Ctrl + Alt + Mind: Reprogramming Students' Psychological Well-Being through Computational Thinking and Mindfulness

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***Abstract*—** The psychological well-being of university students, shows how well they can deal with the schoolwork, feelings and social demands of higher education. It is widely accepted that psychological well-being helps enhance students' academic performance achievement and life satisfaction. In this context, mindfulness and computational thinking are emerging as essential mental and emotional skills that are useful and influence students' mental health outcomes. This study attempts to investigate how computation acts as a bridge contemplating mindfulness and its relationship. With psychological well-being among Indian university students. A sample of 281 university students were surveyed using standardized self-report instruments. Data were analyzed using partial least squares structural equation modeling by SmartPLS 4.0. The measurement model was rigorously estimated to confirm that it met the necessary validity and reliability standards. The structural model assessed direct and indirect relationships between variables. Computational thinking has made direct contributions to psychological well-being, confirming its importance as a cognitive factor in improving mental health. Mediation analysis further demonstrated that computational thinking partially mediates the relationship between mindfulness and psychological well-being, as supported by a variance accounted for (VAF) value 26%, indicating partial mediation. These findings suggest that well-being is influenced not only by emotional regulation through mindfulness, but also by the cognitive ability to think critically and solve problems effectively.

***Keywords* -**computational thinking, mindfulness, psychological well-being, mediation, PLS-SEM

I. INTRODUCTION

Mindfulness, which is acute awareness of the present moment and openness and non-judgment, improves mental health, whereas psychological well-being (PWB) reduces stress, anxiety, and depression and promotes self-regulation, self-compassion, and life satisfaction (Brown & Ryan, 2003; Dawson et al., 2019) whereas computational thinking is a cognitive approach that breaks down intricate problems into simpler components. Both mindfulness and computational thinking include iterative, logical, and adaptive reasoning.

According to studies, technology-delivered mindfulness programs reduce depression, anxiety, and stress while increasing positive emotions, happiness, compassion, and trait awareness. It is important to note that these effects last at least a month after the intervention (Conley et al., 2024; Alrashdi, 2023). Systematic reviews show that online mindfulness (MF) reduces psychological distress, although less than active controls (Alrashdi et al., 2023).

Computational thinking (CT) modules improve metacognition, executive function, and socio-emotional learning, according to contemporary research. Most research measures academic or cognitive outcomes, not mental health markers (Candeias et al., 2025; Markandan, 2022). Many integrative programs combine mindfulness with computerized cognitive training to improve executive function, default-mode network regulation, and depression symptoms. This shows a neurocognitive link between mindfulness and cognitive training (Bursky et al., 2022). However, empirical studies on how critical thinking and mindfulness affect students' mental health are rare.

Clear theoretical frameworks that incorporate Mindfulness, PWB, and CT are lacking in the literature. Studies often neglect the third component, relegating it to secondary status or as an outcome variable (Ritter & Álvarez, 2020). Mapping and systematic reviews study CT for emotional regulation and social-emotional learning, but they rarely construct formal models of how mindfulness may regulate or moderate CT learning. Educational practices guides recommend paired activities like using CT to teach mindful practices, but they lack empirical theory testing (Filipe et al., 2021).

Few studies specifically incorporate Mindfulness and CT. Morales-Urrutia et al. (2021) found that short mindfulness-focused sessions before programming tasks improved performance, contentment, and motivation in

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10–12-year-old Curriculum resources also suggest CT-framed Mindfulness activities and unplugged lesson sets for younger students, but most are descriptive or based on pilot studies (Filipe et al., 2021). The literature shows little direct evidence relating Mindfulness, PWB, and CT simultaneously, with various approaches and little focus on underlying mechanisms or diverse participant populations.

A. Computational Thinking as a Mediator

CT improves psychological well-being by fostering mastery, competence, and self-efficacy in life's obstacles (Denning & Tedre, 2019; Voogt et al., 2015). Mindful techniques improve attentional control and emotional regulation, which aid CT's systematic and rational problem-solving (Kabat-Zinn, 2003; Bishop et al., 2004). Therefore, mindfulness enhances cognitive resources needed to navigate complex situations. Thus, CT explains how mindfulness's attentional and self-regulatory benefits improve mental health. Mindfulness reduces negative emotions while psychological well-being promotes acceptance, which improves CT. This gives people cognitive methods to overcome obstacles.

II. OBJECTIVE

To investigate the mediating role of computational thinking in the relationship between mindfulness and psychological well-being among students enrolled in higher education institutions in India.

III. METHODOLOGY

In this research, survey method was employed as it is widely used quantitative method in social science research. Surveys help prevent data manipulation, allowing researchers to accurately represent real conditions (Asogwa et al., 2022; Damian et al., 2022; Ozdal et al., 2022). In present study data analysis was performed by using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.0. The reliability and validity of the measurement model' were examined by assessing composite reliability (CR), and average variance extracted (AVE). Additionally, discriminant validity was evaluated following the Fornell-Larcker criterion to confirm the distinctiveness of the latent constructs.

A. Participants and data collection procedure

For this study, data were obtained from a sample of 281 university pupils, studied in higher education programs. The participants comprised a majority of female participants (53%) and male participants (47%). The age distribution indicated that most participants were young adults, with 87.2% falling within the 15–25 age range and 12.8% belonging to the 26–35 age group.

Participants were selected through a convenience sampling technique from various parts of India, viz. West Bengal, Jharkhand, Jammu, Bihar, and Tamil Nadu. We used Google Forms to collect the data since it enables us to collect data online, which makes the process more flexible and easier. (Galang et al., 2022; Olcek et al., 2022; Paramitha et al., 2021).

Everyone who took part was an adult and gave their written consent before the online survey, keeping it all anonymous. There was no missing data, and no incentives were offered to the participants. Data was gathered from July to August 2025.

B. Tools

The present piece of study used three standardized self-report scales-

- Computational Thinking- The Computational Thinking of students was acquired by the score obtained through a 29-item scale developed by Korkmaz, Cakir, and Özden (2017).
- Psychological Well-being- 18-item scale composed by Ryff et al. (2010).
- Mindfulness- The Mindful Attention Awareness Scale (MASS) scale has 15 items formed by Brown and Ryan (2003).

IV. DATA ANALYSIS

TABLE I. INTERPRETATION OF RELIABILITY AND VALIDITY

	Cronbach's alpha	rho_a	rho_c	AVE
Computational Thinking	0.917	0.920	0.929	0.505
Mindfulness	0.835	0.843	0.875	0.501
Psychological	0.828	0.817	0.815	0.503

well-being				

The measurement model showed a satisfactory level of reliability and validity. Values of Cronbach's alpha for all constructs (0.828–0.917) exceeded the 0.70 threshold, confirming strong internal consistency. Composite reliability (rho_a = 0.817–0.920; rho_c = 0.815–0.929) also indicated good construct reliability. The average variance extracted (AVE) values (0.501 - 0.505) were all greater than 0.50, proving that convergent validity existed. The constructs of CT, mindfulness, and PWB demonstrated adequate reliability and validity, confirming their application in structural models.

TABLE II. DISCRIMINANT VALIDITY- FORNELL-LARCKER CRITERIA

	Computational Thinking	Mindfulness	Psychological well-being
Computational Thinking	0.711		
Mindfulness	0.348	0.708	
Psychological well-being	0.358	0.290	0.556

The Fornell-Larker criterion worked for all types of buildings. The square roots of the AVE for CT (0.711), mindfulness (0.708), and PWB (0.556) surpassed the inter-building correlations linked to them. This shows that each construct has more variation with its own indicators than with other constructs, which proves that they are different.

TABLE III. PATH COEFFICIENTS

	Original sample (O)	Mean	ST DEV	t value	P value
Computational Thinking -> Psychological well-being	0.292	0.309	0.06	4.788	0.000
Mindfulness -> Computational Thinking	0.348	0.361	0.06	5.371	0.000
Mindfulness -> Psychological well-being	0.188	0.199	0.06	2.832	0.005

The structural model results revealed that all hypothesized paths were statistically significant. CT had a positive and significant effect on PWB ($\beta = 0.292$, $t = 4.788$, $p < 0.001$), indicating that higher levels of CT are associated with improved well-being. Mindfulness significantly predicted CT ($\beta = 0.348$, $t = 5.371$, $p < 0.001$), suggesting that greater mindfulness enhances CT skills. Additionally, Mindfulness exerted a direct positive influence on PWB ($\beta = 0.188$, $t = 2.832$, $p = 0.005$), confirming its role in promoting well-being. Overall, the findings demonstrate that Mindfulness contributes to PWB both directly and indirectly through CT thereby supporting the proposed model.

TABLE IV. TOTAL INDIRECT EFFECTS

	Original sample (O)	Mean	ST DEV	t value	P value
Mindfulness -> Psychological well-being	0.102	0.111	0.02	3.648	0.000

The results show that Mindfulness has a significant indirect effect on PWB ($\beta = 0.102$, $t = 3.648$, $p < 0.001$). This indicates that part of the effect of Mindfulness on PWB is transmitted through CT. Since, the path is significant ($p < 0.001$), it confirms the presence of a mediation effect in the model.

TABLE V. SPECIFIC INDIRECT EFFECTS

	Original sample (O)	Mean	ST DEV	t value	P value
Mindfulness -> Computational Thinking -> Psychological well-being	0.102	0.111	0.02	3.648	0.000

The results show that the path Mindfulness → CT → PWB is positive and statistically significant ($\beta = 0.102$, $t = 3.648$, $p < 0.001$). This means that CT mediates the relationship between Mindfulness and PWB.

The positive coefficient (0.102) highlights higher levels of Mindfulness enhance CT, which in turn contributes to better PWB. The t-value (3.648) is well above the critical value of 1.96, and the p-value (0.000) confirms that this indirect effect is highly significant.

TABLE VI. TOTAL EFFECTS

	Original sample (O)	Mean	ST DEV	t value	P value
Computational Thinking -> Psychological well-being	0.292	0.309	0.06	4.788	0.000
Mindfulness -> Computational Thinking	0.348	0.361	0.06	5.371	0.000
Mindfulness -> Psychological well-being	0.290	0.310	0.05	5.142	0.000

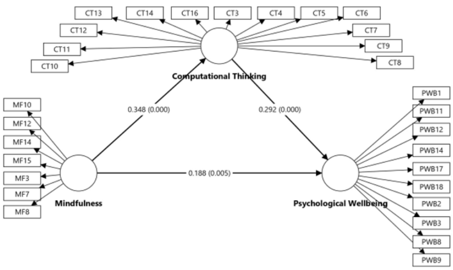

Fig. 1. Structural Model

Fig. 1. and Table VI. -The structural model analysis revealed that all hypothesized paths were statistically significant CT had a positive effect on PWB ($\beta = 0.292$, $t = 4.788$, $p < 0.001$), indicating that individuals with higher CT's skills reported greater well-being. Mindfulness is a substantial predictor of CT ($\beta = 0.348$, $t = 5.371$, $p < 0.001$). Essentially, mindfulness builds up problem-solving and reasoning abilities. Also, mindfulness also had a direct positive effect on PWB ($\beta = 0.290$, t 5.142, $p < 0.001$). Consequently, overall, the findings of this study provide support for the mediation model proposed that mindfulness improves PWB.

A. Mediation Analysis (VAF)

The mediation effect was further evaluated using VAF. The mindfulness indirect effect on PWB via CT was 0.102. The direct effect was 0.290. The total effect was 0.392. The VAF value, which is indirect effect divided the total effect, was at 26%. According to the recommendations from Sarstedt et al. (2017), if the value of a VAF is between 20% and 80%, there is partial mediation. Consequently, the findings hold that CT partially mediates mindfulness and PWB. Mindfulness affects PWB directly and indirectly by enhancing their CT skills.

V. DISCUSSION

The results of this test show that mindfulness significantly increases PWB, both directly and indirectly, collectively, through CT. The direct effect shows that mindfulness independently contributes to better health, which is consistent with previous studies emphasizing its role in improving cognitive flexibility, attentional control, and emotional regulation (Brown and Ryan, 2003; Langer, 2014). At the same time, significant indirect effects through CT highlight a mediated pathway, indicating that mindfulness promotes problem-solving and logical reasoning abilities, which, in turn, contribute to better psychological outcomes (Grover & Pea, 2018).

The VAF analysis further supports this interpretation, showing that 26% of the total effect of mindfulness on psychological health is explained by the mediating role of computational thinking. Since this value falls within the range of 20%-80%, it confirms the partial mediation effect. This suggests that mindfulness directly affects health, but its effect becomes even stronger with the development of CT skills. In other words, people who practice mindfulness not only benefit emotionally, but also receive cognitive benefits that indirectly increase their PWB. These findings enrich the existing literature as they establish CT as a meaningful cognitive mechanism through which mindfulness functions.

VI. CONCLUSION

This study shows the relationships between mindfulness, CT and PWB in the way people adjust to cognitive and emotional demands. The results indicate that mindfulness brings not just direct advantages, but also promotes the cognitive flexibility and organized problem-solving abilities that typify CT. This would improve PWB, suggesting that well-being is supported by not only emotional regulation but also better cognitive processing.

It is noteworthy that we find evidence for mediation analysis that CT significantly but partially mediates the mindfulness-well-being relation. Essentially, PWB can be understood as a multidimensional outcome, whereby intrinsic awareness and cognitive abilities work together to create a synergy. Integrating cognitive skills and mindfulness in educational and psychological interventions can be useful as these insights suggest.

Mindfulness cultivation via computer programming could benefit a range of populations or contexts. Future work could investigate academic achievement, workplace resilience or digital expertise in other populations. Practically, programs that combine mindfulness training with cognitive skills enrichment can provide a more rounded approach to promoting well-being in an increasingly complex environment.

REFERENCES

[1] Alrashdi, D. H., Chen, K. K., Meyer, C., & Gould, R. L. (2023). A Systematic review and meta-analysis of Online Mindfulness-Based Interventions for University Students: An examination of Psychological Distress and Well-being, and Attrition rates. Journal of Technology in Behavioral Science, 9(2), 211–223. https://doi.org/10.1007/s41347-023-00321-6

[2] Asogwa, U. D., Nkanu, C. U., & Sabo, A. (2022). Assessment of e-learning readiness of lecturers and students in federal colleges of education in the Northeast, Nigeria. International Journal of Curriculum and Instruction, 14(1), 455–472. https://ijci.net/index.php/IJCI/article/view/701

[3] Bishop, S. R., Lau, M., Shapiro, S., Carlson, L., Anderson, N. D., Carmody, J., Segal, Z. V., Abbey, S., Speca, M., Velting, D., & Devins, G. (2004). Mindfulness: A proposed operational definition. Clinical Psychology: Science and Practice, 11(3), 230–241. https://doi.org/10.1093/clipsy.bph077

[4] Brown, K. W., & Ryan, R. M. (2003). The benefits of being present: Mindfulness and its role in psychological well-being. Journal of Personality and Social Psychology, 84(4), 822–848. https://doi.org/10.1037/0022-3514.84.4.822

[5] Bursky, M., Egglefield, D. A., Schiff, S. G., Premnath, P., & Sneed, J. R. (2022). Mindfulness-Enhanced Computerized Cognitive Training for Depression: An integrative review and proposed model targeting the Cognitive Control and Default-Mode networks. Brain Sciences, 12(5), 663. https://doi.org/10.3390/brainsci12050663

[6] Candeias, A., Felix, A., Dumitrache, A., Almășan, B., Gencel, I. E., Zadworna, M., Kossakowska, K., Sakellariou, A., Sakellariou, M., Sahin, C., & Taskin, C. S. (2025). Enhancing socio-emotional learning and mental health through computational thinking: a cross-cultural analysis of the COMPUSEL programme. Frontiers in Psychology, 16. https://doi.org/10.3389/fpsyg.2025.1480731

[7] Conley, C. S., Gonzales, C. H., Huguenel, B. M., Rauch, A. A., Kahrilas, I. J., Duffecy, J., & Silton, R. L. (2024). Benefits of a Technology-Delivered Mindfulness Intervention for Psychological Distress and Positive Wellbeing in Depressed College Students: Post-Intervention and Follow-Up Effects from an RCT. Mindfulness, 15(7), 1739–1758. https://doi.org/10.1007/s12671-024-02398-3

[8] Damian, E., Meuleman, B., & van Oorschot, W. (2022). Transparency and replication in cross-national survey research: Identification of problems and possible solutions. Sociological Methods & Research, 51(2), 499–526. https://doi.org/10.1177/0049124119882452

[9] Dawson, A. F., Brown, W. W., Anderson, J., Datta, B., Donald, J. N., Hong, K., ... & Galante, J. (2020). Mindfulness-based interventions for university students: A systematic review and meta-analysis of randomised controlled trials. Applied Psychology: Health and Well-Being, 12(2), 384-410. https://doi.org/10.1111/aphw.12188

[10] Denning, P. J., & Tedre, M. (2021). Computational Thinking: a disciplinary perspective. Informatics in Education. https://doi.org/10.15388/infedu.2021.21

[11] Filipe, M. G., Magalhães, S., Veloso, A. S., Costa, A. F., Ribeiro, L., Araújo, P., Castro, S. L., & Limpo, T. (2021). Exploring the effects of meditation techniques used by Mindfulness-Based Programs on the Cognitive, Social-Emotional, and academic skills of Children: A Systematic review. Frontiers in Psychology, 12. https://doi.org/10.3389/fpsyg.2021.660650

[12] Galang, A., Snow, M. A., Benvenuto, P., & Kim, K. S. (2022). Designing virtual laboratory exercises using Microsoft Forms. Journal of Chemical Education, 99(4), 1620–1627. https://pubs.acs.org/doi/full/10.1021/acs.jchemed.1c01006

[13] Grover, S., & Pea, R. (2018). Computational thinking: a competency whose time has come. In Bloomsbury Academic eBooks. https://doi.org/10.5040/9781350057142.ch-003

[14] Kabat-Zinn, J. (2003). Mindfulness-based interventions in context: Past, present, and future. Clinical Psychology: Science and Practice, 10(2), 144–156. https://doi.org/10.1093/clipsy.bpg016
[15] Langer, E. J. (2014). Mindfulness forward and back. In A. le, C. T. Ngnoumen, & E. J. Langer (Eds.), The Wiley Blackwell handbook of mindfulness (pp. 7–20). Wiley Blackwell. https://doi.org/10.1002/9781118294895.ch1
[16] Markandan, N., Osman, K., & Halim, L. (2022). Integrating computational thinking and empowering metacognitive awareness in STEM education. In Frontiers in Psychology, Frontiers in Psychology [Journal-article]. https://doi.org/10.3389/fpsyg.2022.872593
[17] Morales-Urrutia, E. K., Ocana, J. M., Perez-Marin, D., & Pizarro, C. (2021). Can mindfulness help primary education students to learn how to program with an emotional learning companion? IEEE Access, 9, 6642–6660. https://doi.org/10.1109/access.2021.3049187
[18] Olcek, G., Celik, I., & Basoglu, Y. (2022). The impact of the Covid-19 pandemic on audiology students in Turkey: E-learning, knowledge of teleaudiology, psychological and social status and personal development. Turkish Online Journal of Distance Education, 23(1), 19–42. https://doi.org/10.17718/tojde.1050339
[19] Paramitha, S. T., Komarudin, K., Fitri, M., Anggraeni, L., & Ramadhan, M. G. (2021). Rethinking the relationship between technology and health through online physical education during the pandemic. International Journal of Education in Mathematics, Science and Technology, 10(1), 132–144. https://eric.ed.gov/?id=EJ1330384
[20] Ringle, C. M., Wende, S., and Becker, J.-M. 2024. "SmartPLS 4." Bönningstedt: SmartPLS, https://www.smartpls.com.
[21] Ritter, A., & Alvarez, I. (2020). Mindfulness and executive functions: making the case for elementary school practice. European Journal of Investigation in Health Psychology and Education, 10(1), 544–553. https://doi.org/10.3390/ejihpe10010039
[22] Ryff, C. D., Almeida, D. M., Ayanian, J. Z., Carr, D. S., Cleary, P. D., Coe, C., … Williams, D. R. (2010). *Midlife in the United States (MIDUS 2), 2004-2006 (ICPSR 4652)*. Inter-university Consortium for Political and Social Research. https://doi.org/10.3886/ICPSR04652.v8
[23] Sarstedt, M., Ringle, C. M., & Hair, J. F. (2017). Partial least squares structural equation modeling. In Springer eBooks (pp. 1–40). https://doi.org/10.1007/978-3-319-05542-8_15-1
[24] Tang, X., Yin, Y., Lin, Q., Hadad, R., & Zhai, X. (2020). Assessing computational thinking: A systematic review of empirical studies. Computers & Education, 148, 103798. https://doi.org/10.1016/j.compedu.2019.103798
[25] Voogt, J., Fisser, P., Good, J., Mishra, P., & Yadav, A. (2015). Computational thinking in compulsory education: Towards an agenda for research and practice. Education and Information Technologies, 20(4), 715–728. https://doi.org/10.1007/s10639-015-9412-6