oxygen saturation. The retrieved data is then stored and fed to the digital twin.

YR.no. YR provides a well-documented API for metrological data. To integrate the context data for our digital twin YR is a good source. The available end-points are weather, warnings, air quality, turbulence, icemap and ocean map. This data incorporates current, daily, monthly, and yearly information on temperature, precipitation, and wind.

5.1 Implementation Logic

When it comes to implementation the goal is to have two digital twins combined with a relationship to implement a one-user Fit-twin. The first step would be, to understand how the user digital twin is created. The user digital twin is a digital replica of an actual user. It replicates and is in sync with the real user by input stream of real-time data from the wearables. Figure 5 demonstrates how the input works for the user twin. The implementation is based on Azure digital twins (Azure-DT). Azure furnishes a complete implementation framework for creating digital twins.

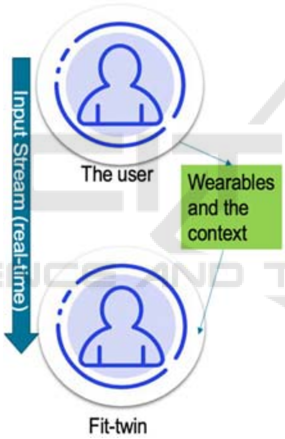

Figure 5: Fit-twin with input stream.

In this proof-of-concept, two digital twins will be implemented and connected to create a Fit-twin. The first step is to create a model of both twins, define the relationship, and connect this model to an actual source to demonstrate a working Fit-twin.

5.1.1 Creating the Model

Azure provides Digital Twin Definition Language (DTDL), which uses JSON-LD, a method to encode linked data to create a model of a twin. This model is a combination of the interface that requires four key components, based on our use case. The key segments are presented with the two models, User-model and the context model.

- User Model

— **Properties:** User profile: ID, Physical attributes, location
— **Telemetry:** Heart rate, SpO2, Activity, Sleep
— **Components**: When we want to combine models, in this case, we will add the context model as part of it.
— **Relationships:** It defines the user model relationship with the context.

- Context model

— **Properties:** Location of the user
— **Telemetry:** Weather, air quality, temperature, warnings
— **Components:** Add the user model as part of the context model
— **Relationships:** It provides information to the user model.

The actual implementation using Visual Studio Code (VS). The code below is the pseudo code of both models.

User-Model: JSON.

```
 "@id": "User-twin;1",
   "@type": "Interface",
   "displayName": "User-twin",
   "contents": [
        {
            "@type": "Telemetry",
            "name": "BMI",
            "schema": "double"
        },
{
            "@type": "Property",
            "name": "Heart_rate",
            "writable": true,
            "schema": "double"
        },
```

Context-model: JSON.

```
  {
            "@type": "Telemetry",
            "name": "Location",
            "schema": "double"
        },
```

Relationship between both:

```
{
            "@type":
"Relationship",
            "name": "contains",
            "target": "context-
twin"
        },
```

5.1.2 Creating an Instance of the Model on Azure

After creating the models, the next step is to upload this model to Azure and define the access roles. After creating an instance, the client applications can directly connect to the digital twin instance. Since we are not using any client application for this proof-of-concept, we will be using a sample Azure twin explorer application (DTe).

5.1.3 Using Azure Twin Explorer, Creating Fit-Twin

Azure twin explorer is used to create twins and connect them to the azure instance. The Fit-twin is connected to the wearables and context twins. The implementation shows any change in the user data or context data in the real world is imitated by the Fit-twin.

- Both twins are presented before and after connecting to the real source.

Figure 6: Fit-twin-user-before on the left, and after connecting to the real source.

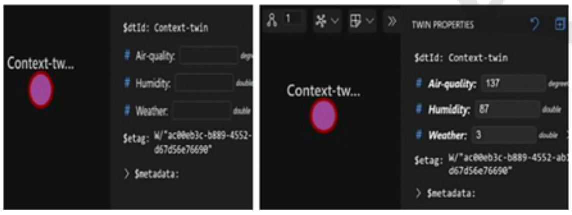

Figure 7: Fit-twin-context- before on the left, and after connecting to the real source.

The client applications can be used, for instance, the Fitbit dashboard in Figure 8 provides a good-looking interface for the twin.

The implementation shows that after connecting to the real source, the user twin will collect and present any change in real-time shown in figure 6. The number of steps taken by the user and other data points will be updated when connected.

This also allows connecting to the real source for context model. Context twin when connected to the API will present real-time data as shown in figure 7.

Figure 8: Client- application example for digital twin.

5.1.4 Architecture Diagram of the Fit-Twin

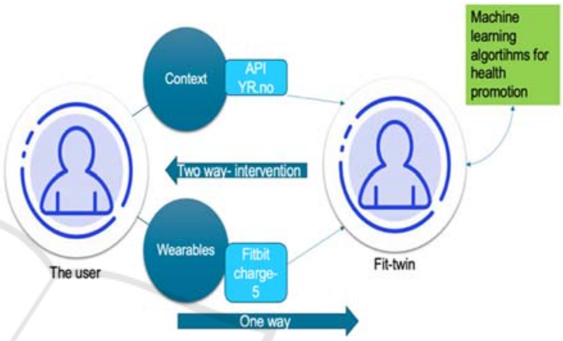

Figure 9: Architecture diagram of the Fit-Twin.

The figure 9 presents the architecture diagram that combines two twins (user and context) into one model. It also presents that each of the models has some properties. The one-way communication from the user to fit-twin is implemented in this proof-of-concept. The two-way communication requires predictive capabilities for interventions.

6 DISCUSSIONS

Fit-twin provides more personalization. Fit-twin combines the user model and the context model. The communication from the sensors to the Fit-twin is considered one-way. The next step is to apply algorithms to the collected data and simulate it.

An example is to simulate the Fit-twin for a walk, whether it is safe for the user to walk between points A and B. The risk prevention mechanism will follow the timely intervention back to the user with information about possible risks.

The two-way communication for Fit-twin requires AI modelling, which will consider all the parameters and provide predictive analytics to predict the situation e.g., A real user can ask whether an activity performed will be beneficial for their health?

Fit-twin can then combine all the parameters and attributes associated with the user to provide an answer.

The risk-free modelling will allow the simulation to be applied on the Fit-twin first before applying it to the actual user. More information about the user collected and applied to the Fit-twin will help achieve precision. The goal is to promote health and prevent risks.

Challenge is with real-time sudden changes, modelling with real-time data is challenging. Another challenge is to either use a generic model or a personalized model.

Fit-twin will also help generate more data (collecting from multiple parameters) that can be used for modelling, to provide timely interventions back to the user.

7 CONCLUSIONS AND FUTURE WORK

Health promotion is to enable users to take control of their health. This increase in control contributes to user empowerment. Wearables along with the context of the user allow personalization and precision. Another innovation that reinforces user empowerment is a digital twin. A digital twin is not just a virtual replica of an asset, it also combines all the properties of the asset e.g., context and state. Digital twins allow 2-way communication between a resource. The availability of wearables and contextual APIs that can provide real-time data highlights the need for creating user-digital twins. In this paper, we developed a digital twin of a user "Fit-twin". The Fit-twin is connected to the real user with wearables and context API. The Fit-twin is created using Azure, Fitbit charge 5, and a local metrological resource for context. The outcome is a Fit-twin that mimics the properties of an actual user. The change in context and state of the user can be seen on the Fit-twin. The provided solution only provides one-way communication for now but provides placeholders to add predictive capabilities for intervention mechanisms.

In future, the Fit-twin will allow Just-in-time interventions generated based on the collected data from multiple parameters of the user. The intervention mechanism will depend on prediction capabilities of AI model to provide the right support to the user at the right time for health promotion or risk prevention.

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