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SIMULATION AND MODEL VALIDATION FOR MENTAL HEALTH FACTORS USING A MULTI-METHODOLOGY HYBRID APPROACH

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ABSTRACT

To promote policy analysis and decision-making in mental health and well-being, simulations are used to scrutinize causal maps and provide policymakers reasonable evidence. This paper proposes and illustrates a multi-methodology hybrid approach by building a hierarchy of models, moving from a systems dynamics model to a simulation based on PageRank to quantify and assess a complex mental health map. The motives are: (1) to aid scenario analysis and comparison for possible policy interventions, (2) to quantify and validate mental health factors, and (3) to gain new insights into the core and confounding factors that affect mental health. The results indicate that the approach identifies factors that cause significant and frequent variation on mental health. Furthermore, validation confirms PageRank accuracy and detects minor fluctuations and variation in model's output behavior.

1 INTRODUCTION

Mental health and well-being is an integral and essential component of health. The WHO constitution states: ”Health is a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity.” An important implication of this definition is that mental health is more than just the absence of mental disorders or disabilities (WHO 2021). Multiple social, psychological, and biological factors determine the level of mental health of a person at any point of time. Poor mental health is also associated with rapid social change, stressful work conditions, gender discrimination, social exclusion, unhealthy lifestyle, physical ill-health and human rights violations (Langellier et al. 2019).

The multitude of factors that influence mental health and well-being are interlinked and form a complex web. While existing research, from sociological or psychological perspective describes the relationships between a few factors very well, it is daunting and nearly impossible to describe all factors in a holistic and complete manner. This difficulty is a barrier in the development of programs that promote mental health and well-being. Such programs must be concerned with mental disorders and broader issues of well-being, a complex, inter-disciplinary societal problem.

The factors that influence mental health and well-being can be represented as a graph or a map (referred as ”map” throughout the article), with links indicating the relationships between them. In the context of a large project, we have developed and validated these maps, with specific target groups. However, scrutinizing these maps from a holistic perspective is a challenging task. The mental health system, as represented by this map consists of sub-systems. Each sub-system follows specific decision-making and policy analysis guidelines, which may override each other. For instance, an intervention in school policy

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may have a significant impact on social life factors. Moreover, each factor has specific impact strength on linking sub-systems. Thus, developing a policy or program to maximize the improvement and minimize the harm to the whole system can be complicated and may increase the likelihood of misinterpretation.

Complex systems are non-linear, evolve asymmetrically, and have no distinct boundary (Cilliers 2013). To enhance the knowledge from complex systems such as mental health and understand how the underlying factors impact human behavior, simulation methods are considered suitable. The dynamic nature of simulation methods facilitates exploring and comparing different policy scenarios (Grune-Yanoff and Weirich 2010). The purpose of using simulation in this study is to identify factors with a significant impact on children's mental health and draw the attention of healthcare professionals' to critical policy options. However, with the increase of complexity, data accuracy and model validation could become a cumbersome task, requiring sophisticated approaches to validate. To mitigate the burden, using ranking algorithms such as PageRank accelerates the quantification (Boodaghian Asl et al. 2021) and simulation process, and amplifies the model accuracy. PageRank is a ranking algorithm that quantifies factors in a network according to the number of connected links and their values (Page et al. 1999).

Simulation aids in predicting the system behavior, provide evidence to confirm the accuracy of scenarios (Ingalls 2011) and hypotheses by observing the consequences (Grune-Yanoff and Weirich 2010), establish confidence over the effectiveness of policy decisions (Atkinson et al. 2017) and avoid barriers (Long and Meadows 2017) by mimicking real-world systems. Agent-based models (ABMs) and system dynamic (SD) simulation are the most common and suitable methods to analyze complex systems from multiple system-level perspectives (Ruiz et al. 2016). SD has been proven beneficial for complex systems analysis from the macro-level perspective, such as complex mental health maps. The method aims to understand the emergent, non-linear and dynamic behavior among complex system factors (Brailsford 2008), and provides insight for policy intervention (Katsaliaki and Mustafee 2011).

In this paper we propose and demonstrate a multi-methodology hybrid (MMH) approach (Eldabi et al. 2019) to develop a simulation based on PageRank and SD methods on a previously developed map for children and young people. The purpose is to use PageRank to quantify factors and use SD simulation to observe the PageRank variation on each factor. The approach can assist policymakers to observe the consequence of multiple scenarios on a particular factor. PageRank accuracy is checked through coding, and *parameter variability* technique (Sargent 2010) is used to compare and detect fluctuation and variation in model's output behavior. The remainder of this paper is divided into background, approach, results and conclusion. The background section discusses the literature review in detail. The approach consists of five different sections which elaborates the adopted map for approach evaluation, quantification of associated links and factors, the proposed hybrid approach, algorithm pseudocode, PageRank accuracy and model's output behavior validation. The results illustrate and describe the simulation and the output behavior. To that end, discussion and conclusion will briefly summarize the main findings, applications, limitations and difficulties.

2 BACKGROUND

Some of the policy-making challenges in healthcare could be how policy is defined within each system, where policymakers may require to act individually or cooperatively (Walt et al. 2008). Other challenges could be the long- and short-term decision-making process, resource limitations, and the limited power of intervention (Walt et al. 2008). A significant amount of research related to healthcare policy analysis was based on explanatory and hypothetical assessment; individual scientist opinion is only from a single discipline perspective (Whitty 2015) such as science or economy, making it challenging to work on multidisciplinary areas (Farley-Ripple et al. 2020).

The implementation of relevant policy intervention depends highly on the impact size and the coverage on specific populations (Campion et al. 2020). Nevertheless, some gaps prevent intervention implementation (Farley-Ripple et al. 2020). The gaps are caused by the lack of knowledge (Farley-Ripple et al. 2020) and training of the healthcare professionals and policymakers; moreover, there is also the absence of information regarding the size and impact of unmet needs, estimated impacts, appropriate policy goal, and the lack of desire and understanding to allocate required resources (Campion et al. 2020). Leeuw et al. (2014) highlighted a few policy barriers to apply theories, where there is a lack of training for healthcare researchers and scientists, lack of criteria for healthcare policies, and lack of research funding (Farley-Ripple et al. 2020). For practical policy intervention, research and analysis need to be in negotiation with stakeholders (Atkinson et al. 2017; Collins 2005). Implementation can go wrong if professionals and policymakers acknowledge policies subjectively (Whitty 2015). Various simulation methods have been used to analyze mental health models to overcome the specified gaps for efficient policy intervention and decision-making process. Simulation helps fill the gaps by advocating evidence of possible scenario outcomes to prevent or promote future events (Ruiz et al. 2016).

Brailsford (2007) discussed that recently SD Simulation is becoming popular in the healthcare field compared to other simulation approaches. Kunc (2019) states that SD provides a better understanding of the organization for strategic management and policy analysis by providing information about the decision consequences. Hence, SD lacks to analyze individual entities (medical staff, patients) (Brailsford 2007) but focuses on the system as a whole (Grune-Yanoff and Weirich 2010). Therefore, SD provides a way to understand the system structure and its emergent behavior (Brailsford 2008); moreover, data quality for SD simulation is not crucial and the focus is more on the model structure (Brailsford 2008). SD has the capability of examining systems as a whole to highlight options for policymakers, which have the most substantial influences on system behavior, and train policymakers (Katsaliaki and Mustafee 2011); the aim is to understand the dynamic behavior of complex non-linear systems and provide insight for policy intervention (Katsaliaki and Mustafee 2011).

In social science, policy studies either used weaker methodologies, or the outcomes were rarely applicable (Whitty 2015) or not taken into consideration (Farley-Ripple et al. 2020). Mental health studies are considered one of the most complex social science branches due to the several linkages to other factors and systems. Perceiving how different policy decisions may impact mental health can be a challenging task. Moreover, providing strong evidence to convince policymakers to take action will require an advanced methodology to study the maps. As Atkins et al. (2006) concluded, in the context of mental health, the combination of iterative and systematic approaches can be more effective. Thus, using SD, which is suitable for policy analysis, with other approaches such as PageRank may provide a more robust methodology to study policy options.

3 APPROACH

3.1 Mental Well-being Map

To demonstrate how the approach works, we used a graph-like map that represents the factors, linkages, flow direction, and link strength. Figure 1 illustrates a map designed to represent factors that influence children and young people mental well-being (Raghothama et al. 2021a; Raghothama et al. 2021b). The map is organized into different categories of *social*, *work*, *education*, *skills*, *relationships*, *family*, and *core*. Each category encompasses unique factors which can have a beneficial or adverse effect on mental well-being. E.g. *Family* category contains factors such as *physical health* which can be triggered by *stress* or *physical exercise*. These factors are interconnected within each category and to surrounding categories' factors, which may impact on the whole map.

3.2 Data Collection and Quantification

Quantification purpose is to facilitate the measurement of a factor in a system to detect fluctuation and variation. The map quantification consists of two steps. First to quantify the associated links, and second to quantify the factors. Each factor in the map is in correlation with one to several linked factors. The correlation coefficient determines the links' strength. Negative and positive correlations affect how factors influence each other (Gleich 2009). To quantify the links, we gathered Pearson correlation coefficients for

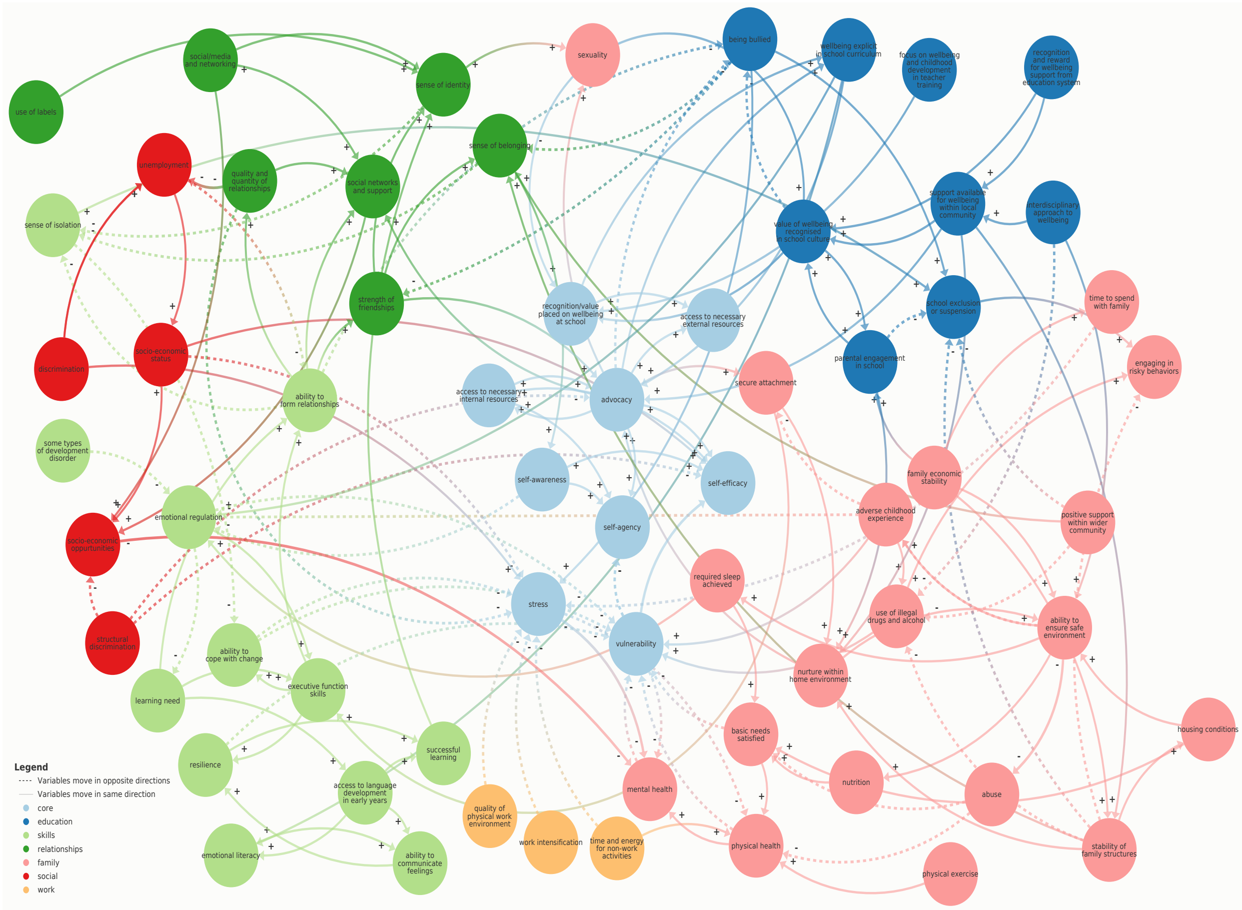

Figure 1: Mental well-being map for children and young people (Raghothama et al. 2021a; Raghothama et al. 2021b).

approximately ten links from various publications related to children and young people's mental health, such as Goswami (2012), Folayan et al. (2020) and Drukker et al. (2003). The remaining of the links are assigned moderate correlation coefficients (±0.5) with respect to data flow direction. Next, PageRank is used to quantify factors in mental health map (Boodaghian Asl et al. 2021). PageRank functions by counting the number of incoming and outgoing links and taking the incoming link's correlation coefficients into consideration, which can have significant impact on factors' rank. Therefore, it is suited to use PageRank to quantify such complex networks. Other parameters which affect PageRank estimation are dangling nodes which happens when the factor in a map has no outgoing link, and data flow direction which is the direction of the link to and from a factor.

Mental health maps consist of both positive and negative links that can provoke rank-sink. Rank-sink occurs when the algorithm is trapped inside a loop of factors which are linked to each other, or the factor has no outgoing link which is called dangling-node. If Rank-sink occurs, the PageRank value exceeds the range of [-1,+1], otherwise the rank should always be inside the range. To overcome this issue, the damping-factor, which is the amount of time the algorithm surfs, has been reduced to $\alpha = 0.65$ (Bressan and Peserico 2009), which is considered a moderate value to avoid possible sinking. The map adopted for this study has no dangling-nodes; however, if necessary, should be listed as input parameter of PageRank. PageRank validation is discussed in section 3.5 and implemented in section 3.4.

3.3 Multi-Methodology Hybrid Approach

Hybrid simulation and modeling is the process of using a simulation method with one or more simulation or non-simulation methods, techniques, or paradigms to enhance system analysis from multiple levels of perspective (Mustafee and Powell 2018). Hybrid approaches allow blending the features of individual methods to obtain better insight into the underlying problem (Mustafee et al. 2015). In this study, the MMH approach is used to build a hierarchy of models, moving from SD model to a simulation based on PageRank to quantify and assess complex mental health maps. The SD model from the MMH approach uses moderate correlation coefficients along with the coefficients from literature to quantify links (which operates as a substitute for Stocks and Flows), and later PageRank is used to iteratively quantify the factors by manipulating the link coefficient. Both methods operate synchronously (Shanthikumar and Sargent 1983). In brief, the approach begins by iterating through each mental health factor using the SD simulation, and gradually updates the incoming links strength through iteration, and dispatch the output as an input parameter for further PageRank measurement. More information on how the model algorithm operates is given in section 3.4.

Following objectives are considered for further policy analysis and decision-making:

1. **Factors causing highest influence on mental health:** The objective is to recognize which factors have significant impact on mental health by selecting several factors as a causation source and observe the rank variation on a target factor.
2. **Factors causing lowest influence on mental health:** The objective is to uncover which factors have insignificant or minor impact on mental health by simulating several factors as a causation source and observing the impact on a target factor.
3. **Factors causing sudden fluctuation:** Some factors' rank is more sensitive to minor changes than others, which may cause sudden fluctuation or dramatic changes in PageRank. By detecting these factors, it could be possible to avoid decisions with obscure consequences.

PageRank is highly sensitive with a slight change of links' strength (Gleich 2009), regardless of the factors closeness, betweenness, and degree of centrality. Considering that the model simulation focuses on updating incoming links strength, consequently, the effect will be highly observable on all the factors with incoming links; factors with no incoming links will remain steady or show insignificant variations.

3.4 Development Procedure

Python programming language and NetworkX package (Hagberg et al. 2008) were used to develop the hybrid simulation approach. Algorithm 1 illustrates the pseudocode for the proposed hybrid approach, the PageRank function validation, and rank-sink detection. The model starts with the input of variables such as: range of simulation, mental factors, associated links and correlation coefficients, which are indicated by *simRange*, *V*, *E* and *W* notations, respectively. A directed graph *G* is defined and initialized with the corresponding input parameters and attributes using the NetworkX library (line 1). Next, on the second and the fourth lines, the simulation iterates through the list of factors indicated by *j* to observe the impact on each target factor, indicated by *i*, and the third line iterates through the simulation value, indicated by *simVal* starting at 1 to register the default PageRank value of each factor. PageRank variation is the result of modification of the incoming links' strength. Thus, if the simulation factor is not the same as target factor (line 5), and the target factor receives incoming links (line 5), the simulation value is multiplied by the correlation coefficients (line 6) in each iteration (line 3). Later, PageRank is calculated with the new given value (line 10). To complete the simulation, the new PageRank measurements are assigned to *Sim* variable (line 21) for further analysis and validation. The PageRank and Graph default values are restored at the end of the corresponding loops (lines 23 and 25).

Two approaches are considered to validate the PageRank. First, to check if rank-sink occurs; next, to evaluate the PageRank function accuracy. To detect rank-sink, the algorithm checks each factors' rank

Algorithm 1: MMH Approach Pseudocode

```
   Input: simRange, V⟨v1, v2, ..., vn⟩, E⟨e11, e12, ..., enn⟩, W⟨w11, w12, ..., wnn⟩
   Output: SimPR[ ], Sim[simRange][n]
1  G ← DiGraph(V, E, W)
2  for i ← 0 to n do
3      for simVal ← 1 to simRange do
4          for j ← 0 to n do
5              if i ≠ j and G[j, i] then
6                  G[j, i, w] ← w[j, i] × simVal
7              end
8          end
9          SimPR ← PageRank(G, α = 0.56)
10         Sum ← 0
11         for k ← 0 to n do
12             if SimPR[k] < −1 or SimPR[k] > 1 then
13                 exit
14             else
15                 Sum ← Sum + SimPR[k]
16             end
17             if Sum ≠ 1 then
18                 exit
19             end
20             Sim[k][j] ← SimPR[k]
21         end
22         SimPR[ ] ← ∅
23     end
24     G ← (V, E, W)
25 end
```

separately; if the rank exceeds the range of [-1,+1] forces the program to exit (lines 13 and 14). For the PageRank function accuracy, it is necessary to check if the sum of all the factors in the given graph is equal to +1 (Lines 18 and 19), otherwise the program exits. Worth mentioning that PageRank returns floating numbers, thus floating point error caused by python interpreter occasionally returns (1.00000004) or (0.99999999) as sum of factors' rank.

3.5 PageRank and Model Behavior Validation

Validation is the approach of checking the accuracy of input data, structure and the developed model through various validation techniques (Sargent 2010). The multi-methodological nature of hybrid approach makes it more challenging to apply validation techniques (Mustafee et al. 2015) especially in the field of healthcare (Eldabi et al. 2016). Only two-thirds of research articles in healthcare simulation performed model validation (Long and Meadows 2017). This study focuses on first validating PageRank accuracy through coding (Sargent 2010) (see section 3.4). Next, *parameter variability* technique is used to detect fluctuation in model output behavior (Sargent 2010).

To increase the degree of confidence for proposed approach, the following are considered to examine:

1. **Model output behavior:** To detect fluctuation or variation in behavior pattern, each category is simulated in isolation and results are compared. An example could be to compare the entire map with *Family+Core* category and *Core* categories. The comparison is applied with two different link strength data-sets.
2. **PageRank function accuracy:** To validate the PageRank function accuracy, the sum of all the factors ranks in each simulation iteration is checked to be equal to (+1).
3. **Rank-sink:** To check if a PageRank sinks, individual factors rank should not exceed the range of [-1,1]. It is also possible to observe the rank-sink during scenario analysis. One way to fix the rank sink is to revise the PageRank function's input parameters.

Model's entities' behavior remain steady regardless of how map behavior's evolve; thus, detecting fluctuation or variation in behavior patterns signifies inaccurate model development, invalid input data or structure. Nonetheless, output behavior analysis is insufficient to confirm the precise underlying reason.

4 RESULTS

4.1 Simulation

To begin with the simulation, it is necessary to define some scenarios. Thus, we select nine factors, all of which are encompassed in the *Core* category, located in the center of the map (Figure 1). In each scenario, we selected some factors, to observe the impact on different mental health factors (as target factors), by measuring target factors' rank variation. Variation is mainly caused by manipulating incoming links' strength of the selected scenario's factor, and the amount of target factor's incoming links.

Table 1: Target Factors, Variations and Simulation Scenarios.

Incoming Links	Target Factors	Variation	Factor causing Highest Variation
11	stress	0.0031	access to necessary external resources
8	vulnerability	0.0080	stress
3	being bullied	0.0052	access to necessary external resources
5	school exclusion or suspension	0.0089	access to necessary external resources
1	abuse	0.0002	advocacy
3	engaging in risky behaviors	0.0034	access to necessary external resources
6	mental health	0.0094	stress
2	quality and quantity of relationships	0.0027	access to necessary external resources
0	use of labels	0.0002	advocacy
1	learning need	0.0009	self-efficacy
4	sense of isolation	0.0051	self-awareness
0	discrimination	0.0002	advocacy
2	unemployment	0.0025	stress
0	time and energy for non-work activities	0.0002	advocacy

Table 1 displays simulation results for few target factors from map, their incoming links, highest rank variation, and the factor causing the highest variation. The overall result indicates that significant rank variations (~ 0.01) are caused by factors such as *stress*, *access to necessary external resources*, *self-agency* and *self-efficacy*. Moderate rank variations (~ 0.005) are mostly caused by factors such as *access to necessary external resources*, hence the insignificant rank variations (~ 0.0002) with no or incoming link is caused by the sensitivity of PageRank algorithm, due to *advocacy*'s high degree of centrality. Moreover, factors such as *access to necessary external resources* frequently causes significant variation on roughly most of the target factors; Yet factors such as *stress* merely causes significant variation on target factors.

To better demonstrate scenario factors' impact on target factors, figure 2 shows four line graphs for *mental health*, *being bullied*, *discrimination* and *unemployment* factors' rank. Each graph represents one target factor influenced by nine different factors. Each line represents rank variation caused by one

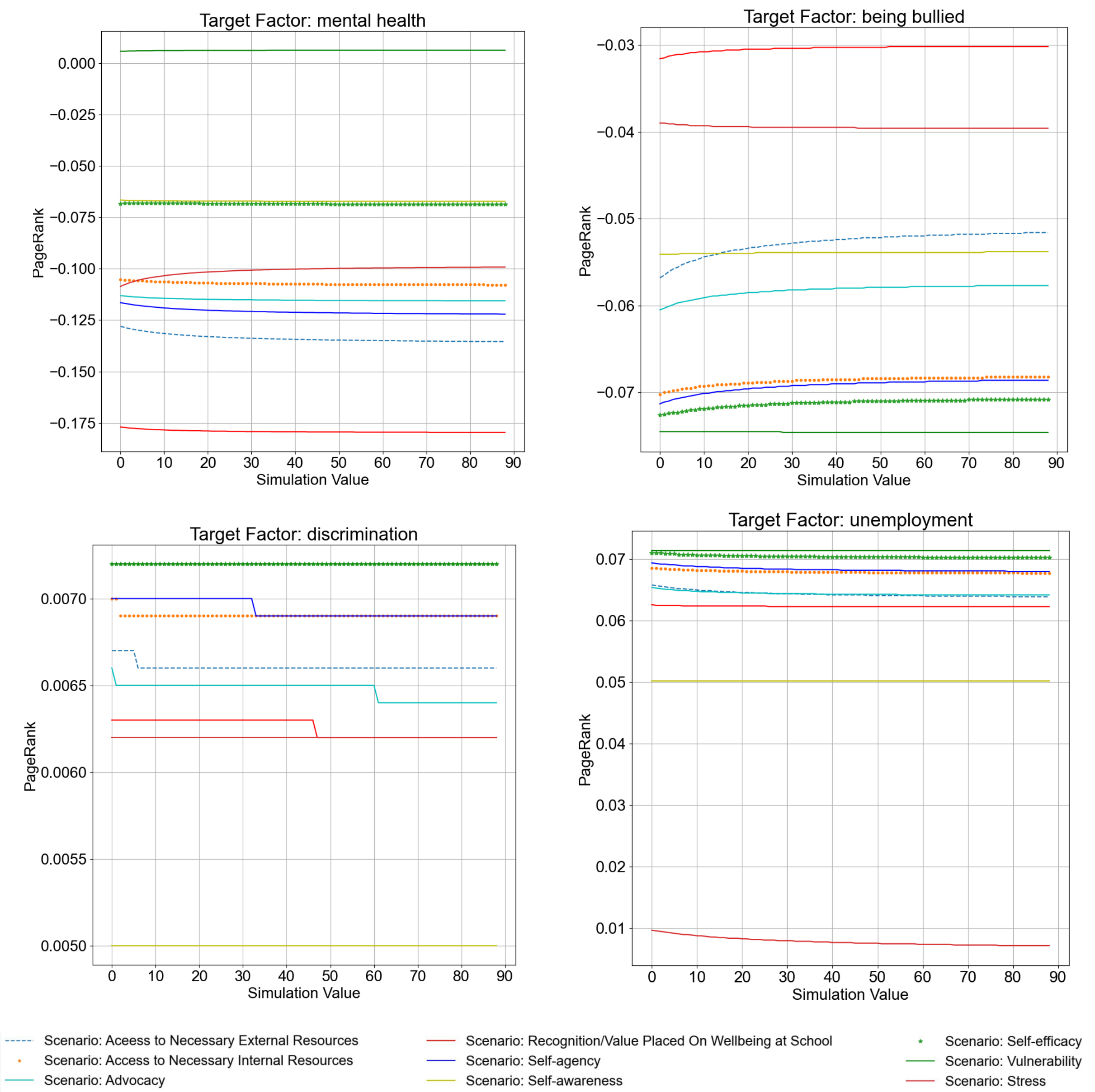

Figure 2: Simulation and Comparison of Scenario's Factors.

scenario's factor. E.g. yellow line illustrates rank variation influenced by *self-awareness*. The *x-axis* displays simulation value, which is used to manipulate link strength of the scenario's factor in each iteration, and observe the target factor's rank variation on *y-axis*. The rank range on *y-axis* is scaled according to the highest and the lowest rank of the target-factor, which signifies of no rank-sink throughout the simulation. Worth noting that since sum of the PageRank values should be equal to (+1), therefore, intensifying certain factors' rank may result in lowering ranks in other factors. The line graph analysis shows *self-awareness* has minor or no impact on target factors. Target factors with no incoming links such as *discrimination* are hardly affected by any scenario's factor. Thus, insignificant variations caused by factors with high degree of centrality such as *advocacy*.

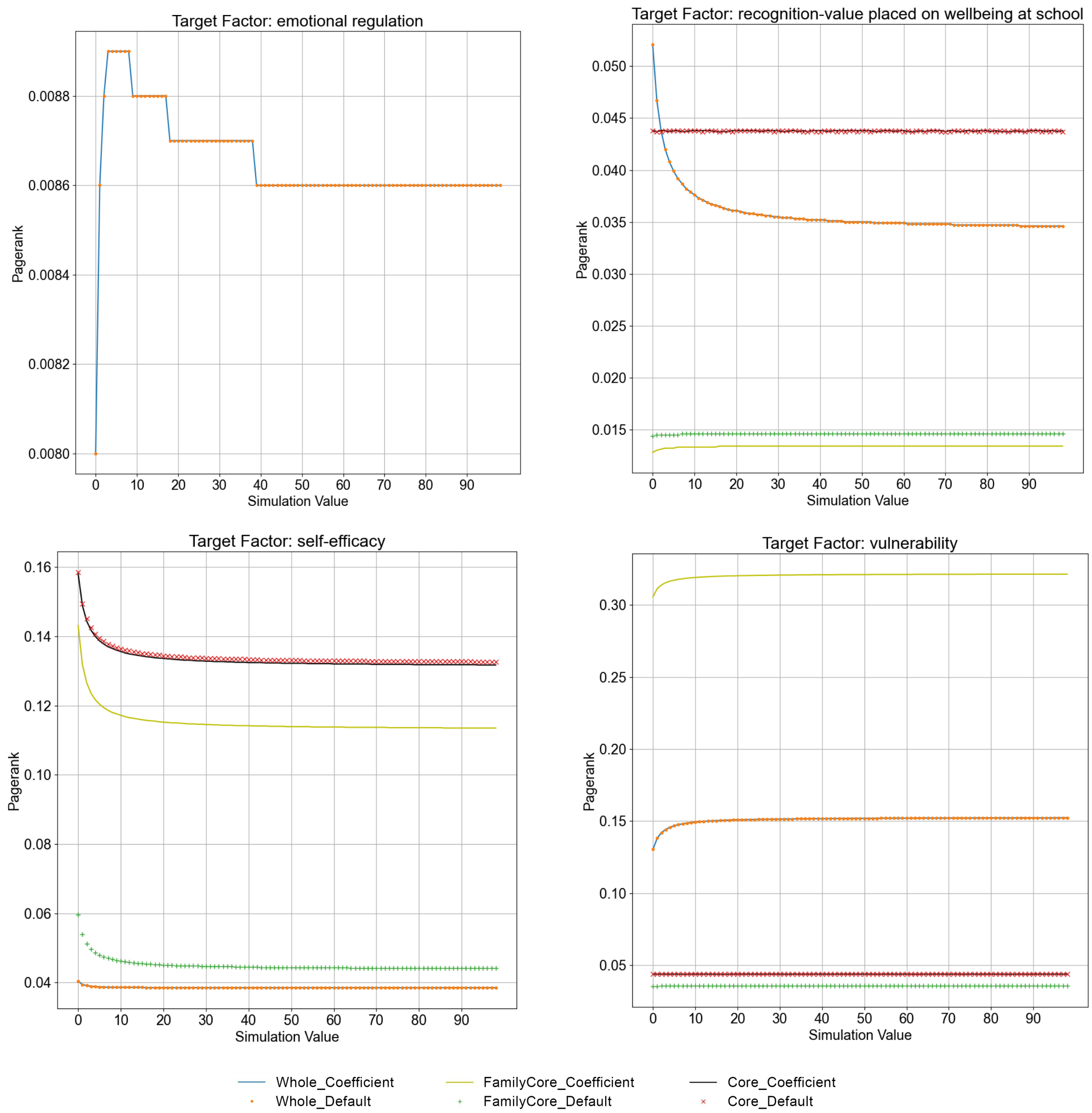

Figure 3: Model Output Behavior Comparison.

4.2 Model Output Behavior validation

To validate model's output behavior, two types of data-sets are defined for links strength: (1) Pearson correlation coefficients with moderate coefficients, and (2) default correlation coefficients of (±1) with respect to data flow direction. To visualize the model output behavior, Figure 3 illustrates only target factors with fluctuation and variation in model's behavior pattern. The goal is to compare both data-sets on the entire map and categories in isolation, and observe dissimilarities in behaviors patterns, and to observe the impact of *advocacy* on mental health factors when located in *Whole*, *Family+Core* and *Core* categories. The *x-axis* and *y-axis* represent the simulation value and target factor's rank, correspondingly. Each line represents rank variation inside different category size. E.g. yellow line indicates target factor's rank variation isolated in *Family+Core* categories with Pearson correlation coefficient data-set. The line graph analysis for model output behavior shows slight rank fluctuation on *emotional regulation*. The second, third, and fourth plots illustrate the comparison of the entire map with the *Core* and *Family+Core* categories with corresponding data-sets. The comparison indicates that *recognition/value placed on wellbeing at school* rank behavior varies when simulating the entire mental health map. In the third plot, model behavior patterns are identical; however, there is a distinct rank variation between two data-sets coefficients when adopting *Family+Core* categories. Finally, on the fourth plot, the comparison indicates dissimilarities in model output behavior when adopting the *Family+Core* categories.

5 DISCUSSION AND CONCLUSION

We proposed a Multi-Methodology Hybrid approach by building a hierarchy of models, using System Dynamic Simulation and PageRank to simulate and assess complex mental health maps. The approach aims to quantify mental factors using link information such as data flow direction, link strength, and the number of associated links. Thus, it makes the simulation model suitable for analyzing alternative maps, overcome the issues related to data gathering by quantifying each mental factor, which in turn mitigates the validation difficulty, and simplifies multiple scenario analysis.

The simulation result was based on target factors' rank variation. The aim was to observe PageRank variation by manipulating the incoming link of scenario's factor. Considering the change was applied to the incoming link of scenario's factor, the factor itself gains the highest rank; thus, to observe influences, we excluded the scenario's factor from the target factors list in each iteration. Additionally, even though links strength and flow direction have a significant impact on target factors, the degree centrality of factors such as *advocacy* and *quantity and quality of relationships* cannot be neglected; however, factors with a high degree of centrality have an insignificant impact on target factors with no incoming links.

Validating the model was limited to detecting PageRank accuracy and inspecting model output behavior. PageRank algorithm facilitates the factors rank validation, which is implemented through coding to detect rank-sink and inaccuracy throughout the simulation. model output behavior is implemented by comparing the target factors ranks within smaller map categories with different data-sets. *Parameter variability* was used to detect fluctuations and output behavior variation. Even though the results revealed the affected target factors, it was hard to distinguish the source of causation and the reason for the change in behavior patterns due to multiple interconnecting links between scenarios' factor and target factors, where the underlying issue may be situated in several links coefficients or map structure. Policymakers may adopt the approach for various purposes, such as (1) gaining insight into critical impacts on mental health, (2) justifying predefined hypotheses and policy options, and (3) scenario comparison and analysis. With the mentioned points, policymakers may enhance and update their knowledge about mental health to improve intervention; confirm previously defined hypotheses accuracy, and ensure the current intervention approach is the optimal solution by comparing and analyzing with other scenarios.

Aspects of the approach increase the model efficiency for various purposes. First, the model could merely be used to rank factors and avoid the difficulty of data gathering. Hence, ranking makes it possible to detect the most influential factors in a large-scale complex systems and consider them as possible intervention options. Second, societies evolve and the factors triggering mental health diverge, thus the approach aids to faster reassess previous knowledge and compare multiple policy options. Furthermore, PageRank considers factors' link strength and data flow direction, which may promote the usage of the proposed simulation approach in other areas, such as making financial decisions in organizations.

One of the limitations encountered during the approach development was gathering sufficient coefficients for the entire map, which led to substituting missing coefficients with moderate correlation coefficient. Other difficulties mainly were related to PageRank sensitivity to data flow direction and dangling nodes, which causes rank-sink; thus, it requires adjusting a reasonable damping factor for PageRank measurement. Since sum of the PageRank values should be precisely (+1), thus, intensifying certain factors' rank may cause lowering ranks in other factors, which makes it harder to understand adverse and beneficial impacts.

Even though simulation results revealed which factors have significant impact on various factors, however, according to the comparison analysis, some factors have reverse impact on target factors. As an example, Fig. 3 illustrates that *stress* causes the highest impact on *mental health* factor, and also indicates that *stress* has beneficial impact on *mental health* factor. Similar issue is evident on *unemployment* target factor, which may imply inaccuracy in model or data.

To conclude, the model has the potential to speed up policy analysis that aims to quantify complex networks, compare scenarios, detect fluctuation, and lowers the flaws in analyzing large-scale complex systems by adopting ranking algorithms, which might be caused by data collection inaccuracy. Furthermore, the flexible nature of the model allows using other simulation methods such as agent-based simulation for micro analysis or adopting different quantification algorithms.

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