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ORIGINAL ARTICLE

A hybrid modeling approach to simulate complex systems and classify behaviors

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Abstract
Many important systems, both natural and artificial, are complex in nature, and models and simulations are one of the main instruments to study them. In this paper, we present an approach where a complex social system is represented at a high level of abstraction as a network, thereby addressing several challenges such as quantification, intervention, adaptation and validation. The network represents the factors that influence the mental health and wellbeing in children and young people. In this article, we present an approach that links a system dynamics simulation to simulate the network and ranking algorithms to measure the vertices' behaviors. The network is enhanced by adding edge strengths in the form of correlations between vertices (established through literature). Such an approach allows us to exploit the network structure to qualify and quantify the vertices of the network, to overlay different processes over the network topology, to add and remove new vertices, and therefore interact dynamically. This in turn allows for the qualification of vertices' importance and network resilience. System dynamics simulation allows for policy analysis, where different scenarios are analyzed by stimulating a set of vertices and the effect over the network is observed. This approach allows for an abstract, flexible, yet comprehensive way of analyzing a complex social network at any scale.

Keywords Simulation and modeling · Ranking algorithm · Complex systems · Mental wellbeing

1 Introduction

Modeling an evolving complex system is challenging due to continuous change. The openness of systems' boundaries allows external influences, and self-organization causes internal influence within the system (Rotmans and Loorbach 2009; Gupta and Misra 2016). This causes change in behavior (Portugali 2012; Mahon et al. 2008) and makes it difficult to perceive the system's dynamics. The complexity is due to having multiple intertwined parts within the system (Plsek and Greenhalgh 2001). A generic approach is required to reassess the system's behavior with every change. Such systems can be represented and analyzed using a network structure of vertices and the edges as vertices' connections. Therefore, we suggest an approach which constructs a model based on one of the system's fundamental properties to rank the vertices based on each change. Our proposed approach combines a ranking algorithm with a simulation method where the algorithm reassesses vertices' ranks based on their topological structure, edge values, and the system's boundary with every change.

Complex systems can be represented as a network-like structure of vertices and edges (Ladyman et al. 2013). The networks that represent similar systems may have different abstraction levels (de Bruijn and Herder 2009; Borsboom et al. 2021). Such networks represent the equilibrium state and broad view of a complex system. However, because of complex systems' self-organizing and openness features (Rotmans and Loorbach 2009; Portugali 2012), a slight influence may impact multiple vertices and produce unexpected behavior change. Using a simulation method and a

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ranking algorithm, we aim to improve our understanding of the system's dynamics and its behavior types within a given network.

Vertices within a complex system have diverse functionalities that indicate and limit their behavior within a distinct range (de Bruijn and Herder 2009; Ladyman et al. 2013). For example, within a complex social system, *stress* (can be a vertex) functions differently from *exercise* (can also be a vertex). Both of these vertices are connected and influence each other based on the edge directions and values (Page et al. 1998; Gleich 2009, 2015). The edge values indicate the strength of the influence between two vertices. A slight change in *exercise* level may lead to a drastic behavioral change in stress level; however, the opposite may not be valid. Another uncertainty is establishing boundaries (de Bruijn and Herder 2009; Read 2012; Johnson 2012), which depends on the network representing these vertices (Aboutaleb and Monsuez 2015); two networks may represent different aspects of the same system depending on the underlying issue (Batty 2015). To handle these uncertainties, a ranking algorithm provides functionality to each vertex based on their topological structure, incoming edges' values, and network scale, which also normalizes the behavior range.

A single tampering diffuses throughout the complex system, which causes behavior change in multiple vertices (Rotmans and Loorbach 2009). For example, in a complex transport system, changing *road pay toll* may affect the behavior of multiple vertices; for example, a drop in *congestion* and *emission* gives an improvement in *road safety* and *travel time* and promotes the *use of alternate roads*. Such behaviors may appear incrementally or suddenly and may remain temporarily or permanently in the system (Bertelsen 2003; Duit and Galaz 2008), which may indicate a new emergent or chaotic behavior (Rotmans and Loorbach 2009; Portugali 2012). This may uncover essential knowledge concerning the system behavior types, the validity of the underlying network, or the model.

An adaptive model can help to uncover values that may cause fluctuation or variation in a system's behavior and perceive vertex's behavior limitations. For example, we can detect ranks that cause peculiar vertex behavior by tuning edge values. Another function that such models may provide is the accuracy of the network representing the complex system. For example, by removing or adding one or more vertices, we can observe if the system continues to show similar behavior. Such information increases the validity of the network and further realizes chaos or emergent behavior in a system.

When representing a complex system, some networks can be reduced to a minimum number of vertices to better perceive their connections and behaviors. The growth in the number of vertices and edges increases the system's complexity. This leads to unpredictability and uncertainty in perceiving behavior and future states from a large-scale network perspective. It may become difficult to decompose (Branlat and Woods 2010; Boes et al. 2015) or use such reductionist approaches (Plsek and Greenhalgh 2001; Aboutaleb and Monsuez 2015; Sijmons 2012) as the intended behavior may never emerge. Thus, a holistic view (Aboutaleb and Monsuez 2015; Sterman 2006) is needed to reveal the vertices' behavior as the target system changes and evolves.

Approaches such as interviews and surveys are generally used to collect data and quantify the vertices in complex networks that represent mental wellbeing factors. This requires to understand the range of variation and interval for each specific vertex, design surveys and interviews, collect data, analyze and normalize the data, and apply it to the network for simulation. Such methods, even though useful, can be applicable for subset of vertices; however, as complex networks evolve, it becomes time-consuming, computationally expensive, and challenging to collect data and quantify them. Additionally, decomposition prevents observing the system behavior from a holistic perspective. Coupling a ranking algorithm with system dynamic simulation method quickly quantifies the vertices in such complex networks within a normalized variation range, and adjusts the ranks with every change and scale.

We propose a hybrid modeling approach that uses PageRank to assess vertices' behavior states by ranking them based on incoming edge values and topological structure. Next, by coupling the PageRank to system dynamic simulation, the model iterates over each vertice's incoming edges, modifies its values, and reassesses the vertex rank. The model iterates through multiple scenarios based on data from a complex network for children's and young people's mental wellbeing (Raghothama et al. 2023a, b). Using comparison analysis we uncover behavior and their types, detect outlier ranks and suspicious behavior, verify the assessment, and validate the model's output behavior.

The remainder of the paper discusses the modeling challenges and the importance of such approaches for policy analysis. Next, we describe our approach in detail and give a walk-through of the experiment. The results illustrate different behavior types based on the changes in edge values and network scale. To that end, we discuss and conclude our findings, including various types of behaviors, limitations, applicability, and the objectives of the approach.

2 Background

Change in the system may happen due to the openness (Portugali 2012; Read 2012) of system boundaries and its structures toward self-organization (Sijmons 2012). Openness refers to the system's ability to evolve and change. Data modification or system growth causes change in systems behavior (Rotmans and Loorbach 2009; Kudyba 2018). Due to continuous change, the behavior of these systems becomes unpredictable and causes uncertainty to predict its future state (Rotmans and Loorbach 2009; Batty 2015), such as the behavior type.

Handling changes through modeling is a challenging task without prior knowledge of each vertex behavior in current and future states (Allen 2011). The consequences are uncertain, and the behaviors are unpredictable (Branlat and Woods 2010; Marshall 2012). A modeling approach is required to continuously measure this variation to observe the behavior's future state by readjusting its information to fit the change.

Decomposition approaches become less informative when dealing with evolving complex systems (Branlat and Woods 2010; Boes et al. 2015). Such approaches are used to perceive the system from a subsystem's perspective; however, the challenge with such approaches is that it is impossible to observe the emergent behavior caused from a larger-scale network perspective with a higher degree of connectivity (Ladyman et al. 2013). The larger these systems become, the harder it becomes to understand the system's behavior.

Network boundaries may differ depending on which aspects of the system they represent (Batty 2015). An evolving complex system may lead to the emergence of a new behavioral aspect that was not investigated previously by modelers. To observe newly emergent behaviors, it may require re-representation of the network and the generation of a new model, or it may require continuously revising the previous networks and models to fit into the evolved system without losing critical information. Instead of creating multiple models to observe such behaviors, a generic model is required to handle the changes in systems' boundaries. To overcome this issue, a self-adaptive (Boes et al. 2015) model can continuously adapt the vertices' ranks after each modification.

Our approach uses a ranking algorithm to facilitate the modeling of the evolving complex networks (Kudyba 2018). The ranking algorithm ranks vertices within a normalized range, where the rank does not exceed that range. This is done according to the network topology and incoming edge values. When a system evolves, a new vertex and edge are added, or the edge values are changed. In this case, the approach readjusts the vertices' ranks based on the change. By maintaining vertices' ranks after each change, the algorithm causes a probability distribution over all the vertices within the network where the sum of all the ranks converge to 1.0 (Brin and Page 1998). Linking a ranking algorithm to a simulation method provides a pattern of ranks for each vertex, which allows uncovering different behavior types and further validates the underlying network.

Representing a system as a network of vertices and edges allows policymakers to better understand the relationship between its parts and therefore come up with better policy options (Thorngate and Tavakoli 2009). Modeling allows policymakers to view the future states of various intervention scenarios (Grüne-Yanoff and Weirich 2010; Batty 2015; Sterman 2006). Models that simulate complex networks should provide policymakers with means to self-learn (Thorngate and Tavakoli 2009; Sterman 2006) without the presence of modelers or experts. Further, these models should be flexible enough to cover multiple scenario analyses from different network perspectives to achieve rigorous decisions or be able to expand the system.

Policymakers and professionals can cause external influences through interventions and change system behavior (Marshall 2012). Difficulty arises when these changes happen within different sub-systems and contradict each other when viewed from the whole system perspective (Johnson 2012; Sterman 2006). The lack of adaptiveness in modeling can be risky since the results will be for a situation that no longer exists (Branlat and Woods 2010) and may mislead policymakers and professionals in making a proper decision (Sterman 2006).

An adaptive approach grants models flexibility for readjustment, so that policymakers manage scenario analysis from various organizational perspectives for unforeseen situation (Walt et al. 2008; Sterman 2006). Adaptive modeling approaches not only provide policymakers with information on where the significant variation happens, but also assist observing diverse behavior for various subsystems, and further adding and analyzing new vertices' impact which are not part of the system yet. Such observations can alert policymakers of intervention consequences of different network scales for a situation which is yet to happen.

3 Hybrid modeling approach

A network which represents a complex system contains vertices which are labeled with information about the system parts, such as *stress* or *vulnerability*, and have behavior indicated by the edges values and directions. A ranking algorithm such as PageRank (Page et al. 1998; Gleich 2015) quantifies the vertices based on each vertex topological position and the incoming edges values. PageRank's primary use is to rank web pages in Google Search engine to display them from the most important to the least. Thus, in this approach, we influence the system by changing each vertex's incoming edges' values. Figure 1 flowchart represents the modeling approach flowchart. We combined the PageRank algorithm to system dynamic simulation to iterate over the vertices, influence the vertices, and reassess the vertices' ranks after each influence.

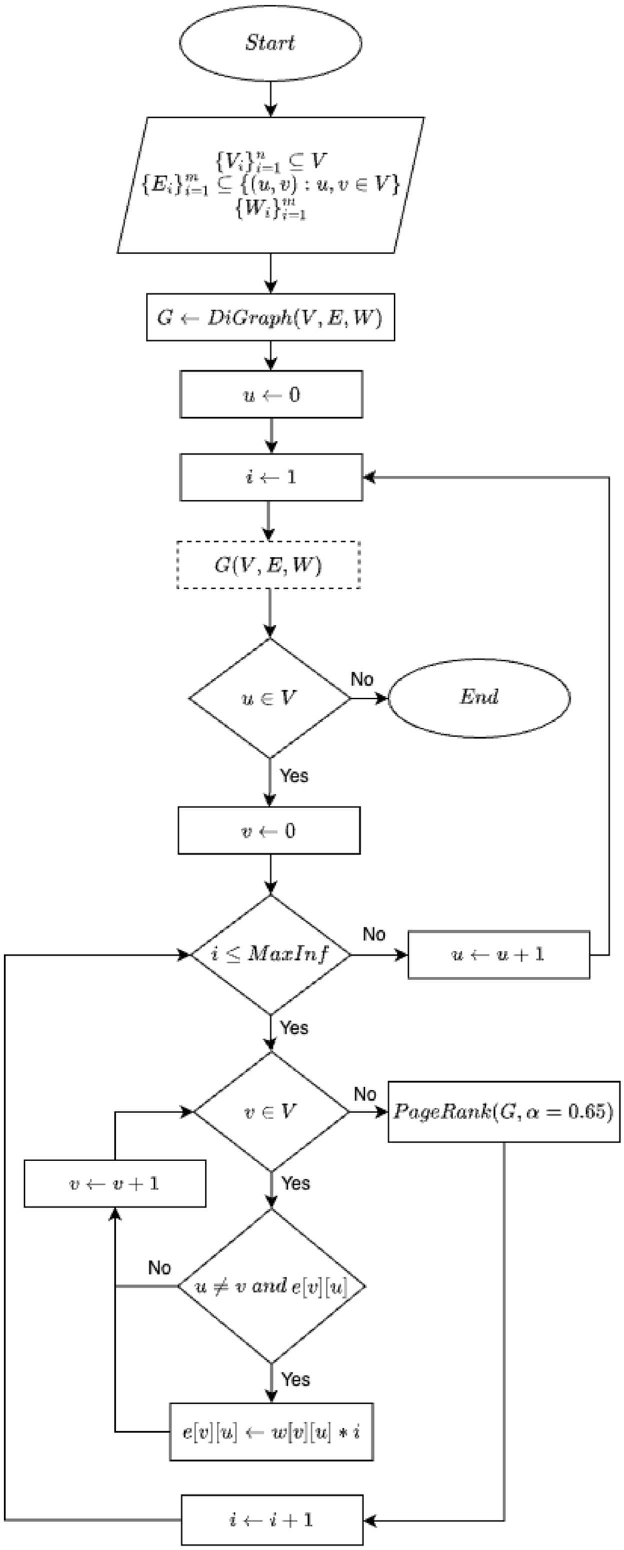

Fig. 1 Hybrid modeling approach flowchart

We use the following input variables to construct the model:

- **List of vertices** *V*: The list represents the system parts and the number of the parts indicate the network scale.
- **List of edges** *E*: The list represents the edges which connects the vertices. As the network scale changes, the connectivity also changes.
- **List of values** *W*: The list represents the edge values. Each value indicates the influence strength between pair of vertices.

Based on the input variables, we construct a directed graph *G* using the list of vertices *V*, edges *E* and edges' values *W* of a network. Furthermore, we have an *influence factor* which is used to influence the incoming edge values. In Fig. 1, we represent the *influence factor* with *i*, which begins at 1 and increases to *MaxInf*. *MaxInf* is the maximum value to influence the system. The model iterates over each vertex *u* one by one, identifies the incoming edges *e[v][u]* through *v* vertices, and influences the *e[v][u]* by multiplying *w[v][u]* to the *influence factor*: *i*. After each influence, we assess all the vertices' ranks using PageRank and increase the *influence factor* by 1. The procedure continues for all the available vertices in the network until there is no vertex *u* to modify.

There are two options for testing scenarios: individually or collectively. Individual scenario analysis ignores the impact of other scenario influences by resetting the edge values to their initial values. On the contrary, collective scenario analysis considers the impact of multiple scenario influences concurrently. As a result, in collective scenario analysis, policymakers can observe the influence of multiple decisions on their system. The function *G(V,E,W)* (dashed block in Fig. 1) allows resetting the graph to its initial state.

We developed the model using Python in the PyCharm IDE. The main library that we used to construct the directed graph and use the PageRank algorithm is Networkx (Hagberg et al. 2008). We set the PageRank's damping factor α to 0.65 and used pagerank-numpy, which handles the quantification of vertices with negative incoming links, to avoid invalid output behavior. There are 64 vertices and 167 edges, which take approximately 44 s to run the model for the whole network and simulate the effect of each vertex on the rest of the vertices as the value changes. This indicates that the model can handle significantly larger networks as well. Hence, based on the memory-profiler (Pedregosa and Gervais 2022) Python package measurement, the memory usage to run the model for the whole network is approximately 70.9 megabytes, which is insignificant. As a result, no specific hardware is required to run the model simulation.

It is noteworthy that aside from the damping factor, there are other input parameters, and tuning them depends on the underlying network type and structure. It is necessary to tune these parameters to avoid outlier values and observe proper behavior. One of the reasons that a model may show invalid behavior is the presence of vertices with no outgoing edges.

Such vertices are called dangling nodes (Page et al. 1998; Gleich 2015) and the behavior can cause rank sink. Similar behavior can be observed when there is a cluster of vertices linking each other (Page et al. 1998; Gleich 2015) and create a cycle. Negative edge values (Gleich 2009) also may trigger the rank sink. A suitable damping factor (Bressan and Peserico 2009) is required to avoid this behavior by reducing the probability of iteration over the vertices. Based on our experiments, a damping factor within the range of [0.3,0.65] is considered suitable for such networks, else the system will show no dynamic or permanent rank sinks.

The model provides a list of ranks for each vertex, which illustrates their behavior and types based on the given network. Behaviors can be categorized into four types: 1) permanent incremental variation, 2) temporal incremental variation, 3) temporal sudden fluctuation, and 4) permanent sudden fluctuation. These behaviors emerge due to the significant influences in various parts of the system and the changes in edge's *influence factor*. Hence, with respect to the number of incoming edges and values, vertices can have one of the aforementioned behaviors. Both temporal and permanent variations happen incrementally. Due to the intertwined nature of complex systems containing negative and positive correlation coefficients, vertices may also show temporal behaviors. On the contrary, fluctuations can have other underlying reasons. Permanent fluctuations can be due to a missing edge or a vertex in a network, and temporal fluctuations can be due to a new emergent or chaotic behavior. Both temporal and permanent fluctuations may lead to rank sink. Tuning the damping factor adjusts a reasonable probability of iteration over such vertices to avoid sinking (Bressan and Peserico 2009). Nevertheless, an improper damping factor causes rank convergence and may prevent observing any behavior.

Linking PageRank with system dynamic simulation facilitates the model with verification and validation features. First, it allows verifying whether the sum of all the ranks converges to 1.0 (Brin and Page 1998). This is due to the probability distribution of the PageRank over the whole network, which also allows verification of the algorithm's accuracy. Second, it allows validating the model's output behavior by checking if each vertex's rank lies within the range of $[-1, +1]$. The feature can also be used to detect rank sinks (Page et al. 1998; Gleich 2015).

4 Experiment

We performed the experiments using the network illustrated in Fig. 2, which represents the factors that describe children's and young people's mental wellbeing (Raghothama et al. 2023a, b). The network structure is validated by the experts in the field through multiple workshops. The network has factors categorized into *Core*, *Education*, *Family*, *Social*, *Skills*, *Work*, and *Relationships* each with different vertices connected through edges.

Three experiments were designed for three different purposes. The aim of the first experiment was to identify the most influential vertices from both a global and local PageRank perspective (Boodaghian Asl et al. 2021b); this allows policymakers to perceive external and internal leverage points. The aim of the second experiment was to run multiple simulation scenarios and validate the model output behavior (Boodaghian Asl et al. 2021a); this allows policymakers to identify the optimal scenarios for intervention. For this article, we ran multiple scenario experiments to observe vertices' behaviors and classify their types, which helps to understand the target system functionality and the underlying network validity.

For the first experiment (Boodaghian Asl et al. 2021b), we assigned each edge's value to ($\pm$ 1.0) based on the edges' correlation types (negative or positive). To quantify the vertices, we use PageRank in two different ways: global and local PageRank. Using a path analysis method, we iterated over all the vertices and listed all the paths connecting two vertices. To calculate the local PageRank, we isolate the listed paths from the rest of the vertices. However, to calculate the global PageRank, we considered the impact of the rest of the vertices on the listed paths. Finally, we measure the global and local rank divergence to identify the fluctuations in system behavior.

For the second experiment (Boodaghian Asl et al. 2021a), we prepared two different lists as edge values. The first list contained ± 1 correlation coefficients, and the second list contained correlation coefficients collected from various literature. Despite an exhaustive search, we could only find correlation coefficients for ten edges from the following papers: (Goswami 2012), (Folayan et al. 2020), (Drukker et al. 2003), (Im and Kim 2012), (Rajmil et al. 2003), (Ramirez et al. 2015), (Wang et al. 2018), (Baldwin et al. 2011), (Assari et al. 2020), (Assari et al. 2018), and (Saab and Klinger 2010), which mainly cover the *Core*, *Family*, and *Education* sub-networks. The coefficients were encoded into a network, with the rest of the edges staying at moderate correlation coefficients of ± 0.5 depending on the correlation type. The reason for this choice is that the correlation coefficient range varies between the range of $[-1, +1]$; hence, by assigning the missing values to moderate correlation coefficients, we avoid biased behavior. During the experiment, we simulate and validate the output behavior using both lists, which were mainly from the *Core* and *Family* networks. To observe the system behavior on different scales, we segregated the network (2) into *Core*, *CoreFamily*, and the *Whole* network. This is due to the diverse correlation coefficients collected from different papers. *Core* represents

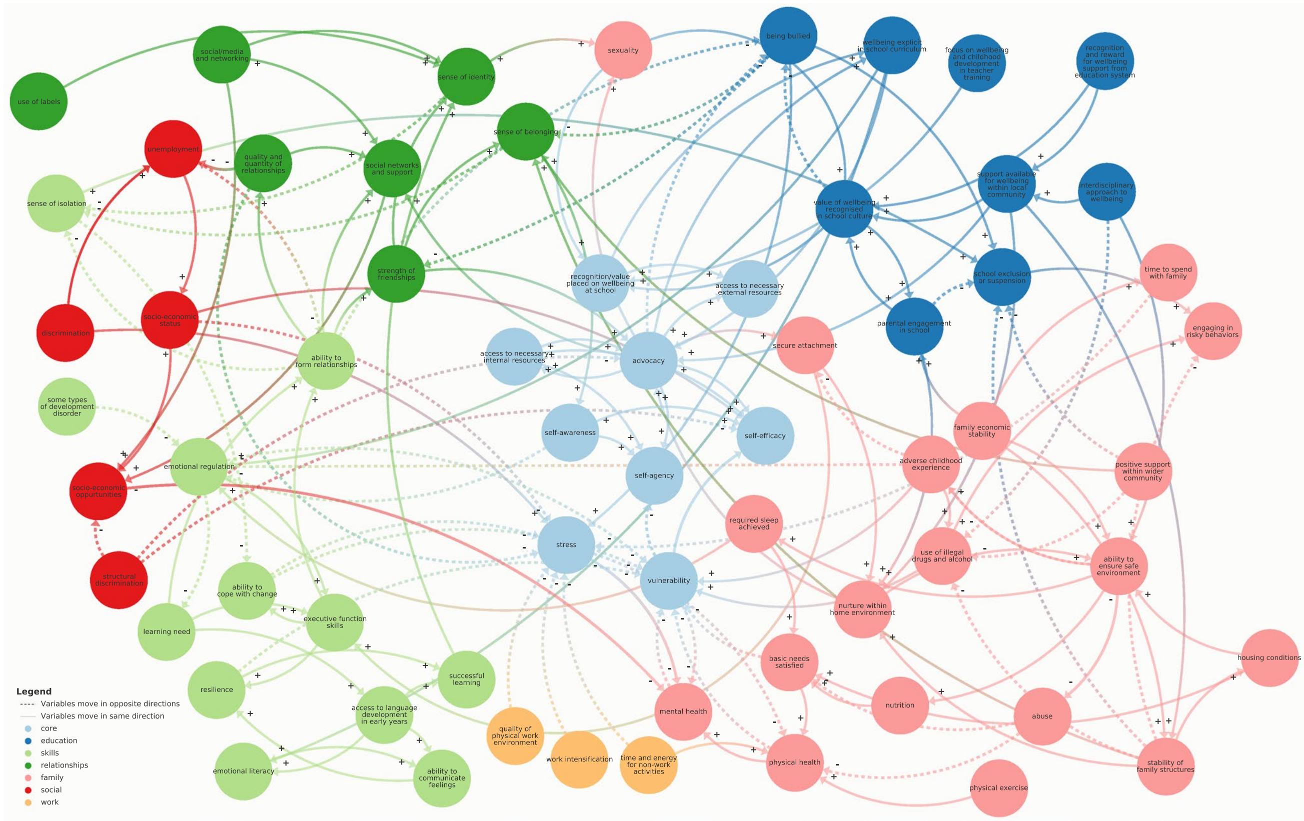

Fig. 2 Complex network for children and young people mental wellbeing (Raghothama et al. 2023a, b)

the central part of the network where the system begins to evolve (note that we have excluded *Stress* from the network, since it is indirectly connected to *Core*). Next, we append *Family* to *Core* and construct a new network. This allowed us to observe and compare the behavior as the network evolves, based on the influence on the incoming edge values and the rank variation.

For the third experiment, which is the main focus of this article, we modify the following data to observe system behavior:

- **Edge value**: In this case, we use the *influence factor* i, which starts from 1 to $MaxInf=100$, to change the edges value $e[v][u]$ and observe the variation in vertices ranks.
- **Network scale**: In this case, we prepared the following networks with different scales to illustrate the rank variation as the network evolves by segregation of the mental wellbeing network in Fig. 2:
  - **Core**: The sub-network contains only the vertices from the *Core* sub-network.
  - **CoreFamily**: The sub-network contains the vertices from the *Family* and *Core* sub-networks.
  - **CoreFamilyEducation**: The sub-network contains the vertices from the *Education*, *Core* and *Family* sub-networks.
  - **Whole**: This represents the mental wellbeing network.

This modification causes a change in each vertex's rank. As *influence factor* increases gradually, we can observe how vertices' behaviors vary. Furthermore, we can compare and observe the behaviors and their types within different network scales. As a result, each vertex in a corresponding network will possess a list of ranks through which we can observe behaviors' fluctuations and variations.

5 Results

We selected six different scenarios to present the results based on the model simulation. Each scenario analysis is based on the individual simulation to observe the influence of the *source* vertex on the *target* vertex. The *source* vertex is where we use the *influence factor* to modify the incoming edges' values, and the *target* vertex is where we observe the indirect impact. Since the sum of all the ranks in a given

Table 1 Scenarios

Source	Target	Sub-networks
Advocacy	Vulnerability	Core/Core
Self-efficacy	Vulnerability	Core/Core
Family economy stability	Secure attachment	Family/Family
Housing condition	Secure attachment	Family/Family
Being bullied	Abuse	Education/Family
Being bullied	Secure Attachment	Education/Family

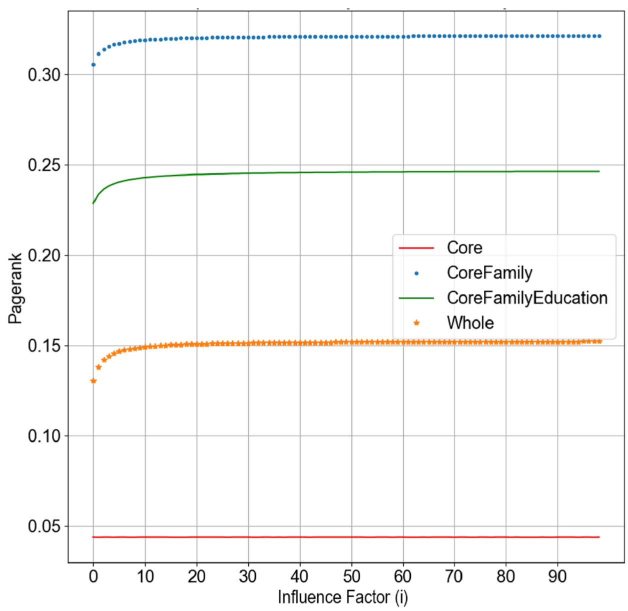

Fig. 3 Impact of *advocacy* on *vulnerability*

network should be equal to 1, thus, a rank change in a *source* vertex affects the rank in any *target* vertices. In this way, we can observe the behaviors and their types as the ranks vary. Both the *source* and *target* vertices are indirectly linked and can be from different sub-networks. Table 1 displays six scenarios' sources, targets and the sub-network these vertices belong. Each scenario is illustrated through a 2D graph, where the x-axis represents the *influence factor*, and the y-axis represents the *target* vertex changing rank. In each graph, we illustrate the *target* vertex behavior within different network scales.

Our scenario analysis shows variation in vertices' ranks when we modify the *source* vertex incoming edges values or change the network scale. Figures 3 and 4 show the *vulnerability* vertex behavior based on the change in two *sources*. Figure 3 illustrate a positive behavior of *vulnerability* when we influence the *advocacy* vertex, however, same *target* vertex have negative behavior when the influence is on the *self-efficacy* vertex. These behaviors only become visible when the network evolves. As an example, when the network is

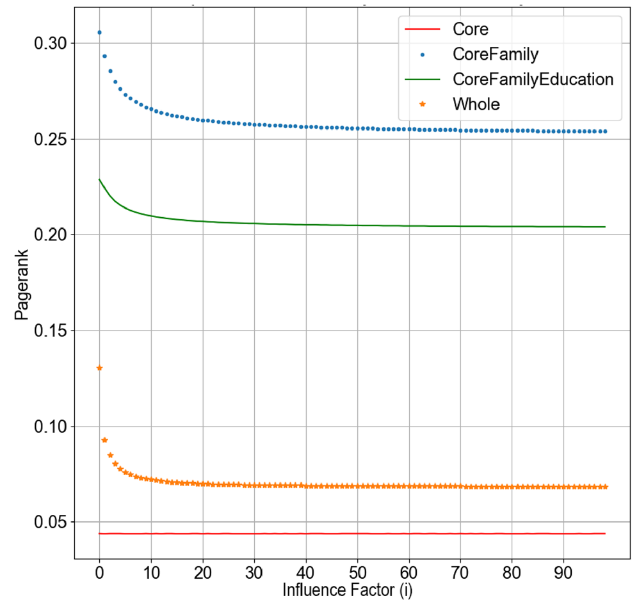

Fig. 4 Impact of *self-efficacy* on *vulnerability*

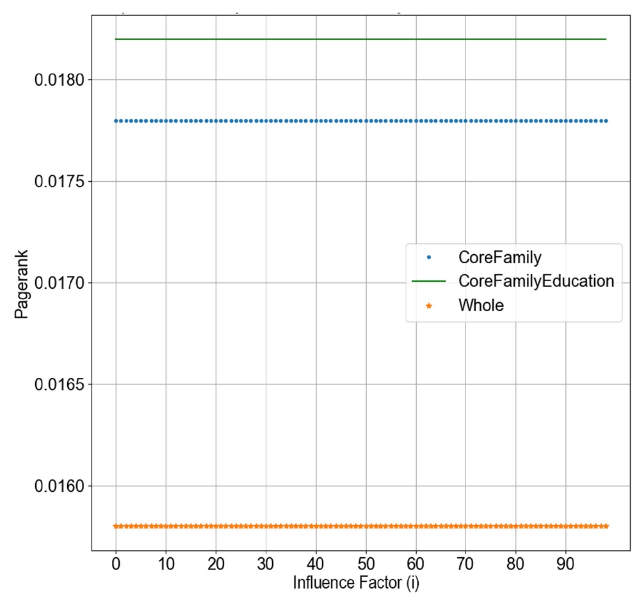

Fig. 5 Impact of *family economic stability* on *secure attachment*

at its smallest scale (*Core*), *vulnerability* show no behavior variation in both scenarios. Overall, *vulnerability* has a permanent incremental variation behavior type.

Further scenario analysis indicates that some *target* vertices' behaviors stay steady throughout the simulation, irrespective of the change in edge values or network scale. Figures 5 and 6 illustrate two behaviors of *secure attachment* based on the change applied to *family economic stability* and *housing conditions* incoming edges' values. In this scenario, *secure attachment* behavior stays

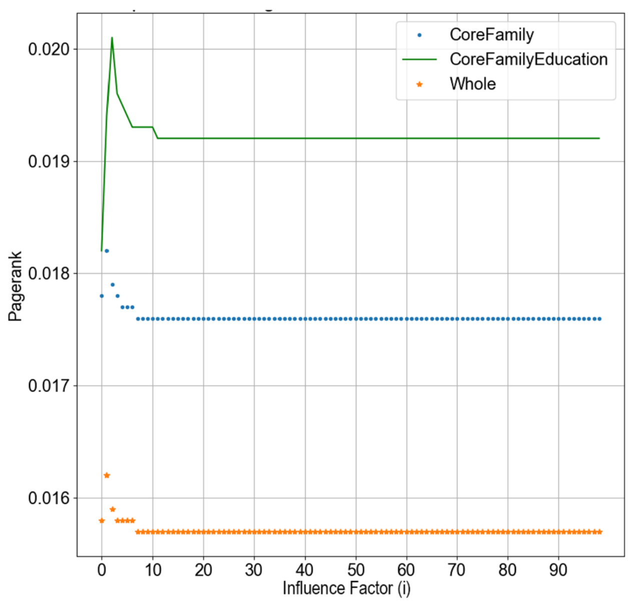

Fig. 6 Impact of *housing conditions* on *secure attachment*

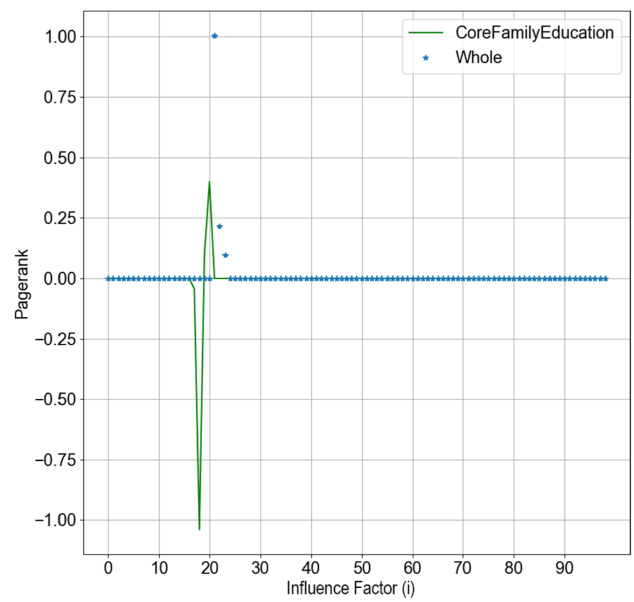

Fig. 7 Impact of *being bullied* on *abuse*

steady irrespective of changes or network growth. This is due to the *family economic stability* having no incoming edge to influence the system. On the contrary, *secure attachment* behavior shows permanent, sudden fluctuations before becoming steady. From the simulation perspective, *secure attachment* shows higher (~ 0.001) variation within the *CoreFamilyEducation* network compared to other networks.

In the last four scenarios, we compare two different *target* vertices' behaviors from the same *source* of influence. Figures 7 and 8 illustrate the influence of *being bullied* on *abuse* and *secure attachment*. In both scenarios, *being bullied* causes temporal sudden fluctuation on target vertices where the fluctuation has a positive impact on the *whole* network and also a negative impact on the *CoreFamilyEducation* network. Such fluctuations are prone to rank sink, which has values out of the $[-1, +1]$ range. The outcome also indicates that *being bullied* is prone to temporal sudden fluctuation regardless of the network scale. Due to high fluctuations and rank sinks, vertices behavior is flat on the graph, which requires further numerical analysis to observe minor variation. The figures also illustrate negative ranks caused by negative correlation coefficients.

To that end, the results illustrate that the significant change in vertices behavior mainly occur before the edge value reaches a value of 30 (illustrated on the *x-axes* of the graphs). Following this, vertices resemble steady behavior. This is due to the PageRank probability distribution throughout the network (Brin and Page 1998). The results also illustrate that, as the network evolves, vertices have significant behavioral variation to adapt to changes. This can be due to the emergence of highly influential vertices, which are absent in small-scale networks.

6 Discussion

The data extracted from model simulations shows permanent incremental variation as the network evolves. PageRank's functionality is to rank web pages in order to sort and display

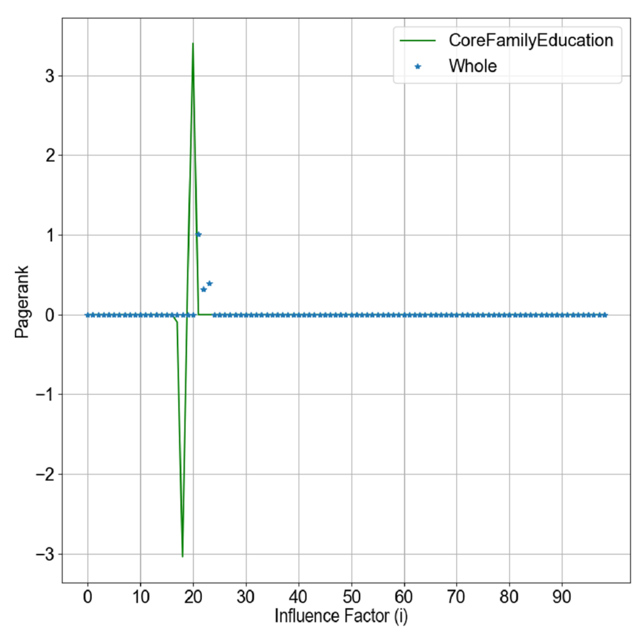

Fig. 8 Impact of *being bullied* on *secure attachment*

them from the highest to lowest ranks. Our objective is to quantify the vertices within the complex network to provide a way to observe behavior adaptation. Vertices' rank changes as a network evolves, and their popularity may shift as other vertices join the network. This behavior divergence can be due to the presence of a highly influential vertex from a common sub-network such as *family* (Figs. 3, 4). Both temporal incremental variation and temporal sudden fluctuation appeared only within the edge value of [5,10] approximately and may indicate a new emergent or chaotic behavior (3). However, PageRank treats vertices according to their topological position in the network and not their content or intended representation (Page et al. 1998; Gleich 2015). Whether using a ranking algorithm or data to quantify, incoming edges and their values steer the behavior, and by modifying them, we advance the impact strength. Thus, vertices adaptive behavior is clearly observable by altering incoming edge values, irrespective of the quantification approach. Finally, permanent sudden fluctuation can be due to various reasons, such as the presence or absence of a vertex or edge, dangling nodes (Ipsen and Selee 2007), or cyclic network (Page et al. 1998; Gleich 2015). If the behavior persists as the network evolves, it may require further validation of the underlying network (Rotmans and Loorbach 2009). Due to the adjustment of the damping factor to 0.65, the result revealed no permanent fluctuation (known as rank sink) (Page et al. 1998; Bressan and Peserico 2009; Gleich 2015). The results also reveal that as the simulation progresses, vertices' behavior varies insignificantly and follows steady behavior; moreover, vertices' behavior change insignificantly in small-scale networks, and as the network evolves, vertex behavior shows significant variation.

PageRank is compatible with different network types, but may require tuning the input parameters. PageRank was developed to overcome the challenge of the growing number of web pages on the World Wide Web (Page et al. 1998; Gleich 2015). Within a complex mental wellbeing network, vertices' rank varies, but the behavior follows a uniform pattern. The model simulation output reveals that if a complex network consists of both negative and positive correlation coefficients, some vertices' ranks may vary in the range of $[-1, +1]$ (Figs. 7, 8); else, vertices' ranks vary in the range of [0,+1]. However, PageRank is sensitive to a vertex's degree of connectivity. From the model output, we also learned that vertices with no incoming edges, such as *work intensification* or *family economic stability*, cannot cause a change in vertices' behavior; as a result, the network shows no stable behavior. Both incoming and outgoing edges play a significant role in influencing the rank. Through our approach, the behavior of vertices with no incoming edge remains stable, and their impact on the network remains unchanged. Conversely, vertices with no outgoing edge absorb the rank if the damping factor and the number of iterations are high. This may require modelers to consider representing vertices with minimum in and out degrees when developing a complex network. Furthermore, the algorithm has no properties of its own. Such algorithms only consider the number of incoming and outgoing edges with a minimum of two connected vertices. Whether the network represents a biological structure (Farhana Nimmy and Shohelur Rahman 2014; Kaushal and Singh 2020) or a local area network, PageRank measurement is purely from a topological perspective.

Scenario analyses assist policymakers in determining which interventions have significant benefits. Interventions may show peculiar impact when considering other organizations' influences (Thorngate and Tavakoli 2009) and contradict each other. To avoid contradictions, the approach has the potential to facilitate scenario analysis from multiple network perspectives. Figures 3 and 4 illustrate two different policy interventions influencing *vulnerability*. Within the *Core* network, intervention causes no impact, but when considering networks such as *Family*, *Education* or *Whole*, *vulnerability* begins to show greater behavior change. From policymakers' perspective within *Core*, both *advocacy* and *self-efficacy* have no impact on *Vulnerability*, when viewed from other networks' (organizations') perspective, *self-efficacy* has a negative impact, yet *advocacy* causes beneficial impact. Furthermore, fluctuations may reveal leverage points to intervene.

Linking PageRank and systems dynamic simulation can reinforce validation for complex network modeling. To assure the ranks adapt to changes, the sum of all the vertices' ranks should converge to 1.0 (Brin and Page 1998) with each change; otherwise, the approach is unreliable to maintain its adaptive feature. This requires further investigation, which may uncover inaccuracies in the model's structure or input parameters. Another feature that promotes validation is the ability to uncover permanent outliers. Outliers may emerge through permanent sudden fluctuation and lead to rank sink (Page et al. 1998; Gleich 2015), which may require precise tuning of PageRank parameters (Bressan and Peserico 2009).

Tuning PageRank impacts vertices behavior within a complex system (Bressan and Peserico 2009; Gleich 2009). Parameters such as type of network, number of iterations, probability of iteration, edge value and type, and number of incoming and outgoing edges can contribute to observing proper behavior. In this paper, the mental wellbeing network had no dangling node, which means vertices had outgoing edge(s); however, due to cyclic topology, rank sinks may occur, which is handled by adjusting the damping factor. For a more precise output, it is required to repeat the experiment by tuning other parameters such as dangling nodes and number of iterations, which may provide a more accurate outcome about the underlying system.

Even though the approach handles adaptation and reveals where and when fluctuation and variation occur, due to the intertwined nature of complex systems, many vertices within the path can trigger such behaviors. For example, Figs. 7 and 8 show two temporal sudden fluctuations. Both fluctuations emerge in two networks with the same edge value from the same vertex *being bullied*. This means that either *being bullied* or other vertices in the same path cause this behavior. Thus, pattern and path analysis are required to confirm the precise vertex of fluctuation. Additionally, such behaviors can have various reasons, such as chaotic behavior, new emergent behavior, or misrepresentation of the system, which may raise uncertainty about their validity. Other limitations include the lack of data gathered from various publications. Combining data from multiple experiments and sources into a network can potentially inflate the uncertainty, increase the risk of bias, and give incorrect system behavior. Due to the limited research in these areas, the collected data were only for the *Core*, *Family* and *Education* networks. More data and analysis are required to ascertain their validity.

Various analyses are performed to observe the vertices' behavior and co-linearity. In this article, we illustrate the behavior of *abuse* and *secure attachment*, which are not directly connected. Both are affected by changing the value of *being bullied*. The analysis was performed on other vertices that are not directly connected to *abuse* or to *secure attachment*. The result indicates that the impact of *being bullied* emerges in similar behavior on many vertices in the network. Further results of such analysis are illustrated by Boodaghian Asl et al. (2021a) that indicate in which scenarios vertices emerge co-linearity and uncover which scenarios cause significant adverse and beneficial changes through variance analysis. Furthermore, Boodaghian Asl et al. (2021b) also indicates the divergence of the local and global ranks and which vertices cause significant change in the rank through path analysis. As a result, both articles (Boodaghian Asl et al. 2021a) and (Boodaghian Asl et al. 2021a) indicate that the presence of *recognition value placed on wellbeing at school* vertex within the path causes significant behavior change.

7 Conclusion

This study proposes a hybrid approach that constructs a model based on a system's fundamental properties, which in turn allows the model to adapt to changes occurring in edge value and network topology. The primary objective was to quantify the network to perceive where and when fluctuations and variations occur in the vertex's behavior. Additionally, the approach facilitates objectives such as instant quantification and simulation and promotes model verification and validation. These objectives may serve various purposes, such as supporting policymakers to uncover leverage points from different networks' perspectives, helping researchers investigate and justify hypotheses, and assisting modelers with objective validation by uncovering outlier values and inaccurate behavior.

The approach facilitates four types of simulation analysis. First, a single scenario can be analyzed and compared from multiple network perspectives. Such analysis can help to determine which sub-network encompasses the most influential vertices and the causes of significant impact. Second, it can be referred as multi-scenario analysis. The purpose is to investigate the impact of a single vertex on multiple target vertices. Such analysis can help to perceive which vertices are significantly influenced by the modification from a single network perspective. The third type is to analyze the impact of multiple vertices on a single target vertex, which may help to spot the leverage points with the highest impact. Finally, the approach can analyze vertices' impact type and strength before implementing them into the real system.

We classified vertices' behaviors into four types: 1) permanent incremental variation, 2) temporal incremental variation, 3) temporal sudden fluctuation, and 4) permanent sudden fluctuation. Due to the intertwined and complex nature of these systems, such behaviors may happen to various vertices simultaneously and raise uncertainty and unpredictability. By adopting PageRank, our modeling approach provides functionality, behavior limitations, and boundary uncertainties to vertices. Thus, vertices are quantified according to the network topology and incoming edge value. This also limits the behavior of the vertices to perform within a certain range. For boundary uncertainty, PageRank's adaptive feature allows network analysis on any scale as long as the model maintains its adaptiveness. PageRank performs well with various abstraction levels; hence, it becomes difficult to perceive information regarding the validity of the underlying network, whether it is ill-structured or not. Therefore, we can only provide behavior types, which may require further analysis and expert knowledge to scrutinize the causes of peculiar behaviors.

The model also has advantages over other simulation approaches. First, by relying on network topology, we can provide insight about the system's behavior without the need for too much data. Second, we can analyze a new aspect that is not defined in the real system yet. Our approach has the ability to change the network's scale instantly. Such a feature allows adding vertices, which are not previously defined, and analyzing their impact before adding them to the real system. Moreover, since the model iterates over edges by modifying the strength, it will allow policymakers to observe various behaviors of the vertices within the network.

To conclude, our approach confirms that the model continuously adapts the vertices' ranks to the changes. The outcome reveals that a significant rank change occurs in the beginning of simulation and gradually becomes insignificant and steady. Furthermore, the approach identifies which vertices can have a positive or negative impact on children's mental wellbeing by measuring the variance of ranks and which sub-networks encompass the most influential vertices by running the same experiment with different combinations of sub-networks. In this experiment, the outcome suggests vertices located within *Family* and *Education* sub-networks cause behavior changes and also indicates that the variance is comparatively higher when other sub-networks such as *Relationships* and *Social* influence the behavior (Figs. 3, 4). In general, the model's flexibility allows vertex analysis from multiple network perspectives.

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