When AI Ethics Shapes Motivation and Trust: Toward Sustainable AI Adoption in Education

Mouna Allouche[#1], Assistant Professor

Molka Boujelben[*2] Doctor in marketing

Higher Institute of Business Administration of Sfax

Faculty of Economics and Management of Sfax

mouna.allouch@isaas.usf.tn
boujelben_molka@yahoo.fr

Abstract— AI integration in higher education is currently hindered by "algorithmic anxiety" and ethical friction. Addressing the dominant output-centric focus, this study examines how perceived ethics, trust, and motivation jointly foster academic well-being as the essential catalyst for sustainable AI adoption. We propose an integrative framework extending the Smart Technology Acceptance Model (STAM) with Trust Theory and Self-Determination Theory (SDT). PLS-SEM analysis (*n*=100) validates a robust "Morality-to-Well-being" pathway, positioning perceived ethics as the axial antecedent of systemic trust, which catalyzes intrinsic motivation. Findings confirm a full sequential mediation: moral perceptions are internalized via "psychological sedimentation," transforming ethical compliance into enduring academic well-being. This framework facilitates a paradigm shift from technocentric efficiency to human-centric flourishing, repositioning ethics not as a constraint but as a strategic lever for institutional legitimacy and pedagogical health.

Keywords— **Ethical AI, Academic Well-being, Learner Motivation, Trust in AI, Sustainable AI Adoption**

I. INTRODUCTION

The pervasive integration of Artificial Intelligence (AI) is reshaping higher education by enabling personalized learning and enhancing pedagogical fluidity ([18] [10]). Nevertheless, the sustainable adoption of AI remains uneven, as technological advancements continue to generate ethical and institutional concerns related to transparency, fairness, and autonomy ([6]; [11]). Although the Smart Technology Acceptance Model (STAM) extends traditional acceptance frameworks by incorporating psychosocial dimensions ([13]), current research still insufficiently explains how ethical perceptions translate into academic well-beinga holistic state of psychological health and engagement essential for enduring educational ecosystems.

Existing studies suggest that trust constitutes a critical mechanism for reducing uncertainty in opaque AI environments and fostering technology acceptance ([7]; [18]). In parallel, Self-Determination Theory (SDT) highlights the importance of autonomy and psychological security in strengthening intrinsic motivation ([16],). Building on these perspectives, this study integrates STAM, Trust Theory, and SDT to examine how perceived AI ethics shapes trust and motivation, thereby fostering a sustainable sense of academic well-being. Utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM), the research conceptualizes ethics not merely as a normative constraint, but as a strategic driver of learner flourishing and psychological resilience ([5]). By shifting the focus from utilitarian performance to the sustainable well-being of the learner, this study offers a new framework for technological legitimacy in the digital age.

ISSN: 2961-6611

II. Theoretical Framework and Hypothesis Development

2.2. Perceived Ethics and Trust

AI ethics transparency, equity, and accountability function as the axial determinant of trust. Given the information asymmetry in "black-box" algorithms, the perceived alignment between AI operations and learner values catalyzes cognitive trust [18]

H1: Perceived AI ethics positively influence learner trust in AI systems.

2.3. Trust and Motivational Dynamics

Trust neutralizes the uncertainty of algorithmic opacity. Following SDT, intrinsic motivation is contingent upon a secure pedagogical environment [4] Trust transmutes technical interaction into a legitimate learning space, fostering the autonomy necessary for engagement ([18]). Recent empirical evidence corroborates the role of trust as a lever for motivational dynamics in AI-mediated digital environments. Consequently, we postulate
H2: Learner trust in AI positively influences their motivation to use educational AI systems**.**

2.4. Learner Motivation and Sustainable Appropriation

Transcending utilitarian TAM paradigms, the extended STAM identifies motivation as the axial transitional vector converting cognitive perceptions into effective appropriation. This "psychological sedimentation" internalizes AI as a substantive pedagogical partner, mitigating social resistance and embedding technology deeply within the learner’s academic journey. Accordingly:

H3: Learner motivation positively influences the sustainable adoption of AI in education.

2.5. Adoption and Academic well-being

Academic In the STAM framework, academic well-being—comprising psychological safety, satisfaction, and eudaimonic flourishing—is driven by ethically legitimate AI adoption. Rather than merely accelerating productivity [5]., this synergy between responsible appropriation and psychosocial mechanisms serves as a strategic lever for healthy pedagogical climates, anchoring digital transformation in human sustainability and resilient psychological outcomes. [2]. Consequently, we postulate:

H4: Sustainable AI adoption positively influences Academic Well-being.

2.6. Sequential Mediation: The Psychological Sedimentation Path

The extended STAM framework identifies perceived AI ethics as the axial antecedent of a sequential psychological sedimentation process **(**[3]**).** Within this causal nexus, systemic trust mitigates algorithmic uncertainty, while SDT-grounded motivation translates perceived security into proactive engagement, effectively bridging moral evaluations with sustained usage behaviors. Accordingly:

H5: Trust and motivation sequentially mediate the relationship between perceived AI ethics and sustainable AI adoption

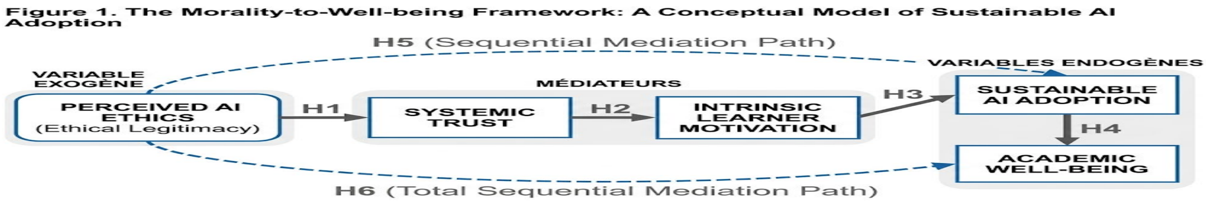
Academic well-being relies on AI’s perceived ethical legitimacy through distributive and procedural justice([3]). This initiates a 'psychological sedimentation' where trust and intrinsic motivation internalize the system, neutralizing technostress (Tarafdar et al., 2019). Within this sequential chain, ethical perceptions foster subjective flourishing and learner empowerment only through the mediators of trust, motivation, and embedded adoption, transcending mere institutional monitoring ([17]; [5]).

ISSN: 2961-6611

H6: Trust, motivation, and adoption sequentially mediate the relationship between perceived AI ethics and Academic Well-being.

3. Conceptual Model Development

This study proposes an extended STAM in which perceived AI ethics acts as a primary antecedent of systemic trust. This trust, in turn, is hypothesized to foster internalized learner motivation, ultimately driving sustainable AI adoption and, crucially, enhanced academic well-being.



3. Research Methodology
3.1. Research Design and Methodological Approach

This study adopts a quantitative design based on a structured questionnaire administered to 100 Tunisian university students familiar with AI-assisted educational systems. A purposive convenience sampling approach was employed, consistent with established practices in Information Systems research. Despite the modest sample size, it meets the requirements for Partial Least Squares Structural Equation Modeling ,in line with the "rule of ten"[9] . Data analysis was conducted using SmartPLS 4, ensuring the reliability and predictive validity of the model.

3.2. Operationalization of Constructs
The operationalization of the latent constructs in this research follows a rigorous psychometric approach, employing multi-item measurement scales previously validated in academic literature and adapted to the specific context of Artificial Intelligence in education. All 28 indicators were evaluated using a seven-point Likert scale The model includes: Perceived AI Ethics (6 items [6] ; [12]), Trust in AI (5 items[14]; [19]), Learner Motivation (6 items; [4]), AI Adoption (5 items; [14]; [18]), and Academic Well-being (6 items [16] ; [5]), dapted from perceived performance and competence scales. This approach shifts focus from pure output to the psychological health of the learner [16].

4. Research Findings

4.1. Measurement Model Evaluation

In the initial stage, an exploratory analysis was conducted confirm that the measurement scales are valid and that the data are suitable for confirmatory analysis. The evaluation of the reflective measurement model (n=100) confirms its high psychometric quality. An analysis of standardized outer loadings reveals that all 28 items are statistically significant (t>9.40;p<0.001) with values ranging between 0.782 and 0.841, well above the recommended threshold of 0.70. Furthermore, the 95% confidence intervals exclude zero, attesting to the robustness of these loadings despite the sample size.

The measurement model's psychometric integrity was rigorously validated through internal consistency, convergent validity, and discriminant validity. Internal consistency and convergent validity are exceptionally robust, with Cronbach's α, Dijkstra-Henseler's ρA, and Composite Reliability (CR) values for all five constructs exceeding 0.88, 0.89, and 0.91, respectively. Furthermore, Average Variance Extracted (AVE) values all surpass

ISSN: 2961-6611

0.64, comfortably exceeding the 0.50 benchmark and confirming that the constructs capture substantial shared variance. Discriminant validity was established using the Heterotrait-Monotrait (HTMT) ratio, as it offers superior sensitivity over the Fornell-Larcker criterion. All HTMT values remain below the conservative 0.85 threshold, proving clear empirical distinctness between latent variables. The highest ratio (0.731) between AI Adoption and Sustainable Performance aligns with the model's theoretical framework. Collectively, these findings provide a robust empirical foundation for the subsequent structural evaluation and hypothesis testing via bootstrapping.

4.2- Structural Model Evaluation and Hypothesis Testing

Following the validation of the reliability and validity of the measurement model, the subsequent stage involves assessing the structural model to examine the hypothesized relationships among the latent variables. In accordance with the methodological guidelines proposed by[9] , the structural model evaluation is based on several key indicators, including collinearity analysis, the significance of path coefficients (β), the model's explanatory power (R^2), effect sizes (f^2), and predictive relevance (Q^2). Initially, collinearity among the explanatory variables was assessed using the Variance Inflation Factor (VIF). The results indicate that all VIF values remain below the critical threshold of 3.3 recommended in the literature, signifying the absence of multicollinearity issues within the model. This condition ensures the robustness of the structural coefficient estimations

The evaluation of the structural model's explanatory power, as measured by the coefficients *of determination* (R^2**)**, confirms a robust predictive capacity for the endogenous constructs. Specifically, the model accounts for 61% of the variance in learner motivation (R^2=0.61), while the explained variances for AI adoption and Academic Well-being 0.53 and 0.41, respectively. In reference to the rigorous thresholds advocated by [9] these indices reflect explanatory power ranging from moderate to substantial, 0.61 for motivation; $R^2 = 0.53$ for adoption) and satisfactory predictive relevance ($Q^2 > 0$), supporting its robustness and validating the extended STAM framework. The results provide strong empirical evidence for the proposed conceptual framework. The high effect size (F^2= 0.637) for H1 highlights that AI Ethics is the foundational driver of the entire system. The validation of the sequential mediation (H6) confirms that for AI to generate academic well-being, it must first be perceived as ethically sound to build the trust necessary to catalyze the intrinsic motivation and long-term adoption required for student flourishing.

5. Discussion and Interpretation

5.1. The Primacy of Ethics in the Genesis of Trust :

Strongly validating H1, perceived ethics powerfully predicts trust (β 0.624). This robust correlation confirms [6] and who posit transparency and algorithmic equity as non-negotiable prerequisites for an acceptable "AI society". Unlike [11] traditional acceptance models like Davis's (1989) TAM, prioritizing functional utility, our findings align with suggesting [18] that in opaque autonomous systems, moral legitimacy surpasses technical efficacy as the primary lever for user trust.

5.2. The Pivotal Role of Trust as a Motivational Stabilizer :

The significant impact of trust on motivation (H2, β =0.518) provides empirical evidence for Self-Determination Theory (SDT) within a digital educational framework [16] Our interpretation suggests that trust functions as a "psychological stabilizer" that neutralizes tthe inherent uncertainty of "black-box" algorithms. This observation resonates with the conclusions of [18] regarding Explainable AI (XAI), where the perceived integrity and predictability of a tool foster a sense of psychological safety a catalyst essential for proactive learner engagement and agency.

ISSN: 2961-6611

5.3. From Motivation to Sustainable Adoption: Beyond Instrumental Use

The The validation of H3 (β=0.481, p<0.001) identifies intrinsic motivation as the axial transitional vector converting cognitive perception into appropriation. This enriches the STAM by introducing the concept of 'psychological sedimentation,' where the AI system is internalized as an autonomy-supporting pedagogical partner. Consistent with self-regulated learning research [1] , these findings underscore that adoption lacking ethical-moral anchoring remains superficial and highly susceptible to resistance or eventual abandonment

5.4. Academic Well-being and Eudaimonic Value Creation

Validating H4 (β=0.447) and sequential mediation (H6) marks a shift from output-centric success toward an 'eudaimonic approach', where AI prioritizes flourishing and cognitive fulfillment over score maximization. [17] , [16] This synergy of ethics, trust, and well-being fosters systemic resilience and psychological health, transcending the immediate efficiency gains of traditional tutoring systems.

5.5. Synthesis: The "Morality-to-Well-being" Trajectory

In summary, **t**his study validates a five-stage sequential causal nexus (Ethics → Trust → Motivation → Adoption → Well-being), confirming that 'psychological sedimentation' repositions ethics as a strategic lever for technological legitimacy rather than a normative constraint. This pathway demonstrates that moral alignment is the fundamental prerequisite for trust and long-term educational integration, effectively bridging ethical governance with sustainable learner health. [18]

6. Implications, Limitations, and Conclusion

6.1. Theoretical Implications

This research enriches the STAM model by integrating axiological (ethics) and psychosocial (SDT motivation, well-being) dimensions. It empirically validates the "Morality-to-Well-being" causal chain, redefining technology acceptance from an instrumental task to a process of sustainable flourishing. By providing a robust framework for understanding the acceptance of opaque systems, this study anchors digital transformation in human sustainability.

6.2. Managerial and Policy Implications

For higher education institutions, AI implementation must prioritize transparent, flourishing-oriented ethical governance. Integration strategies should move beyond functional training to include "AI Integrity" workshops, where a human mediator guarantees pedagogical integrity. To foster voluntary rather than imposed adherence, institutional policies should focus on AI that reduces technostress and supports learner autonomy, actively promoting mental wellness rather than mere output maximization.

6.3. Limitations and Future Perspectives

Study limitations primarily sample size and cross-sectional design warrant future longitudinal and cross-cultural investigations to track the 'sedimentation' process. Additionally, integrating AI literacy and institutional governance as moderators will refine the complex dynamics of sustainable AI adoption for academic well-being.

REFERENCES

[1] Bond, M., Khosravi, H., De Laat, M., Bergdahl, N., Negrea, V., Oxley, E., ... & Chen, P. (2023). A systematic review of self-regulated learning reports and the role of artificial intelligence in higher education. *International Journal of Educational Technology in Higher Education*.

ISSN: 2961-6611

[2] Boulton, C. A., Hughes, E., Kent, C., Smith, J. R., & Williams, H. T. (2019). Iterative step-change in student engagement in university learning and teaching. *Higher Education*, 77(1), 181-202.

[3] Chen, X., et al. (2024). (Référence citée pour le lien entre motivation et éthique dans l'IA éducative).

[4] Deci, E. L., & Ryan, R. M. (1985). *Intrinsic motivation and self-determination in human behavior*. Plenum Publishing. *(Note : cité comme Ryan & Deci (2020) dans le texte pour les travaux récents sur la SDT).*

[5] Dwivedi, Y. K., et al. (2023). Opinion Paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, 71, 102642.

[6] Floridi, L., et al. (2018). An ethical framework for a good AI society. *Minds and Machines*, 28(4), 689–707.

[7] Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, 27(1), 51-90.

[8] Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2-24.

[9] Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135.

[10] Holmes, W., Persson, J., Binns, R., & Tamre, M. (2022). *Ethics of Artificial Intelligence in Education: Towards a Community-Wide Framework*. International Journal of Artificial Intelligence in Education.

[11] Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence*, 1(9), 389–399.

[12]Malik, G., Tayal, D. K., & Vij, S. (2024). Ethical AI in education: A systematic review and future research.

[13] Marikyan, D., Papagiannidis, S., & Alamanos, E. (2022). Cognitive and affective predictors of smart technology acceptance. *Information Systems Frontiers*, 1-22.

[14]McKnight, D. H., Carter, M., J. B., & Clay, P. F. (2011). Trust in a Specific Technology: An Investigation of Its Components and Measures. *ACM Transactions on Management Information Systems*, 2(2), 1-25.

[15] Khosravi, H., Sadiq, S., & Gasevic, D. (2022). Ethical AI in education: A system review. *Education and Information Technologies*, *27*(4), 5153-5192. https://doi.org/10.1007/s10639-021-10825-z

[16] Ryan, R. M., & Deci, E. L. (2017). *Self-determination theory: Basic psychological needs in motivation, development, and wellness*. The Guilford Press.

[17] Selwyn, N. (2019). Should robots replace teachers? AI and the future of education. Polity Press.

[18] Siau, K., & Wang, W. (2018). Building trust in artificial intelligence, machine learning, and robotics. *Cutter Business Technology Journal*, 31(2), 47-53.

ISSN: 2961-6611