A Temporal Causal Network Model of Student Mental Well-being

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Abstract. Mental well-being is a complex construct, which is studied in many disciplines. Understanding student mental well-being (StMWB) is considered vital, as students with higher mental well-being tend to perform better academically, exhibit greater engagement, and develop essential skills for their future. In this article, we propose a temporal causal network model to capture the dynamics of well-being by identifying multidimensional factors that contribute to an individual's optimal well-being and modeling them computationally. Furthermore, through what-if simulations, we examine how various interventions can influence these factors and how their interplay can impact an individual's overall well-being. Finally, we address the limitations and future directions of using the designed model to gain further insights into StMWB, and using it as a basis for interventions to promote well-being.

Keywords: Computational Model, Student Mental Well-being, Causal Model.

1 Introduction

Student Mental Well-being (StMWB) holds an important role in the overall well-being of a society [31]. Students with optimal well-being benefit from higher self-esteem, better coping skills, and sustained motivation, to achieve higher academic goals [23]. In contrast, a student with poor well-being may struggle with hindered attention span, and classroom expectations may never be met. Early detection of disruptive behavior enables timely support to help alter their future trajectory [21]. Hence, it is crucial to enhance our understanding of StMWB, and to develop effective and high-reach interventions that improve poor StMWB.

StMWB is a multifaceted construct based on many related factors, e.g., positive emotions, attitudes, or social interactions [36]. Thus, comprehending the role of these factors and analyzing their interplay can help develop a better understanding of well-being. Recently StMWB has gained much attention [9, 27, 38], however, a deeper understanding is still required to see which psychological, social, or behavioral (and/or other) factors or components may contribute to the well-being of students.

To achieve this, the current paper aims to study the dynamics of StMWB by computational modeling and simulation. In particular, a temporal-causal network modeling approach is used [34]. This approach is based on the assumption that StMWB can best be conceptualized as a network of interacting components, rather than as a latent construct underlying (some of) these aspects [4]. Temporal-causal network models allow researchers to explore the underlying mechanisms of complex mental processes by analyzing their evolution dynamics in a systematic manner. They enable visualization of processes as networks while capturing their inherently multifaceted nature. To date, such models have not often been applied to estimate Student Mental Well-being with the aim to develop interventions.

In this article, we aim to design a temporal-causal network model to understand the dynamics of the factors involved in StMWB. In the future, we aim to use this model in the 'real-time' setting, for instance, to predict and offer (an automated) support to improve students' mental well-being. The remainder of the article is organized as follows. Section 2 reviews the state of the art in mental well-being research and the approaches used to understand well-being by computational modeling. Section 3 outlines the selection of relevant literature used to design the computational model. Section 4 describes the computational modeling approach used, and Section 5 presents several simulation experiments to examine the influence of hypothetical interventions on StMWB. Finally, Section 6 discusses and concludes the article.

2 Related Work

Mental well-being has been a focal point of much research, and various disciplines offer useful methods to gain deeper insights of the mental well-being construct [2, 23, 32]. In this section, we aim to a) understand the relevant factors involved in StMWB and, b) explain how different computational approaches can be used to understand and support mental well-being.

2.1 Understanding StMWB

Mental health has been defined as absence of mental illness such as depression or anxiety. Keyes' model differentiates between the two dimensions of mental health, i.e., absence of psychopathology and presence of well-being [37]. Research on the *psychopathological* aspect of mental health and its assessment is well-established, but a clear and consistent definition of mental well-being is still lacking [23]. According to the World Health Organization (WHO), if an individual has the ability to develop their potential, work productively, and contribute to society while having positive relationships, then their well-being is optimally nurtured [16, 23].

Well-being is often addressed according to various dimensions. For instance, it not only encompasses cognitive and affective factors related to well-being like life satisfaction, purpose in life, and positive emotions [23], but it is also closely connected to the social factors related to well-being [16, 23, 37]. Psychological well-being comes from life-span developmental perspectives and involves the realization of personal potential, self-actualization and social cohesion [28], and is often interchangeably used with eudaimonic well-being [12]. It can help to improve emotional and, thus overall well-being [23].

2.2 Computational Approaches and Well-being

Computational approaches can be useful for understanding and explaining psychological or social phenomena by conceptualizing these phenomena as a network of interacting factors and representing these factors and their interactions in a computational format [1, 4, 15]. Here, we discuss such network-based approaches to explain the (causal) factors for an individual's mental well-being.

A *psychological network* presents a (symptoms) network of a mental phenomenon or disorder (e.g., grief, suicidal behavior), where different nodes or variables represent symptoms and connections reflect causal or statistical relations among them, operating on a discrete unit of time. *Control theory* principles can then be applied to identify central nodes related to the disorder and a simulated intervention helps to estimate the efficacy of treatment. The main aim is to see the (instantaneous) effects of a (hypothetical) treatment in a network. This can be used for optimization of an intervention for mental health [15, 38]. While control theory focusses on node centrality, Briganti et al. used longitudinal data to infer contemporaneous and temporal networks. The idea was to test the strength of associations between two or more components at the same time point, and their temporal effects [6]. While they focus more on 'stationary associations' among components, a deeper understanding is required to investigate the dynamics between such components.

Borsboom et al. use *network theory* to posit complex phenomena (e.g., mental disorders) by linking the related symptoms in a causal way, based on myriads of biological, psychological and social mechanisms. These networks can help to explain the emergence of a phenomenon, i.e., how an event(s) can activate a dormant symptoms network, effecting other symptoms in that network. This event can be an experimental or natural intervention, and if certain causal relations are sufficiently strong, symptoms can combine to generate the related outcome (e.g., behavior, illness, or support), which can sustain for a longer time. This work primarily relies on (deterministic) 'observable' variables, causes, or symptoms (e.g., low mood, insomnia) [4]. Inspired by this approach, *Temporal-Causal Network Modeling* uses an explicit notion of state activations during a unit of time, and we can identify the dynamics of underlying observable/latent causes while addressing their adaptive nature over time [34]. Causal modeling can help understand different phenomena in (health) diagnoses and interventions, by suggesting a clear agenda for future research/implementation [4, 34].

3 Selection of Literature for the Computational Model

In this section, we present a comprehensive literature review conducted with the aim to design the computational model (addressed further). More specifically, the approach taken here aims to come up with an extensive list of concepts that play a role in dynamics of StMWB, as well as the temporal-causal relationships between those concepts. Specifically, we queried articles from journals (i.e., PubMed, APA PsycArticles, APA PsycInfo, ERIC, MEDLINE, Psychology and Behavioral Sciences Collection, CINAHL, Academic Search Premier), conferences (ERIC proceedings, Web of Science, and SCOPUS), and Open Dissertations till October 2023. As for the search terms used, we combined keywords related to mental well-being (e.g., “well-being” or “well-being”) with those referring to students in higher education (e.g., “higher education”, “bachelor”, “masters”, “university”), and incorporated a dynamic aspect by including terms such as “real-time data capture”, “repeated”, “ecological momentary assessment”, and “daily diary”. The latter was done because we focus on studies that use real time measurement of factors related to StMWB. Details of the search terms per database can be viewed on our project page [5]. Based on these search terms, we retrieved 328 unique articles. As part of the initial screening process abstracts were reviewed, and 155 articles were chosen for full-text screening. This step resulted in 99 studies which particularly focus on specific data collection methods (i.e., EMA or daily diary study).

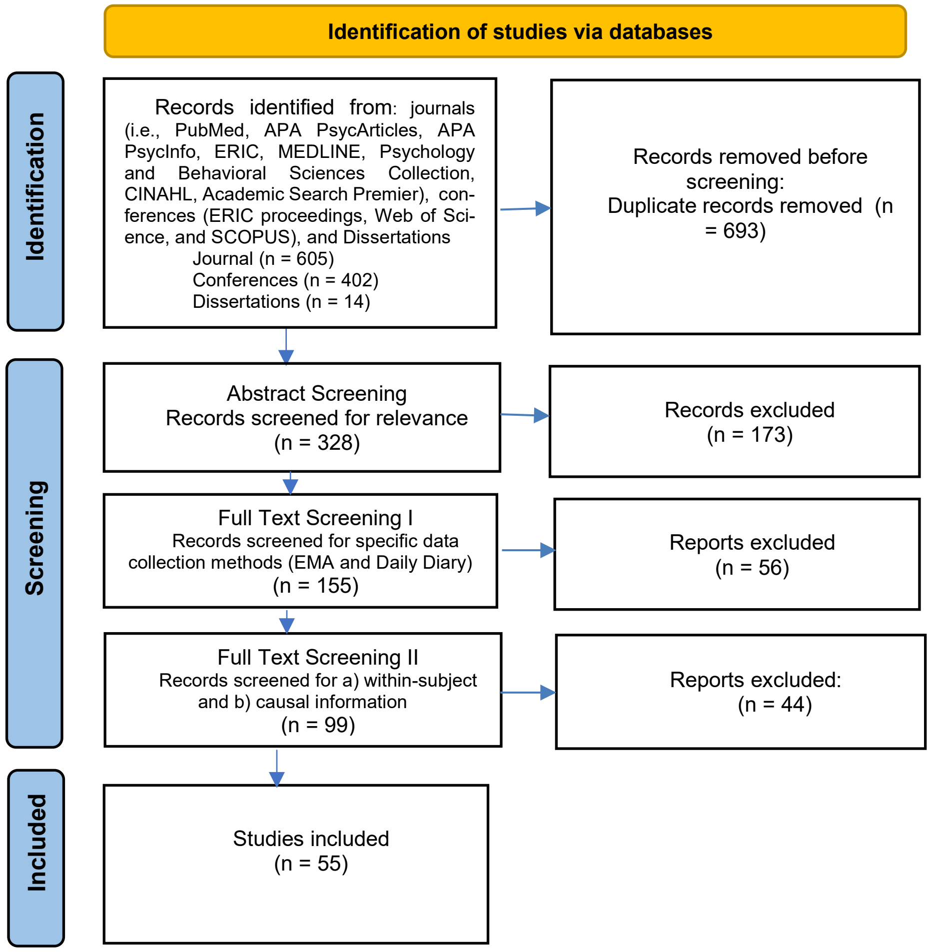

Figure 1: Flow Diagram for Systematic Review

In addition to extracting a list of concepts related to StMWB (e.g., Leisure Time or Self-esteem) from the literature, our second aim was to identify causal relations among these components, in the context of an individual student. For this reason, these 99 articles were further screened for a) a within-subject study design, and b) having causal information. So, any study that compared well-being components between different groups (i.e., between-subject design) was excluded. Moreover, any study that analyzed correlational data without any causal relation between the relevant concepts was excluded. Figure 1 displays the PRISMA flow-diagram for the review process. In the end, we ended up with 55 articles after the last step of screening, which we could use to extract causal information. To this end, three researchers conducted independent analysis of the selected articles to extract phrases reflecting causality.

To investigate the presence of a causal mechanism, we extracted phrases containing text elements such as ‘includes’, ‘because’, ‘causes’, and ‘influence’ (see [5] for the complete set of search terms). These phrases were analyzed to identify potential causal relationships between two or more components. To illustrate this process further, consider the following phrase: “*higher levels of subjective satisfaction with sleep in the previous night significantly predicted higher levels of positive affect and lower levels of negative affect the following day*”. This sentence can be interpreted as highlighting the role of sleep quality in predicting higher levels of positive affect within participants [9]. The individual findings were then systematically compared and integrated through the thematic integration process, ensuring a comprehensive and unified interpretation of within-subject causal phrases with the interacting components. Information regarding the articles and the extracted phrases can be found online[1]. The resulting inferences were subsequently used to develop the computational model presented in Section 4.

4 Temporal-Causal Network Modeling

As mentioned in Section 2.2, different approaches can be used to capture the causal mechanisms of complex processes in a computational format. Due to the practical challenges regarding the availability of (multidimensional) data, causal modeling, and specifically temporal-causal network modeling, offers a suitable solution to formalize the underlying dynamics of complex socio-psychological phenomena [34]. Therefore, this is the approach taken in the current paper to model the dynamics of StMWB. In Section 4.1, we explain how we extracted causal relationships between two or more components of StMWB from the 55 articles discussed above. In Section 4.2, we explain the temporal-causal network model of StMWB that was developed based on these causal relationships.

4.1 Establishing Causality

We used temporal-causal network modeling to develop our model, which allows us to reflect the interactions between various components (i.e., observable or latent). A *temporal-causal network model* is a conceptual representation of *states* and *connections* represented by nodes and edges respectively. In the real world, these states show how different factors or components are related to StMWB, representing a temporal-causal

[1] https://osf.io/7bmxv/files/osfstorage

relationship among them. For instance, ‘*relaxation contributes to recovery experiences*’ [7], can be represented as $X_1 \rightarrow Y$ (where X_1 = relax and Y = recovery). A variation in strength in X_1 can directly influence Y. Thus, the impact on Y after a certain time period Δt, can be computed by considering its value at time t (i.e., $Y(t)$) along with the impact from all incoming states including X_1 (i.e., relax), by using the difference equation as [34]:

$$Y(t+\Delta t) = Y(t) + \boldsymbol{\eta}_Y \left[\mathbf{c}_Y\left(\boldsymbol{\omega}_{X_1,Y} X_1(t); : : ; \boldsymbol{\omega}_{X_k,Y} X_k(t)\right) - Y(t)\right]\Delta t \quad \ldots\ldots\ldots (1)$$

where X_1, …, X_k are a set of states that have a causal influence[2] on state Y

- $\boldsymbol{\omega}_{X_i,Y}$ = connection strength or magnitude by which states X_i influence state Y, which usually varies between 0 and 1. A suppression effect on Y is represented by a negative connection weight.
- $\boldsymbol{\eta}_Y$ = speed factor with which state Y changes its value over time; values range between 0 and 1.
- $\mathbf{c}_Y$ **(..)**= combination function used to compute the causal (aggregated) impact of all incoming states (X_i : i = 1 ... n) on state Y. A library is available online [22] with combination functions to compute the aggregated impact of Y.
- Δt = step size of the time for each interaction from states X_i to Y.

After extracting phrases related to causality (as discussed in Section 3), initially we identified 77 components (represented by states) with 161 causal relations (represented by connections) to model student mental well-being. In a causal model, all states and connections should reflect a unique phenomenon; therefore, at this stage, we performed *refactorization* of states and connections. The aim of this step was to reduce the complexity of the model, and to make it more concise in terms of variables or states. In ‘*state refactorization*’, we merged states with commonalities under intuitive names. For instance, sleep quantity and quality were merged as ‘optimal sleep’, and comfort and relaxed as ‘relaxed’. Similarly, positive affect, happiness, energetic, and positive emotion were identified under the umbrella term ‘positive emotion’. As a next step, we removed all states with fewer than 2 incoming connections. The reason is that the literature gathered in Section 3 indicates that they play a relatively minor role within the phenomenon of well-being (e.g., neuroticism, or being vegetarian). As a result, we were left with 40 states in total. With the reduction of the number of states, we had many overlapping connections, which were removed for consistency. Subsequently, we conducted ‘*connection refactorization*’ to investigate duplicate connections and to understand the underlying contributing factors.

During ‘*connection refactorization*’, we removed a direct connection between two states if there was already an indirect connection. For example, physical activity leads to good sleep [26] and sleep leads to life satisfaction [13, 18], so the direct connection from physical activity to life satisfaction [13, 40] was removed. To avoid any errors or false conclusions, this step was taken cautiously, so we removed only the connections

[2] Note that we cannot always be sure if a certain association between two variables reported in the literature is actually causal. Nevertheless, when developing a computational model, we *assume* that the associations in question are causal.

with path length less than or equal to 2. For the second step, we included some connections while removing others, for instance, we included a connection from 'positive emotions' to 'resilience' while removing the connections from 'positive emotions' to 'autonomy' and 'environmental mastery' [8]. At this stage, we had 134 connections with 40 states (See Table 1 for details).

While establishing the causal-temporal relations in our model, we observed that the literature reviewed in Section 3 overlooks some general yet notable influences between psychological states. For instance, research indicates that, "feeling self-content promotes higher self-esteem" [25], or that "stress is a negative emotional state that can be both a cause and a consequence of procrastination" [30]. These causal relations were not captured yet because they are not specific for the literature on student mental well-being. Hence, at this stage (i.e., after refactorization), our model still lacked such causal information (e.g., self_contentment promotes self_esteem). To make our model more complete, as a final step, we included these additional connections or edges. For instance, a new causal connection from self-contentment (i.e., favorable self-comparison and self-acceptance) to self-esteem was introduced, resulting in 17 such connections. To ensure consistency, we subsequently performed connection refactorization one more time. Our final computational model comprised 40 states with 113 causal connections (see Section 4.2). A log that describes the entire procedure of deriving causal-temporal relations can be viewed here[3].

4.2 Temporal-Causal Network Model of Student Mental Well-being

Figure 2 presents a visual representation of the complete temporal-causal network model for student mental well-being. Here, every oval represents a component (or state) that plays a role in the dynamics of the well-being of an individual, and its role in the network was established according to the steps described in Section 4.1. As can be seen in the figure, some states do not have any incoming arrows and thus can be considered as *input* states, while others do not have any outgoing arrows and thus can be considered as *outcome* states. For instance, states on the left of the model, like *media-obsession*, *openness,* or *self-confidence*, can be considered as input states, while *loneliness* or *recovered* can be considered as outcome (or observable) states. A concise explanation of each state in the model is shown in Table 1. The model has two types of connections, i.e., black arrows and red arrows, showing positive (i.e., $\boldsymbol{\omega}_{X_i,\mathrm{Y}} > 0$), and negative connections (i.e., $\boldsymbol{\omega}_{X_i,\mathrm{Y}} < 0$), respectively.

If we look closely into the model, the interaction of different factors (states) is shown by the arrows. For instance, if the individual is self-contented [29, 39] and has enough social-support [10], their self-esteem would increase (shown by *self-contentment →* *self-esteem* and *social-support → self-esteem*). Similarly, if they are optimistic about their future [8], their coping skills would improve (since *optimistic → coping-skills*). As these states have a positive connection towards life-satisfaction (represented by a black arrow), life satisfaction of the individual will also be improved.

[3] https://osf.io/7bmxv/files/osfstorage

Figure 2 also explains the underlying causes and effects in relation to these factors as described in the literature. For instance, the phrase "development of self-esteem, its outcomes, and its active protection and promotion are critical to the improvement of both mental and physical health" [20], is represented by the arrow *self-esteem → self-care*. Therefore, feeling self-content not only promotes higher self-esteem, but also indirectly influences self-care of an individual. All of these states play a cascading role in increasing satisfaction with life. Moreover, some states act as an input as well as an outcome state at the same time (e.g., *positive-emotion* or *negative-emotion*). Such states are part of feedback loops in the network, and thus cannot only be observed as an outcome, but also play a role in the further development of the well-being of the individual. For example, positive emotions on the one hand can be observed (e.g., via a smile), but on the other hand, they can also help an individual feel more content (represented by *positive-emotion → self-content*). Similarly, negative emotions (e.g., sadness or anxiety) cannot only be observed (e.g., with a frowning face), but can also decrease the self-content of an individual.

To enable the model to calculate the dynamics of the network over time, all speed factors and connection weights are assigned values in the range [0,1]. All connection weights are positive except for the suppressing (negative) connections, shown by the red arrows: e.g., *media-obsession → optimal-sleep*; *fomo → life-satisfaction*; *socially-energetic → self-erasure*; and more. For each temporal-causal relationship, the aggregated impact of the set of old states on a new state is computed by Equation 1.

To illustrate this further, when a person feels happy, *positive-emotion* is greater than 0.5 and *negative-emotion* is less than 0.5. Let us assume their values to be 1 and 0, respectively. Then, for the connection *positive-emotion → self-content*, we assume the parameters of *self-content* to be: $\eta_{\text{self\_contentment}} = 0.05$, $\Delta t = 0.5$, and $\boldsymbol{\omega}_{\text{positive\_emotion,self\_content}} = 0.7$. With its value as 0.239 at time point $t = 60$. Then by using the identity function (i.e., $\mathbf{c}_Y = \mathbf{id}(V) = V$) in Equation 1, the value at $t = 60.5$ is:

$$\begin{aligned} \text{self\_contentment } (60 + 0.5) &= 0.239 + 0.05 * ((0.7 * 1) - 0.239) * 0.5 \\ &= 0.25 \end{aligned}$$

Table 1 shows that we used three types of combination functions ($\mathbf{c}_Y$) to simulate our model, i.e.:

1. Eighteen states use the identity function, $\mathbf{id}(V) = V$.
2. Six states use the scaled-sum function, $\mathbf{ssum}_\lambda(V_1, \dots, V_k) = (V_1 + \dots + V_k)/\lambda$ with $\lambda > 0$
3. The rest of the states are computed by using the advanced-logistic function expressed as:

$$\mathbf{alogistic}_{\sigma,\tau}(V_1, \dots, V_k) = [(1/(1 + \mathbf{e}^{-\sigma(V_1+..+V_k-\tau)}) - (1/(1 + \mathbf{e}^{\sigma\tau}))]\,(1 + \mathbf{e}^{-\sigma\tau}) \text{ with } \sigma, \tau \geq 0$$

where σ = steepness of the curve, τ = threshold, and V = the impact of single state X computed by $\boldsymbol{\omega}_{X,Y} * X(t)$.

The choice of a combination function was made based on the number of incoming connections or the behavior of a state, with the possible outcomes ranging from 0 to 1 (inclusive). For instance, the identity function was used for a state with one incoming connection, while scaled-sum was used for states with more incoming connections. The advanced-logistic function was used for the states that could be activated after a certain threshold (e.g., *positive_emotion*, *negative_emotion*, *recovered*). Software environments in Python are available to simulate the designed models systematically. These environments take a declarative specification containing the features of the models and are extensively used for simulation [22].

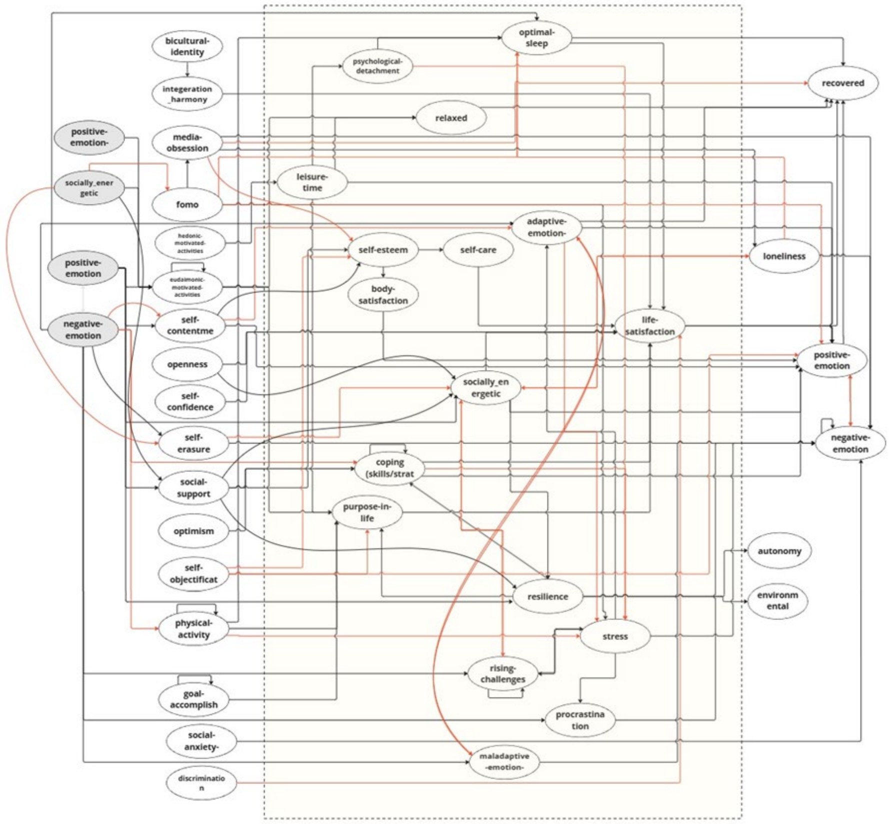

Figure 2: Visual Representation of the Model of StMWB

Table 1. An overview of the states used in computational model presented in Figure 2.

State	Meaning/Context	Combination Function
(bi)cultural-identity	If a person has two or more cultural identities.	id(V)
integration-harmony	Understanding individual differences.	id(V)
(media-)obsession	Compulsive feeling towards media (e.g., digital media).	$\mathrm{ssum}_\lambda(V_1, \ldots, V_k)$
fomo	Fear of missing out	id(V)
hedonic-motivated-activities	Activities seeking pleasure.	id(V)
eudaimonic-motivated-activities	Meaningful life.	$\mathrm{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k)$
self-contentment	A state of peace with oneself.	id(V)
openness	Open-minded and insightfulness: from Big Five.	id(V)
self-confidence	Personal characteristics to ensure achieving goals.	id(V)
self-erasure	Neglecting oneself.	id(V)
social-support	Support from positive relationships (e.g., family support or a friend).	$\mathrm{ssum}_\lambda(V_1, \ldots, V_k)$
optimism	Optimism toward the future.	id(V)

self-objectification	Similar to public self-consciousness and objective self-awareness.	$\mathrm{id}(V)$
physical-activity	Physical activity over a period of minutes to hours.	$\mathrm{ssum}_{\lambda}(V_1, \ldots, V_k)$
goal-accomplishment	Alignment of making progress with your goal.	$\mathrm{id}(V)$
social-anxiety-disorder	Excessive concerns about making an undesirable social impression.	$\mathrm{id}(V)$
discrimination	Prejudicial attitudes.	$\mathrm{id}(V)$
recovered	Feeling recovered and lack of (morning) depletion.	$\mathrm{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k)$
loneliness	Lack of quality or quantity in social relationships.	$\mathrm{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k)$
positive-emotion	Happiness and pleasurable experiences.	$\mathrm{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k)$
negative-emotion	Feelings in response to unpleasant experiences, challenges, or threats.	$\mathrm{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k)$
autonomy	Ability to act, make decisions independently.	$\mathrm{id}(V)$
environmental-mastery	Ability to manage personal needs, goals, and challenges.	$\mathrm{id}(V)$
psychological-detachment	A state in which people mentally disconnect from their work/school and do not think about the related issues while they are away.	$\mathrm{id}(V)$
optimal-sleep	Optimal sleep: sleep duration and quality of sleep.	$\mathrm{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k)$
leisure-time	Time when you can relax and do things that you enjoy.	$\mathrm{id}(V)$
self-care	Process to ensure the holistic well-being of oneself.	$\mathrm{id}(V)$
relaxed	Feeling relaxed and at comfort in what you do.	$\mathrm{ssum}_{\lambda}(V_1, \ldots, V_k)$
coping (skills/strategy) usage	Skill that can increase the ability to deal with daily hassles or stressors.	$\mathrm{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k)$
self-esteem	Positive evaluation of oneself.	$\mathrm{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k)$
socially-energetic	Outgoing gratification (combines extraversion and social interactions).	$\mathrm{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k)$
life-satisfaction	Judgment of one's overall life quality.	$\mathrm{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k)$
maladaptive-emotion-regulation (strategy use)	Ineffective or harmful ways individuals manage and respond to their emotions, e.g., by rumination.	$\mathrm{id}(V)$
adaptive-emotion-regulation	Regulating ones emotion e.g., with mindfulness.	$\mathrm{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k)$
procrastination	Delaying of tasks.	$\mathrm{ssum}_{\lambda}(V_1, \ldots, V_k)$
rising-challenges	When difficulties arise, or accumulates.	$\mathrm{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k)$
body-satisfaction	Importance of social commentary attached to appearance (BoPo).	$\mathrm{id}(V)$
stress	Stress.	$\mathrm{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k)$
purpose-in-life	Extent to which you judge your lives to be meaningful.	$\mathrm{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k)$
resilience	Ability to adapt, recover from challenges.	$\mathrm{ssum}_{\lambda}(V_1, \ldots, V_k)$

5 Simulation Experiments

To illustrate the behavior of the model through concrete use cases, in this section, we aim to discuss three simulation scenarios. First, we present a default scenario that illustrates the interplay of the various components of well-being and how they contribute to the optimal well-being of an individual (i.e., student). Then, we present a scenario that shows how media-obsession, along with fear of missing out (fomo), may reduce well-being, and finally, a scenario that explains how social interactions or supportive relationships can improve the well-being of an individual. These scenarios are some of the possible outcomes from the declarative specification used to design the model.

5.1 Optimal Mental Well-being of an Individual

As a first example, we show the dynamics for a scenario in which a student has an 'optimal' well-being. This use case can be understood in terms of the following statement from of a student that explains well-being:

> *"I think well-being for me means, kind of like all aspects of yourself are balanced and working in harmony. For me I would think of my mental health, I would think of my physical health. My social health, ... and things like that."*

Or,

> *"I think of like social, mental, and physical well-being. I guess [well-being] encompasses those things. It encompasses or puts everything together. Kind of linking everything, so yeah, having a good balance for everything, having a good well-being."*([32], p. 92)

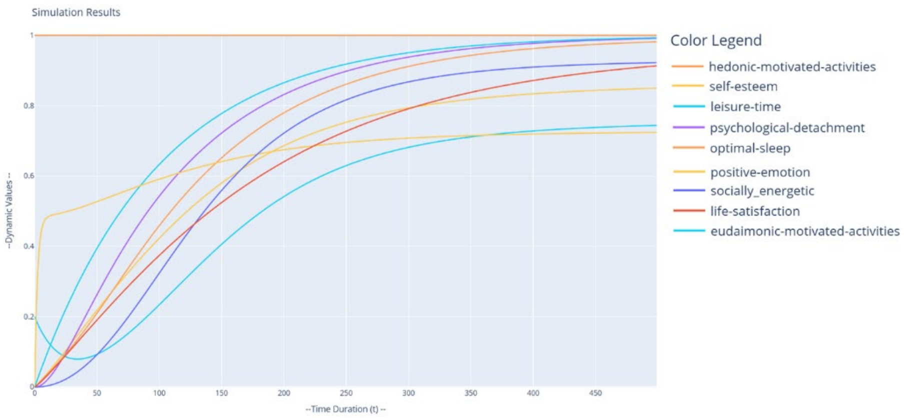

Figure 3: Optimal well-being of an individual

Using our computational model, we are able to simulate this scenario by setting the parameters to appropriate values, of which the result is shown in Figure 3. The figure indicates that the individual reaches an 'optimal' well-being because all relevant states increase over time (approaching 1). As time progresses, all the states related to well-being start to increase. An increase in *self-esteem* of an individual improves his/her *life-satisfaction* (red). Also, a remarkable effect on *eudaimonic-motivated-activities* (turquoise) can be observed: initially, the value of this state decreases from 0.2 to 0.1, since *positive-emotion* was set low, but with the increase in *positive-emotion* (mustard line – after $t > 25$), its value starts increasing until 0.7. Please note that to achieve these results, the initial values of *self-contentment*, *openness*, *self-confidence*, *physical activity*, and goal accomplishment was set to 0.7, while *hedonic-motivated-activities* and *integration-harmony* were set to 1 (not shown in the figure). Similarly, states with a negative impact on well-being, like *self-erasure*, *media-obsession*, or *fomo*, were set to 0. In contrast, by setting some of the parameters related to optimal well-being to lower values, simulation scenarios can be generated reflecting impaired well-being.

5.2 Impact of Media Obsession on Mental Well-being

A second case we consider here concerns the impact of media obsession and fear of missing out (fomo) on mental well-being. To this end, consider the following scenario:

> "*I kept seeing everyone enjoying life online and I felt so isolated and alone. At times feeling deliberately left out.*" ([11], p.4670)

Or, consider the following quote by a 28-year-old adult:

> "*I always feel like I haven't done enough... I expected to be at point X or at a "wow" point, or to be in more places in the world, or to be in a relationship... I'm terrified of aging and not achieving... it scares me..*" ([19], p. 32671)

Development of *obsession* and *fomo* is not a one-day process; therefore, Figure 4 reflects the behavioral dynamics in three phases. The first phase ($t < 300$: shown by the green block) shows that well-being increases over time, where an individual is physically active (*physical-activity* with starting value = 0.7 – purple curve) and *socially-energetic* (blue curve). However, in the second phase ($t = 300 - 950$), (s)he starts getting more obsessed with media (i.e., from $t = 300$: turquoise) and experiencing fomo (purple), which negatively impacts their well-being. Thus, a decrease is observed in their well-being, which is reflected by the states, for instance, *life-satisfaction* (red), being *socially-energetic* (blue), feeling *relaxed* (reddish-pink), and *eudaimonic-motivated-activities* (light blue) start to decrease after t = 300.

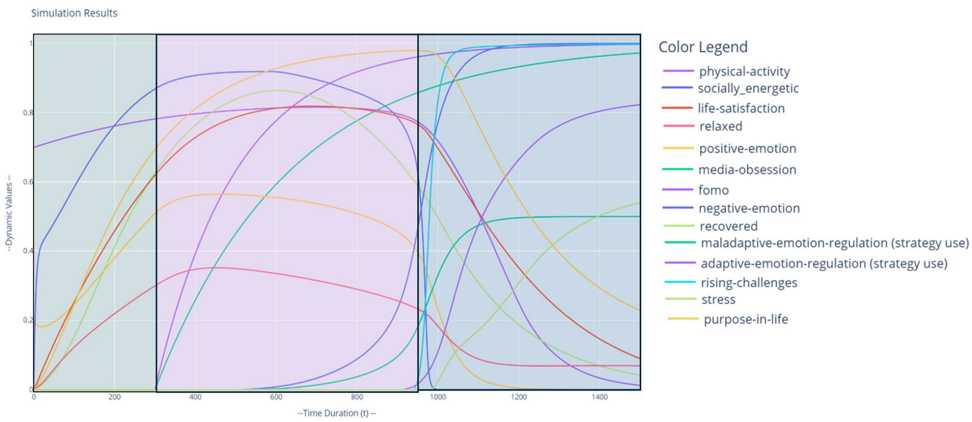

Figure 4: Gradual increase in Media Obsession and FOMO can lead to poor well-being

After $t = 590$, there is an increase in *loneliness* (magenta) and *negative-emotions* (dark blue). Due to the media obsession and compromised well-being, *negative-emotions* start to grow in the third phase (t between 600 - 1200) and challenges become high (see *rising-challenges* in third phase $t > 800$). This not only increases *stress* but also leads to *procrastination* (mustard; value > 0.7) and *loneliness* (magenta; value > 0.5). As a result, the individual tends to use emotion regulation strategies (*adaptive regulation strategy*: purple and *maladaptive regulation strategy*: turquoise) to lower their negative emotions and *stress*. However, due to the constant increase of obsession and fomo, the respective states of well-being (e.g., *positive-emotions*, *optimal-sleep*, *life-satisfaction*, *socially-energetic,* or *purpose-in-life*) continue to stay low, and the states related to poor well-being (e.g., *procrastination*, *negative-emotion*, *loneliness*, *stress*, *self-erasure*) continue to increase.

5.3 Impact of Social Interactions on Mental Well-being

Social interactions and social support can help improve the well-being of an individual [36]. As an illustration of this phenomenon, consider the following scenario:

"It took me a while, but I now have … eight friends, and I am more confident … because I have these people … will back me up" ([32], p. 93)

Figure 5 depicts this situation with a simulation of the impact of *social-support* on the mental well-being of a student. The simulation results show that a sufficient level of social support (at $t = 300$: blue) can reasonably help a person feel energetic, hereby improving their overall well-being (by *social-energetic* after $t > 300$). This increases the related states shown in the figure.

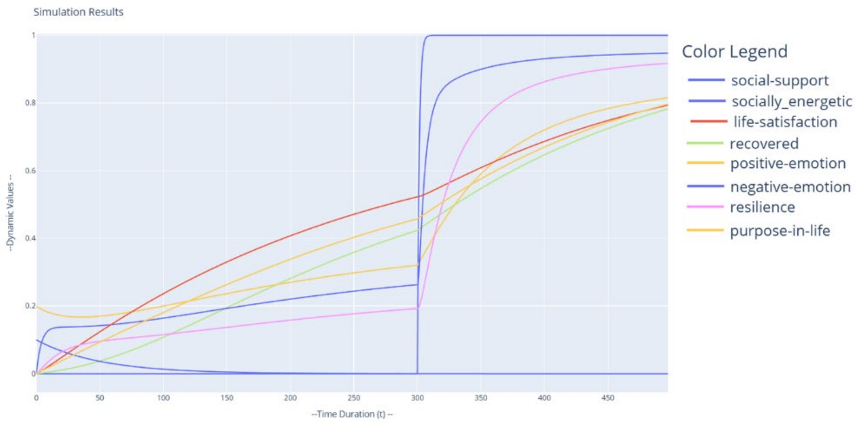

Figure 5: Impact of social support to improve well-being

Note that the values for the components related to poor well-being are reduced to a minimum in this scenario. For instance, *negative-emotion* (blue) was 0.1 at the start, but with the increase of well-being (after $t = 0$), its value reaches almost 0 at $t = 200$. To understand the impact of social interactions, in the presence of fomo and media-obsession, think of a scenario presented by an obsessed individual, i.e.,

"Never felt like keeping [my smartphone] away from me. As such I have never left the phone. I use for it for around eight hours… It is not more important than my family members… just a gadget for me." ([17], p.784)

Or,

"Actually, things are different when I am at home … I do not have to look at mobile phone a lot … I usually spend time with my siblings … here things are different … I am alone so all I get to do is mobile phone … so in [the] college hostel [a] mobile phone is very much required." ([17], p.784)

Figure 6 shows the impact on social interaction/support if a person has almost constant *fomo* and/or (*media-*)*obsession* (value = 0.6). Because of constant values for fomo and obsession, it can be observed that states related to poor well-being start to increase (e.g., *loneliness* – magenta; *procrastination* – mustard; *negative-emotions* – blue;

rising-challenges – turquoise; *stress* – green), and the states related to optimal well-being show decreasing dynamics (e.g., *positive-emotion*, *optimal-sleep* or *eudaimonic-motivated-activities* from 0.2 to almost 0). However, when a person enters into an interaction or receives *social-support* (at $t = 300$), his well-being begins to improve (*positive-emotion*, *optimal-sleep,* or *eudaimonic-motivated-activities* from 0 to almost 0.3), improving *life-satisfaction* (value from 0.1 to 0.3). The components related to poor well-being start to decrease (e.g., *negative-emotions* – blue from 0.66 to 0.6; *procrastination* – mustard; *rising-challenges* – turquoise 0.65 to 0.64; *stress* – green 0.1 to 0.05). They also experience a greater sense of *purpose-in-life* (mustard), thus there is an increase from 0.3 to 0.7, as they feel motivated. Interestingly, *loneliness* (value = 0.36) does not show any dynamics further; this represents that loneliness does not actually reduce, and the whole episode can be regarded as a deviation from his current psychological state.

Since the nature of a person is not changing, *openness* has a constant (value – 0.1). As a result, when the interaction may become passive or does not exist anymore (at $t = 500$), (s)he doesn't feel *socially-energetic* (value from 0.06 to 0), and, as obsession does not decrease over time, their optimal well-being starts to decrease again. This can be explained by the following scenario:

> *"Sometimes because of this mobile phone, somehow I feel lost. When people are talking… busy on your mobile phone…Especially with friends…Like you are not in a proper state sometimes."* ([17], p.785)

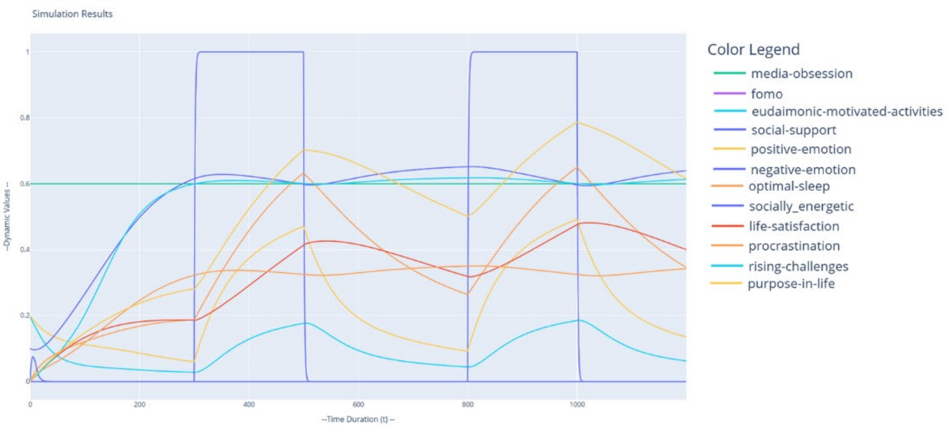

Figure 6: Impact of social support on improving well-being

These simulations indicate that providing social support can help improve the well-being of an individual. This aligns with previous research showing the impact of social support in promoting positive mental health outcomes [14, 36].

6 Discussion and Conclusion

In this article, we presented a dynamic computational model for student mental well-being, developed using a temporal-causal network modeling approach. The model was constructed by taking a holistic perspective, i.e., by identifying all relevant (behavioral, social, and psychological) factors as well as their causal relationships through an extensive literature search. Simulation experiments reflect different scenarios showing how these factors interact dynamically and play a role in shaping the well-being of an individual. In particular, to illustrate the workings of the model, we investigated how media obsession and fomo have a negative impact, and how social support (by an individual or digital intervention) can positively contribute to well-being.

Considering the limitations of our study, we estimated causal relations by using literature focusing only on real-time momentary assessments and daily diary studies. As a result, any retrospective perspective, such as information regarding memories or learning from experiences over time, was not incorporated. Also, although we interpreted the extracted phrases in a temporal-causal way, we are aware that some of them were not necessarily causal (e.g., self-esteem is associated with body image [33]), and we had to make a few assumptions for StMWB, based on observations or additional literature (e.g., feeling self-content promotes higher self-esteem [25]). Their causal relationship can be investigated further by using analysis techniques like Granger Causality or Randomized Controlled Trials. Granger Causality identifies predictive relationships within observational data [24], while Randomized Controlled Trials provide a means of determining cause-and-effect in mental well-being [35]. In the future, we aim to investigate the impact of (natural or experimental) interventions on mental health and well-being. We also aim to investigate the contributing role of other factors towards the mental well-being of a student (e.g., *positive-emotion*, *openness*, and *eudaimonic-activities*).

The usefulness of computational models heavily depends on the completeness and correctness of the underlying causal mechanisms. A model with a sufficiently good representation of reality can be used for explanation, control, and possibly even prediction of the mental well-being [3] of a student. Due to our extensive literature-based approach, we believe that our model is one of the most comprehensive computational models of StMWB currently available. As such, it offers promising possibilities to investigate the well-being of students through 'what-if' simulations. By simulating hypothetical changes such as interventions at an individual level, the model can generate further insights on how to promote resilience, adaptation, and academic success. At the same time, it must be acknowledged that during the design phase, we made a number of simplifying assumptions. For example, we removed states with a minimum number of connections. While this improved the clarity by model simplification, it also raises a possibility of excluding relevant components of well-being.

As the model mainly uses a declarative specification to understand and simulate StMWB, therefore, as a future step, we aim to verify it's behavior by collecting relevant empirical data (e.g., using EMA studies). This way, by comparing the model's predictions with the real-world data, we will be able to test and further fine-tune our model. In the longer term, we also aim to integrate the designed model in our supporting conversational agent (which is being developed in the context of the 'What's Bothering You' project), allowing it to predict students' well-being as part of long-term human-agent conversations.

7 Acknowledgements

This study was conducted as a part of the ‘What’s Bothering You’ project (https://www.ou.nl/en/onderzoek-onderwijswetenschappen-psychologie-whats-bothering-you), supported by funding from ZonMW (Grant No. 09120012110041). We gratefully acknowledge ZonMW for their support in facilitating this research.

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