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Sustainable Smartphone-Based Healthcare Systems: A Systems Engineering Approach to Assess the Efficacy of Respiratory Monitoring Apps

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Abstract: Recent technological developments along with advances in smart healthcare have been rapidly changing the healthcare industry and improving outcomes for patients. To ensure reliable smartphone-based healthcare interfaces with high levels of efficacy, a system dynamics model with sustainability indicators is proposed. The focus of this paper is smartphone-based breathing monitoring systems that could possibly use breathing sounds as the data acquisition input. This can especially be useful for the self-testing procedure of the ongoing global COVID-19 crisis in which the lungs are attacked and breathing is affected. The method of investigation is based on a systems engineering approach using system dynamics modeling. In this paper, first, a causal model for a smartphone-based respiratory function monitoring is introduced. Then, a systems thinking approach is applied to propose a system dynamics model of the smartphone-based respiratory function monitoring system. The system dynamics model investigates the level of efficacy and sustainability of the system by studying the behavior of various factors of the system including patient wellbeing and care, cost, convenience, user friendliness, in addition to other embedded software and hardware breathing monitoring system design and performance metrics (e.g., accuracy, real-time response, etc.). The sustainability level is also studied through introducing various indicators that directly relate to the three pillars of sustainability. Various scenarios have been applied and tested on the proposed model. The results depict the dynamics of the model for the efficacy and sustainability of smartphone-based breathing monitoring systems. The proposed ideas provide a clear insight to envision sustainable and effective smartphone-based healthcare monitoring systems.

Keywords: system dynamics; modeling; systems engineering; sustainability; respiration

1. Introduction

1.1. Background

The advent of mobile (m)-health, smart (s)-health, and electronic (e)-health have been made possible by the ever-growing advances of technology in various areas. Specifically, smartphone devices and applications (Apps) with internet connectivity and communication features offer suitable platforms in this regard. Presently, more than 100,000 smart/mobile health applications are available in the online market of Android and iOS. As technology and healthcare continue to evolve side-by-side, the number is predicted to grow even further with an exponential rise [1,2].

Smartphones are presently equipped with various sensors such as microphone for audio, camera for image and video, gyroscopes for movement and acceleration, and touch-screen fingerprinting bio-metrics, etc. Thus, many physiological/biomedical related data can be acquired directly using the smartphone device and can then be processed and analyzed by an App running on the smartphone's processor chip. Some smartphone-based healthcare monitoring systems may require additional hardware and/or sensors that are wearable or attached to the smartphone device to collect the physiological data [3]. The embedded, real-time hardware and software co-design nature of smartphones allow for fast integration and dissemination of health-related data for continuous monitoring of the health status. Furthermore, the connectivity features of the smartphone provide a network of health-related data that can be exchanged among users, patients, healthcare providers and physicians. Such network of mobile health is extremely helpful to identify the onset or progression of certain diseases, some of which may require immediate attention/action for life threatening patient conditions.

As yet, smartphone-based healthcare monitoring systems and Apps have been extensively researched in the literature [4–9]. The impact of such Apps is broad as they enable decision/diagnostic support and/or offer treatment aids. To name a few, some smartphone-based healthcare applications (or algorithms than can be implemented as a smartphone App) monitor and assess the lung functionality and respiration [10–12], while others focus on the heart [1,13,14], and/or brain/mental status [6,15]. There are also several applications that monitor and evaluate other body organs such as the eye for vision [16] and pressure [17], as well as screening the skin for suspicious lesions [9,18] or the ear for hearing functionality [8,19], and several more [1,13]. The underlying basis of data analysis in almost all smartphone-based healthcare monitoring App algorithms is machine learning. Nonetheless, there is room for more improvements. Especially that controlling the disease and the level of overall patient wellbeing outcome often define the efficacy of such applications.

Breathing is one of the most essential and usually involuntary functions of the body that human beings lives heavily depend upon. Most respiratory and lung-related diseases lead to chronic airway inflammation, associated with changes to airway tract structure and function, and can cause devastating and life threatening effects. The symptoms include, but are not limited to breathlessness, chest tightness, airflow limitations, wheezing sounds and coughing. Pneumonia, lung cancer, sleep apnea (pause of breath during sleep), and chronic lower respiratory diseases including the chronic obstructive pulmonary disease (COPD) and asthma are such diseases [20,21].

According to [20–25], respiratory diseases have been listed among the third-leading cause of death in the developed world and worldwide in the recent years. On the other hand, at the time this research is being conducted, the Coronavirus (COVID-19) outbreak and crisis is in effect and has been reported to be the world-wide pandemic in March 2020, with over 117,000 fatalities in the U.S. alone so far, and over 446,000 deaths across the globe as a result of shortness of breath, pneumonia and/or other breathing disorders [26,27]. This is while the projected numbers of those who will be contracted with coronavirus leading to breathing complications and death are unfortunately increasing drastically [28].

Traditionally, non-invasive diagnostic modalities are primarily used by healthcare personnel at clinics to diagnose breathing diseases. The assessments, however, are generally followed by more complex tools including pulmonary function testing (PFT), chest high resolution computed tomography (HRCT), bronchoscopy [29] and in certain cases, invasive modalities such as biopsy. The highly imposing costs and early detection necessity for more effective treatment planning outcomes, show the persuasive need for automated breathing monitoring systems that can aid in prevention, early detection, and treatment of prevailing respiratory diseases.

Many automatic respiratory monitoring systems have been introduced, some of which collect respiratory data using contact, non-contact or semi-contact sensors and provide computerized respiratory auscultation data analyses and interfaces [30–32]. However, reliable personalized hand-held breathing monitoring systems, specifically those that can be configured with smartphone devices and Apps, are not only more attractive and convenient for users/patients, but can also play a significant role in the overall health and wellbeing of patients, by saving and/or improving many lives. These systems offer patient wellbeing through continuously monitoring the respiratory function for early diagnosis, decision support, self testing and preventative feedback. They can additionally offer treatment aids such as breathing regulation and/or inhaling aids (i.e., with additional hardware). To this end, smartphone-based breathing monitoring systems that can serve as self-testing kits and/or breathing regulation aid for coronavirus seems very appealing presently specifically, as self quarantine and social distancing is a necessity to suppress the spread of this extremely contagious virus. If such smartphone-based breathing monitoring/diagnostic systems are fully implemented and operational, users can perform self-testing individually by just a few clicks on the smartphone, at their own convenience, at home.

Respiratory data can be acquired by different means such as digital stethoscopes for lung/breathing sounds (acoustic signals), and electronic or mechanic spirometers for lung volume/capacity by measuring the airflow. An attractive solution for smartphone-based respiratory data collection could be breathing sounds acquired from the microphone of the smartphone.

Each cycle of the breathing sound (the acoustic breathing signal) is divided into four phases (Figure 1): inspiratory phase (referring to inhale/inflow of air to the lungs), inspiratory pause (when incoming airflow stops), expiratory phase (referring to exhale/outflow of air from the lungs) and expiratory pause (when outgoing airflow stops). A large collection of terms for respiratory sounds has been introduced by the Computer-Respiratory-Sound-Analysis (CORSA) society [33], with over 162 terms. The generic well-defined lung-related sound terms are normal breath sounds, adventitious sounds, and breath sounds (that include both normal and adventitious sounds) [34]. Adventitious sounds are characterized by certain frequency-based features and are generally associated with pulmonary-related complications such as pulmonary oedema, pneumonia, tracheal stenosis, asthma, bronchitis and apnea. Machine learning and frequency analysis of breathing sounds can reveal many differentiating characteristics of various breathing complications, and possibly the disease severity level [10,12,34–37].

To date, many smartphone-based breathing monitoring systems/Apps have been introduced for the purpose of breathing aids and/or analysis and detection [10–12,35,37–43]. Table 1 displays a summary list of smartphone-based respiratory monitoring systems available in the literature/market. The table includes specifications for each of the systems in terms of respiratory data acquisition input type, purpose of the system representing the respiratory monitoring capability, breathing data analysis accuracy, and cost. For example, one such system, which is completely non-invasive, is an interactive real-time breathing-monitoring framework using breathing sounds [10,36,44,45]. The acoustic respiratory data, acquired using a microphone embedded within the smartphone, is analyzed to identify normal/abnormal breathing sounds, estimate lung capacity [46,47], and also provide synchronous virtual animations of the lung inflating and deflating as the user inhales and exhales [10]. Breathing sound signals are analyzed via frequency domain techniques and machine learning is used to classify the signal into inhale and exhale phases or pauses [36]. See Figure 1.

Sustainability has become one of the most fundamental challenges over time. Sustainability considers the needs of future generations while realizing the needs of present generations [48]. According to the Brundtland report [49], sustainability integrates three components including social development, economic development, and environmental protection. These components are known as the three pillars of sustainability that are interdependent and mutually reinforcing [50].

Sustainability faces complex issues caused by the intricate and unbalanced interactions that impact decision making at social, economic and environmental levels [51]. An interdisciplinary approach such as systems engineering is required to deal with these issues. By definition, systems engineering is "a transdisciplinary and integrative approach to enable the successful realization, use, and retirement of engineered systems, using systems principles and concepts, and scientific, technological, and management methods" [52]. Systems engineering is an interdisciplinary field of engineering which addresses large and complex systems. One of the goals of systems engineering is to better understand the behavior of a system and its problems. This discipline deals with large and complex systems and focuses on the system as a whole.

Healthcare systems are complex and critical systems since they deal with people's health and wellbeing. These systems include elements and components that interact in highly complex and variable manners [53]. The components can include key stakeholders such as doctors, patients, and hospitals [54]. The World Health Organization (WHO) also emphasizes on the importance of understanding the impact of system complexity on patient care in healthcare systems [55]. Systems engineering can also help to address the complex sustainability challenges in healthcare systems.

In general, systems thinking offers a full/complete view of a system. This approach considers the entire world as a complex system and determines the relation and connections among various factors of the system [56]. The idea of system dynamics was primarily introduced by Forrester [57] which focuses on the composition and behavior/dynamics of the system factors and their interrelationships. Both system dynamics and systems thinking are supporting elements of systems engineering. In recent years, system dynamics has been deployed in many healthcare areas [58–61].

Table 1. A sample list of various smartphone-based breathing monitoring systems/Apps.

Reference	Data Acquisition	Purpose/Respiratory Monitoring Capability	Breathing Data Analysis Accuracy	Cost to Customer
[10]	Breathing sounds	Lung augmentation and animation, breathing phases and lung volume estimation, breathing regulation aid	90%	N/A
[11]	Breathing sounds	Pediatric asthma detection	within 5% $\pm$ 1.5 of sprirometry	N/A
[12]	Cough sounds	Diagnosing acute respiratory illnesses in children	$\approx$77% on average	N/A
[35]	Breathing sounds	Differentiating normal and abnormal lung sounds for various respiratory diseases	$\approx$75%	N/A
[37]	Breathing sounds, cough sounds and voice of speaking	Detect COVID-19	In progress, not reported	Free once App is launched
[38]	Wireless spirometer	Monitor asthma	Not reported	Free App + $100 Spirometer
[39]	Breathing sound blow	Estimate lung air volume	within 5% of commercial devices	Free
[40]	Breathing sounds	Breathing phases detection and breathing training	75.5%	N/A
[41]	Wearable biosensors	Chronic Respiratory Disease Monitoring	Not reported	N/A
[42]	Photoplethysmographic (PPG) imaging	Respiratory rate estimation	97.8%	N/A
[43]	Thermal camera	Respiration training	Not reported	N/A

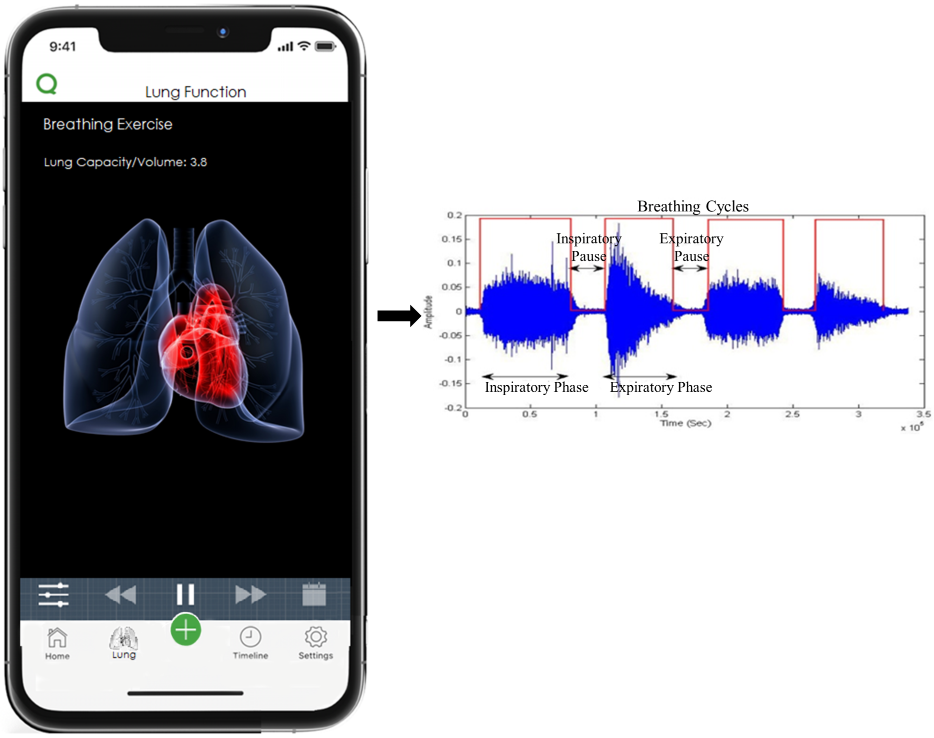

Figure 1. Breathing sound cycles.

1.2. Contribution

This paper focuses on a system dynamics model for sustainable smartphone-based respiratory monitoring systems including, but not limited to those that could possibly use breathing sounds as the sensing input. Assessing the sustainability and efficacy level of such Apps are the focal points of investigation in this research. To accomplish this objective, we introduce a complex system dynamics model with various factors and their interrelationships along with feedback loops.

A systems thinking perspective is applied to explore the factors and factor relationships that impact sustainability and efficacy. First, a causal model is presented that illustrates the factor and factor relationships and the nature of these relationships. Then, a system dynamics model is presented that models the behavior of the factor and factor relationships and would assist in decision making. This approach would help understand the non-linear behavior of complex systems.

To observe the efficacy and sustainability of smartphone-based respiratory monitoring, the model has been thoroughly tested and the simulations results reflect the dynamics of the model in various scenarios. As system dynamics modeling has not been previously applied to smartphone-based respiratory monitoring, this research provides a novel contribution in this regard.

1.3. Paper Organization

The remainder of this paper is organized as follows. In Section 2, the proposed causal model is introduced followed by sustainability indicators along with the structure of our proposed system dynamics model for smartphone-based breathing monitoring systems. The results of the system dynamics simulation for the baseline and various scenarios are presented and discussed in Section 3. The model validation is also discussed in the same section. Finally, concluding remarks and future directions appear in Section 4.

2. Proposed Methodology

The overall hypothesis of this research is to show how the performance metrics of smartphone-based breathing monitoring Apps/devices along with various social, economical and environmental factors impact the efficacy (sustainability) of smartphone-based respiratory function monitoring systems. The methodology of our study design is based on a systems engineering approach using system dynamics modeling. For this, a causal model for smartphone-based respiratory function monitoring is first introduced. A systems thinking approach is then applied, in which a system dynamics model is proposed to assess the sustainability level (level of efficacy) of smartphone-based respiratory function monitoring.

2.1. Causal Model

Patients confront many challenges when faced with selecting the most effective and sustainable smartphone-based healthcare monitoring system. A systems thinking method is proposed to determine the various factor and interrelationships to address these challenges.

A causal model is used to assist the system dynamics representation of complex systems. Basically, causal models provide a graphical illustration of the feedback relationship between factors and factor interconnections. The key information about the hypotheses for each factor can be found within the causal model diagrams. The structure of a causal model includes elements (factors) and arrows (causal links). The arrowhead direction in the diagram indicates the sequence of the factor relationships, and the sign given to each link signifies either an increasing (+) or decreasing (−) relationship.

We have identified a set a factors and their interrelationships as a result of extensive review of the current state-of-the-art mobile-based healthcare Apps (Table 1) considering the main attributes for patients in a causal model [10–12,35,37–43,62,63]. The causal model can assist patients determine the efficacy and sustainability of the selected service by defining the key categories of factors and their interconnections. In this paper, we are specifically interested in studying smartphone-based breathing monitoring Apps. The main focus is to investigate the key attributes and service performance of such applications to determine the level of efficacy and sustainability. Figure 2 depicts the overall view of the causal model proposed in this paper. The hypothesis of each factor is embedded within the non-linear increasing and/or decreasing relationship and feedback it may have with other factors. As can be seen from the causal model Figure, when different system design and performance metrics and factors such as respiratory data acquisition feasibility, level of performance, user friendliness, breathing software management, data security and privacy factors increase, the level of efficacy and sustainability of the selected service would also increase.

It is noteworthy to mention that all the relationships for the level of efficacy of service also apply similarly to determine the level of sustainability, which is the main focal study point of this research. Therefore, the factors "level of efficacy of service" and "level of sustainability", though by definition are not the same, are used interchangeably in this paper for their factor relationships.

According to [64], the level of patient wellbeing indicates the level of proper health, security, safety, and happiness of the patient. In a similar manner, patient satisfaction can be defined as a healthcare recipient's reaction to prominent aspects of the context, process as well as the result of their service experience [65].

The respiratory data acquisition feasibility factor mainly deals with the embedded hardware aspects of the system and expresses how feasible it is to collect respiratory data from the phone or an external wearable device and how convenient this would be for the patient. In the context of this paper, breathing sounds can be acquired by the smartphone's microphone or a digital stethoscope attached to the smartphone device. These breathing sounds can be used as the respiratory data acquisition input to the respiratory monitoring system/App [11,12,35,40]. Though, other methods of respiratory data acquisition exist for respiratory function monitoring Apps [41,42] as can be seen from Table 1, breathing sounds are perhaps the most convenient ones, as they do not require additional wearable hardware/sensor attachments. This feature increases the respiratory data acquisition feasibility level.

Embedded software modules such as the acoustic breathing signal processing and analysis algorithm in addition to the latest version of the App being available for download and updates are part of the breathing software management factor. The respiratory monitoring capability (or level) factor represents the depth of which the software's respiratory features (details) are monitored and displayed by the App. Moreover, the user friendliness factor indicates the convenience or the ease of using the application and the interface. Furthermore, the response rate factor denotes the response speed of the breathing data analysis algorithm followed by the internet connectivity rate or speed which could be displayed on the user's screen. It is also implied that the data security and privacy factor plays an important role in the breathing software management factor by enabling user authentication and preserving confidentiality of patient data.

Figure 2. Causal model of smartphone-based respiratory monitoring systems.

The cost of service factor would be considered to be the main starting point of one of the feedback relationships in the causal model. As the cost of the App increases, the level of patient satisfaction is anticipated to decrease. This is while, increase in patient satisfaction will increase the level of efficacy and/or sustainability. At the same time, the level of patient wellbeing is expected to increase as the efficacy increases. This is in large, due to the fact that mobile health Apps provide informative feedback/guidelines to the patients. Patients follow those guidelines which mostly include preventative/diagnostic/treatment plans, leading to overall improvements in their health and wellbeing [62,63]. Furthermore, when the level of patient wellbeing improves, the number of patients with social/medical risk factors is projected to decline. On one hand, more patients with social/medical risk factors will likely increase the level of demand for the App. On the other hand, a rise in demand, is anticipated to reduce the cost of service. Cost of service also adversely affects the level of demand. However, this relationship is already accounted for by the feedback loop presented. A reinforcing feedback loop would begin with patient satisfaction connecting to the level of efficacy of service, level of patient wellbeing, returning to patient satisfaction. As the patient wellbeing factor improves, patient satisfaction will also likely increase since patients evaluate their received services and experience positively [59]. With the rise in the number of customers using the applications, the total number of breathing disorders is expected to decrease due to the real-time patient care and information the Apps offer. Finally, the wellbeing of patients is anticipated to diminish as the total number of the patients with lung/respiratory related diseases grows.

2.2. Categories of Sustainability

As stated earlier, a sustainable system should address the three pillars of sustainability which include social, economic and environmental components.

We identified five main categories of sustainability factors for smartphone-based breathing monitoring systems. These include: (1) Patient-related, (2) Resource-related, (3) Environment-related, (4) Finance-related and (5) Quality-related categories of sustainability.

All the five major categories of sustainability are interrelated and span through the three pillars of sustainability to some extent. This is clearly seen from the Figure of the causal model (Figure 2). For example, Patient and Quality categories mainly correspond to the social pillar but also relate to the economic pillar. On the other hand, the Resource category can partly be incorporated in all pillars.

The factors themselves correspond to one or more categories. Table 2 illustrates the category that each group of interrelated factors belong to. The group of smartphone performance metric factors include, but are not limited to level of performance, response rate, breathing software management, data security and privacy, and respiratory data acquisition factors. Patient status factors include level of patient wellbeing, quantity of patients with social/medical risk factors, number of breathing disorders and patient satisfaction. Cost related factors encompass cost of service and the actual need and level of demand. Resource related factors include battery, internet connectivity and GPS/location tracking factors.

To ensure a sustainable system, there must a balance among the three pillars of sustainability. In what follows, we propose a system dynamics model to conceptualize the level of efficacy of the smartphone-based breathing monitoring system. As mentioned earlier, in the proposed model, the level of efficacy also represents the sustainability of the system as they follow similar dynamics. In the results section, the dynamics of the model for various scenarios reflect how sustainability is balanced and maintained.

Table 2. Sustainability categories and factors.

Category	Patient	Resource	Environment	Finance	Quality
Smartphone performance metrics		✓			✓
Patient status factors	✓				✓
Cost related factors				✓	
Resource related factors		✓	✓		

2.3. System Dynamics Model

A system dynamics model of a smartphone-based breathing monitoring App is introduced in this section. To assess the effect of various changes in the factors and the impact on other factors as well as the efficacy of the selected service (and/or sustainability), a system dynamics model considering a subset of the proposed causal model is illustrated in Figure 3. A system dynamics model experiments various scenarios of the system and can evaluate the dynamic consequences of several decisions without interrupting the actual system itself. Variables of the system dynamics simulation model have underlying equations representing the nature of the factors and their interrelationships.

System dynamics model elements include stocks, flows, and auxiliary variables. The proposed system dynamics model is designed using Vensim® Pro [66] software. Figure 3 depicts an illustration of the system dynamics model structure.

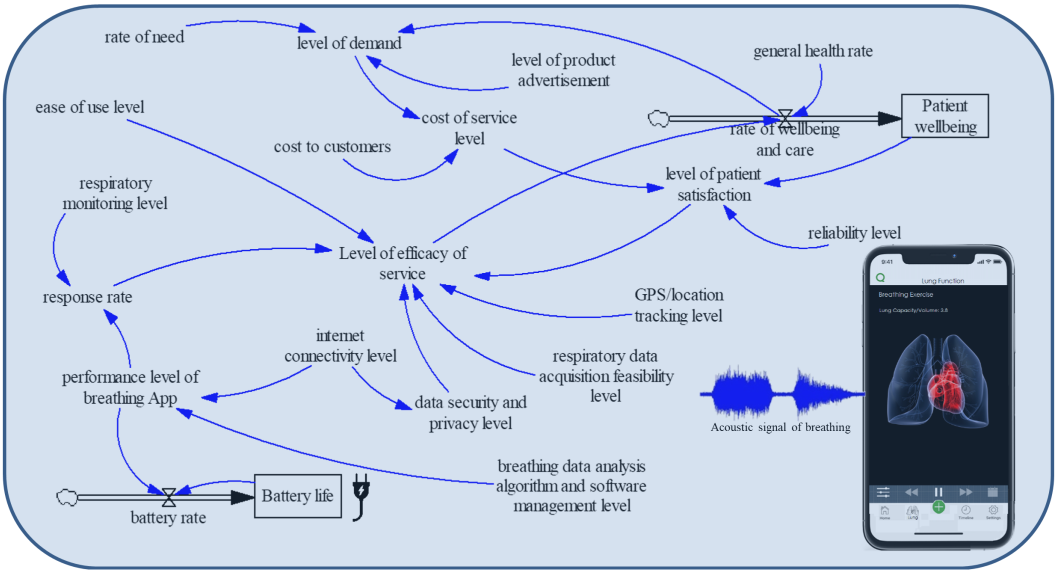

Figure 3. System dynamics model of a smartphone-based breathing monitoring system.

Table 3 displays a clear mapping of each of the system dynamics factors presented in Figure 3 to the five main categories of sustainability defined in Section 2.2. For better clarity, the system dynamics parameters are sub-divided into four groups of factors: (1) Smartphone performance metric factors, (2) Patient status factors, (3) Cost related factors and (4) Resource related factors.

Table 3. System dynamics model factors and sustainability categories.

Sustainability Category	**Patient**	**Resource**	**Environment**	**Finance**	**Quality**
Smartphone performance metric factors:					
respiratory data acquisition feasibility level		✓			✓
breathing data analysis algorithm and software management level		✓			✓
respiratory monitoring level		✓			✓
ease of use level		✓			✓
response rate		✓			✓
performance level of breathing App		✓			✓
data security and privacy level		✓			✓
Patient status factors:					
Patient wellbeing	✓				✓
rate of wellbeing and care	✓				✓
reliability level	✓				✓
general health rate	✓				✓
level of patient satisfaction	✓				✓
Cost related factors:					
cost to customers				✓	
level of product advertisement				✓	
rate of need	✓			✓	
level of demand	✓			✓	
cost of service level				✓	
Resource related factors:					
internet connectivity level		✓	✓		✓
GPS/location tracking level		✓	✓		✓
Battery life		✓	✓		
batter rate		✓	✓		

3. Validation and Simulation Results

3.1. Model Validation

In the context of this paper, validation approves whether the system dynamics model represented is useful and offers sustainability (and/or efficacy). Model validation also checks to ascertain if the model represents an actual system and whether it is proper for the purpose it is providing. Sterman [67] proposed guidelines for building confidence in system dynamics models. In this section, we follow those guidelines to validate our model for (1) its structure, (2) behavior and (3) the implications of the user's policy.

3.1.1. Structural Tests

Validation starts with the model's structural tests. Validation tests of the model structure includes a series of tests such as structural, parameter and dimensional consistency tests. Such tests do not yield numerical values, and rather check for the model structure resulting in either no errors (i.e., passed the test) or errors (i.e., test failed). The Vensim simulation software used in this work has the capability of checking for the model structure in terms of parameters, equations, units and boundaries, at the stage that the system dynamics model is designed. The structure validation tests can be carried out as many times at each stage of designing the model before running any simulations; e.g., when adding, modifying or removing any of the components (factors) of the model and/or their interconnections; to ensure the structure is valid in terms of the dimensions and boundaries. We carried out this structure validation test using Vensim software after inserting all our factors and their interconnections for the model design. Structure tests do not involve simulation runs with several systems/people or inputs, and merely test the structure of the model. We have performed these structural tests directly using the compilation feature of the software tool. The structural compilation of the model returned with no error. Hence, our model passed these structural validation tests satisfactorily.

3.1.2. Behavior Tests

Validation tests of the model behavior includes a series of tests such as family member, behavior reproduction and extreme condition tests.

Family member tests refer to tests that assess whether the model can reproduce the behavior of other examples of systems in the same family (class) of the model. Systems that are based on system dynamics modeling are examples of other systems in the same class of our proposed model. This requires historical data to be fed to our model for validation. However, to the best of our knowledge, this is the first attempt of applying system dynamics modeling to evaluate the level of efficacy (or sustainability) of smartphone-based breathing monitoring Apps, and actual patient data using the Apps have not been collected. Therefore, historical data does not exist at this point of time to conduct family member tests. Nevertheless, the underlying basis of system dynamics modeling is founded upon factors and their interrelations, shown by auxiliary variables, flows and stocks. In addition, the functions of the factors in our model do not include any randomness. Due to this inherent nature, family member tests of the system dynamics models will always reproduce the same behavior for a given class of model and set of inputs.

Behavior reproduction tests check whether the model is able to always reproduce the same behavior under a given scenario (condition). Behavior tests are performed after the model is populated with inputs representing the scenarios. Various testing scenarios and simulation runs are explained in more detail in Section 3.2. Since the factor relationships in the model are not based on any random variable generation, and are rather deterministic non-linear functions with feedback relations, they will always reproduce the same behavior/results for any given scenario with defined input variable settings. The behavior of the model is checked against changes in various factors as well as extreme conditions. Since the model was able to run within the defined boundaries in various conditions (scenarios) and always produced the same results presented in Section 3.2, our model passed these behavior validation tests of reproduction. Furthermore, the model validation tests we carried out considered the two extreme cases of high extreme and low extreme. In the low extreme test, all the system dynamics input variables were set at the low extreme of 0. In this test, we observed that the sustainability level (level of efficacy) initially started at $1.57 \times 10^{-10} \approx 0$, and became 0 in the remaining days. Moreover, in the high extreme test, the system dynamics input variables were set at the high extreme of 100%, and were found to be producing results within the accepted boundaries of 0 and 100%.

The behavior reproduction and extreme condition validation tests were conducted 7 times for the testing scenarios (Baseline and the 6 different scenarios explained in Section 3.2) plus the two extreme conditions (low extreme and high extreme). These are simulation runs of the model by setting the inputs to the values described for each scenario. In these simulations, we assumed that the efficacy (and/or sustainability) level of one smartphone-based breathing monitoring system (App) is being assessed. Since clinical trials with patient consent over long durations are required for conducting the tests on actual people, we have carried out simulation runs instead by inserting normalized values as percentages resembling on average, a ratio fairly close to the ratio of the true numbers. This gives a total of 9 tests conducted for the behavior validation tests, which our model is observed to have satisfied, as the results are reproducible and fall within the accepted boundaries.

3.1.3. Policy Tests

Validation tests of policy include tests such as system improvement and behavior prediction. These tests assess the impact of different policies on parameters in various conditions. Such tests require additional data collection and information from various entities (i.e., users, App developers, physicians, etc.) in order to be validated. Clinical trials with several months or years of data collection would be required to perform such tests.

3.2. Testing Scenarios and Simulation Runs

The goal here is to observe the effect of various factors including social, economic and environmental factors as well as the respiratory monitoring embedded system design and performance metrics on sustainability and/or the efficacy of the service. The input variables of our model are the breathing monitoring App's design and performance metrics including ease of use level, respiratory monitoring level, respiratory data (i.e., acoustic signal of breathing) analysis algorithm and software management level, internet connectivity level, respiratory data acquisition feasibility level, GPS/location tracking level, and reliability level in addition to cost and rate of need inputs. In this section, we will show the effects of various combinations of changes with these input variables. Though there are many input design metrics that would impact the efficacy of service and/or sustainability of the system, we focus on those measures that are mostly related to the design of breathing monitoring Apps for the focus study of this research.

For consistency, the factors and initial values are assumed to be normalized between 0 and 1 throughout the simulations, where 0 represents the worst case efficacy and 1 (or 100%) indicates the best level of efficacy of service (and/or sustainability level).

Each of the scenarios presented hereafter, have different input parameter settings which are presented in Table 4 and further explained in the description of each scenario as well. In the simulations, we can see how changing different input values impact the sustainability and/or efficacy level.

For m-health and particularly, smartphone-based healthcare Apps, it is reasonable to assume a period of 2–3 weeks to determine the efficacy of a ubiquitous smartphone App. Therefore, a time step of one day was considered and set as the point of calculation. A total of 25 days was simulated for the system dynamics model of sustainability and/or efficacy.

Table 4. Parameter settings for all scenarios.

Parameter	Ease of Use Level	Respiratory Monitoring Level	Breathing Data Analysis Algorithm and Software Management Level	Respiratory Data Acquisition Feasibility Level	Cost to Customer	All Other Input Variables
Baseline	50%	50%	50%	50%	50%	50%
Scenario 1	50%	50%	**90%**	50%	50%	50%
Scenario 2	50%	**30%**	50%	50%	50%	50%
Scenario 3	50%	50%	50%	50%	**80%**	50%
Scenario 4	**80%**	**80%**	**80%**	**80%**	50%	50%
Scenario 5	**30%**	**40%**	**70%**	**90%**	50%	50%
Scenario 6	**40%**	**40%**	**40%**	**40%**	50%	50%

3.2.1. Baseline

Initially, a base scenario is considered as the baseline for assessment. In this scenario, all the variables related to the system design and performance metrics and the other input variables of the model are initialized to 50% (or 0.5), representing an average case performance for the base. Similarly, the cost to the customer is set at 50%, reflecting the average (mean) cost of the most frequently downloaded paid breathing monitoring Apps, which can be approximately $5.00 per month. Table 4 shows the parameter (input variable) settings for the baseline scenario. We also scaled the level of efficacy auxiliary function and added an offset value, in order to stay within the normalized range between 0 and 1 and also to ensure that the baseline scenario reflects an average sustainability level (0.5).

With these settings of the base scenario, the efficacy of service (or sustainability level) will remain the same until the battery is depleted. That is when the device shuts down and the performance and ultimately the efficacy will shift towards zero. This also implies that the system is not sustainable. However, for the purpose of testing the model and displaying the simulation results, we assume the mobile phone has sufficient power to run the App. The efficacy/sustainability level will thus, not undergo any significant changes for the baseline scenario with this assumption.

Figure 4 displays the dynamics of the simulation for the base scenario. The numerical results of the baseline scenario simulation on the sustainability level for a few days is also shown in Table 5. For the next scenarios explained hereafter, the baseline results are compared with different combinations of changes on the input variables.

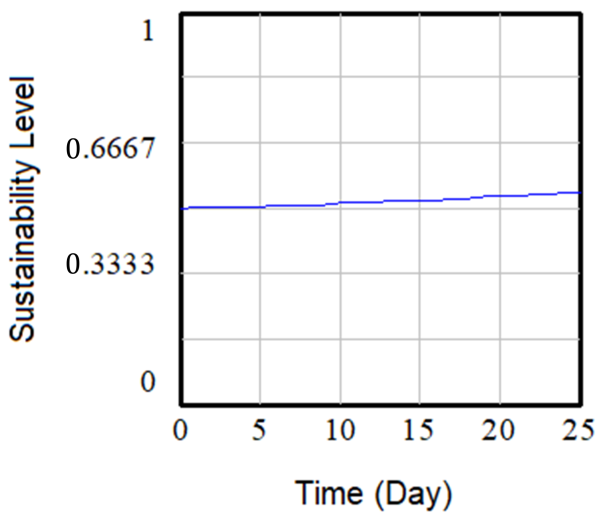

Figure 4. Sustainability level (level of efficacy of service) for the baseline scenario with all factors initialized as average case performance.

Table 5. Sustainability level (level of efficacy of service) numerical values for various scenarios.

Time (Day)	0	1	2	10	20	25
Baseline	0.5	0.500	0.501	0.511	0.529	0.540
Scenario 1	0.501	0.502	0.504	0.521	0.554	0.577
Scenario 2	0.499	0.4999	0.500	0.506	0.516	0.523
Scenario 3	0.499	0.500	0.501	0.511	0.534	0.550
Scenario 4	0.508	0.5136	0.519	0.587	0.744	0.874
Scenario 5	0.500	0.501	0.502	0.513	0.535	0.550
Scenario 6	0.499	0.499	0.499	0.503	0.510	0.515

3.2.2. Scenario 1

We observe the effect of changing one of the respiratory monitoring system/App design and performance metrics on the efficacy of the service and/or sustainability in this scenario. We set the breathing signal analysis algorithm and software management level at 90% and keep the remaining variables of the model as the baseline case. Table 4 shows the parameter (input variable) settings for scenario 1. The dynamics of the simulation for the baseline along with the various scenarios can be seen in Figure 5. As shown in Figure 5, the sustainability level slightly increased for scenario 1, as expected. Table 5 also reports the numeric values of the results of sustainability in this scenario.

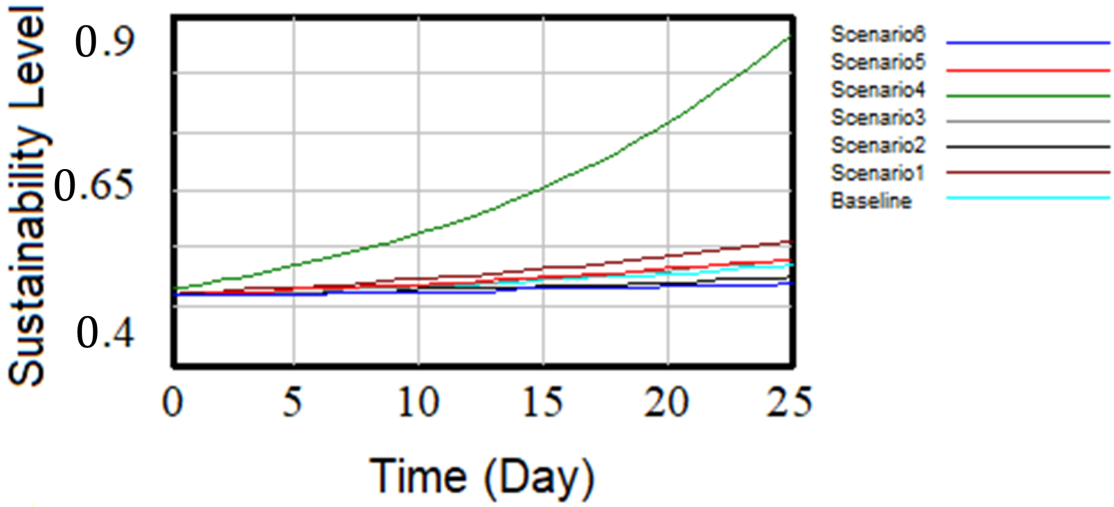

Figure 5. Dynamics of the sustainability level (level of efficacy of service) for all scenarios.

3.2.3. Scenario 2

In this scenario, we would want to examine a case where one of the respiratory monitoring App/system design and performance metrics is decreased. For this, we set the respiratory monitoring level to 30%. Table 4 shows the parameter (input variable) settings for scenario 2. We anticipate that this change would slightly lower the efficacy of the service and hence lower the sustainability as well. The results are plotted as a curve along with the other scenarios in the graph represented in Figure 5. The numerical values are also tabulated in Table 5.

3.2.4. Scenario 3

For scenario 3, we would want to see the effect of an economic factor on the efficacy of service and/or sustainability. Thus, we modify the cost of the breathing monitoring App. We set the cost at 80%. Table 4 shows the parameter (input variable) settings for scenario 3. When the cost increases, patient satisfaction is expected to decline. In this case, we expect the sustainability level to initially decrease. In the remaining days, sustainability slightly increases because of the dynamics of the system. The dynamics of the simulation in this scenario along with the other scenarios can be observed from Figure 5. Table 5 also demonstrates the numerical values of the results.

3.2.5. Scenario 4

It is clear that most input design metrics would have an impact on the sustainability level and/or efficacy of service. We will be considering the metrics that are mostly related to the design of the breathing monitoring App for the purpose of this paper. In this scenario, we will focus on ease of use, respiratory monitoring level, breathing signal/data analysis algorithm and software management level, and respiratory data acquisition feasibility level. These four input factors will be set at 80%. All other factors will remain as the baseline scenario. Table 4 shows the parameter (input variable) settings for scenario 4. As expected, the efficacy and/or sustainability level is significantly enhanced. The dynamics of the efficacy of service and/or sustainability in this scenario is presented in Figure 5 and Table 5.

3.2.6. Scenario 5

In this scenario, we are interested in seeing the effect of a combination of changes in the breathing monitoring App design metrics on the sustainability and/or efficacy of the service. We want to see how simultaneously increasing or decreasing some of these metrics would impact the sustainability level. For the purpose of testing, ease of use is set at 30%, respiratory monitoring level set at 40%, breathing signal (data) analysis algorithm and software management level set at 70%, and respiratory data acquisition feasibility level is set at 90%. Table 4 shows the parameter (input variable) settings for scenario 5. Figure 5 and Table 5 demonstrate the results of this scenario in comparison to other previous scenarios.

3.2.7. Scenario 6

We evaluate a case where all the four breathing monitoring App design metrics are set as 40%. Table 4 shows the parameter (input variable) settings for scenario 6. In such scenario, we expect to see a reduced sustainability level. Figure 5 and Table 5 represent the dynamics of all scenarios tested.

Overall, Figure 5 and Table 5 display a summary of all the results obtained. Specifically, from Figure 5, it is clearly observed how the results of each scenario of simulation relate or differ from the baseline as well as the other scenarios.

4. Conclusions and Future Directions

A systems engineering perspective for sustainable smartphone-based healthcare monitoring applications was studied in this paper. As breathing disorders can result in severe and life threatening conditions, and mobile/smart breathing monitoring tools are popular in the market, smartphone-based breathing monitoring was specifically studied in this research.

We first developed a causal model, followed by categorizing the main factors of the model to sustainability pillars. We then proposed a system dynamics model of a smartphone-based breathing monitoring App/system to assess the efficacy of the service and/or sustainability level. This was achieved through a balancing approach represented by the model. The model included factors of the breathing monitoring device/App including level of performance (performance level of breathing App), ease of use, feasibility, etc., along with social, economic and environmental factors such as patient wellbeing, cost, level of demand and battery. To the best of our knowledge, system dynamics modeling has not been applied to smartphone-based respiratory monitoring Apps. This study offered a novel contribution in this context.

It was observed from the simulation results of the system dynamics model that factors pertaining to the breathing monitoring App design have the highest impact on the level of efficacy and/or sustainability. The dynamics and exponential variations of the sustainability level were clearly noted in the graphs of scenarios 4, 5, and 6.

This paper provided an insight of how various factors influence the level of efficacy and sustainability of the breathing monitoring App by studying the dynamics of the model. In the future, additional factors including patient care, rate of users, the physicians and healthcare professionals' satisfaction as well as more comprehensive factors of the breathing monitoring system level metrics and their relationships (e.g., accuracy, complexity of the breathing signal analysis algorithm, etc.) can be incorporated in the model to reflect the dynamics of system level efficacy and/or sustainability more precisely.

To administer tests on live subjects and perceive patient care and wellbeing factors more realistically, the healthcare informatics and/or patient related statistics shall be acquired over a long period of time (i.e., several months or even years). Once the numbers are obtained from live subjects, the results can be compared and contrasted with the simulations. However, such long-term clinical trials are beyond the scope of this paper. Nonetheless, we believe the realistic results of live subjects will not be far from our simulation results. The simulations performed realistically captured a snapshot of the behavior of the model in various scenarios. We expect that the dynamics of the efficacy (sustainability) level of the system for live subjects would closely resemble our simulations. In addition, the fact that our model satisfied the behavior validation tests, proves that the model would run even under unexpected and/or extreme conditions and would produce results within the expected range of the simulations. Regardless, the ideas presented can still be deployed as self-test breathing monitoring Apps for the ongoing global COVID-19 pandemic, where users can check their breathing pattern frequently through these Apps. It is anticipated that the outcomes of this research regarding the dynamics of the efficacy and/or sustainability level, would assist users, patients and healthcare professions in determining the most suitable mobile health Apps and many other important decision/policy making steps.

The proposed systems engineering approach along with the introduced system dynamics model enables visualizing the efficacy and sustainability dynamics of smartphone-based healthcare monitoring systems. With the presented ideas in this paper, it would be interesting to see that through minor fine-tuning, the proposed model can be applied to other smartphone-based healthcare monitoring systems including, but not limited to mental status, heart status, eye pressure, as well as skin lesion, and blood pressure monitoring Apps.

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