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Communication

Efficacy of Smart EEG Monitoring Amidst the COVID-19 Pandemic

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Abstract: Ever since the COVID-19 pandemic has majorly altered diagnosis and prognosis practices, the need for telemedicine and mobile/electronic health has never been more appreciated. Drastic complications of the pandemic such as burdens on the social and employment status resulting from extended quarantine and physical distancing, has also negatively impacted mental health. Doctors and healthcare workers have seen more than just the lungs affected by COVID-19. Neurological complications including stroke, headache, and seizures have been reported for populations of patients. Most mental conditions can be detected using the Electroencephalogram (EEG) signal. Brain disorders, neurodegenerative diseases, seizure/epilepsy, sleep/fatigue, stress, and depression have certain characteristics in the EEG wave, which clearly differentiate them from normal conditions. Smartphone apps analyzing the EEG signal have been introduced in the market. However, the efficacy of such apps has not been thoroughly investigated. Factors and their inter-relationships impacting efficacy can be studied through a causal model. This short communications/perspective paper outlines the initial premises of a system dynamics approach to assess the efficacy of smart EEG monitoring apps amid the pandemic, that could be revolutionary for patient well-being and care policies.

Keywords: EEG; smartphone app; COVID-19 pandemic; causal model; systems engineering; system dynamics

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1. Introduction

Telemedicine, telecare, and e-health using smartphone-based healthcare apps has never been appreciated more than ever, as quarantine, social/physical distancing and remote activities have become the norm during the COVID-19 pandemic.

In the midst of the pandemic, doctors and healthcare workers have seen more than just the lungs affected by COVID-19. The research strategies, overall management and treatment plan of many health conditions including cardiovascular diseases [1], autism [2], and several mental conditions [3] have been heavily impacted by COVID-19. Neurological complications including stroke, headache, and seizures have been reported in some population of patients (over 600) [4] during the pandemic. In addition, increased level of stress and depression among individuals as a result of social distancing, losing family members, friends, and/or jobs during the pandemic must not be overlooked. Researchers from Baylor College of Medicine and the University of Pittsburgh have been collecting data and studying commonalities of how COVID-19 affects the brain with a focus on Electroencephalograph (EEG) abnormalities of the brain during the pandemic [5]. Their findings indicate slow or abnormal electrical discharge in the EEG signal, mostly in the frontal lobe of the brain, and possibly irreversible damages the neurological disease may have caused to the brain. They have however, noted that EEG must be collected and examined on a much larger number and range of patients to have a closer look at the frontal lobe. Though the COVID-19 vaccine was released in late 2020, until everyone across the globe has access to the vaccine and can get vaccinated, it will take some time; perhaps months to approximately a year. Until then, for a foreseeable future, the pandemic and its effects will remain on the vast majority of sectors in all societies. This calls for more research avenues in the field of EEG and COVID, particularly with the help of convenient smartphone technology during the ongoing pandemic.

Electroencephalography (EEG) is a non-stationary signal representing the bio-electric activity of the brain, which is generally collected using multiple or single-channel electrodes pasted on the scalp. EEG signal analysis unveils many properties that can be used to detect various mental/cognitive conditions including stress, depression, sleep/fatigue/drowsiness, as well as brain diseases/disorders including stroke, seizure/epilepsy, Alzheimer's diseases, in addition to several neurodegenerative disorders such as Parkinson, Multiple Sclerosis (MS), and Amyotrophic Lateral Sclerosis (ALS), among others. The analysis of EEG often involves a series of signal processing steps using digital band-pass filters to decompose the EEG signal into five frequency bands, followed by machine/deep learning to detect or classify a condition [6,7]. Recent advances in real-time EEG monitoring include the development of wearable and portable devices (e.g., NeuroSky MindWave) that can acquire the signal using EEG headsets which are interfaced with smartphone-based apps for further analysis and processing [8]. Figure 1 conceptually illustrates a sample EEG monitoring app that can identify the mental health status among various conditions or disorders. The efficacy of such apps in terms of the level they sustain patient well-being and care, however, has not been thoroughly studied.

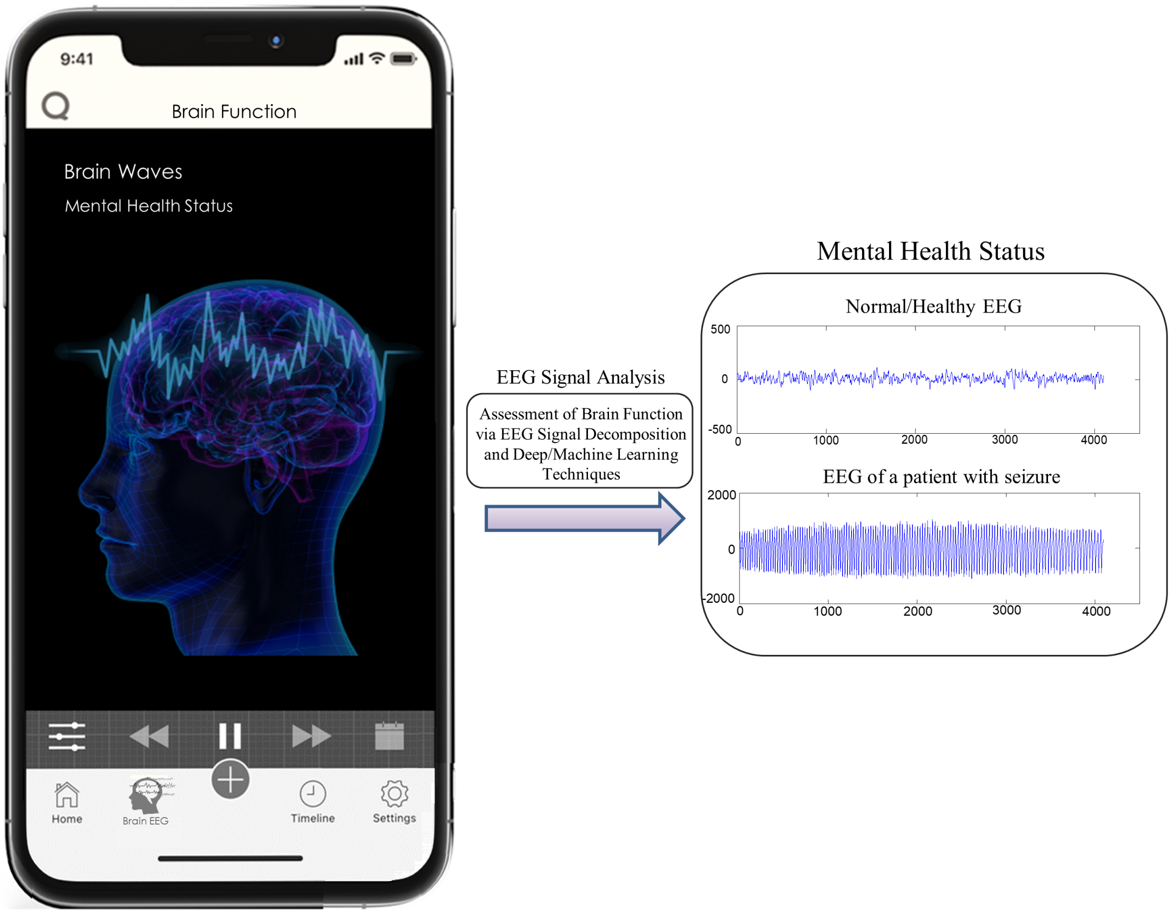

Figure 1. Brain function monitoring using EEG (Electroencephalography) analysis app.

With the ever-increasing evolution of technology and healthcare, side-by-side, smartphone technology has become an integral part of daily lives, offering an inclusive platform for telemedicine, as well as remote, mobile, and smart healthcare monitoring. On one hand the processing power, computing capabilities, and portable embedded sensors of smartphones allow for the acquisition of biomedical signals/images of a physiological/health condition, as well as the analysis of these acquired data using signal/image processing and machine/deep learning techniques. On the other hand, the connectivity features allow for communication between the caregivers and patients. There are already several thousands of mobile and smartphone-based health applications available in the online market, with the trend continuing to grow exponentially [9–11]. Some smartphone-based e-health apps underway, or the ones already developed, concentrate on the brain functionality/mental health status [7,8,12,13], while others monitor the heart [14–17], or lung [18–20] activity. Furthermore, smart healthcare tools and ideas for assessing the skin health [21], eye pressure [22], and those pertaining to hearing aids [23] have also been reported, among many others. The efficacy of healthcare monitoring apps is usually considered by the depth (level) of which it maintains patient well-being and care.

As more smartphone-based EEG monitoring apps with new features are developed and introduced in the e-health market, the interaction among factors representing these features (e.g., performance metrics, social and economic factors) and their relationships result in a more complex system. Systems engineering is a method capable of dealing with such complexity. Systems engineering assists to better understand the behavior of a system and its problems. One of the most common approaches in systems engineering is systems thinking. Systems thinking is known as a holistic approach, where the whole world would be seen as a complex system and the goal is to comprehend the factors and factor inter-relationships [24]. In the context of this paper, systems thinking can be used to realize how various elements in the smartphone-based EEG monitoring app interact. Furthermore, system dynamics is an approach within systems thinking, first developed by Forrester [25]. System dynamics offers support to understand the dynamic feedback behavior and structure in complex systems. Moreover, causal models are tools within system dynamics that provide a graphical representation of the system factors and their relationships. There are various areas within healthcare that have used applications of system dynamics and causal models [26–31].

System dynamics modeling is a computer-aided approach for analyzing and solving problems with a focus on policy analysis and design [32]. Computer Aided Design (CAD) software tools in general, allow the use of a software application with underlying algorithms to help create, optimize, simulate and test a design. There are several CAD software packages for system dynamics modeling, simulation and validation. Vensim, iThink, Stella, Dynamo, and Powersim are among the well-known CAD tools for system dynamics.

This paper conceptualizes the efficacy of smartphone-based EEG monitoring apps/systems from a systems engineering perspective, particularly during the COVID-19 pandemic.

2. Proposed Ideas and Perspectives

2.1. Causal Model

In this short communications/perspectives article, we propose a causal model as a systems engineering approach to explore the factor and factor relationships impacting the efficacy of smartphone-based EEG monitoring apps.

Causal models offer the core base for system dynamics modeling and provide a graphical representation of the system factors and their relationships. The diagrams provide important information regarding the hypotheses within each factor. Figure 2 depicts an illustration of our proposed causal model. Factor elements along with their causal links (arrows) are presented in a causal model diagram, where the sign of each arrow indicates an increasing (+) or decreasing (−) relationship. The structure of the model may include feedback and nonlinear (complex) increasing/decreasing relationships among the factors.

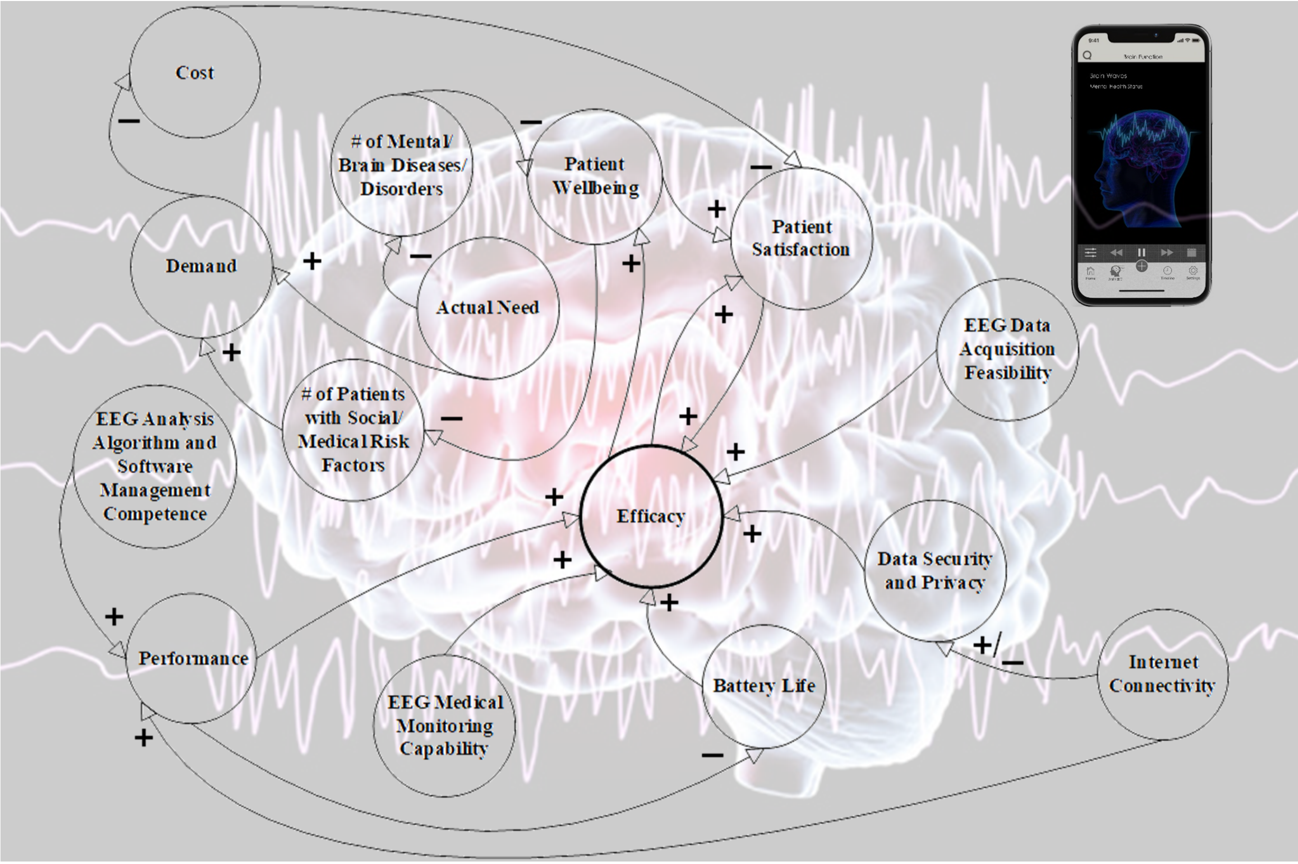

Figure 2. Causal model of a smartphone-based EEG (Electroencephalography) monitoring system.

After reviewing a large body of literature related to causal models and system dynamics modeling in healthcare applications in general [33,34], and EEG monitoring systems in particular [35,36], we selected a set of factors and their relationships for determining the efficacy of smartphone-based EEG monitoring systems. As causal models offer a holistic view, various factors from social, economical and technological aspects should be considered in the model. Several other aspects and factors can be included in the model to observe more detailed dynamics as well. In this paper, we propose a simplified causal model. A subset of the social factors that we have selected in our model include "# of Patients with Social/Medical Risk Factors", "Patient Wellbeing", "Patent Satisfaction", and "# of Mental Brain Diseases/Disorders" factors. These social factors can directly or indirectly impact the overall efficacy. On the other hand, "Cost", "Demand", and "Actual Need" are the economical factors we have selected to create the proposed model. The economical factors indirectly impact the efficacy. The technological factors most relevant to the problem of interest include system design and performance metrics such as "EEG Analysis Algorithm and Software Management Competence", "EEG Medical Monitoring Capability", "EEG Data Acquisition Feasibility", "Battery Life", "Internet Connectivity", "Data Security and Privacy" and "Performance". These technological factors were chosen from user experience and device characteristic stand points, influencing the overall efficacy.

Some of the chosen factors can span in more than one category. For example, "Demand" and "Actual Need" can be considered to be both economical and social factors. The reason for selecting the introduced factors in the causal model is that from a logical point of view, these factors can impact the overall efficacy through cause and effect, as the model includes hypothesized relationships between the factors [31].

In the proposed causal model, we suggest that factors such as patient well-being and satisfaction [27,37,38], cost, EEG data acquisition feasibility, EEG analysis algorithm and software/app management competence, and EEG medical monitoring capability as well as the app's performance, would be considered the most prominent factors determining the efficacy of the EEG monitoring app. Our proposed casual model in Figure 2 includes more set of factors and factor relationships relevant to smartphone-based EEG monitoring. As can be seen, when the performance measure factor of the EEG app improves, the efficacy increases.

To comprehend the proposed causal model, the logical impacts of cause and effect should be considered among the factors. The reader is suggested to start following the causal model from a factor point in the diagram, such as "Internet Connectivity". As "Internet Connectivity" improves, the "Performance" factor is expected to improve as well. The performance of the EEG analysis algorithm of a smart-phone app heavily relies on seamless cloud connectivity. Any interruption or delay in the connection will negatively reflect on the performance of EEG signal analysis. With "Performance" improvement, the "Efficacy" of the overall model will increase. There is a bidirectional relationship between the "Efficacy" and "Patient Satisfaction". One of the factors influencing "Efficacy" is the level of satisfaction of the users/patients. Looking at the causal model, as the level of patient well-being increases, patient satisfaction also improves, and this in turn increases the "Efficacy" of the studied model. On the other hand, improvements in the overall "Efficacy" can increase the level of satisfaction and user experience with the EEG smartphone app. As the number of people with mental/brain diseases increases, their overall health will degrade drastically, resulting in negatively impacting the overall "Patient Wellbeing" factor. Moreover, the "Actual Need" for the EEG smartphone app would result in more effective considerations, diagnostics, and treatment policies for better management of mental/brain diseases and disorders, and in the long run, would reduce the number of such illnesses.

2.2. System Dynamics Model

We suggest a system dynamics model; with the proposed core causal model in mind; to investigate the behavior of the smartphone-based EEG monitoring system model factors and to evaluate the efficacy of the app/system. Figure 3 presents the proposed system dynamics model in perspective.

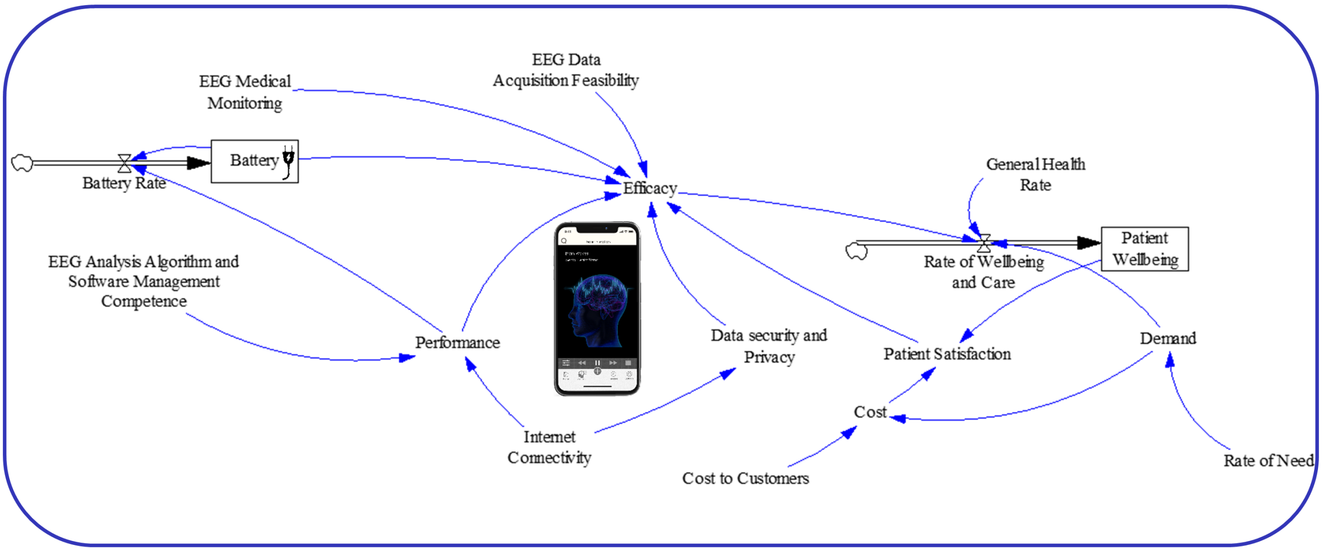

Figure 3. System dynamics model of EEG (Electroencephalography) monitoring app.

We have outlined a preliminary system dynamics model using the Vensim® Pro software [39], presented in Figure 3. The model entails a subset of the proposed causal model, in which stocks (patient wellbeing, battery), flows (rate of wellbeing and care, battery rate), and auxiliary variables (efficacy, performance, etc.) are presented. The factors that are only seen at the source of an arrow in the system dynamics model are inputs to the system. To simplify the model, the range of the factors in the proposed system dynamics model can be represented as percentages or values between 0 and 1, to determine a level of which the factor is quantified with respect to its maximum capacity/capability. For example, "Data security and privacy" of 0.5 reflects half of the best quantified data security and privacy level that the users experience. The model is created based on underlying relationships between the factors where those with increasing effects can be multiplied directly, while those with decreasing effects can be multiplied by $1 - x_{factor}$, assuming x_{factor} is the factor quantity at the source of the arrow affecting another factor. To observe the dynamics of the model factors that influence the efficacy of the EEG monitoring app, various settings and cases/scenarios can be applied to the system dynamics model. Because of the dynamics of model and the fact that many factors impact one another and have different routes and feedback relations, the factors contribute differently when determining the efficacy.

3. Validation

The proposed system dynamics model, as a subset of the overall causal model, is validated in this section.

In system dynamics, validation is performed to confirm that the represented model is useful and can achieve the goals it was designed for. Model validation guidelines can be found in [40–42]. The two main validation aspects include structural and behavioral validity tests.

Structural model validation has been confirmed using the Vensim Pro software package version 7.3.5 (Ventana Systems, Inc., Harvard, MA, USA) [39] that features a series of built-in structural tests. As the architecture of the model has been completed with no errors, these validity tests have been satisfied.

To validate the behavior, the model should be tested under different cases/scenarios with changing factors as well as extreme conditions.

Preliminary Simulations

Long-term data collection with clinical trials, specifically during the pandemic, would be required to observe the behavior and perform complete validity tests for different cases and extreme conditions. Nonetheless, we have conducted preliminary simulations with synthetic data and time steps of one day for 25 days using Vensim Pro software version 7.3.5 (Ventana Systems, Inc., Harvard, MA, USA) [39] to validate the behavior of the proposed model and to confirm that the model is able to run under different cases.

Validity tests of the behavior under extreme conditions can be conducted for the low and high extremes. As can be seen from Figure 3, the input parameters of the proposed system dynamics model include variables such as "EEG Medical Monitoring", "EEG Data Acquisition Feasibility", "EEG Analysis Algorithm and Software Management Competence", "Internet Connectivity", and "Cost to Customers", among others. The low extreme condition implies that all input variables are set to the extreme low (i.e., absolute zero or near zero). On the other hand, the high extreme condition would imply that all input variables are set to the high extreme (i.e., absolute one or 100%). Figure 4 illustrates the simulation run of the model under extreme conditions. As can be seen, the dynamics of the overall Efficacy is within the meaningful range of 0 to 1 for both extremes, where the high extreme depicts the best achieving Efficacy, while the low extreme shows the worst Efficacy. Successful run of the model under these extreme conditions indicates that the model passes the behavior validity tests.

Moreover, we conducted preliminary simulations for two additional cases. Case 1 is the case where the "EEG Analysis Algorithm and Software Management Competence" input is set to 0.9, and the remaining input variables are set to a moderate value of 0.5. In Case 2, the input variables related to the technological factors such as "EEG Medical Monitoring", "EEG Data Acquisition Feasibility", "EEG Analysis Algorithm and Software Management Competence", and "Internet Connectivity" are all set to 0.8, while the rest of the inputs are kept at 0.5. Figure 5 shows the simulation run of the dynamics of Efficacy for these two cases. The simulation run demonstrates that the efficacy increases as the technological factors are at higher levels. These preliminary simulations also validate that the model is able to successfully run, thus validating the behavior tests.

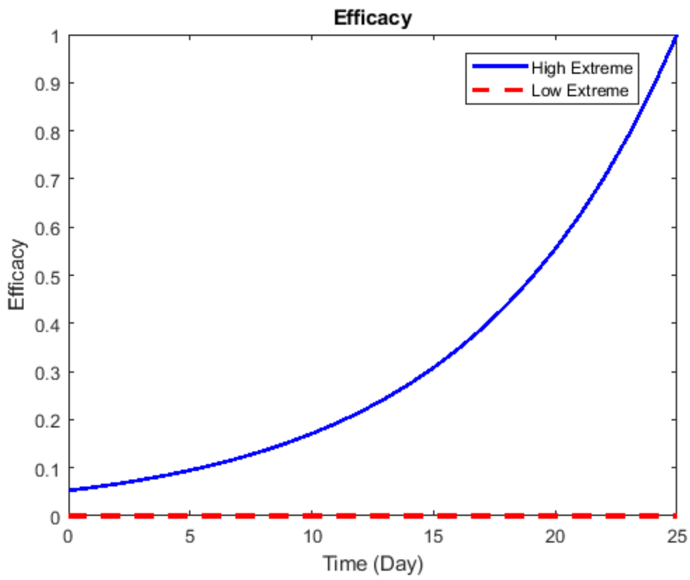

Figure 4. Extreme cases validation.

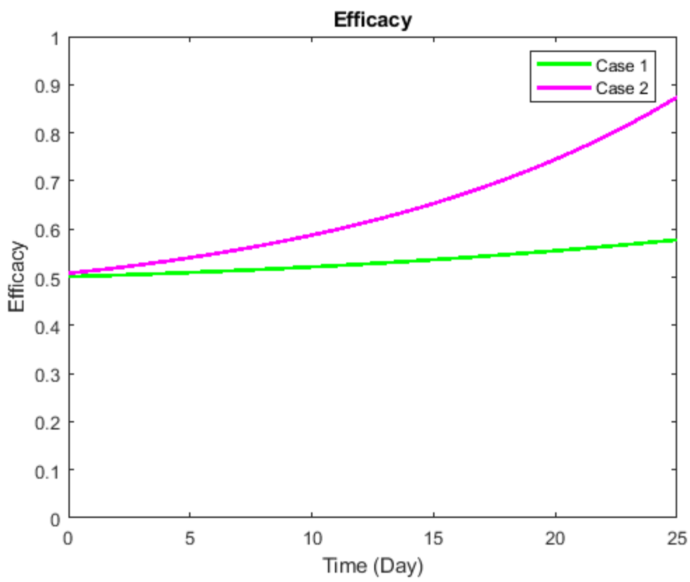

Figure 5. Simulation validation of two case settings.

4. Discussion and Expected Outcome

With the perspective ideas and premises proposed in this short communications/ perspectives paper, the actual results and outcomes are yet to be explored and validated. Nevertheless, according to the preliminary simulations, we expect the app's performance and the EEG medical monitoring capability factors, including the EEG analysis algorithm and software management competence, to have the highest impact on the efficacy of the smartphone-based EEG monitoring app.

In addition to performance measure factors, data pertaining to social factors such as patient well-being, satisfaction and care with clinical implications, can be collected and studied over the course of months and years, to observe the precise dynamics of the model. We anticipate that such system dynamics modeling would reveal the complex dynamics of various factors of smartphone-based EEG monitoring.

The limitations of this study are mainly associated with the limitations of system dynamics modeling in general, which can be divided into user-related, technical, and application related challenges [43]. The most common challenge is dealing with the complexity of the model. More complex models make it difficult for the users to understand and interpret the pieces of the model. A model guide may be required to effectively overcome the technical challenges pertaining to the complexity of the model. In addition, challenges such as incompatible time scales between simulations, actual implementations, and informed policy or decision-making processes may result in over-simplified models, leading to inaccurate results. Nonetheless, the system dynamics approach introduced in this paper can potentially demonstrate the efficacy of smart EEG monitoring for better management and care.

The outcomes of this research would be of utmost importance if this study is especially performed at the time of the COVID-19 pandemic, given the higher acceptance/accessibility of smartphone-based telehealth care. Furthermore, with the rise of stress and depression levels, and degrading mental health status (detected by EEG), amid the COVID-19 pandemic, the proposed study would be transformative in largely assisting system developers as well as policy and decision makers to improve overall patient well-being and care.

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Conflicts of Interest: The authors declare no conflict of interest.

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