mathematics

Article

Hybrid Modeling of Anxiety Propagation in Response to Threat Stimuli Flow

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Abstract: Previous studies have demonstrated that the rates of anxiety have been constantly increasing worldwide in recent years. To understand this phenomenon, based on the complemented cognitive model TVAPA of anxiety, the hybrid method of modeling and simulating the dynamics of anxiety in the population is proposed. The suggested method combines agent-based modeling, dynamic systems modeling with differential equations, and machine learning methods. The four-level STAI methodology is applied to assess anxiety in the proposed models. Sentiment analysis of social media content is used to identify the parameters of triggering stimuli flow. The proposed models were implemented and verified using open access data sets. Created models are characterized by simplicity, and the parameters used in them have a clear socio-informational meaning. The developed models can be calibrated by applying statistical methods according to indicators of anxiety measured at discrete sets of time intervals by associating them with parameters of the threat stimuli flow taken from statistical data and/or Internet content tracking data.

Keywords: anxiety level; information processing model of anxiety; threat stimuli; agent-based modeling; system dynamics; compartmental modeling

MSC: 37M10

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Citation: Sakalauskas, L.; Denisov, V.; Dirzyte, A. Hybrid Modeling of Anxiety Propagation in Response to Threat Stimuli Flow. *Mathematics* **2023**, *11*, 4121. https://doi.org/10.3390/math11194121

Academic Editors: George B. Kleiner, Vladimir Mazalov and Maxim A. Rybachuk

Received: 3 August 2023
Revised: 16 September 2023
Accepted: 25 September 2023
Published: 29 September 2023

1. Introduction

Anxiety is a complex psychological phenomenon influenced by various factors, including cognitive, emotional, and physiological processes [1]. However, understanding of anxiety propagation mechanisms is limited [2]. A hybrid modeling approach may facilitate integrating multiple aspects of anxiety propagation, providing a more comprehensive understanding of anxiety as a response to threat stimuli.

Anxiety, one of the primary emotions, has evolved as a crucial mechanism for survival and the ability to deal with threatening stimuli [1]. However, under certain circumstances, this response can become overly intense or dysfunctional, leading to the manifestation of anxiety disorders [1]. The hybrid modeling approach can be valuable for researchers, as anxiety disorders are prevalent mental health conditions that can severely impact individuals' quality of life, and by studying how anxiety propagates in response to threat stimuli, researchers can identify potential critical points, leading to the development of more effective prevention tailored to specific anxiety triggers and propagation patterns. Next, individuals respond to threat stimuli differently, and hybrid modeling can help identify individual differences and promote the development of personalized approaches, improving outcomes for those affected by anxiety.

The prevalence of those affected by anxiety at the highest level (anxiety disorders, including phobic, social, obsessive compulsive (OCD), post-traumatic (PTSD), or generalized anxiety), manifesting in symptoms of apprehension, motor tension, and autonomic overactivity, in 2017 varied from 2.5 to 7 percent by country, and 284 million people (179 million females and 105 million males) experienced them globally. In 2019, the prevalence slightly increased: 301 million people were living with an anxiety disorder, including 58 million children and adolescents [3]. Furthermore, recent research reported that anxiety disorders affect approximately 34% of adults during their lifetime in the US and are associated with significant distress and impairment [2]. Following this, by modeling anxiety propagation, it is potentially possible to identify early warning signs or markers associated with heightened anxiety responses. This information can be used for prevention or early intervention strategies, helping individuals manage their anxiety before it escalates into a more severe condition.

As indicated by the World Health Organization, the COVID-19 pandemic triggered a 25% increase in the prevalence of anxiety worldwide [4]. Numerous studies revealed a specifically pandemic-related increase in the rates of anxiety [5,6], stress [7,8], poor sleep quality [9,10], burnout [11], PTSD [12], and unsatisfactory psychological well-being [13]. Recent surveys revealed that nearly 8 in 10 adults (78%) disclosed they were anxious due to the coronavirus pandemic [14]. In 2022/23, an average of 37.1% of women and 29.9% of men reported high levels of anxiety; from July to September 2022, 59.4% experienced 'low' or 'very low' levels, whereas 40.5% of people experienced 'medium' or 'high' levels of anxiety [15]. The data suggest that the rise of anxiety is a global concern that needs thoughtful consideration and deeper analysis of factors possibly contributing to this phenomenon.

Researchers presume that some of the psychological costs of the pandemic can hardly be controlled, for example, the levels of traumatic stress related to COVID-19, which is a new type of trauma [12], but the COVID-19-related anxiety can be monitored and relatively kept under control [16–18]. Exploring anxiety propagation can provide valuable data for public health policy. Understanding how threat stimuli flow impacts different populations can inform policies aimed at reducing societal anxiety levels and promoting mental well-being.

On the whole, the concept of anxiety spans generations, as the notion of 'dukkha,' signifying anxious impatience, was targeted by many meditative and religious practices for hundreds of years [19]. Thus, anxiety might serve as a fundamental concept for grasping and modeling various social phenomena related to both individual and societal emotional states, as indicated by previous models, e.g., Plutchik's three-color model [20]. Russell's circumplex model of affect [21,22], the pleasure–arousal–dominance model [23].

Next, more challenges in the world might contribute to the further increase in anxiety and its disorders: climate crises, local conflicts, economic burdens, natural disasters, and there is a conceptual and analytical gap in understanding the driving forces behind the growing challenges of societal sustainability, social complexity, behavioral operations, and social cohesion. Therefore, analyzing the hybrid modeling of anxiety propagation in response to threat stimuli flow is important as it deepens understanding of anxiety and may lead to advancements with broader implications for research in mathematical psychology and mathematical sociology.

This study aims to contribute to the development of a hybrid model of anxiety and its dynamics in response to the flow of threat stimuli. Hopefully, hybrid modeling could be applied for the analysis, forecasting, and management of anxiety-related scenarios. Based on a cognitive theory of anxiety [24], we presumed that anxiety is related to information-processing patterns and an increase in anxiety corresponds to stimuli perceived as potentially dangerous threats. The proposed hybrid modeling approach combines agent and dynamic systems modeling with differential equations and machine learning methods.

The rest of the paper is organized as follows: Section 2 delves into the cognitive model of anxiety, outlining the key concepts related to anxiety's cyclical nature. Section 3 elucidates the research's foundation, encompassing a sentiment analysis technique for measuring stimulus-induced emotional responses (Section 3.1), a multi-method modeling approach (Section 3.2), and details regarding the anxiety scales and datasets employed

(Section 3.3). Section 4 explores the outcomes, featuring multi-agent modeling of anxiety propagation with its formulation (Section 4.1.1) and refinement (Section 4.1.2), along with compartmental modeling represented by a mathematical model (Section 4.2.1). Subsequently, Section 5 provides a discussion and conclusions based on the research findings, and Section 6 discusses the limitations and future directions.

2. Background: Cognitive Model of Anxiety

2.1. Anxiety Reactions

Previous research described anxiety as a multidimensional reaction to actual or potential dangers, combining cognitive, somatic, emotional, and behavioral components representing evolutionary mechanisms to cope with threatening stimuli [1]. From the neurobiological point, human anxiety reactions are assumed to be mediated by genetic background, the amygdala, hippocampus, cingulate cortex, hypothalamus, serotonergic, gamma-aminobutyric acidergic, adrenocortical systems, and various brainstem areas [1,25]. The nature–nurture interplay is viewed as possibly increasing the risk of developing excessive anxiety; for example, the brain-derived neurotrophic factor gene (BDNFMet at codon 66) in interaction with early life stress was found to predict neuroticism and higher anxiety [26].

However, from the cognitive point, anxiety reactions are predominantly cognitive phenomena, related to informational triggers or the perception of threats [27–29]. The cognitive model of anxiety and anxiety disorders refers to distorted cognitive processes [30,31]. Abnormalities in appraisal or biased information processing are considered to play a central role in triggering anxiety and its disorders [24].

People with anxiety disorders attend differently to threat-relevant compared with non-threat stimuli. Previous research demonstrated sensitivity to threat stimulus features; however, phobic individuals do not display reliably slowed temporal disengagement from threat-relevant stimuli [32]. Highly arousing threat stimuli have adverse effects on cognition and performance, and previous research revealed that the impact of negative affective stimuli on cognition critically depends on subjective threat perception [33].

Cognitive specificity of misleading beliefs is considered to predispose or maintain anxiety [24,34,35]. Anxiety sensitivity, intolerance of uncertainty, and pathological worry are among the central concepts related to the cognitive model of anxiety [36].

Anxiety sensitivity refers to the tendency to misinterpret as dangerous, suddenly occurring, relatively severe, and unexplained physical anxiety symptoms. Anxiety sensitivity is also linked to panic reactions and hypochondriasis [37] and is based on beliefs that anxiety-related sensations and symptoms such as palpitations, dizziness, and sweating have harmful physical, psychological, or social consequences.

Pathological worry refers to the tendency to excessively, out of proportion to the actual problem, focus on specific topics perceived as uncontrollable and potentially damaging. Pathological worry is also linked to general anxiety disorder and serves to avoid potential dangers. Pathological worry can also be accompanied by obsessive thoughts and is usually triggered by specific events or perceptions of threats [38].

Intolerance of uncertainty refers to difficulty with ambiguity and unpredictable change [39] and a need for cognitive closure, i.e., any answer on a given topic [40]. Intolerance of uncertainty is exposed via maladaptive emotional, cognitive, and behavioral reactions to ambiguous situations and attempts to control the future and is linked to obsessive compulsive disorder. Intolerance of uncertainty is also characterized by the unacceptance of even "tiny bits" of uncertainty, as well as disproportionate anticipation that an undesirable event may occur, no matter how small the probability of its occurrence is.

2.2. The Cycle of Anxiety in the Cognitive Model

The cognitive model of health anxiety [41] assumes that mild symptoms (e.g., faster breathing) might be interpreted as signs of a serious illness, and this interpretation might lead to an increase in anxiety, which in turn will lead to overestimation of symptoms.

Research on earlier pandemics found that overestimation of the threat is associated with increased anxiety [42,43].

The overall cognitive model of anxiety, based on previous studies and models (e.g., [24]), demonstrates the cycle of anxiety (Figure 1). Depending on the perceived threat stimuli, several levels of anxiety can be identified. Studies on the impact of the coronavirus around the world have shown that as the number of infections rises, an increasing number of individuals have been observed to develop "coronaphobia" [44,45], not to mention a 25% increase in anxiety disorders [46]. From a cognitive perspective, the prevalence of anxiety during the COVID-19 pandemic was associated with the perceived risk of contracting viral disease [47].

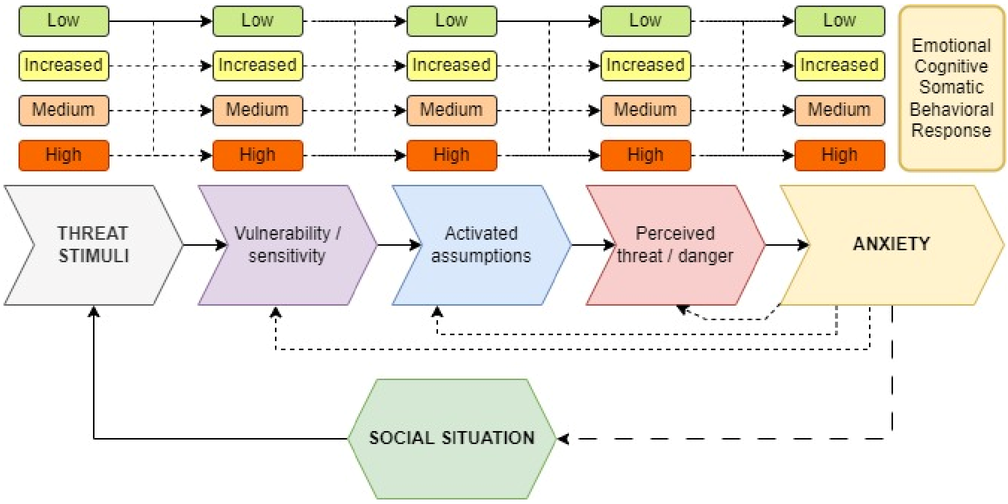


Figure 1. Complemented cognitive model TVAPA of anxiety in response to threat stimuli.

Interestingly, some studies reported dissimilar results regarding associations between the level of knowledge about the virus and anxiety level. Research reported that the level of knowledge about the virus was related to increased anxiety [47], and decreased worry [48], or no significant correlation was found [49].

Based on the cognitive theory of anxiety [24], it can be assumed that informational factors are the main anxiety-inducing stimuli that determine the level of anxiety in individuals and the whole population. From the point of view of this theory, an important part of the anxiety mechanism is the stimuli that trigger it, which also becomes negative information that spreads in the social space. Indeed, the anxiety cycle can be significantly influenced by threat stimuli, triggering events (e.g., media reports), and predisposing factors (e.g., general vulnerability to anxiety). Regarding triggering events, the media might play a central role. For example, previous studies demonstrated that media consumption during pandemics was positively associated with anxiety [50,51], as media messages repeatedly applied emotionally dramatic narratives [28,52]. In addition, studies during the pandemic have shown that anxious people were hyper-absorbed in their use of the Internet related to COVID-19 and their search for worrying information, which both reflects and reinforces safety-seeking behavior [28,29]. Several studies have shown that repeated or excessive health-related Internet searches were common safety-seeking behaviors associated with increased anxiety and worry [27,53].

Thus, this research aims to develop a comprehensive hybrid modeling framework that would allow the integration of a cognitive model of anxiety with real-world data to investigate and understand the dynamic process of anxiety propagation in response to threat stimuli flow.

3. Materials and Methods

3.1. The Sentiment Analysis for Measuring Triggering Stimuli Flow

The content of social media is one of the possible triggers of anxiety [54]. Sentiment analysis can help identify and extract subjective information about anxiety and emotional levels from web media content. Sentiment analysis using deep learning techniques has been widely explored during the last decade. Social networks are sources of threat stimulus flows, where large news portals spread their information, allowing comments to be left under their published news articles [55,56], and the world's largest websites such as Youtube.com, Facebook.com, and Wikipedia.org are based on the core principle that the content of these platforms is created and uploaded by their visitors [57,58]. Such interactivity allows users of social networks not only to learn something new but also to share their opinions on the topic of articles or information presented in another way. The popularity of the social web shows that internet users value the ability to express opinions, share knowledge, and/or demonstrate their creativity. In the context of this study, it is the process of learning about how the public perceives information published in the media and social networks.

Thus, news channels have a direct impact on public anxiety, when the flow of anxiety-inducing stimuli is created not only by direct information, but is also multiplied by users themselves by exchanging information and commenting on it. The last observation enables sentiment analysis to identify and extract subjective information about anxiety and emotional levels from web media content.

It should be noted that when studying the impact of media content on the change in anxiety levels, it is not necessary to thoroughly study all of its content. After all, it is enough to only study control sources, similar to determining body temperature, it is enough to measure it only at one control point of the body. It is relevant to study how anxiety affects the whole population, without trying to estimate each individual's level of anxiety with great precision since the occurred errors are integrated into the general normal variance of the measured indicators [59]. In this case, comparing simple sentiment analysis methods using rule- and dictionary-based systems is sufficient to assess the general anxiety level of the population.

Solving more complex tasks of identifying specific sources of anxiety manifestations depending on anxiety stimuli may require the use of text classification methods and sentiment analysis based on machine and deep learning technologies [60–62]. Bidirectional transform coding (BERT) is gaining more and more attention and has been successfully applied to deep sentiment analysis tasks. Applying the BERT model to masked speech modeling provides a deeper sense of the context and flow of speech than unidirectional speech models (Figure 2).

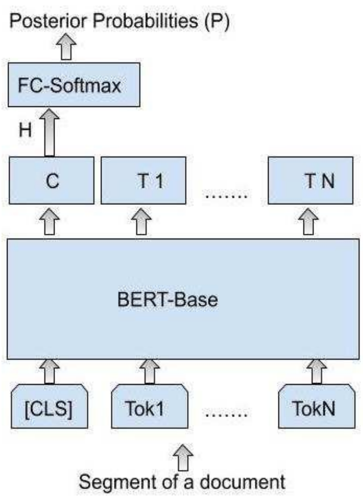


Figure 2. Sentiment analysis by BERT method [63].

Media are classified to a level of concern using the method developed by R. Pappagari (see [63]). In such a way, the application of machine learning techniques helps to identify additional input variables and their properties in developing a hybrid model.

In this article, to investigate public anxiety level responses to the COVID-19 pandemic, a control database of article headlines from the popular Lithuania media portal Delfi has been created and examined using rule-based and dictionary-based systems.

3.2. Multi-Method Modeling Approach

The multi-method modeling approach applied here results in a series of models that are constructed using different modeling paradigms. Despite their differences, all of these models have the characteristics of conceptual modeling and are primarily designed to better understand the spread of anxiety in the population in response to threat stimuli flow. At the same time, "what-if" scenarios modeling at both individual and aggregated (i.e., population) levels will assist policymakers in implementing and coordinating prevention and control measures during potentially dangerous events, evaluating the effectiveness of these measures, and, thus helping to reduce anxiety responses in the society.

Following the recent trends in epidemiological modeling [64–67], two prevailing computational modeling and simulation approaches in the field are selected here to model the spread of anxiety: system dynamics and agent-based modeling. While equation-based system dynamics models possess a high level of abstraction and their state variables are aggregates in character, the agent-based models can vary from low-level models representing individual real-world objects to rather abstract ones where agents represent big groups of individuals or even the whole population. In his seminal book on simulation modeling [68], Borshchev provided an exhaustive explanation of both modeling methods along with numerous examples of their application. A more recent comparison of them can be found in [67], where two case studies on the spread of the COVID-19 pandemic were carried out using both approaches. In particular, the authors conclude that equation-based models are faster but still simplistic, while agent-based models require more computational capabilities but are closer to the system under study and, therefore, more realistic.

It should also be mentioned that fundamental concepts and classical models of mathematical epidemiology were formulated and analyzed as continuous system dynamics models [69]. Meanwhile, there are distinct limitations associated with aggregate modeling when the focus is on the interactions or social contacts [64].

The agent-based modeling method has its drawbacks as well. It is less formal, its discrete and stochastic nature requires much more detail, numerous parameters and a variety of behavioral rules to be specified. As a result, working with agent-based models is more time-consuming, they require much more computational power and memory capacity for their execution.

Since both of the aforementioned methods have their strengths and weaknesses, many recent studies focus on comparing them and choosing the most suitable simulation method for the system under consideration [67].

In this work, we apply a different approach. As a cognitive model of anxiety implies, it is important to look at the system from different perspectives, being able to combine individual behavior and interactions between discrete agents with the population-wide continuous dynamics. Therefore, we propose a hybrid, multi-method modeling approach. First, we design separate agent-based and system dynamics models, test their basic assumptions, refine the model structure, and then, based on these results, delineate the directions of their further integration in a truly hybrid simulation model of the spread of anxiety.

To facilitate this integration, two more model design decisions were made: framing the studied system in a unified way suitable for both modeling methods, and selecting a simulation modeling platform that not only supports different methods but enables the modeler to combine them in a single hybrid model. As for the later decision, the *AnyLogic*© v. 8.8.1 (The AnyLogic Company, AnyLogic Europe: 67 Avenue Franklin Roosevelt, Avon-Fontainebleau, 77210 France) simulation system [68] was selected, which supports system dynamics, agent-based, and discrete event simulation modeling methods. The system provides visual modeling tools and standard graphical notations for specifying a model built by any of the supported methods. Moreover, these methods can be used in any combination to design a hybrid model of a complex system under study. Model development is based on the object-oriented programming paradigm, and some Java code scripts may be required to complete the model, but there is no need for professional software development skills.

3.3. Anxiety Scales and Datasets Used

Further, the finite population of anxious N individuals will be considered. Anxiety can be modeled on a discrete or continuous scale. In the first case, the level of anxiety is considered to be measured on a discrete scale that acquires K finite values, such as K = 4 or K = 7, etc. In particular, according to the State-Trait Anxiety Inventory (STAI), a commonly used measure of trait and state anxiety, four levels of anxiety can be distinguished (K = 4), from the lowest to the highest [70]. In the case of a continuous scale, it is assumed that anxiety can acquire any real value from the finite interval, which will be considered unitary for simplicity.

In this study, only publicly available anxiety datasets were used for model development and comparison with modeling results. The main data source comes from the Seasonally adjusted quarterly estimates of anxiety in the UK, provided by the Office for National Statistics [15]. Studies of the emotional climate of Lithuania, conducted by the Center for Human Studies and Baltic Studies during the COVID-19 quarantine period, show similar dynamics of the emotional state of the Lithuanian people. However, the publicly available data of this research contain only dynamics of general anxiety along with anger and other emotions, without splitting it into levels.

4. Results

4.1. Multi-Agent Modeling of the Anxiety Propagation

4.1.1. Model Formulation

Agent-based modeling (ABM) is often a primary choice to begin building a model of a new phenomenon with rather superficial *a priori* knowledge about it. Even if modelers do not know how the entire system behaves or what its main state variables and their relationships are, they can start identifying individual objects (i.e., agents) and defining their behavior, then grouping them and calculating necessary statistics, thus developing agent-based or individual-based models. Therefore, using this approach, the researcher is interested in how macro phenomena are emerging from micro-level behavior among a heterogeneous set of interacting agents [71]. In the field of simulation of complex social systems, agent-based modeling provides the means to directly represent the way people behave and interact, and then to study the population-wide effect of these interactions [72]. The process for developing a specific ABM model for the spread of anxiety is outlined below. The structure of the model is formulated based on the following basic assumptions.

Although pandemics were characterized by an increase in anxiety and dynamical spread through the population, the patterns of this spreading phenomenon are not yet sufficiently well studied. To this end, the main focus should be on modeling the sources of anxiety-provoking stimuli, based on the cognitive model of anxiety. The analysis of the literature shows that the main flow of triggering information consists of messages and news generated by media sources, which are then rebroadcast on online social networks, OSN [49]. It should be noted that this flow has the properties of ordinality and markovity to a large degree, so it can be considered as following a Poisson process with time-dependent intensity. It is not inconceivable that anxiety can be and is transmitted by anxious individuals, analogous to how rumors are transmitted in their propagation model or a contagion is transmitted in epidemiological models. In this way, it is reasonable to use the well-known anxiety measurement scales and model the probabilities of individuals in the population belonging to the corresponding scale levels and circulating among the latter ones.

Thus, the intensity of the transition from one level of anxiety to another mainly depends on the intensity of the propagation of anxiety stimuli. It is reasonable to test the assumption that the transition to a higher level of anxiety may require a more intense flow of stimuli. It can also be assumed that the intensity of the transition to a higher level of anxiety may also depend on the probability of more anxious individuals. In the latter case, the anxiety propagation model becomes similar to the rumor propagation model [73,74].

Finally, a rather deep analogy with the innovation spread model (Bass dynamics) can be considered as well [75]. Here, the mechanism of transition from one level of anxiety to another, which depends on the intensity of the propagation of anxiety stimuli, seems to be similar to the flow of innovative product adoption by advertising, meanwhile, as the mechanism based on social contacts and interaction of individuals is reminiscent of a word-of-mouth effect in the simulation model of Bass dynamics [68,72].

The individual behavior of an agent can be specified using different approaches, mainly based either on graphical modeling tools or code scripts. In most cases, the agents have a notion of state, they interact with each other, and their reactions depend on the state they are in [76,77].

A particular ABM model of the spread of anxiety is presented below. The model is implemented using *AnyLogic*© v. 8.8.1 simulation system [68], which provides a visual modeling tool to specify the behavior of agents. The Statecharts used in *AnyLogic* for that purpose are an enhanced state machine formalism proposed by David Harel [78]. These diagrams are widely used today in software engineering as a part of the standard *Unified Modeling Language* (*UML*) [79]. Statecharts enable the modeler to graphically describe the event- and time-driven behavior by representing the following main elements of ABMs: different states of the agents and transitions between them, events that trigger those transitions, timing, and actions that the agent makes during its lifetime, composite states that enable specification of modes of agent operation. All these elements were employed in the iterative development of the ABM model of the spread of anxiety.

At the first iteration, the agent states and different types of transitions between them were formulated based on the model assumptions and the resident agent's behavioral rules. The result of this iteration is an initial version of the model with the basic model structure defined, allowing the model to be run to test the validity of these premises. The completed state chart diagram of the model is presented in Figure 3.

This four-state anxiety spread model implements several types of transitions between states. The first type of transition between anxiety states is triggered by the alarming stimuli from media. In this rate-based transition, the time interval is drawn from an exponential distribution parameterized with the given rate parameter, i.e., *StEffectiviness*. So, the execution of this transition may lead to a state change, for example, from the Low-level Anxiety state to the Increased Anxiety state.

The second type of forward transition between anxiety states is based on the idea that the people are being influenced by the media to adopt the fear and then, having adopted it (i.e., already being in the next anxiety level), spread the word of mouth (*WOMi*) about that. Here, the communication between people is modeled by the message-sending mechanism, when agents react to messages from other agents. Being at one of the three higher levels of anxiety and performing internal state transition (shown in Figure 3), agents randomly send different messages to other agents. These messages cover the range from "danger" (sent by the agent being in *IncrAnxiety*) and "so bad" (*AboveAveAnxiety*) to "fear" (*HighAnxiety*). The received messages trigger the transition from the lower level state to the higher one according to the *Contact Rate* and *Probability of Adoption* parameters. The backward transition *Quit* is controlled here by a specified timeout (in days).

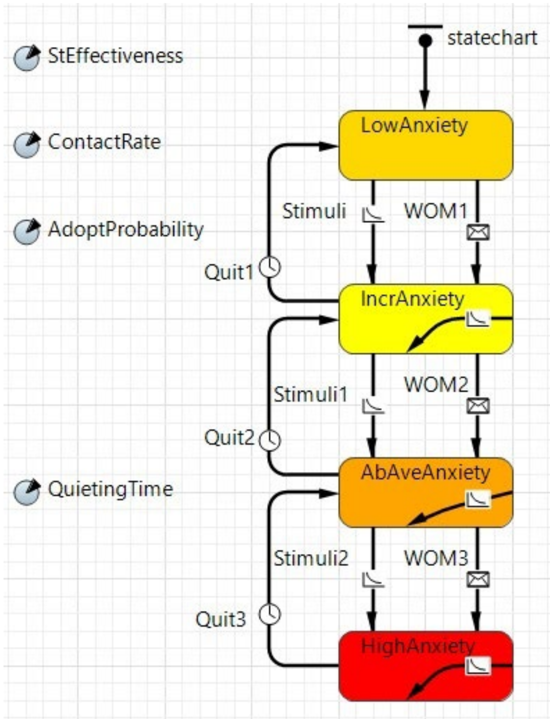


Figure 3. Development of the ABM model of the spread of anxiety: UML Statechart diagram of the Resident agent class in the initial version of the model.

In this version of the model, the initial distribution of agents among states is not defined, so they are in the lower anxiety state. The reason for this is to determine whether the proposed population mechanisms allow agents to reach a certain final stationary distribution and whether this distribution is comparable to the available observation data.

The initial values of model parameters were chosen based on the literature on innovation spread models (Bass dynamics) mentioned above [68,72,75], and the time-dependent *Quit_n* parameters were set based on the domain expert recommendation. Then, parameter values were adjusted according to the results of parameter variation experiments involving multiple runs of an already constructed model.

Often agents are spatial objects, i.e., they live in space (continuous, discrete, geographical) and have some mobility features. Agent distribution in space can also be used for animation purposes, which improves the model usability and the explanatory value of the results for different groups of model stakeholders. Although in this model the agents have no spatial features, their dynamics are visualized in a continuous environment of rectangular shape, properly configured in the *AnyLogic* system (see Figure 4).

For the results of a typical modeling scenario presented in Figure 4, the statistics were calculated for each of four groups of agents (i.e., number of agents being in four different states of anxiety level), and were then dynamically represented as time plots as well as time-stack and pie charts. The pie charts show the changes in the distribution of anxiety in the population of 10,000 agents in terms of the percentage of individual agents belonging to a particular anxiety level. The duration of the simulation used in this scenario is usually sufficient to achieve a stable distribution, and the population size is set large enough to represent smooth trajectories on the time graph.

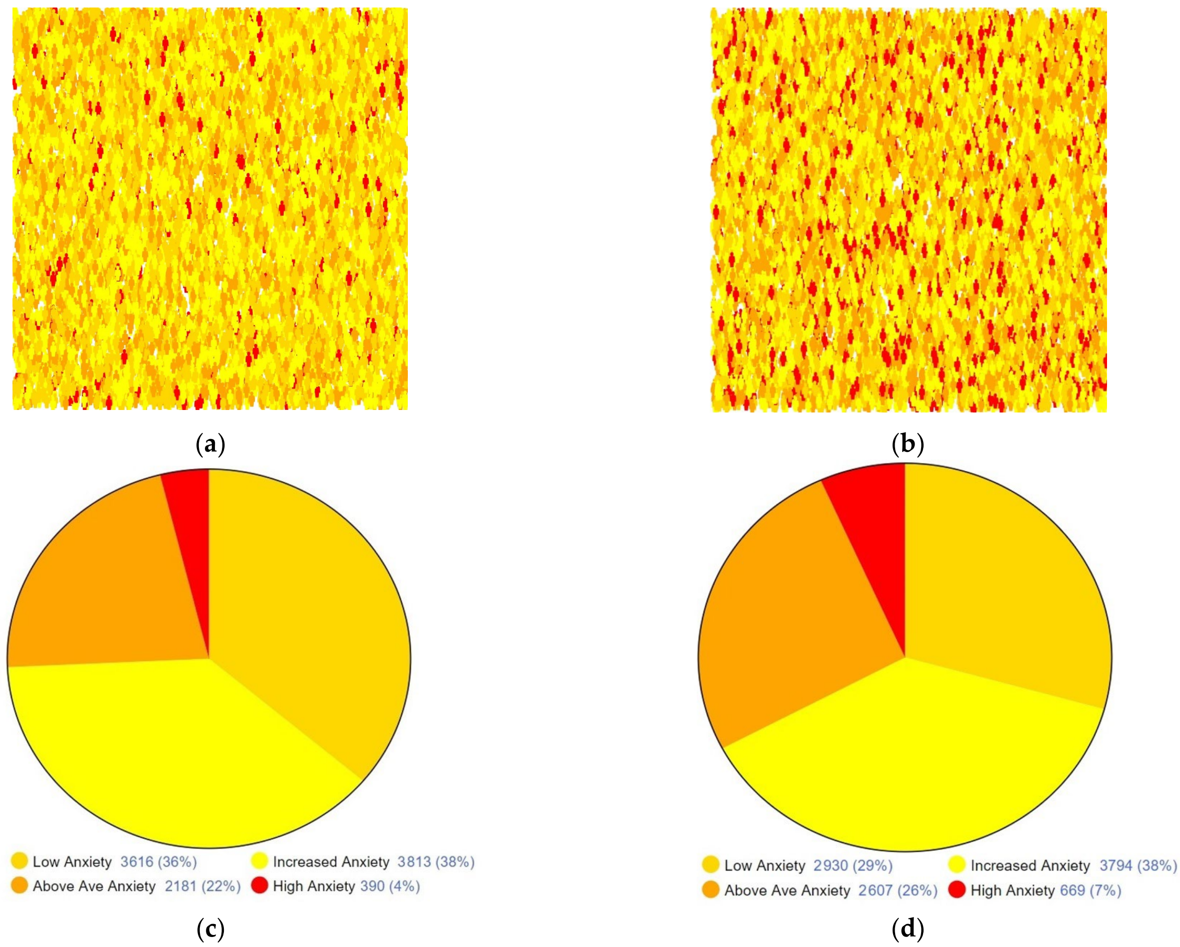


Figure 4. ABM model results. Visualizations (**a**,**b**) and numerical results (**c**,**d**) of the anxiety progression over time in the population of 10,000 agents. Duration of simulation 200 steps: (**a**,**c**) intermediate state (at time step = 100); (**b**,**d**) final state (at time step = 200).

Figure 5 shows the comparison of modeling results with the estimates of anxiety levels from the selected dataset [15]. While the quarterly estimates of anxiety provided are too coarse for a detailed analysis and comparison with the output of the daily step model, they can be used to highlight the general trend in model behavior and to suggest possible directions for improving the model.

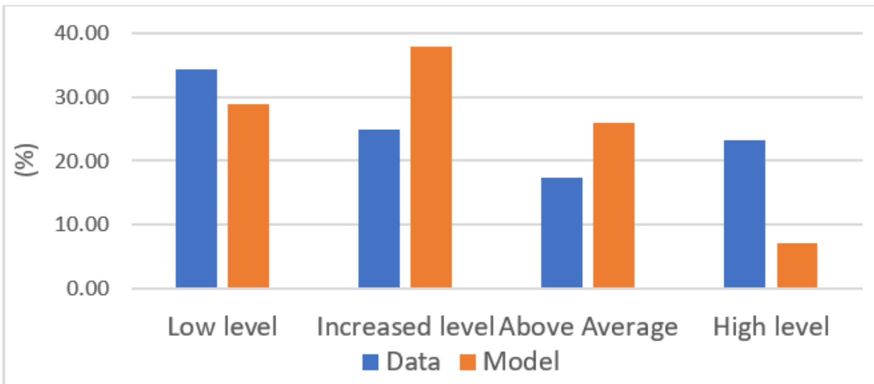


Figure 5. ABM model results vs. statistical data of anxiety levels. Data: seasonally adjusted quarterly estimates, time period: July to September 2020 (Q3). Model: simulation starts from the beginning of the year 2020, provided results correspond to the final state presented in Figure 4d.

The results presented in Figure 5 demonstrate the typical behavior of the initial version of the model: it tends to underestimate the percentage of agents at a high level of anxiety while accumulating most of them at medium levels.

4.1.2. Model Refinement

Several model development iterations were performed, resulting in a significantly expanded Statechart diagram of the Resident agent (Figure 6).

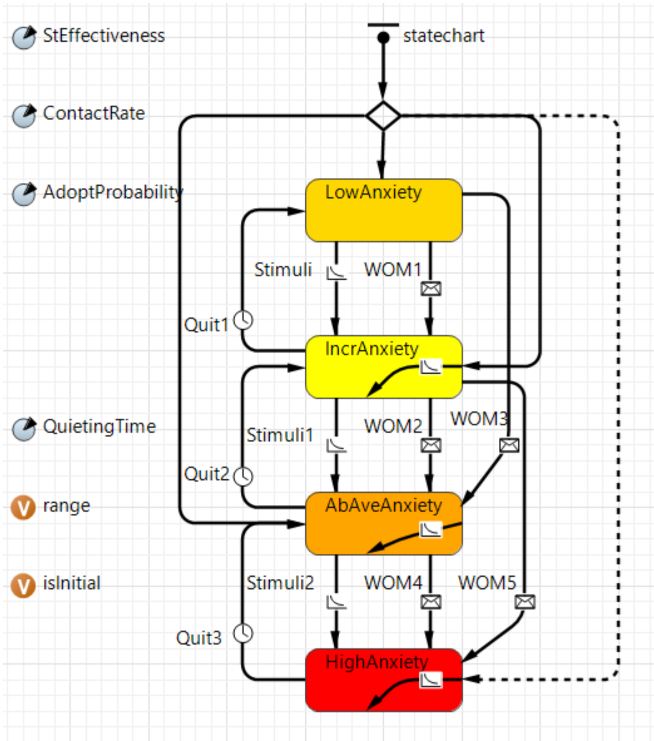


Figure 6. Enhanced ABM model of the spread of anxiety: Statechart of the Resident agent.

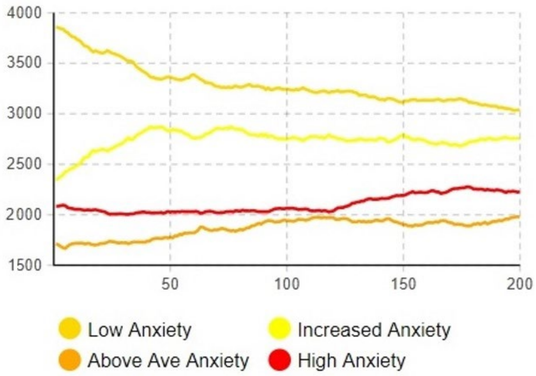
First, a branch element that represents a transition branching from the initial state is introduced to the Resident's state chart. It allows for the initial distribution of agents into anxiety groups to be set depending on the value of the resident's random parameter *range* and the boolean variable *is initial*. The desired initial distribution is specified in the *initial_distribution* parameter as a *uniform()* probability distribution function.

The mechanism of internal transitions has also been improved. Splitting of each single *WOM* transition from the low anxiety states (*LowAnxiety* and *IncrAnxiety*) into two transitions is introduced to represent rather subtle relationships between State anxiety and Trait anxiety. The STAI concept suggests that while anxiety as an emotional state exists at a given moment in time and at a certain level of intensity, trait anxiety indicates relatively stable individual differences in the predisposition to anxiety. The stronger the anxiety trait, the more likely the person will experience a more intense rise in anxiety in a threatening situation. As Spielberger points out in 1983, persons with high trait anxiety are also more likely to respond with greater increases in the intensity of state anxiety in situations that involve interpersonal relationships and threaten self-esteem.

To represent this heterogeneity in the population concerning the differences in individual vulnerability to threat stimuli (see Figure 1), in addition to former single transitions (*WOM1* and *WOM2*), two new transitions to the higher anxiety level (*WOM3* and *WOM5*) were introduced in the refined model.

Finally, making the whole transition mechanism more consistent, the backward transitions *QuitN* are controlled now not by fixed timeout values, but by randomly distributed ones within the specified range around QuietingTime.

The modeling results of the enhanced model are presented in Figure 7. The same modeling scenario as before is applied here for the 2020 pandemic (see Figures 4 and 5). However, there are also some differences. In the improved model, the initial anxiety state is now defined at the beginning of the simulation based on observational data from the ONS dataset [15].



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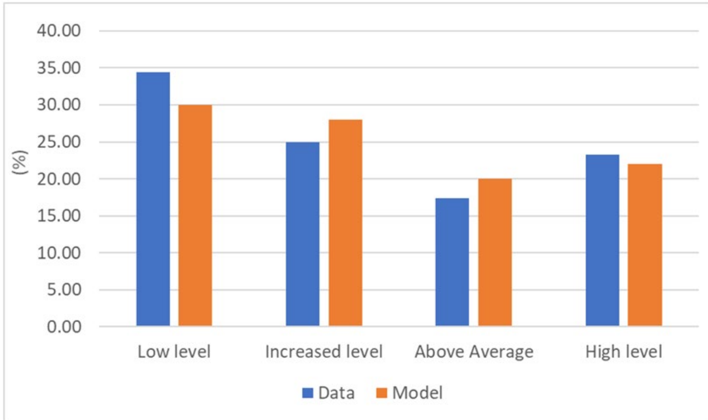


(**b**)

Figure 7. Simulation results of the enhanced ABM model. (**a**) Dynamics of anxiety levels in the population of 10,000 agents. Initial anxiety distribution is set by the quarterly estimates from the ONS dataset (period: October to December 2020 (Q4)). Simulation starts from the beginning of the year 2020, duration of simulation 200 steps; (**b**) model results at the final step = 200 vs. statistical data of anxiety levels. Data: quarterly estimates from the ONS dataset (period: July to September 2020 (Q3)).

The presented results show that the enhanced ABM model with its refined transitions performs much better compared to the original version of the model, especially when modeling higher levels of anxiety. These results also suggest that representing heterogeneity in the population improves the explanatory potential and predictive accuracy of the model.

4.2. Compartmental Modeling

4.2.1. Mathematical Model of Anxiety Propagation

Agent-based models allow for detailed assessment of many individual processes occurring in a population, while aggregate or compartmental models are used to model system dynamics at a higher level of abstraction. In the latter case, parts of the population with different levels of anxiety act as separate compartments. Thus, the compartmental model consists of several interconnected compartments in which the following processes take place—the exchange of components between individual compartments, and the transformation of compartments into each other. Usually, the compartmental model is written as a system of differential equations [64,80].

Epidemiological models are often used to better explain user adoption and abandonment of social networks, where adoption is analogous to infection and abandonment is analogous to recovery. We modify the traditional SIR model of disease spread by incorporating infectious recovery dynamics such that contact between a recovered and infected member of the population is required for recovery.

So, the population consists of individuals whose anxiety corresponds to one of the 4 levels, according to STAI. Let the parts of the corresponding anxiety level in the population at the time t be $P_1(t)$, $P_2(t)$, $P_3(t)$, $P_4(t)$. Obviously,

$$P_1(t) + P_2(t) + P_3(t) + P_4(t) = 1. \quad (1)$$

Suppose that the probability of an individual moving to a higher level of anxiety depends on the intensity of the stimuli flow. Let us say anxiety is slumping in intensity $\mu > 0$. So, the probabilities of belonging to any group of anxiety levels forms the Markov chain:

$$P1 \leftrightarrow P2 \leftrightarrow P3 \leftrightarrow P4. \tag{2}$$

Let us introduce the function $\alpha_i(t)$ to model the transition to states with higher probabilities of anxiety in dependence on infection intensity, the intensity of media information, stimulating anxiety, or transfer of anxiety in the population from one agent to another, similar to the classical rumor spread model, etc. (Dietz (1967) [73], Sun et al. (2021) [74]). For instance, for modeling negative media impact, the following model is in use:

$$\alpha_i(t) = I(t) \cdot \beta + P_i \cdot \gamma \tag{3}$$

(or modeling anxiety transfer from one agent to another $\alpha_i(t) = P_i \cdot \gamma$), where β is normalizing constant, obtained from statistical data, $I_i(t)$ is the intensity of stimuli flow. Let us say anxiety is slumping in intensity $\mu > 0$. So, the probabilities of belonging to any group of anxiety levels form the Markov chain:

$$\begin{gathered} \frac{dP_1}{dt} = -\alpha_2(t) \cdot P_1 + \mu \cdot P_2 \\ \frac{dP_i}{dt} = -(\mu + \alpha_i(t)) \cdot P_i + \mu \cdot P_{i+1} + \alpha_{i-1}(t) \cdot P_{i-1}, \ \ 1 < i < K, \\ \frac{dP_K}{dt} = -\mu \cdot P_K + \alpha_{K-1}(t) \cdot P_{K-1} \end{gathered} \tag{4}$$

It should be noted that the proposed model is characterized by simplicity, and the parameters used in it have a clear socio-informational meaning, so they can be evaluated using the data of the population and the cognitive flow affecting it.

4.2.2. Applied System Dynamics Model

A system dynamics modeling approach and, in particular, a simulation system supporting the stock-and-flow diagramming method [68,81] is usually a proper choice for computer implementation of compartmental models. Thus, differently from the agent-based modelling approach presented above, which works with systems at a micro level and applies a down-top approach, the systems dynamics (SD) investigates a system at a much higher abstraction level (population level) and is rather a top-down methodology.

To simulate the system defined by Equation (4), an applied system dynamics model of four anxiety levels (population groups) has been developed and implemented using the same *AnyLogic©* v. 8.8.1 simulation system. In the system dynamics terms, it means that a stock and flow diagram of the model is created representing state variables (as stocks) and their rates of change (flows). Stocks are often described as levels or accumulations, they represent the memory of the system and are sources of disequilibrium. Informational relationships (links) define the feedback loops (balancing or reinforcing) and express the causality in the system [68,75]. The resulting stock and flow diagram of the model is presented in Figure 8.

The model diagram also includes parameters (*a*, *miu*), dynamic variable *I_alarm* and a table function *Nm*. The later elements are used to represent a threat stimuli flow formed in a particular social situation (see. Figure 1). According to the cognitive approach applied here, it is the most important forcing factor of increasing anxiety level in the population. An example of a numerical input used in different modeling scenarios is illustrated in Figure 9, where the number of alarming messages in the media *I(t)* is directly introduced into the model by an empirical table function *Nm* (shown as a time plot as well). This function is constructed using the results of sentiment analysis applied to identify and extract subjective information about anxiety and emotional level from the web media content.

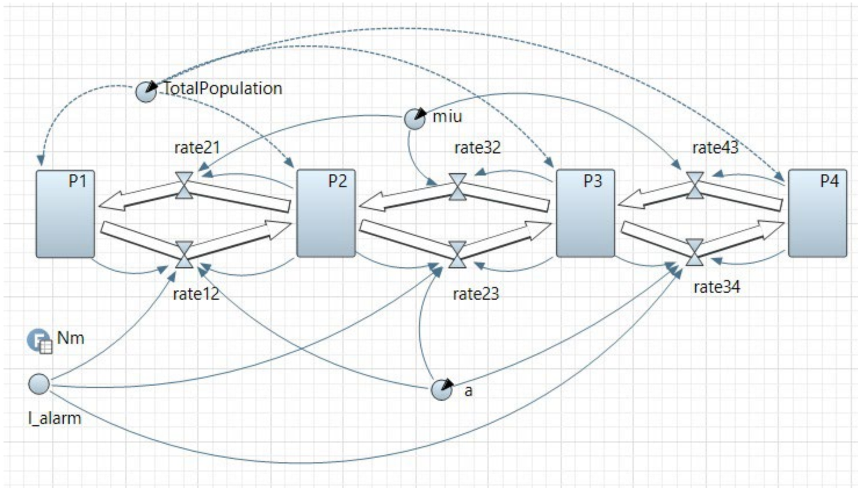


Figure 8. Stock and flow diagram of the system dynamics model of anxiety propagation.

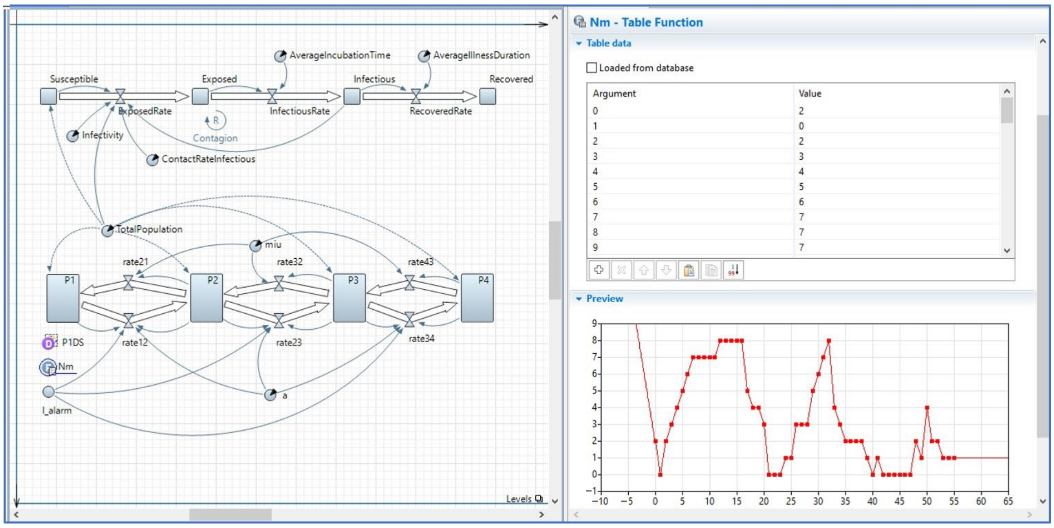
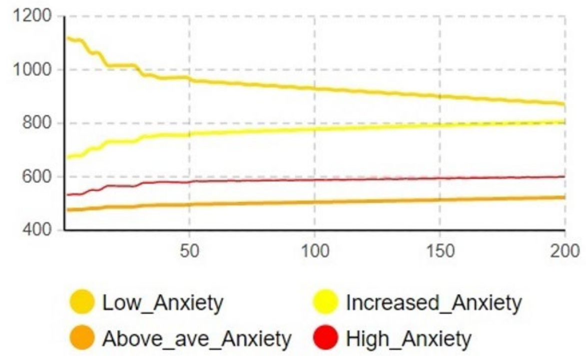


Figure 9. Data on alarming stimuli from the media (model input as a table function).

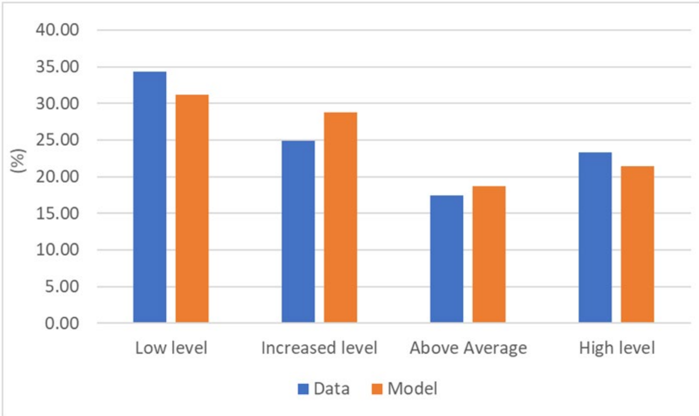
The actual data sample shown in the figure represents the two-month period of alarming stimuli data extracted from the most popular mass media portal in Lithuania in the Spring of 2021. Further observations show rather high levels of alarming stimuli from the media during the peak and saturation period of the pandemic, often with periodical oscillations around the average level. Then, in the following period, this stimuli flow continues to oscillate with a much lower level of intensity. So, the dynamic variable *I_alarm()* combines a table function *Nm* with an appropriate approximation of the stimuli flow by a periodic function to continue simulation in the following time period.

Once established, the system dynamics model of anxiety propagation can be easily combined with other submodels representing the dynamics of a specific threat. This possibility is also illustrated in Figure 9, where the anxiety model is complemented by a standard SEIR epidemic model to provide a direct effect of the epidemic level of COVID-19 infection on the spread of anxiety throughout the population.

The simulation results of the system dynamics model are presented in Figure 10. In order to be able to compare the simulation results with the results of the improved ABM model, the same simulation period is used. The simulation starts at the beginning of the pandemic year 2020, the initial values of the state variables (P1–P4) are set according to the data on anxiety levels from the final dataset of the previous year, 2019 [15].



(**a**)



(**b**)

Figure 10. Simulation results of the system dynamic (SD) model. (**a**) Dynamics of anxiety levels in the population of Lithuania. Initial anxiety distribution is set by the quarterly estimates from the ONS dataset (period: October to December 2019 (Q4)). Simulation starts from the beginning of the year 2020, duration of simulation 200 steps; (**b**) model results at the final step = 200 vs. statistical data of anxiety levels. Data: quarterly estimates from the ONS dataset (period: July to September 2020 (Q3)).

This simulation scenario represents the distribution of anxiety levels in the Lithuanian population, which has a total population of 2,800,000. Although the ABM model used a significantly smaller number of agents in the population, the results of the models can be compared by expressing them as a percentage of individuals in the population at each of the four anxiety levels (i.e., Figures 7b and 10b).

Since both models are built on the same basic hypothesis and to some extent are only different approximations of the same mathematical model defined by the system of Equation (4), the results of their modeling are also very similar. However, due to its aggregated nature, a system dynamics model is much faster and can be used to execute a whole range of computer experiments with various "what-if" scenarios that require running the model multiple times. In turn, the developed ABM model of anxiety has a much higher explanatory potential for a stratified population and can be used to study the rather subtle dynamics of interactions between individuals belonging to different anxiety groups. In particular, this allows for a comparative analysis of the influence of exogenous (media and social networks) and endogenous (individual contacts, WOM) factors on the dynamics of general anxiety and its levels in the population.

5. Discussion and Conclusions

This article presents the hybrid methodology for modeling and simulation of anxiety dynamics within a population, grounded in the cognitive framework of anxiety. Within the context of this methodology and the proposed models, anxiety is postulated to be triggered and driven by a flow of stimuli perceived as threatening. In contemporary society, such stimulus streams are frequently generated by media outlets and subsequently amplified by individuals through their dissemination of information on social networks. In this regard, the developed models exhibit noteworthy parallels with the classical rumor propagation model [73,74].

The stimuli responsible for triggering anxiety can be associated with a spectrum of social phenomena and processes, including but not limited to pandemics, epidemics, armed conflicts, and socio-environmental challenges. Of notable significance is the role of social media content [54]. This assumption leads to sentiment analysis techniques to identify and extract information about anxiety levels and emotional states from web-based media content. In this way, the application of machine learning techniques helps identify additional input variables and their properties when developing a hybrid model.

The well-known four-level STAI methodology is applied here to assess anxiety in both proposed models, where standardized questionnaires are the main tool for assessing the level of anxiety. Thus, two streams are generated: anxiety-triggering impulses (stimuli) and the current level of anxiety in a population. The developed modeling method combines agent-based modeling, dynamic systems modeling with differential equations, and machine learning methods. The application of two different modeling paradigms allows us to study such a complex social–psychological phenomenon as the spread of anxiety at different levels of abstraction: from the aggregated continuous dynamics of the entire population to the interaction of individuals and their groups with each other and their surrounding environment.

While the agent-based model allows for representing individual differences in vulnerability and further cognitive reactions (see Figure 1), the system dynamics model, with its aggregated parameters, is better suited for simulating already perceived threats.

At the same time, despite the fact that these models were created using different methods, their simulation results show good agreement with real statistical data and a fairly similar distribution of anxiety levels among the population. This allows us to anticipate their further integration when creating a single hybrid model. In particular, the ability of system dynamics stocks to accumulate agent properties can be used to trigger a statechart transition based on a threshold condition. It would be interesting to test whether this mechanism would improve the logic of WOM transitions, and also to consider introducing an indirect social impact factor [72] into the hybrid model.

It should be noted that implemented models are characterized by simplicity, and the parameters used in them have a clear socio-informational meaning, so they can be evaluated using the data of the population and the cognitive flow affecting it. Besides, the developed models can be also calibrated by applying statistical methods (e.g., maximal likelihood) according to indicators of social anxiety measured at discrete sets of time intervals by associating them with parameters of the flow of anxiety-inducing stimuli taken from statistical data and/or Internet content tracking data.

Practical Implications

Utilizing a hybrid modeling approach could aid in the integration of various aspects of anxiety propagation, offering a more comprehensive grasp of how anxiety manifests in response to threatening stimuli. Examining how anxiety propagates in response to threat stimuli can pinpoint crucial junctures, paving the way for more effective prevention strategies tailored to specific anxiety triggers and propagation patterns. Given the diverse responses of individuals to threat stimuli, hybrid modeling proves instrumental in identifying and understanding these individual differences, promoting the development of personalized approaches. Delving into the dynamics of anxiety propagation also promises to yield valuable insights for public health policy. Gaining an understanding of how the flow of threat stimuli affects different population groups can inform policy decisions aimed at reducing societal anxiety levels and bolstering overall mental well-being. Finally, hybrid modeling of anxiety propagation in response to threat stimuli flow enriches the understanding of anxiety, potentially leading to advancements with broader implications for research in mathematical psychology and mathematical sociology.

6. Limitations and Future Directions

Despite the fact that the main components of the proposed hybrid method for modeling the spread of anxiety among the population have been implemented and tested, the entire modeling process is still at the conceptual modeling stage. Both applied models require further development and their parameters should be estimated based on data collected solely for this purpose.

Future research should be focused in two directions. First of all, the developed models need to be validated and applied to the modeling, forecasting, and management of the dynamics of more complex combinations of basic emotions, associating them with the dynamics of the environment and neurobiological factors. After expanding the set of applied models in this way, their thorough mathematical analysis should be developed as well by further developing stochastic differential equations models and stochastic diffusion-type differential equations with partial derivatives and studying their properties, existence of solutions, and parameter estimation. In the latter case, it is particularly relevant to develop and study effective recursive algorithms that allow solving parameter evaluation, forecasting, and management tasks in real-time, using online monitoring data of emotions and the environment.

Author Contributions: Conceptualization, L.S., V.D. and A.D.; methodology, L.S.; software, V.D.; verification, V.D.; formal analysis, L.S. and A.D.; investigation, V.D.; writing—original draft preparation, L.S., V.D. and A.D.; writing—review and editing, L.S., V.D. and A.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data available in a publicly accessible repository that does not issue DOIs [15].

Acknowledgments: The authors would like to thank Alexander Topaj for his technical support and valuable suggestions about the peculiarities of agent-based model implementation in the *AnyLogic*© simulation system. They express their gratitude for the referee's valuable suggestions about the improvement of the manuscript.

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

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