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Analyzing the Direct and Indirect Factors Affecting Stress Levels and Mental Stability in University Students: A Parameter Estimation Approach

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ABSTRACT

The prevalence of mental stress and its effect on university students continue to escalate worldwide despite existing control measure in order to promote good health among university students has been a major concern. This study explores the parameter estimations of both direct and indirect factors affecting stress, academic performance, health conditions and mental stability among university students using Ordinary Differential Equations (ODEs) through the application of initial value problem. Direct factors include academic workload, social media usage, and procrastination habits, while indirect factors covers social support, financial concerns, and living situations. The model findings indicate that an increase in the rate of these factors correlates with heightened stress level and decreased mental stability. Specifically, an increase in the rate of direct and indirect factors by 0.5 results in a 38% reduction in stress and an exponential increase in mental stability, whereas an escalation by a rate of 10 leads to a 78% increase in stress levels. These results underscore the critical impact of both direct and indirect stressors on students' mental health and highlight the need for effective management strategies to mitigate the adverse effects of these factors.

Keywords. Mental stress, parameter estimation, direct factors, indirect factors, university

1. Introduction

University life is often characterized by heightened stress levels, which can significantly impact students' academic performance and overall well-being. Stress and mental instability are recognized as critical factors influencing not only students' psychological health but also their academic achievements and daily functioning (Johnson & Smith, 2021).
Recent studies have shown that direct factors such as academic workload, social media usage, and procrastination habits play a pivotal role in aggravating stress levels among students (Brown & Green, 2022). Additionally, indirect factors including social support, financial concerns, and living conditions further compound these stressors, affecting students' mental stability(Lee et al., 2023). Understanding the interactions between these factors and their impact on stress levels is crucial for developing effective interventions aimed at improving student well-being.

Mathematical modeling offers a robust framework for analyzing and predicting the effects of various factors on stress and mental stability. By employing initial value problem model equations, researchers can simulate the dynamic interactions between stressors and mental health outcomes. These models enable the quantification of the effects of both direct and indirect factors, providing valuable insights into how changes in these factors influence stress levels and mental stability. Previous work in mathematical modeling has demonstrated its utility in predicting the impacts of stress-related variables on individual and group health outcomes (Chen et al., 2023). Such models not only enhance our understanding of the underlying mechanisms but also aid in designing targeted interventions and support systems.

This study applies model equations with initial value problem to estimate the parameters of direct and indirect factors influencing stress and mental stability among university students.

Mathematical modeling, a method for translating real-world phenomena into mathematical frameworks, is increasingly applied to analyze mental stress among university students a group particularly vulnerable due to academic and social pressures. Recent years have seen a significant rise in reported mental health issues in this demographic, driven by academic pressure, financial burden, societal expectations, and

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personal challenges. Applying mathematical models allows researchers to quantify and predict the effects of stress on academic performance, identify key contributing factors, and propose targeted interventions. However, most existing research does not systematically combine mathematical modeling and optimization analysis to address the multifaceted interplay between stress and academic outcomes.

Studies confirm that chronic mental stress is a leading factor in psychological distress among students, adversely impacting their well-being and functioning. Individual differences such as gender, grade level, and personal coping mechanisms strongly mediate this relationship, while social connectivity can either buffer or exacerbate stress's impact. Academic pressures (deadlines, exams), relationships, financial concerns, and living situations are prominent stressors, each contributing differently to an individual's overall stress levels. The unique combination of these factors and their interactions highlights the importance of a comprehensive analytical framework to understand and manage stress effectively in academic settings (Wang et al., 2025).

Despite the promise of mathematical modeling, a clear gap remains in the integration of empirical data and advanced optimization analyses to yield holistic insights. This research intends to bridge that gap by employing rigorous mathematical modeling to analyze how various determinants contribute to stress and to identify optimized strategies for its mitigation among university students. The developed model is designed to pinpoint critical stressors and evaluate the effectiveness of different intervention strategies, ultimately promoting student well-being and academic success (Khouldi et al., 2025).

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The study's objectives are threefold: to develop and solve a mathematical model examining student stress, to analyze the effect of mental stress on academic and general health, and to propose optimal strategies for stress reduction rooted in mathematical analysis. Results aim to inform educational policymakers and mental health professionals, empower universities to design healthier academic environments, and encourage proactive measures that foster supportive learning spaces (Mailizar et al., 2022).

The scope of this research is limited to undergraduate students at Lagos State University, University of Lagos, and Anchor University Lagos, especially those in selected disciplines. Delays in data collection posed a minor limitation. Nevertheless, key terms such as mental stress, academic performance, optimization analysis, and targeted interventions are clearly defined to guide both the methodology and interpretation of findings.

Ultimately, this approach seeks not just to advance academic understanding but to have real-world impact by shaping support systems and interventions that can meaningfully improve student well-being. By raising awareness of the connection between mental health and academic performance, the research contributes to broader efforts to prioritize psychological wellness within educational systems (Appiah et al., 2021).

2. Literature Review

The literature review highlights the importance of understanding stress among undergraduate students, particularly in the complex environment of higher education. It emphasizes the role of mathematical modeling as a rigorous framework to analyze stress dynamics, optimize interventions, and promote healthier academic environments. Models in this context serve as simplified abstractions that identify key variables and their interrelations, helping researchers forecast and mitigate stress effects systematically (Hritonenko & Yatsenko, 2013; Giordana et al., 2013). Such modeling provides quantifiable insights into stressors affecting academic performance and wellbeing, allowing for precision in evaluating

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coping strategies (Bender, 2000).

Different types of mathematical models are employed, including dynamic, empirical, and deterministic models. Dynamic models use differential equations to simulate continuous changes in stress variables over time, enabling prediction of stress development, academic outcomes, and optimal intervention periods. Empirical models, built on observed data, are useful when theoretical knowledge is limited, employing statistical and machine learning techniques to relate input and output factors in stress scenarios (Pang-Ning Tan et al., 2019; Morrison, 2015). Deterministic models assume known relationships without randomness, providing precise predictions relevant in fields like epidemiology and engineering, and can be adapted for stress analysis by defining variables, relationships, and solving relevant equations (Mathai & Haubold, 2017).

Applications of mathematical modeling extend across disciplines, including engineering, economics, biology, and social sciences, illustrating their versatility in understanding complex systems. In the context of student stress, models help simulate long-term effects, identify critical intervention points, and assess the efficacy of management techniques. Optimal analysis, which incorporates optimization methods alongside modeling, aims to optimize factors such as academic workload and coping mechanisms to minimize stress. This comprehensive approach supports tailored and efficient stress management strategies in academic settings (Sherali et al., 2013; Martinez et al., 2023).

Empirical studies reviewed emphasize various factors influencing student stress and mental health. For instance, research in Tanzania found that mental distress among undergraduates was about 14%, linked to living conditions, family history, and academic performance, with social support mitigating distress (Innocent Mboya et al., 2020). Mathematical modeling studies forecast stress effects and offer tools to identify at-risk students and tailor interventions (Smith et al., 2023). Reviews of stress management programs acknowledge variability in effectiveness, underscoring the need for context-specific strategies (Lopez et al., 2023). Additionally, social support plays a crucial role in lowering stress, reinforcing the value of fostering supportive academic environments to enhance student wellbeing (Williams & Taylor, 2023).

3. Methodology

The method of consecutive reaction model was adopted in this research. The model diagram that mimic the consecutive reaction model is give in Figure 1.

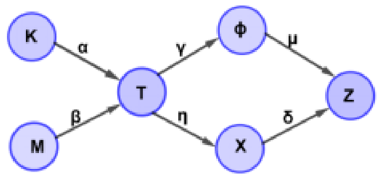

Figure 1: Model Diagram for Direct and Indirect Stress

Where K= Direct factors (Academic workload, procrastination habits, social media usage)

M= Indirect factors (Financial concerns, living situation, social support)

T= Stress level

ϕ=Academic performance

X = Health condition (Physical health, Mental health)

Z = Mental stability

3.2 Model equation

The model equations that shows the interaction between the direct and indirect factors with stress, academic performance, health condition and mental stability are given by the initial value problems (IVP) in equations (1) to (6),

$$\frac{dk}{dt} = -\alpha k, \forall\ K(0) = K_0 \tag{1}$$

$$\frac{dM}{dt} = -\beta M, \quad \forall\ M(0) = M_0 \tag{2}$$

$$\frac{dT}{dt} = \alpha k + \beta M - (\gamma + \eta)T, \quad \forall\ T(0) = T_0 \tag{3}$$

$$\frac{d\phi}{dt} = \gamma T - \mu\phi, \quad \forall \quad \phi(0) = 0 \tag{4}$$

$$\frac{dX}{dt} = \eta T - \delta X, \quad \forall\ X(0) = 0 \tag{5}$$

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$$\frac{dZ}{dt} = \mu\phi + \delta X, \quad \forall Z(0) = 0 \qquad (6)$$

From equation (1) by separating the variable we have

$$\frac{1}{K} dk = -\alpha dt \qquad (7)$$

Integrating both sides, we obtain

$$\int \frac{1}{K} dk = -\alpha \int dt \qquad (8)$$

$$\ln k = -\alpha t + c_1 \qquad (9)$$

$$e^{\ln k} = e^{-\alpha t + c_1} \qquad (10)$$

$$K(t) = e^{-\alpha t} \times e^{c_1} \quad \text{let} \quad e^{c_1} = A \qquad (11)$$

$$K(t) = Ae^{-\alpha t} \qquad (12)$$

$$\text{at time } t = 0, K(0) = K_0$$

$$K(0) = Ae^{-\alpha(0)} \Rightarrow K_0 = Ae^0 \Rightarrow K_0 = A \qquad (13)$$

Putting equation (13) into equation (12), we obtain

$$K(t) = K_0 e^{-\alpha t} \qquad (14)$$

Equation (14) is the model equation for the rate of change of direct factors with time.

From equation (2), separating the variables, we have,

$$\frac{1}{M} dM = -\beta dt \qquad (15)$$

Integrating both sides of equation (15) we obtain

$$\int \frac{1}{M} dM = -\beta \int dt \qquad (16)$$

$$\ln M = -\beta t + c_2 \qquad (17)$$

$$e^{\ln M} = e^{-\beta t + c_2} \qquad (18)$$

$$K(t) = e^{-\beta t} \times e^{c_2}$$

let $e^{c_2} = B$ (19)

$$M(t) = Be^{-\beta t} \qquad (20)$$

$$\text{at time } t = 0, M(0) = M_0$$

$$M(0) = Be^{-\beta(0)} \Rightarrow M_0 = Be^0 \Rightarrow M_0 = B \qquad (21)$$

Substitute equation (21) into equation (20), we obtain

$$M(t) = M_0 e^{-\beta t} \qquad (22)$$

Equation (22) is the model equation for the rate of change of indirect factors with time.

From equation (3), applying separation of variables method, we obtain

$$\frac{dT}{dt} + (\gamma + \eta)T = \alpha k + \beta M \qquad (23)$$

Applying integrating factor method

$$I.F = e^{\int (\gamma+\eta)dt} = e^{(\gamma+\eta)\int dt} = e^{(\gamma+\eta)t} \qquad (24)$$

Multiplying eqn (23) by the integrating factor to obtain

$$e^{(\gamma+\eta)t}\left[\frac{dT}{dt} + (\gamma+\eta)T\right] = \left[\alpha k + \beta M\right]e^{(\gamma+\eta)t} \qquad (25)$$

$$\frac{d}{dt}\left(T \cdot e^{(\gamma+\eta)t}\right) = \alpha k e^{(\gamma+\eta)t} + \beta M e^{(\gamma+\eta)t} \qquad (26)$$

$$\frac{d}{dt}\left(T \cdot e^{(\gamma+\eta)t}\right) = \alpha K_0 e^{-\alpha t} \cdot e^{(\gamma+\eta)t} + \beta M_0 e^{-\beta t} \cdot e^{(\gamma+\eta)t} \qquad (27)$$

Integrating both sides of equation (27) with respect to t, we obtain

$$T \cdot e^{(\gamma+\eta)t} = \alpha K_0 \int e^{(\gamma+\eta-\alpha)t} dt + \beta M_0 \int e^{(\gamma+\eta-\beta)t} dt \qquad (28)$$

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$$T \cdot e^{(\gamma+\eta)t} = \frac{\alpha K_0}{(\gamma+\eta-\alpha)} e^{(\gamma+\eta-\alpha)t} + \frac{\beta M_0}{(\gamma+\eta-\beta)} e^{(\gamma+\eta-\beta)t} + C_3 \tag{29}$$

$T(0)e^{(\gamma+\eta)0}$ at t = 0, T(0)=0

$$T \cdot e^{(\gamma+\eta)t} = \frac{\alpha K_0}{(\gamma+\eta-\alpha)} e^{(\gamma+\eta-\alpha)0} + \frac{\beta M_0}{(\gamma+\eta-\beta)} e^{(\gamma+\eta-\beta)0} + C_3 \tag{30}$$

$$0 = \frac{\alpha K_0}{(\gamma+\eta-\alpha)} + \frac{\beta M_0}{(\gamma+\eta-\beta)} + C_3 \tag{31}$$

$$C_3 = -\frac{\alpha K_0}{(\gamma+\eta-\alpha)} - \frac{\beta M_0}{(\gamma+\eta-\beta)} \tag{32}$$

Substituting equation (32) into equation (29), we obtain

$$T = \left[\frac{\alpha K_0}{(\gamma+\eta-\alpha)} e^{(\gamma+\eta-\alpha)t} + \frac{\beta M_0}{(\gamma+\eta-\beta)} e^{(\gamma+\eta-\beta)t} - \frac{\alpha K_0}{(\gamma+\eta-\alpha)} - \frac{\beta M_0}{(\gamma+\eta-\beta)}\right] e^{-(\gamma+\eta)t} \tag{33}$$

Equation (33) is the model equation for the rate of change of stress level with time.

From equation (4) separating the variable we have

$$\frac{d\phi}{dt} + \mu\phi = \gamma T(t) \tag{34}$$

Using integrating factor method, we obtain

$$I.F = e^{\int \mu dt} = e^{\mu \int dt} = e^{\mu t} \tag{35}$$

Multiplying equation (34) with the integrating factor we obtain

$$e^{\mu t}\left[\frac{d\phi}{dt} + \mu\phi\right] = e^{\mu t}\gamma\left[\frac{\alpha K_0}{(\gamma+\eta-\alpha)} e^{(\gamma+\eta-\alpha)t} + \frac{\beta M_0}{(\gamma+\eta-\beta)} e^{(\gamma+\eta-\beta)t} - \frac{\alpha K_0}{(\gamma+\eta-\alpha)} - \frac{\beta M_0}{(\gamma+\eta-\beta)}\right] e^{-(\gamma+\eta)t}$$

(36)

Integrating both sides of equation (36) and applying the initial conditions at time

$t = 0, \phi(0) = 0$, we have

$$\begin{aligned}
\Phi(t) :=\ & \Bigg(\frac{1}{(\gamma-\beta+\eta)(\gamma-\alpha+\eta)} \Bigg(\gamma \Bigg(\frac{1}{-\gamma-\eta+\mu} \Big(\big(\big((M_0 + K_0)\beta - K_0(\gamma+\eta) \big)\alpha \\
& - \beta M_0 (\gamma+\eta) \big) e^{t(-\gamma-\eta+\mu)} \Big) + \frac{\alpha K_0 (\gamma-\beta+\eta) e^{t(-\alpha+\mu)}}{-\alpha+\mu} \\
& + \frac{\beta M_0 (\gamma-\alpha+\eta) e^{t(-\beta+\mu)}}{-\beta+\mu} \Bigg) \Bigg) \\
& - \frac{1}{(\gamma-\beta+\eta)(\gamma-\alpha+\eta)} \Bigg(\gamma \Bigg(\frac{\big((M_0 + K_0)\beta - K_0(\gamma+\eta) \big)\alpha - \beta M_0(\gamma+\eta)}{-\gamma-\eta+\mu} \\
& + \frac{\alpha K_0 (\gamma-\beta+\eta)}{-\alpha+\mu} + \frac{\beta M_0 (\gamma-\alpha+\eta)}{-\beta+\mu} \Bigg) \Bigg) \Bigg) e^{-\mu t}
\end{aligned} \tag{37}$$

From equation (5) Separating the variables, we obtain $\frac{dX}{dt} + \delta X = \eta T$ (38)

Solving equation (38), we obtain

$$e^{\delta t}\left[\frac{d\phi}{dt} + \mu\phi\right] = \eta e^{\delta t}\left[\frac{\alpha K_0}{(\gamma+\eta-\alpha)} e^{(\gamma+\eta-\alpha)t} + \frac{\beta M_0}{(\gamma+\eta-\beta)} e^{(\gamma+\eta-\beta)t} - \frac{\alpha K_0}{(\gamma+\eta-\alpha)} - \frac{\beta M_0}{(\gamma+\eta-\beta)}\right] e^{-(\gamma+\eta)t} \tag{39}$$

Integrating both sides of equation (39) and applying the initial condition at time $t = 0, X(0) = 0$, we obtain

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$$X(t)=\left[\begin{array}{c}\dfrac{1}{(\gamma-\beta+\eta)(\gamma-\alpha+\eta)}\left[\eta\left[\begin{array}{c}\dfrac{1}{-\gamma+\delta-\eta}\left(\left(\left((M_0+K_0)\beta-K_0(\gamma+\eta)\right)\alpha-\beta M_0(\gamma+\eta)\right)e^{-t(\gamma-\delta+\eta)}\right)+\\ \dfrac{\alpha K_0(\gamma-\beta+\eta)e^{-t(\alpha-\delta)}}{-\alpha+\delta}+\dfrac{\beta M_0(\gamma-\alpha+\eta)e^{-t(\beta-\delta)}}{-\beta+\delta}\end{array}\right]\right]-\\ \dfrac{1}{(\gamma-\beta+\eta)(\gamma-\alpha+\eta)}\left[\eta\left[\dfrac{\left((M_0+K_0)\beta-K_0(\gamma+\eta)\right)\alpha-\beta M_0(\gamma+\eta)}{-\gamma+\delta-\eta}+\dfrac{\alpha K_0(\gamma-\beta+\eta)}{-\alpha+\delta}+\dfrac{\beta M_0(\gamma-\alpha+\eta)}{-\beta+\delta}\right]\right]\end{array}\right] \quad (40)$$

From equation 6 $\dfrac{dZ}{dt}=\mu\phi+\delta X$ Similarly by using the same method we obtain

$$Z(t)=\left[\begin{array}{c}\dfrac{\begin{array}{c}(\beta-\delta)((-\eta+\mu)\delta-\mu\gamma)(-\alpha+\mu)(\gamma+\eta)\left(\left((-M_0-K_0)\beta+K_0(\gamma+\eta)\right)\alpha+\beta M_0(\gamma+\eta)\right)(\alpha-\delta)\\ (-\beta+\mu)\,e^{-(\gamma+\eta)t}\end{array}}{-\gamma-\eta}\\ \begin{array}{c}-\eta(\gamma-\alpha+\eta)(-\gamma-\eta+\mu)\left(\left((M_0+K_0)\beta-\delta K_0\right)\alpha-\beta\delta M_0\right)(-\alpha+\mu)(\gamma-\beta+\eta)(-\beta+\mu)e^{-\delta t}+\\ (\gamma-\delta+\eta)\end{array}\\ \left(\begin{array}{c}-\left(\left((-M_0-K_0)\beta+\mu K_0\right)\alpha+\mu\beta M_0\right)\gamma(\gamma-\alpha+\mu)(\beta-\delta)(\gamma-\beta+\eta)(\alpha-\delta)e^{-\mu t}+(\gamma+\eta-\mu)\\ \left(\begin{array}{c}-K_0\left((-\delta\eta-\gamma\mu)\alpha+\mu\delta(\gamma+\eta)\right)(\beta-\delta)(\gamma-\beta+\eta)(-\beta+\mu)e^{-\alpha t}-(\gamma-\alpha+\eta)\\ (-\alpha+\mu)\left((-\delta\eta-\gamma\mu)\beta+\mu\delta(\gamma+\eta)\right)(\alpha-\delta)M_0e^{-\delta\lambda}\end{array}\right)\end{array}\right)\end{array}\right]$$

$$\begin{array}{l}/\left((\gamma-\beta+\eta)(\gamma-\alpha+\eta)(-\gamma-\eta+\mu)(-\alpha+\mu)(-\beta+\mu)(\gamma-\delta+\eta)(\alpha-\delta)(\beta-\delta)\right)-\\ \left[\begin{array}{c}\dfrac{(\beta-\delta)((-\eta+\mu)\delta-\mu\gamma)(-\alpha+\mu)(\gamma+\eta)(((-M_0-K_0)\beta+K_0(\gamma+\eta))(\alpha+\beta M_0(\gamma+\eta))(\alpha-\delta)(-\beta+\mu)}{-\gamma-\eta}\\ -\eta(\gamma-\alpha+\eta)(-\gamma-\eta+\mu)(((M_0+K_0)\beta+\mu\delta(\gamma+\eta))(\alpha-\delta)M_0))\end{array}\right]/\\ ((\gamma-\beta+\eta)(\gamma-\alpha+\eta)(-\gamma-\eta+\mu)(-\alpha+\mu)(-\beta+\mu)(\gamma-\delta+\eta)(\alpha-\delta)(\beta-\delta)\end{array} \quad (41)$$

4. Results and Discussions

The results of the parameter estimate from the analytic solutions for each parameters are obtained from the analysis above with a graphical presentation of each, in the figures below as it relates to each parameter in consideration by using Maple soft.

4.1 Graphical Representation of Results and Discussion

The graphical presentation of each parameters with their results and discussions are given in the section below:

4.1.1 Parameter estimation from the analytic solutions in equation (1) to (41)
The parameter estimation of each parameter obtained are presented in terms of computation as seen below:

To study the effect of α on the internal factor when all the parameters are kept constant except α. The simulation values for α = 1.0, 1.5, and 2.0.

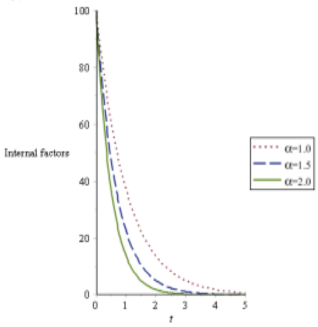

Figure 1. Effect of α on internal factors with respect to time.

Computation 1

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Figure 1 shows the effect of α on internal factors. As α increases, internal factors reduce over time.
This implies that the exponential drop of internal factors over time increases the stress level of a student.

Computation 2

To study the effect of β on the External factors when all the parameters are kept constant except β. The simulation values for β = 1.0, 1.5, and 2.0.

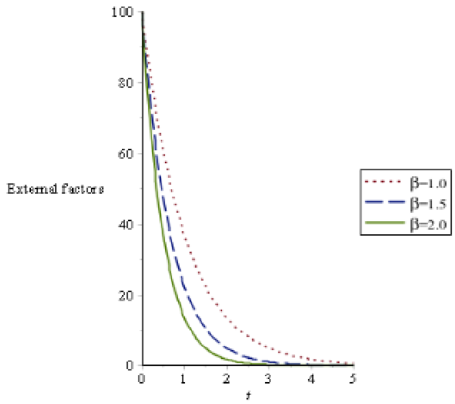

Figure 2. Effect of β on External factors with respect to time.

Figure 2 shows the effect of β on internal factors. As β increases, internal factors reduce over time.
This implies that the exponential drop of External factors over time increases the stress level of a student.

Computation 3

To study the effect of α on stress when all the parameters are kept constant except α. The simulation values for α = 1.0, 1.5, and 2.0.

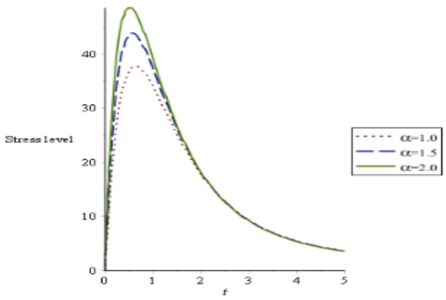

Figure 3. Effect of α on stress.

Figure 3 depicts the effect of α on stress level. As α increases and the stress level also increases. As alpha increases from 1.0, 1.5 and 2.0, the optimum stress level also increases from 38% to 46% and 49% respectively.

Computation 4

To study the effect of β on stress when all the parameters are kept constant except β. The simulation values for β = 1.0, 1.5, and 2.0

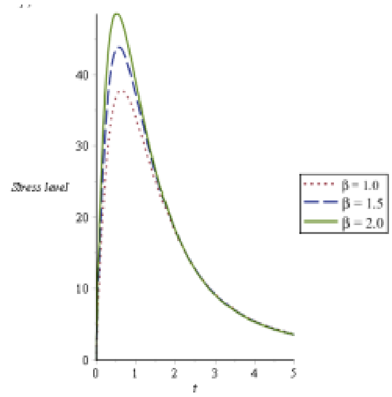

Figure 4. Effect of β on stress.

Figure 4 depicts the effect of β on stress level. As β increases and the stress level also increases. As β increases from 1.0, 1.5 and 2.0, the optimum stress level also increases from 37% to 44% and 48% respectively.

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Computation 5

To study the effect of η on health conditions when all the parameters are kept constant except η. The simulation values for η = 1.0, 1.5, and 2.0

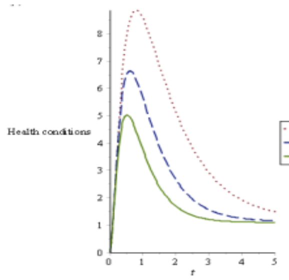

Figure 5. Effect of η on Health condition.

Figure 5 depicts the effect of η on health conditions. As η increases and health conditions are reduced. As η increases from 1.0, 1.5 and 2.0, the health condition of students also decreases from 87% to 66% and 50% respectively. This implies that health conditions can be greatly affected by the increase in the rate at which stress comes into a student's life. This agrees with the work of Varian , (1992).

Computation 6

To study the effect of γ on academic performance when all the parameters are kept constant except γ. The simulation values for γ = 1.0, 1.5, and 2.0. Figure 6 demonstrates the effect of γ on academic performance. As γ increases, academic performance reduces. This implies that academic performance can be greatly affected by the increase in the rate at which stress comes into a student's life. This agrees with the work of Michaela *et, al.,*(2020).

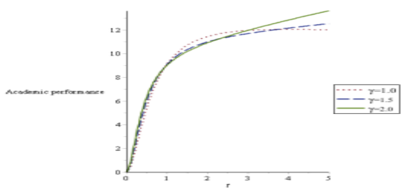

Figure 6. Effect of γ on Academic Performance.

Computation 7

To study the effect of μ on mental stability when all the parameters are kept constant except μ. The simulation values for μ = 1.0, 1.5, and 2.0.

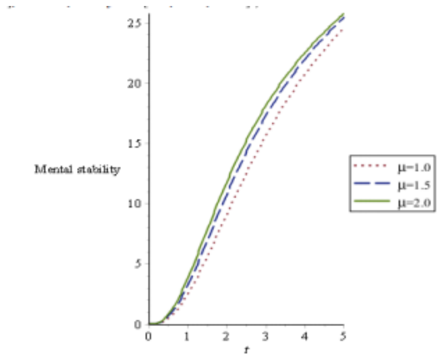

Figure 7. Effect of μ on mental stability.

Figure 7 shows the effect of μ on mental stability. As μ increases mental stability increases over time. This implies that mental stability depends on the rate at which Academic performance of students increases or reduces. This agrees with the work of Innocent *et. al.,* (2020).

Computation 8.

To study the effect of δ on mental stability when all the parameters are kept constant except δ. The simulation values for δ= 1.0, 1.5, and 2.0

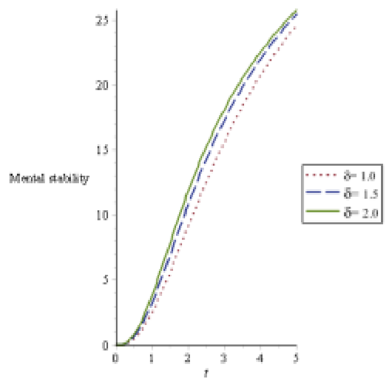

Figure 8. Effect of δ on mental stability

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Figure 8 illustrates the effect of δ on mental stability. As δ increases mental stability increases over time. This implies that mental stability depends on the rate at which mental health increases or reduces. This agrees with the work of Innocent *et al.,* (2020).

Mathematical models were formulated and solved to understand the effect of mental stress among university students. ODEs were formulated and solved analytically. To illustrate the findings, numerical simulations were performed. The observations indicate that stress levels decrease when the factors contributing to academic, personal and societal pressure are mitigated. Specifically, the reduction in stress levels is achieved by reducing procrastination habits, academic workload and financial burdens, and increasing support and coping mechanisms for students for which are both direct and indirect factors. Additionally, the overall stress, decreases when effective stress management programs are implemented.

Hence, the results of our numerical experiment and parameter estimation demonstrate that significant progress can be made in reducing mental stress among university students by implementing appropriate measures to address academic pressures and provide adequate support systems.

5. Conclusion

In conclusion, we have developed mathematical models to understand the effect of mental stress among university students using a set of empirical models and ordinary differential equations. These equations demonstrate that vulnerable students gradually experience increased stress through various academic, personal and external factors.

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