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Resiliency and Risk Assessment of Smart Vision-Based Skin Screening Applications with Dynamics Modeling

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Abstract: The prevalence of skin diseases remains a concern, leading to a rising demand for the advancement of smart, portable, and non-invasive automated systems and applications. These sought-after technologies allow for the screening of skin lesions through captured images, offering improved and accessible healthcare solutions. Clinical methods include visual inspection by dermatologists; computer-aided vision-based image analysis at healthcare settings; and, lastly, biopsy tests, which are often costly and painful. Given the rise of artificial intelligence-based techniques for image segmentation, analysis, and classification, there remains a need to investigate the resiliency of personalized smartphone (hand-held) skin screening systems with respect to identified risks. This study represents a unique integration of distinct fields pertaining to smart vision-based skin lesion screening, resiliency, risk assessment, and system dynamics. The main focus is to explore the dynamics within the supply chain network of smart skin-lesion-screening systems. With the overarching aim of enhancing health, well-being, and sustainability, this research introduces a new framework designed to evaluate the resiliency of smart skin-lesion-screening applications. The proposed framework incorporates system dynamics modeling within a novel subset of a causal model. It considers the interactions and activities among key factors with unique mapping of capability and vulnerability attributes for effective risk assessment and management. The model has been rigorously tested under various case scenarios and settings. The simulation results offer insights into the model's dynamics, demonstrating the fact that enhancing the skin screening device/app factors directly improves the resiliency level. Overall, this proposed framework marks an essential step toward comprehending and enhancing the overall resiliency of smart skin-lesion-screening systems.

Keywords: digital health; human well-being; skin lesion screening; resiliency; risk assessment; system dynamics

Citation: Faezipour, M.; Faezipour, M.; Pourreza, S. Resiliency and Risk Assessment of Smart Vision-Based Skin Screening Applications with Dynamics Modeling. *Sustainability* **2023**, *15*, 13832. https://doi.org/10.3390/su151813832

Academic Editor: Gilberto Santos

Received: 2 August 2023
Revised: 8 September 2023
Accepted: 15 September 2023
Published: 17 September 2023

1. Introduction

1.1. Background and Significance

Dermatological research reveals that approximately 20% of Americans experience skin cancer at some point in their lives [1,2]. Tragically, two Americans lose their lives to skin cancer every hour [1], with a significant portion of these fatalities linked to melanoma [1–5]. Detecting the disease early and intervening promptly has been proven to enhance the chances of successful treatment [6]. For instance, when melanoma is identified before progressing beyond stage one, the five-year survival rates can increase up to 99% [6,7]. Leveraging smart vision-based technology can aid in identifying suspicious skin lesions, potentially reducing their transformation into melanoma [8].

Apart from skin cancer, various (skin) diseases or conditions (e.g., skin burn) are diagnosed by abnormal skin lesion detection [9,10]. Currently, the standard method for diagnosing skin conditions involves visual inspection by a dermatologist [9–11]. However, this approach is subjective and susceptible to human errors, with detection sensitivities and specificities ranging from 55% to 83%, depending on the dermatologist's experience and the availability of dermoscopic monitoring [12–17]. In cases where cancer is suspected, a biopsy is often ordered, but it has been found that nearly 25% of all skin biopsies performed in the U.S. are unnecessary for detecting skin cancer [18,19]. Moreover, even when a lesion is identified early, visual inspection may not always detect changes due to limited record-keeping precision in patient records, long intervals between visits, and changes in the attending physician [20,21]. Smartphone-based skin lesion screening apps equipped with artificial intelligence (AI)-based data/image analysis and digital image databases enable mobile-automated evaluation options for suspicious skin lesions using self-captured images.

Currently, there are some ongoing efforts to develop fully automated, non-invasive, and non-contact techniques that allow users to conveniently assess the skin lesion images from the comfort of their homes [22]. Most computer-aided techniques rely on skin lesion images taken in clinical settings and require high-end processors to analyze images for segmentation and classification purposes [23]. On the other hand, the idea of smartphone-based applications capable of conveniently screening skin lesions holds great appeal for the general public.

The emergence of mobile and electronic health applications has been driven by the widespread adoption of smartphones, offering online communication and connectivity features. The COVID-19 pandemic further accelerated the prevalence of smartphone-based remote and telemedicine platforms. Smartphones are equipped with embedded sensors and smart processor chips, allowing for the collection of various physiological data. The acquired data are typically processed through smartphone apps and transformed into meaningful information for the user. To date, the online stores have seen the development of over 100,000 mobile and electronic health applications, with many more currently in progress [24,25].

In the realm of intelligent healthcare monitoring, automated decision-support frameworks heavily rely on AI-assisted models that incorporate machine/deep learning, signal/image processing, and data analysis techniques. These frameworks are applied to the collected digital health data to extract valuable insights. Several examples of such techniques include monitoring the heart's status through the analysis of electrocardiogram (ECG) signals [26,27], assessing brain and mental status via electroencephalogram (EEG) signals [28], analyzing breathing and respiratory patterns using breathing sounds [29–32], conducting skin lesion analysis through images [22,33,34], and determining eye diseases [35,36]. Notably, some of these techniques have been successfully implemented into smartphone applications [24,37].

While there have been attempts to develop automated skin lesion classification algorithms using image analysis and machine/deep learning techniques [38,39], some even implemented on hand-held devices [22,40–45], further scientific advancements are needed to achieve better performance [8]. Particularly, existing solutions tend to overlook the impact of other socio-economic factors of smart skin-lesion screening in a larger picture to assess and manage the risks. Exploring these aspects could lead to sustainable solutions for improved health.

A fully smart skin-lesion-screening technique has been previously developed [22], with further implementation as a smartphone app [46]. The methods involve computer-aided (vision-based) image processing and machine learning to classify benign, atypical, and melanoma skin lesion images with over 95% accuracy. The portable system comprises two main components. A real-time alert system has been developed addressing skin burn prevention caused by sunlight, introducing a novel equation to calculate the time required for skin to burn. This alert aims to assist users in safeguarding their skin from harmful effects. The second component involves automated image analysis, which includes various steps. Image acquisition occurs through an iPhone equipped with a dermatoscope (dermoscope) for magnification [47]. Subsequently, the analysis incorporates hair detection and exclusion, achieved through a gray image mask and reconstruction technique. Lesion segmentation is then performed using binary image masks, filtering, and active contours. Furthermore, the system employs feature extraction techniques encompassing parameters from 2-D fast Fourier transform, 2-D discrete cosine transform, complexity feature set, color feature set, and pigment network feature set, as well as lesion-shape features, lesion-orientation features, lesion-margin features, and lesion-intensity pattern features [22]. For classification purposes, a two-level support vector machine classifier is employed. The user can capture images of their skin moles, and the image processing module will classify these moles into specific categories: benign, atypical, or melanoma. If a mole falls under the atypical or melanoma category, the system will alert the user to seek medical assistance promptly. This comprehensive approach aims to empower individuals with the knowledge and early detection capabilities needed to take proactive measures in their skin health, presented in Figure 1.

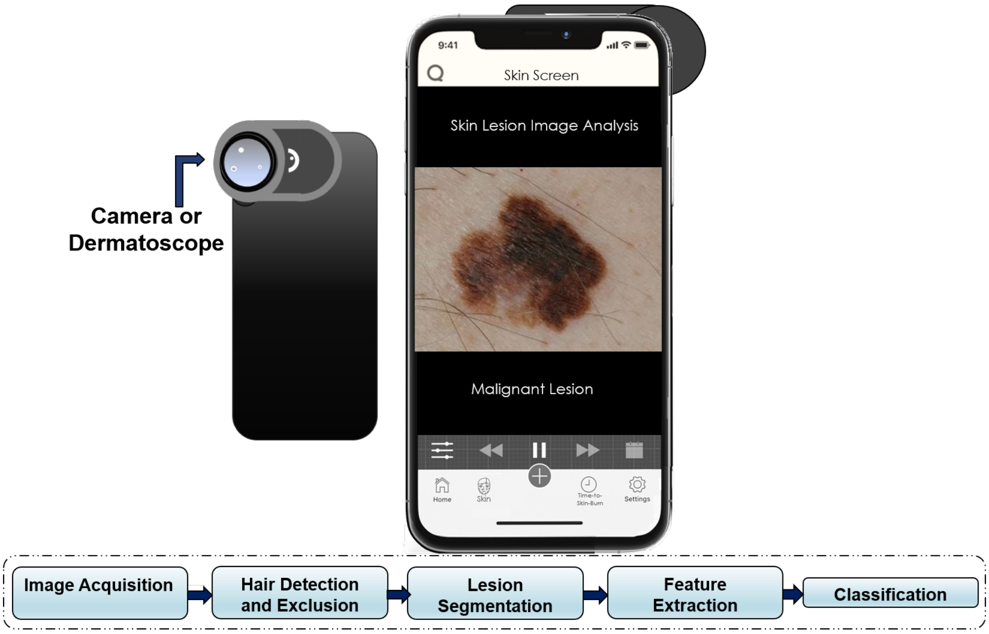

Figure 1. Skin lesion class determination from smartphone dermatoscope images.

This paper proposes a framework for better risk assessment and management by determining the resiliency of smart skin-lesion-screening apps (such as the one referenced above). A systems perspective is essential when considering the overall smart skin-lesion-screening network, given the involvement of numerous players and enablers (called factors). Taking a systems approach allows for a more comprehensive understanding of the inter-relationships among these factors. To achieve this, system dynamics are employed as a systems perspective method. This approach captures the dynamic interactions within a system from a holistic standpoint, enabling the study of the system's behavior [48,49]. Utilizing a causal model, which is a tool within system dynamics, helps visualize the concepts and inter-relationships effectively. One of the strengths of system dynamics is its ability to address non-linear relationships and feedback scenarios within a system [50]. Initially developed by Jay Forrester, system dynamics primarily served as a decision-making and modeling tool in business and industrial management [51]. Over time, its applications have expanded to various healthcare areas [52–59] and even in certain aspects of smart healthcare [60–63]. However, the literature that assesses the risks of system dynamics for health-based monitoring systems remains limited. By embracing a systems perspective, integrating risk assessment and system dynamics can enhance the understanding and effectiveness of smart skin screening tools for sustainably improved healthcare outcomes.

1.2. Key Contributions and Novelty

This paper introduces a novel framework for smart vision-based skin lesion risk assessment through modeling the resiliency of smartphone-based skin lesion screening applications. The framework utilizes a system dynamics modeling approach to analyze the interactions and activities among the key factors of the system holistically. The factors mainly include the smartphone app/device factors (software and hardware) as well as the social-economic factors in a bigger picture of the society. By adequately mapping the factors of the model to known risk terminologies, in conjunction with a systems engineering and system dynamics perspective, the proposed framework can effectively reflect the dynamics of the resiliency level of the system.

The primary objective of this work is to establish a comprehensive framework of smart vision-based skin lesion risk assessment that effectively describes the resiliency level and evaluates the interactions within the system, providing meaningful insights into the key factors involved. Through this work, a comprehensive evaluation of the resiliency of smart skin-lesion-screening apps becomes possible, leading to valuable insights and a significant impact on skin health. By adopting a systems perspective, the proposed framework enables the identification of various factors and their inter-relationships within the system. The application of system dynamics modeling for the resiliency of smart skin-lesion-screening apps is a novel approach as it has not been previously explored. Hence, the proposed research offers innovative insights in this specific domain, contributing to a deeper understanding of the dynamics of the resiliency of skin screening applications and possible associated risks. Risk management strategies can be suggested by carefully observing the dynamics of the resiliency level.

In order to address the complexities of the problems at hand, a holistic systems approach becomes essential. This approach allows for a comprehensive understanding of the intricate behavior of system factors, taking into account both linear and non-linear relationships, as well as feedback loop interactions. Given the involvement of multiple factors and their intricate inter-relationships, a complex system is proposed. Evaluating the performance of such systems involves a root cause analysis [64]. We provide a comprehensive description of risk management and resiliency in the context of smart skin-lesion screening. On the other hand, system dynamics employ causal models to depict cause and effect relationships among factors. As a result, a causal model is initially introduced to illustrate the key factors and their inter-relationships within the proposed framework. Subsequently, a system dynamics model is proposed based on this causal model. To evaluate the resiliency level of the skin lesion screening app, several simulations have been conducted and are presented in this study. These simulations serve to test the capabilities and effectiveness of the framework (resiliency) in dealing with the complex nature of the skin lesion screening system and the associated risks, providing valuable insights for further refinement and improvement.

The remainder of this paper is organized as follows. Section 2 describes the definition of risk management and resiliency for this work. In Section 3, the causal model is introduced followed by the structure of our proposed system dynamics model. We present the simulation results of the model in Section 4 and provide a discussion in Section 5. Finally, concluding remarks and future directions appear in Section 6.

2. Risk Management and Resiliency

To comprehend the proposed framework better, in this section, we elaborate on risk management and resiliency definitions pertaining to a system (or network).

Risk management is the process of identifying, assessing, managing, and monitoring risks in a supply chain [65], as shown in Figure 2. The stages of this process are summarized below:

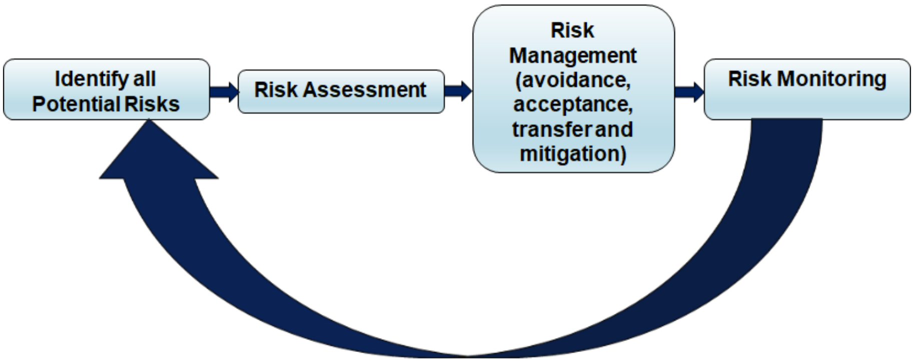

Figure 2. Risk management cycle.

1. Risk identification: This stage involves discovering all relevant risks that can influence the operations within an enterprise (or system) [66]. These risks might stem from internal and external sources relative to the boundaries of the enterprise [67]. Internal sources generally include production delays, equipment breakdown, or accidents, while external sources mainly include pandemics, cyber-attacks, natural disasters, production or quality problems at the suppliers' plants, or transportation accidents [68].
2. Risk assessment: Supply chain risks are commonly characterized by the probability of their occurrence and the severity of their impact. This stage of the process involves assessing these factors for the identified risks from the risk identification stage [66]. Additionally, in this stage, the risks are ranked based on the enterprise's risk threshold or tolerance [68].
3. Risk management: In this stage, strategies for the probability or severity of the identified supply chain risks are determined. This encompasses options such as risk acceptance (i.e., taking no action to mitigate the risk) and devising approaches for risk avoidance, transfer, or mitigation [69].
4. Risk monitoring: This stage involves assessing the efficacy of the risk treatment strategies that have been developed or implemented in the previous stage. It also includes identifying ways to improve and update the stages of the risk management process based on the learning gathered [66,68].

Resiliency has been variously defined by numerous authors, encompassing concepts such as the ability to respond to unexpected disruptions and recover normal functioning [70], the system's ability to revert to its initial condition or transition to a more favorable state following an interruption [67], and the ability to not only survive but also adapt and thrive amidst turbulent changes [71].

In the context of our framework, we define resiliency as the ability of the system to operate in a desirable and acceptable manner, specifically after interruption or unexpected scenarios. It is a measure of robustness of the system in response to any changes or events. In general, enterprises seek to achieve system-level resiliency by minimizing the downtime of their systems during failures. Resiliency has been extensively studied and applied across various disciplines, encompassing the concepts of robustness, fault-tolerance, and agility, as researchers have recognized its significance. The concept of resiliency in engineering is a relatively new concept [72]. The proposed framework includes human interactions with engineering technology, i.e., the skin lesion app under investigation in this paper. Engineering resiliency can be paraphrased as the combined measure of a system's ability to passively withstand and survive (reliability) and its proactive capacity to recover and restore functionality (restoration) [73]. Resiliency is generally defined as the inherent capability of a system to adapt and maintain its functionality when faced with disruptions and unforeseen alterations [74]. In resiliency engineering, it is emphasized that comprehending the typical operation of a technical system is crucial, alongside comprehending its failure modes [75]. In addition, resiliency has also been defined as the capacity of a system to withstand both external and internal disturbances without experiencing a disruption in its intended function. Alternatively, according to American Society of Mechanical Engineering (ASME), if the function is temporarily interrupted, resiliency involves the system's ability to promptly restore the function to its full operation [76].

Risk management and resiliency terms are generally expressed with respect to *vulnerability* and *capability* definitions [77]. Gallop [78] described vulnerability as the degree of sensitivity of a system (the degree to which the system is affected or altered by disturbances), its responsiveness to risks, and the degree of exposition to disturbing events. Additionally, references [79–81] defined vulnerability as factors that make a system susceptible to disruptions, where vulnerabilities should be managed through capabilities. Researchers in [80,81] also explain that capabilities enable a system to anticipate and overcome disruptions. Furthermore, principles encompassing the reduction in failures, the mitigation of impacts, the implementation of administrative controls and procedures, flexibility, controllability, and early detection contribute to the resiliency and risk management of a system [82].

This paper explores the dynamics of the resiliency of the smart skin-lesion-screening app supply chain network by identifying the vulnerability and capability of the factors involved. The results offer valuable insights into the risk management processes. The potential impact of this research can be significantly amplified through the practical application of these methodologies in contemporary skin-lesion monitoring systems [83], leveraging cutting-edge smartphone technology [43–45,84]. Moreover, these methods hold promise for enhancing resiliency and risk assessment within the context of relevant healthcare challenges [42].

3. Materials and Methods

3.1. Causal Model

The causal model of the overall smart skin-lesion-screening framework is presented in Figure 3. The model has been constructed based on certain factors and their underlying relationships by carefully examining the relevant literature [52,54,59,60]. Table 1 illustrates all the factors of our model along with their descriptions as pertained to this work. As can be seen, some of the factors are considered as vulnerability or capability within the system, which have been marked in Table 1. The factors of our model can be grouped into four categories: social, financial, public health, and device/app (hardware/software) factors. Each factor falls within one of these categories, though it may be well connected to others, as seen in the causal model diagram. The factors are inter-related by increasing (+) or decreasing (−) effects on one another, presented by the edges and the sign on the head of the arrows in Figure 3. The model also includes balancing and reinforcing loops denoted as B in blue and R in red, respectively. A balancing loop represents a feedback loop of factors that have both increasing and decreasing signs, to correct a change in the system that is moving away from the starting point, hence having a balancing effect. A reinforcing loop presents a closed feedback loop of factors with only same-sign effects (increase only or decrease only) on one another.

Table 1. Causal model factors.

Factor	Description	Capability	Vulnerability
Resiliency	The ability of the network to provide and maintain an acceptable level of service, and in some cases, to adapt and grow in the face of various faults and challenges, to normal operation [85]	✓	
Health Fulfillment	This refers to the well-being status		
Population with Skin Problems	Percentage of people that have skin problems		

Table 1. *Cont.*

Factor	Description	Capability	Vulnerability
Determinants of Skin Lesion Development	This factor includes environmental, geographical, climate, and demographics attributes that influence the development of skin lesions		✓
Actual Necessity Level	Rate of need		✓
Necessity Level	This refers to demand		✓
App Affordability	Affordability level of the app in terms of cost and best value	✓	
App Consistency	App consistency level across various smartphone vendors	✓	
Accessibility	This refers to convenience of accessing the tool when needed	✓	
Equitability	This refers to the capability of each individual in need having same likelihood of being served	✓	
User Complaint	This represents the severity and/or number of complaints from users		✓
User Contentment	This factor refers to the measure of user's experience/reaction to received services and confidence in the app [25]	✓	
Skin Lesion Screening Viability Process	This refers to the feasibility (viability) of the skin screening method or process (including dermatoscope, smartphone, biopsy, etc.)	✓	
Simplicity of App Interface	This refers to the app's user friendliness level	✓	
Adaptability	The interface should be flexible and adaptable to different user contexts and devices, ensuring usability across various platforms and screen sizes	✓	
Interactivity	This refers to the app's ability in providing interactive user experience	✓	
Equipment Malfunction	This factor represents error or faults in the device		✓
Diagnosis Variability	This refers to variance in diagnoses from one method to another		✓
Data Management Capability	This refers to the app's capability in terms of managing and updating data and, in general, the software	✓	
Realtime Data Sharing	App's ability to collect, update, and transfer information instantly	✓	
Security Breach	This factor consists of attributes compromising security, privacy, and confidentiality such and unauthorized activity		✓
App Functionality	This is the top level technological factor referring to the app performance	✓	
Skin Lesion Algorithm and Software Management Competitiveness	This implies the level of the app's skin lesion analysis algorithm competitiveness among the state-of-art techniques	✓	
Image Resolution	This refers to the quality of image acquired for skin lesion analysis	✓	
Power Supply	This represents the battery level of the smart (hand-held) device	✓	
Skin Lesion Screening App Capability	This refers to the app's capability in terms of including important skin lesion analyses features and functionalities	✓	
Software Malfunction	This refers to software and algorithmic errors		✓
Delay	This represents the delay of app response in terms of time		✓

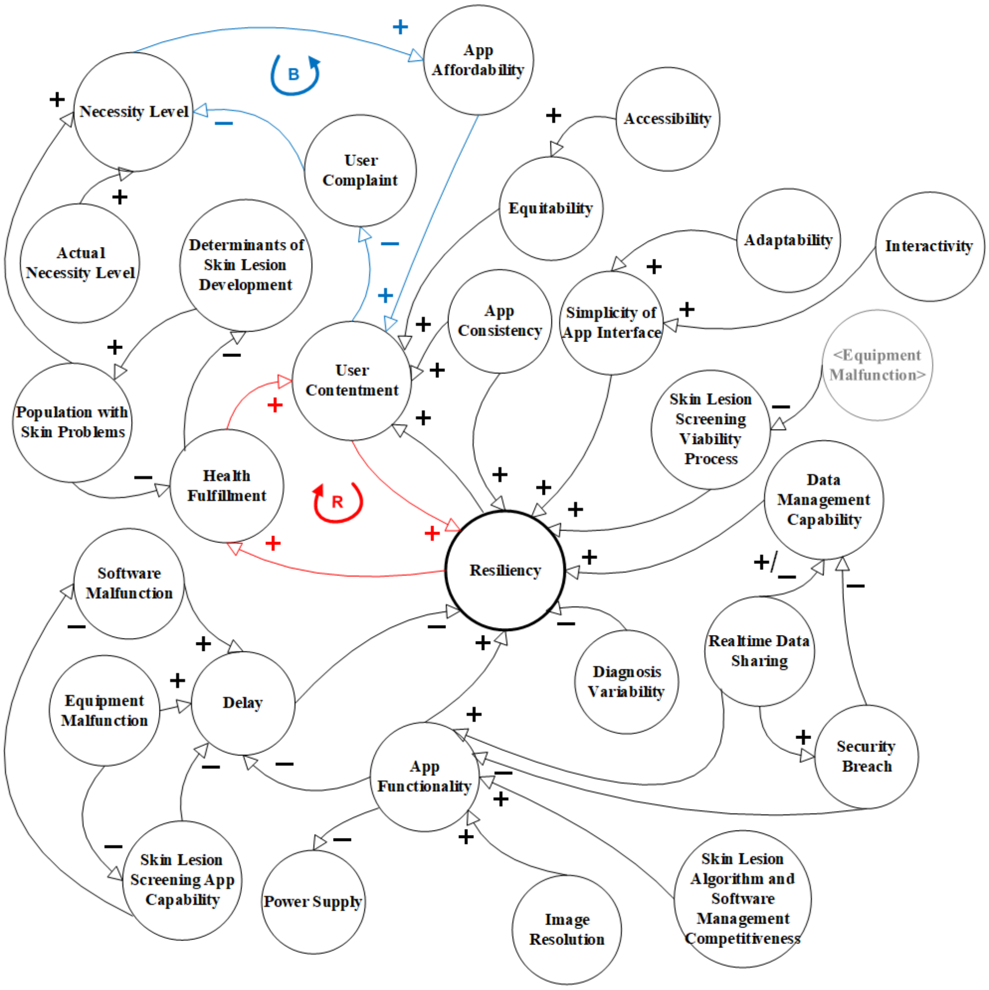

Figure 3. Causal model of smart skin-lesion screening.

The major focus of this model is the resiliency factor, which is shown in the center of Figure 3. As can be seen, several factors impact the resiliency of the model.

3.2. System Dynamics Model

A system dynamics model for the smart skin-lesion-screening framework is developed based on a subset of the newly proposed causal model. Figure 4 illustrates the system dynamics model created using Vensim Pro software v7.3.5 [86].

Attributes corresponding to the factors of the causal model are incorporated in the system dynamics model. We can observe the dynamic behavior and inter-relationships among the factors using the system dynamics model. Figure 4 demonstrates the system dynamics model, which consists of stocks, flows, and auxiliary variables that collectively represent the factors of the smart skin-lesion-screening framework.

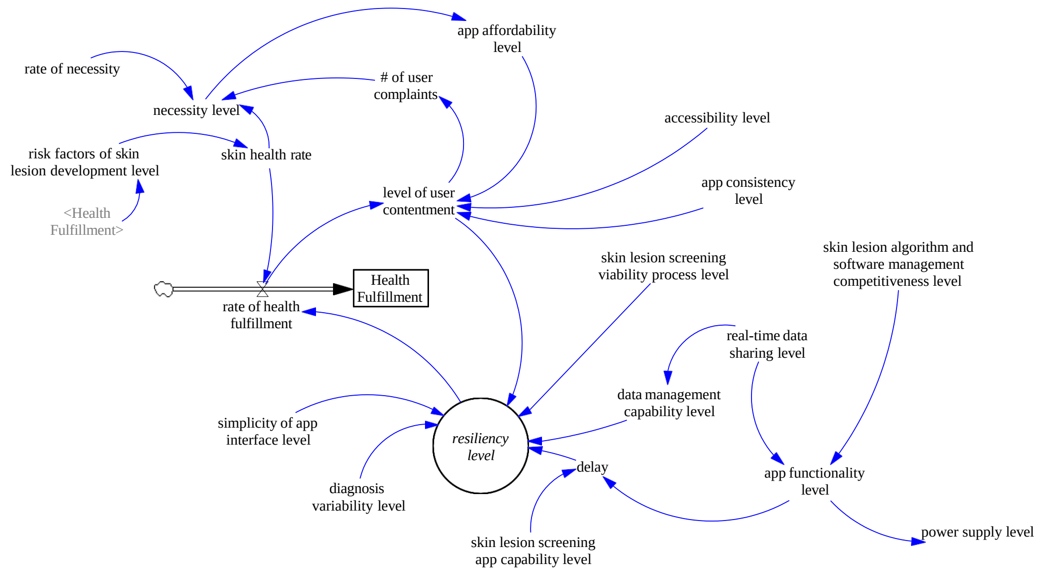

Figure 4. System dynamics model of smart skin-lesion-screening framework.

In this study, the focus is the resiliency level factor depicted in Figure 4, which is also presented in the causal model shown in Figure 3. Through various simulations and case scenarios, we will examine the dynamics of the resiliency level.

The relationships among the model factors that impact the resiliency level are non-linear and involve feedback loops. The variables and factor inter-relations of the system dynamics model depicted in Figure 4 are based on the underlying equations presented afterward (Equations (1)–(6)). The equations describe the mathematical relationships of some key factors in the model. Equation (1) represents the mathematical formulation of the resiliency level. It can be observed that several factors with non-linear relationships influence the resiliency level in our model. We have included a scaling coefficient and an offset parameter in the equation to ensure that the model operates within anticipated and allowable ranges. As seen from the remaining equations, some factors are directly proportional to others (exhibiting increasing relationships), while others are inversely related. Our system dynamics model has been designed by considering the nature of the inter-relationships among the factors according to the aforementioned equations. We will assess the dynamics of resiliency level by testing the system under various case scenarios.

$$\begin{aligned}&\text{Resiliency level} = \\ &A_{Scaling\ Factor} \times [(\textit{data management capability level})\times \\ &(1 - \textit{diagnosis variability level})\times \\ &(\textit{simplicity of app interface level})\times \\ &(\textit{skin lesion screening viability process level})\times \\ &(\textit{level of user contentment}) \times (1 - \textit{delay})] \\ &+ \delta_{Offset}\end{aligned} \quad (1)$$

$$\begin{aligned}&\text{app functionality level} = (\textit{real-time data sharing level})\times \\ &(\textit{skin lesion algorithm and software management competitiveness level})\end{aligned} \quad (2)$$

$$\begin{aligned}&\text{delay} = (1 - \textit{app functionality level})\times \\ &(1 - \textit{skin lesion screening app capability level})\end{aligned} \quad (3)$$

$$\text{level of user contentment} = (\textit{rate of health fulfillment}) \times (\textit{accessibility level}) \times (\textit{app consistency level}) \times (\textit{app affordability level}) \quad (4)$$

$$\text{rate of health fulfillment} = (\textit{skin health rate}) \times (\textit{Resiliency level}) \quad (5)$$

$$\text{necessity level} = (\textit{rate of necessity}) \times (1 - \#\ \textit{of user complaints}) \times (\textit{skin health rate}) \quad (6)$$

4. Results

The primary goal of simulation in this work is to examine the dynamics of the model developed based on the smart skin-lesion-screening framework. In order to assess how different factors in the system dynamics model influence the resiliency level, a range of input variables representing various case scenarios are introduced to the model. The input variables encompass the design and performance criteria measures of the smart skin-lesion-screening app, such as the simplicity of app interface level, the app consistency level, the accessibility level, the skin lesion screening app capability level, the skin lesion algorithm and software management competitiveness level, the real-time data-sharing level, the skin lesion screening viability process level, and the diagnosis variability level. Additionally, the rate of necessity is also an input considered in our system. While numerous factors will impact the resiliency level, our primary focus lies in observing the influence of factors related to the design or performance criteria measures of the skin lesion screening app.

In this study, we utilize normalized values ranging from 0 to 1 for simulation purposes. A value of 0 signifies the lowest extreme (worst case), while a value of 1 corresponds to the highest extreme (best case). The normalization process involves converting the raw (actual) values of factors (inputs) into their normalized counterparts. The conversion takes into account the relationship between the raw factor value and its respective minimum and maximum values. The values of the variables are relative, so a consistent normalization methodology is preferred to see the trends and dynamics when even a small change is applied. There would be a mapping from actual real-world score range to the 0-to-1 range. For real-world scenarios, normalization will be performed relative to the highest and lowest possible values by considering the ratio: $(\textit{Actual\_value} - Min)/(Max - Min)$, where Max and Min refer to the maximum and minimum values of the variable. Thus, the normalized value of the variable will always be between 0 and 1. For many of the factors of the model, such as the simplicity of the app interface level, a Likert scale between 0 and 10 could be used based on the user's experience and/or judgement to determine the actual value, which would then be normalized according to the above ratio. For better consistency of these user-experience specific factors, a set of standard questions regarding certain features of the app, device, or interface with binary decisions should be considered to determine the scale.

It must be noted that the actual values of input factors will be ascertained through the measurement and quantification of real-life data. However, obtaining such data necessitates conducting long-term clinical trials and extensive data collection, which falls outside the scope of this current study. As an alternative approach to investigate the model's dynamics, we employ synthetic data that closely resemble real-world scenarios. These simulated data are generated under various conditions to explore the system's behavior. To facilitate a comprehensive understanding of the system's dynamic behavior and any comparative analysis, the simulated values are constrained within a normalized range of 0 to 1.

We have allocated approximately 25 days as the timeframe for simulation, using a daily time grid with one-day increments. This decision is based on the reasonable assumption that a couple of weeks would be an appropriate period for the skin lesion screening app and any associated changes to gain prevalence for general public/patient use. This timeframe includes the necessary time for patient follow-up and feedback, which aligns with the typical adoption process for most health-related mobile apps [87–90]. While the skin lesion screening app is expected to provide nearly real-time responses (normally within seconds or fractions of a second), the input variables considered in the model typically would not undergo drastic changes within this 25-day timeframe.

In what follows, the dynamics of the resiliency level (the output factor of interest) with respect to other significant factors of the model are examined under various cases in a 3-dimensional (3D) view. The simulation results in 3D allow for a much more detailed analysis of the dynamics of the factors with respect to one another. Some factors are inputs, which are kept constant over the period of 25 days, while other factors change due to the factor inter-relationships governing the model.

The input variable settings in different cases are presented in Table 2. These values are sample testing scenarios that would most probably occur in real-world scenarios encompassing various settings of the smartphone device/design/app performance criteria factors and the socio-economic factors within the system. The chosen values are thus representative of the case scenarios based on the variations in the input parameter values and their impact on the output.

Table 2. Input variable settings for all cases.

Factor / **Case**	**Simplicity of App Interface Level**	**Skin Lesion App Capability Level**	**Skin Lesion Algorithm and Software Management Competitiveness Level**	**Skin Lesion Screening Viability Process Level**	**Diagnosis Variability Level**	**Rate of Necessity**	**All the Other Input Variables**
Baseline	0.5	0.5	0.5	0.5	0.5	0.5	0.5
Case #1	0.5	0.5	**0.9**	0.5	0.5	0.5	0.5
Case #2	0.5	**0.3**	0.5	0.5	0.5	0.5	0.5
Case #3	0.5	0.5	0.5	0.5	0.5	**0.2**	0.5
Case #4	**0.8**	**0.8**	**0.8**	**0.8**	**0.2**	0.5	0.5
Case #5	**0.3**	**0.4**	**0.7**	**0.9**	0.5	0.5	0.5
Case #6	**0.4**	**0.4**	**0.4**	**0.4**	0.5	0.5	0.5

4.1. Baseline Case

A baseline scenario is established as the initial reference and created under the presumption that all input variables are set at their midpoint level of 0.5. We observe the dynamics of the resiliency level under this baseline case from Figure 5. It is evident that the system exhibits minimal dynamic variance in the baseline case, with the resiliency level mostly remaining within the 0.5 level. Subsequently, the responses of the succeeding case scenarios are compared against the baseline case to assess the differences and outcomes.

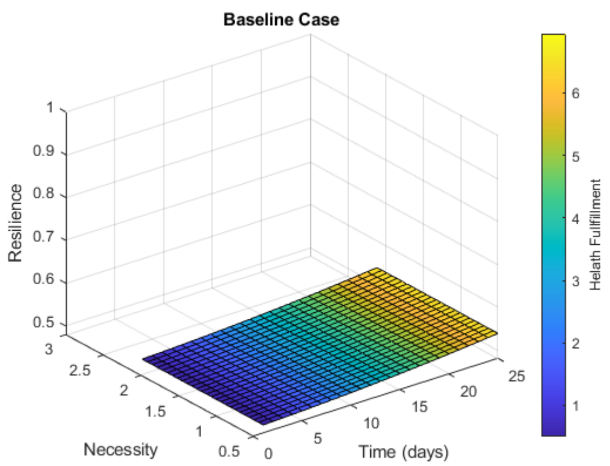

Figure 5. Dynamics of the resiliency in the baseline case.

4.2. Case #1

Case scenario 1 is designed with the assumption that one of the skin lesion screening app's design or performance criteria factors starts with a high value at the input. For this, the skin lesion algorithm and software management competitiveness level is set to 0.9, and the other input variables are kept at their baseline levels. The system's dynamic behavior in this case is illustrated in Figure 6. Evidently, the resiliency level exhibits an increase from the baseline in this case scenario.

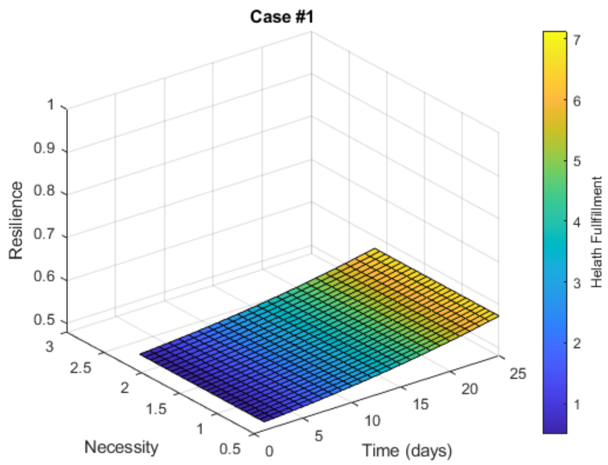

Figure 6. Resiliency level dynamics under case #1.

4.3. Case #2

Case scenario 2 is developed under the assumption that one of the skin lesion screening app's design or performance criteria factors is initially set at a low value. The skin lesion screening app capability level is configured to 0.3 for this case, while the other input variables remain at their baseline levels. The dynamic behavior of the system in this case is illustrated in Figure 7. The resiliency level, as expected, experiences a decrease in case #2 compared to the baseline.

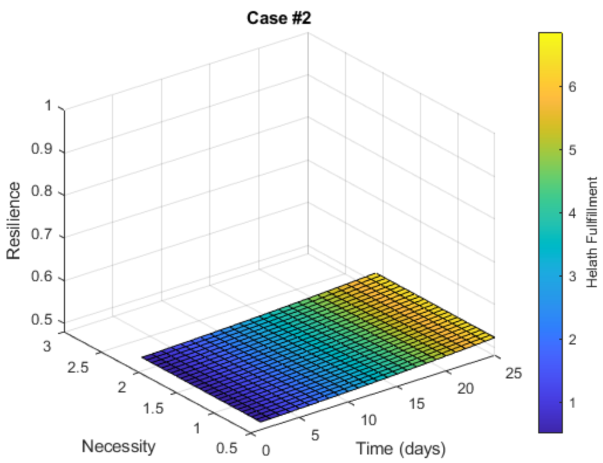

Figure 7. Resiliency level dynamics under case #2.

4.4. Case #3

Case scenario 3 is designed to examine the impact of the economic/social need factors on the dynamics of the resiliency level. Therefore, the rate of necessity is set to 0.2, while the other input variables are kept constant at their baseline levels. The dynamic responses are depicted in Figure 8, where, as anticipated, the resiliency level is slightly reduced in case #3 compared to the baseline scenario.

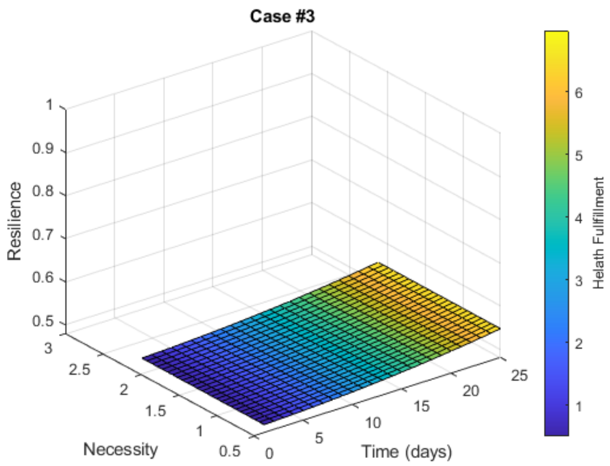

Figure 8. Resiliency level dynamics under case #3.

4.5. Case #4

Simulation case #4 is created with the assumption that the skin lesion screening app's design or performance criteria factors are set to reasonably high values. The simplicity of app interface level, the skin lesion screening app capability level, the skin lesion algorithm and software management competitiveness level, and the skin lesion screening viability process level input factors are all set to 0.8, and the diagnosis variability level is set to 0.2 (reflecting low variance which is better), while the other input variables remain at their baseline levels. The system dynamics behavior in case scenario 4 is visualized in Figure 9, which demonstrates the remarkable improvement of the resiliency level, compared to the baseline response.

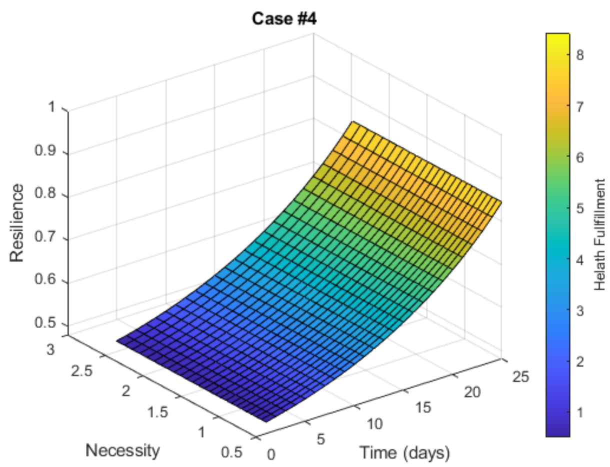

Figure 9. Resiliency level dynamics under case #4.

4.6. Case #5

Case scenario 5 is devised to gain a deeper understanding of the dynamics of the resiliency level under a different combination of inputs for the skin lesion screening app's design or performance criteria factors. In this case scenario, the simplicity of the app interface level is set to 0.3, while the skin lesion screening app capability level is set to 0.4, the skin lesion algorithm and software management competitiveness level is set to 0.7, and the skin lesion screening viability process level is set to 0.9. Other inputs are kept at their baseline levels. The dynamic responses of the resiliency level in case 5 are illustrated in Figure 10.

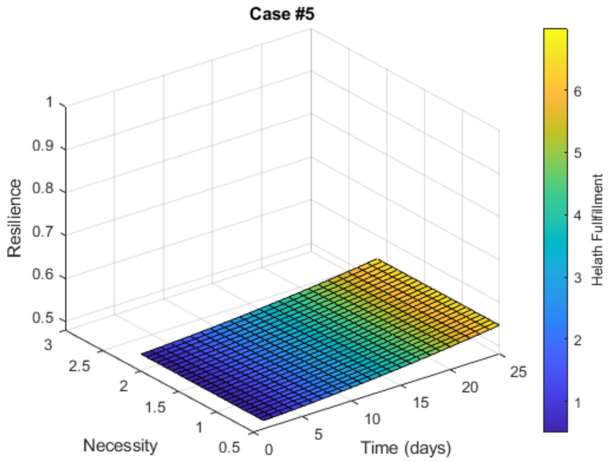

Figure 10. Resiliency level dynamics under case #5.

4.7. Case #6

Case scenario 6 is designed to examine the dynamics of the resiliency level when the skin lesion screening app's design factors are set to a low level. In this case scenario, the input variables related to the skin lesion screening app's design are configured to 0.4 (below the baseline case), while the other input variables are maintained at their baseline (midpoint) level. The system dynamics response in case 6 is illustrated in Figure 11, and as expected, the response is reduced compared to the baseline.

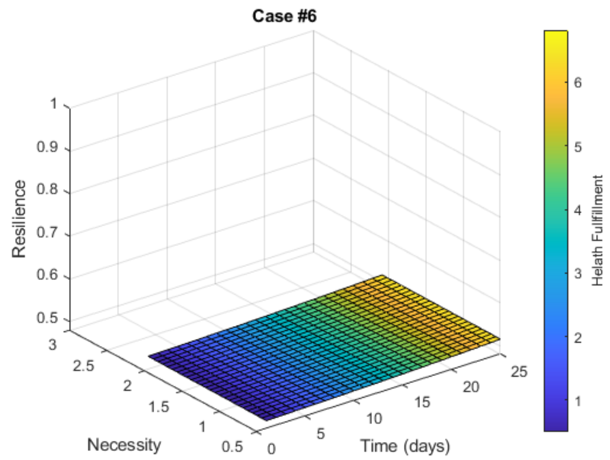

Figure 11. Resiliency level dynamics under case #6.

5. Discussion

The validity of the model has been verified through multiple tests, including assessments of its structure, behavior, and implications on user policy [91–93]. The model performed as anticipated, aligning with the results obtained from the case scenarios, which enhances confidence in the structural validity. Additionally, the model produced expected outcomes even when subjected to extreme input values, successfully passing the behavioral tests. This thorough validation process underscores the reliability and robustness of our model.

The simulation results revealed the dynamic behavior of the resiliency level across diverse case scenarios. Among the factors influencing the resiliency level, we observed that the smart skin-lesion-screening app's factors related to acquisition, hardware (device), software, algorithm, and performance had a more significant impact. Particularly, since the skin lesion algorithm and software management competitiveness level is a capability for this system, we observe an increase in the ability of the network to deliver an acceptable level of service when this factor is reinforced. The increase in the resiliency level compared to the baseline in cases #1, 4, and 5 suggest that various stakeholders in the model, including users, patients, physicians, app builders, and health insurance companies, would experience overall advantages and benefits over time. The enhancement is marginal for case #5, moderate for case #1, and substantial for case #4. Conversely, the reduction in the resiliency level compared to the baseline in cases #2, 3, and 6 imply that the main players within the overall system would experience limited long-term advantages.

The limitations of this study include (i) insufficient real-world data to realistically present the actual test cases and dynamics of the model, and (ii) the existence of a subset of variables depicting some technological and socio-economic factors of the model. Each factor alone could be explored in the context of a whole system considering dependencies and inter-relationships with several other factors. To facilitate this study, a subset of the most representative factors as well as synthetic data with normalized values were utilized, given that the collection and evaluation of long-term data is not within scope of this article. For a more accurate understanding of the realistic dynamics, actual data should be collected over extended periods, spanning months and years.

6. Conclusions

This paper presents a novel framework to assess the resiliency of smartphone-based skin lesion screening applications using system dynamics modeling. While system dynamics modeling has been applied in numerous healthcare contexts, it has not been previously explored in the literature for smartphone-based skin lesion screening. The framework introduces a unique mapping of the factors within the model, with risk assessment factors, including vulnerability or capability, using a systems engineering and system dynamics perspective. Through simulations, we analytically investigated the factors' inter-connections. This work brings together diverse domains, including engineering, AI, risk assessment, and system dynamics. It further integrates design, modeling, simulation, and analysis to provide a comprehensive and innovative contribution to the field.

The proposed model provided a new perspective on the various factors influencing the resiliency of smartphone-based skin lesion screening systems. The results presented in the paper contain simulated synthetic data representative of real-world scenarios. The research findings hold valuable insights for decision and policy makers within supply chain management, from patients, to physicians, to app builders. These insights can help with the maintenance and continuous improvement of this transformative technology, enabling individuals to conveniently and frequently track and monitor their skin health.

In the future, with actual real-life data, the benefits of adopting this framework by all of the stakeholders in the system will aid in more objective skin lesion monitoring, as well as the management of associated risks, using the technology. By performing routine skin screening with the smartphone app within the envisioned sustainable framework, individuals can take proactive measures to safeguard their skin health, fostering a positive impact on overall public health.

Author Contributions: Conceptualization, M.F. (Misagh Faezipour), M.F. (Miad Faezipour) and S.P.; methodology, M.F. (Misagh Faezipour), M.F. (Miad Faezipour) and S.P.; software, M.F. (Misagh Faezipour), M.F. (Miad Faezipour) and S.P.; validation, M.F. (Misagh Faezipour), M.F. (Miad Faezipour) and S.P.; formal analysis, M.F. (Misagh Faezipour), M.F. (Miad Faezipour) and S.P.; investigation, M.F. (Misagh Faezipour), M.F. (Miad Faezipour) and S.P.; resources, M.F. (Misagh Faezipour), M.F. (Miad Faezipour) and S.P.; data curation, M.F. (Misagh Faezipour), M.F. (Miad Faezipour) and S.P.; writing—original draft preparation, M.F. (Misagh Faezipour), M.F. (Miad Faezipour) and S.P.; writing—review and editing, M.F. (Misagh Faezipour), M.F. (Miad Faezipour) and S.P.; visualization, M.F. (Misagh Faezipour), M.F. (Miad Faezipour) and S.P.; supervision, M.F. (Misagh Faezipour), M.F. (Miad Faezipour) and S.P.; and project administration, M.F. (Misagh Faezipour), M.F. (Miad Faezipour) and S.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: This research does not involve the collection of any new data. The results presented are derived from simulated data generated through synthetic testing case scenarios.

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

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