The 4th International Conference on Education Innovation and Social Science, August 2025
ISSN (Online): 2961-9602

NAVIGATING EMOTIONAL DYNAMICS IN AI ADOPTION: INTEGRATING GRIEF CYCLE WITH TAM IN THE CONTEXT OF CHATGPT USE IN INDONESIAN PUBLIC R&D INSTITUTIONS AND HIGHER EDUCATION

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Keyword

ChatGPT, Grief Cycle, Technology Acceptance Model, AI Ethics

Abstract

This study integrates the Grief Cycle with the Technology Acceptance Model (TAM) to explore the emotional dynamics of adopting ChatGPT, a deep learning-based technology, at Indonesia's National Research and Innovation Agency (BRIN), with implications for enhancing personalized learning in higher education. Synthesizing data from three secondary studies, quantitative TAM analysis, qualitative topic modeling from a 2023 survey, and Grief Cycle analysis of BRIN's organizational changes (2016–2019), this research maps researchers' emotional responses, from denial to acceptance, toward AI adoption. Findings reveal that perceived usefulness drives adoption intent, but ethical concerns, such as risks of dependency and threats to scientific integrity, limit adoption rates. This framework provides novel insights into managing emotional barriers to disruptive technologies in Indonesia's public R&D context. By drawing parallels to higher education, it offers strategies to overcome faculty resistance to AI, supporting personalized learning through adaptive tools like virtual tutors. Policy recommendations, including ethics training and transparency guidelines, promote sustainable and responsible AI adoption in R&D and higher education.

INTRODUCTION

Advances in artificial intelligence (AI), particularly deep learning-based technologies such as ChatGPT, have transformed various sectors, including research and development (R&D) and education, by introducing innovative personalization approaches (OpenAI, 2023; Grimaldi & Ehrler, 2023). Large language models, such as GPT-4, enable the automation of complex tasks, such as literature synthesis, data analysis, and hypothesis generation, with high efficiency and accuracy (Brown et al., 2020). In the R&D sector, AI is used to accelerate scientific innovation, support data-driven decision-making, and personalize research processes, such as summarizing journals or analyzing large datasets (Budiansyah et al., 2024; Lund & Wang, 2023). At the National Research and Innovation Agency (BRIN), for example, ChatGPT has been utilized to improve research efficiency and cross-disciplinary collaboration, despite facing resistance due to ethical concerns, such as the risk of dependency and threats to scientific integrity (Budiansyah et al., 2024). In the education sector, AI has revolutionized learning by providing customized learning materials, adaptive questions, and interactive virtual tutors, which have increased student engagement by up to 30% in digital environments (Zhai et al., 2021; Holmes et al., 2022).

However, the adoption of AI in both sectors is often hindered by emotional and organizational resistance. At BRIN, a study on organizational change from 2016 to 2019 showed that researchers experienced emotional responses that can be explained through the Grief Cycle—denial, anger, bargaining, depression, and acceptance—with low levels of readiness for change, at 3.82 in 2016 and 4.12 in 2019 (Romadona & Setiawan, 2021). Similar resistance is seen in the adoption of ChatGPT, where young researchers are concerned about technological dependence, while senior researchers are more focused on efficiency (Budiansyah et al., 2024). In education, educators face similar challenges, such as fears of plagiarism, algorithmic bias, and reduced human interaction, with 62% of global educators expressing concerns that AI could weaken students' critical thinking skills (UNESCO, 2023; Selwyn, 2022).

The parallels between the adoption of AI in R&D and digital education are highly relevant for understanding digital transformation holistically. In R&D, ChatGPT personalizes the research process, such as providing relevant literature recommendations, similar to how AI in education tailors learning content based on student needs (Chen et al., 2023; Holmes et al., 2022). Initial resistance at BRIN, for example, due to concerns about scientific integrity, reflects educators' fears that AI could encourage plagiarism or reduce student creativity (Tlili et al., 2023). Frustration with the complexity of AI in R&D parallels educators' complaints about the lack of training to integrate technology in the classroom (Selwyn, 2022). Negotiation occurs when researchers selectively use ChatGPT for efficiency, similar to educators adopting AI for automated assessment or task recommendations (Zhai et al., 2021). Depression arises when changes occur too quickly, whether in R&D due to restructuring or in schools due to AI-based curricula (Romadona & Setiawan, 2021; UNESCO, 2023). Acceptance occurs when the benefits of AI are recognized, such as efficiency in R&D or increased student engagement in education (Budiansyah et al., 2024; Chen et al., 2023). AI ethics training is key in both sectors to reduce resistance and promote responsible adoption (Friedrich & Wüstenhagen, 2015; Tlili et al., 2023).

This topic is important because it combines the Grief Cycle, a psychological model rarely used for technology adoption, with the Technology Acceptance Model (TAM) to understand the emotional dynamics of digital transformation (Kübler-Ross, 1969; Davis, 1989). This study is intriguing because it offers a new perspective on how emotions influence the acceptance of deep learning technologies like ChatGPT, drawing insights from the context of developing countries like Indonesia, where technological infrastructure and organizational culture complicate AI adoption (Budiansyah et al., 2024; UNESCO, 2023). Focusing on BRIN, this research provides relevant lessons for digital education, particularly in supporting personalized learning in the era of deep learning.

This paper will develop a conceptual framework integrating the Grief Cycle with TAM to analyze ChatGPT adoption at BRIN, based on secondary data from three studies: quantitative analysis using TAM (2023), qualitative analysis through topic modeling (2023), and organizational change analysis using the Grief Cycle (2016–2019). This paper will map the phases of the Grief Cycle to TAM factors and qualitative themes, such as efficiency and ethical concerns, to explain resistance and acceptance of AI. Implications for digital education will be explored, with policy recommendations for managing AI resistance in personalized learning. This study aims to answer the following questions:

1. How do the phases of the Grief Cycle (denial, anger, bargaining, depression, acceptance) influence the adoption of ChatGPT in Indonesian public R&D institutions?
2. How do ethical concerns moderate the relationship between perceived usefulness and adoption intention within the TAM framework?

Analytical Framework

This framework integrates the Grief Cycle (Kübler-Ross, 1969) with the Technology Acceptance Model (TAM) (Davis, 1989) to explain ChatGPT adoption in R&D. The Grief Cycle consists of five phases:

- Denial: Denying the reality of change.
- Anger: Frustration when resistance fails.
- Bargaining: Seeking ways to accept change.

- Depression: Loss of motivation due to inability to accept.
- Acceptance: Accepting the new reality.

At BRIN, the Grief Cycle is used to analyze responses to organizational change (Romadona & Setiawan, 2021). We adapted it for AI technology adoption, where researchers experience similar emotions toward ChatGPT.

TAM explains technology adoption through perceived usefulness (PU), perceived ease of use (PEU), and behavioral intention (BI) (Davis, 1989). BRIN data show PU as the primary predictor of BI ($\beta = 0.399$, $p < .001$), but PEU is not significant, with ethical concerns weakening adoption (Setiawan, 2025). Topic modeling analysis revealed themes such as efficiency, dependency, and methodological advancement, reflecting the duality of AI's benefits and risks (Budiansyah et al., 2024). This framework maps these themes to the Grief Cycle phases, as shown in Table 1, with parallels to digital education.

Table 1: Comparation of Grief Cycle Phase, Topic Modeling Theme, dan Result of TAM

Grief Cycle Phase	Topic Modeling Theme	Result of TAM	Educational Implications
Denial	Dependability and Scientific Integrity	R^2 BI low (14.6%) due to ethical concerns	Teachers reject AI due to plagiarism risks
Anger	Ethical Considerations	PEU insignificant ($\beta = -0.081$)	Teacher frustration with AI complexity
Bargaining	Decision Support, Methodology Advances	PU significant ($\beta = 0.399$)	Teachers negotiate to use AI ethically
Depression	-	BI→ASU weak ($\beta = 0.122$, $R^2 = 1.5\%$)	Teacher demotivation due to changes in the AI curriculum
Acceptance	Efficiency, Collaboration	PU high ($\beta = 0.399$)	Teachers embrace AI for personalized learning

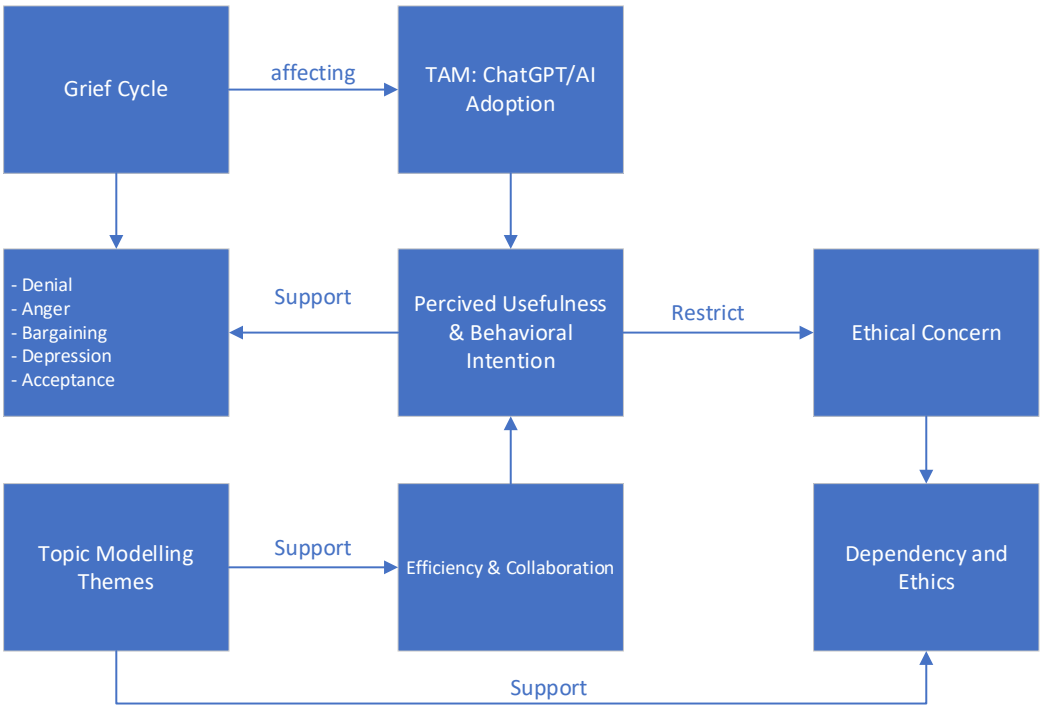

Figure 1: Conceptual Framework Grief Cycle in AI (ChatGPT) Adoption.

METHOD

This study uses a desk research approach, synthesizing secondary data from three BRIN studies:

1. Quantitative Study (SEM/TAM): An online survey of 280 BRIN researchers (May–August 2023) using TAM to measure PU, PEU, BI, and actual system use (ASU) through a 5-point Likert scale. SEM analysis with lavaan software in R showed significant PU ($\beta = 0.399$, $p < .001$), but not PEU ($\beta = -0.081$, $p = 0.186$), with ethical concerns as a moderator (R^2 BI = 14.6%) (Setiawan, 2025).
2. Qualitative Study (Topic Modeling): Qualitative analysis of 205 open-ended responses using Latent Dirichlet Allocation (LDA) and Principal Component Analysis (PCA) yielded seven themes: efficiency, ethics, creativity, decision support, collaboration, dependency, and methodological advancement (Budiansyah et al., 2024).
3. Organizational Change Study (Grief Cycle): Qualitative analysis of organizational change at BRIN (2016–2019) using interviews, observations, and documents mapped researchers' emotional responses to the Grief Cycle phases, with low readiness for change (3.82 in 2016, 4.12 in 2019) (Romadona & Setiawan, 2021).

Research 1 and 2 are part of a single study conducted from May to August 2023 at BRIN. For research number 3, the results are from two studies conducted in 2016 and 2019.
The analysis was conducted by mapping the Grief Cycle phases to topic modeling themes and SEM results through a comparative table (Table 1) and framework diagram (Figure 1). The 2023 survey dataset was used for both quantitative and qualitative studies, but with different analytical focuses.

A synthesis analysis of the three studies was conducted: quantitative analysis using TAM (Setiawan, 2025), qualitative analysis through topic modeling (Budiansyah et al., 2024), and organizational change analysis using the Grief Cycle (Romadona & Setiawan, 2021) was conducted through a qualitative synthesis approach that integrates empirical and theoretical findings to build a conceptual framework. Quantitative data from the TAM study, such as perceived usefulness ($\beta = 0.399$, $p < .001$) and the low R^2 of behavioral intention (14.6%), were linked to qualitative themes from topic modeling (efficiency, dependency, ethics) and phases of the Grief Cycle (denial to acceptance) to map the emotional dynamics of ChatGPT adoption at BRIN. This process involves thematic triangulation, where findings from the three studies are compared to identify consistent patterns, such as how ethical concerns reinforce denial, while efficiency supports acceptance (Friedrich & Wüstenhagen, 2015; Tlili et al., 2023). Thus, this synthesis enables the construction of a coherent framework, which is then analyzed to draw implications for education.

Educational implications are analyzed through an analogy with teacher resistance to AI, where researchers' emotional responses at BRIN to ChatGPT adoption are mapped to similar challenges faced by educators in higher education and schools. This analogy is based on literature showing that resistance to AI technology in education often involves ethical concerns, such as plagiarism, algorithmic bias, and student dependency, which parallel issues of dependency and scientific integrity in R&D (Tlili et al., 2023; Selwyn, 2022). For example, the denial phase in the Grief Cycle at BRIN, caused by fear of losing research autonomy, is similar to teachers' resistance to AI due to concerns about reducing student creativity or academic integrity (UNESCO, 2023; Holmes et al., 2022). This analysis uses a qualitative synthesis of educational studies highlighting how AI ethics training can reduce resistance, thereby supporting personalized learning through deep learning technologies such as ChatGPT (Chen et al., 2023; Zhai et al., 2021). Thus, the educational implications are not merely analogical but also provide practical recommendations, such as the development of Grief Cycle-based training policies for educators, based on empirical evidence from similar contexts (Friedrich & Wüstenhagen, 2015).

RESULTS AND DISCUSSION

This framework integrates the Grief Cycle, Technology Acceptance Model (TAM), and themes from topic modeling to explain the dynamics of ChatGPT adoption at the National Research and Innovation Agency (BRIN), focusing on how researchers' emotional responses influence the adoption process of deep learning-based AI technology. During the rejection phase, themes of dependency and scientific integrity reflect researchers' initial resistance to ChatGPT, driven by ethical concerns such as the risk of over-reliance on AI, which could threaten the

authenticity of research (Budiansyah et al., 2024; Setiawan, 2025). This aligns with the low R^2 value for behavioral intention (BI) of 14.6%, indicating that external factors such as ethics weaken overall adoption intentions (Setiawan, 2025). In a broader context, this resistance is similar to the initial response to organizational changes at BRIN in 2018, where researchers rejected restructuring because it was considered too drastic (Romadona & Setiawan, 2021; Friedrich & Wüstenhagen, 2015). Other studies add that such resistance often emerges in knowledge-intensive organizations when new technologies are perceived as a threat to individual autonomy (Jobin et al., 2019).

Furthermore, the anger phase is reflected in the theme of ethical considerations, where researchers feel frustrated by the complexity of AI, including issues of data privacy and algorithmic bias that can influence research outcomes (Budiansyah et al., 2024). This frustration aligns with the insignificant perceived ease of use (PEU) value (β = -0.081), indicating that ease of use is insufficient to overcome emotional barriers (Setiawan, 2025). Parallel to the anger toward organizational changes at BRIN, such as the 2018 demonstrations opposing structural changes (Romadona & Setiawan, 2021), this phase is also supported by literature highlighting how disruptive technological changes often trigger negative emotional reactions, especially in academic environments where traditional values such as scientific integrity are at stake (Selwyn, 2022; Lund & Wang, 2023). These concerns are further reinforced by findings that anger can reduce adoption motivation, as seen in the low correlation between PEU and BI (Davis, 1989).

During the negotiation phase, themes of decision support and methodological advancement indicate researchers' efforts to use AI ethically, such as integrating ChatGPT for specific tasks like literature synthesis without compromising integrity (Budiansyah et al., 2024). These efforts are supported by a significant perceived usefulness (PU) value (β = 0.399), indicating that researchers are beginning to recognize the benefits of technology in enhancing research efficiency (Setiawan, 2025). This negotiation is similar to the adaptation process during organizational change at BRIN, where researchers negotiate to adjust their workload to new targets (Romadona & Setiawan, 2021). Additional literature emphasizes that the negotiation phase often involves ethical compromises, where users begin to establish internal policies to maximize the benefits of AI while minimizing risks (Jobin et al., 2019; Tlili et al., 2023). This reinforces the role of PU as a bridge toward more mature adoption, as found in studies of technology adoption in scientific organizations (Lund & Wang, 2023).

The depression phase is reflected in the weak relationship between behavioral intention (BI) and actual system usage (ASU) (β = 0.122, R^2 = 1.5%), indicating researchers' demotivation due to their inability to fully accept change (Setiawan, 2025). This demotivation aligns with experiences during BRIN's restructuring, where researchers felt they had lost initiative and were only working routinely (Romadona & Setiawan, 2021). Another study adds that depression in the context of technology adoption is often caused by perceptions of ethical failure, leading to decreased productivity (Friedrich & Wüstenhagen, 2015; Selwyn, 2022). This phase becomes a critical point, where without interventions such as training, AI adoption risks complete failure (Davis, 1989).

Finally, the acceptance phase is reflected in the themes of efficiency and collaboration, which are consistent with high PU values (β = 0.399), especially among senior researchers who see the benefits of AI in improving research output (Budiansyah et al., 2024). This acceptance is similar to the final stage of organizational change at BRIN in 2020, where researchers began to accept the new reality and continue their careers (Romadona & Setiawan, 2021). The literature supports that acceptance often occurs when the benefits of technology outweigh the risks, such as improved efficiency in scientific collaboration (Lund & Wang, 2023; Jobin et al., 2019). This integration overall shows that the Grief Cycle not only explains resistance but also the path to successful adoption, with ethics as the key factor moderating the entire process (Tlili et al., 2023; Friedrich & Wüstenhagen, 2015).

This integration as a whole shows that the Grief Cycle not only explains resistance but also the path to successful adoption, with ethics as a key factor moderating the entire process (Tlili et al., 2023; Friedrich & Wüstenhagen, 2015). The application of this framework in the world of education, particularly in higher education, offers significant practical implications for managing

the adoption of deep learning-based AI technologies such as ChatGPT. In higher education, where faculty and students increasingly rely on AI for personalized learning, such as course material recommendations, literature synthesis, or task data analysis, the Grief Cycle framework can be used to understand and reduce emotional resistance (Chen et al., 2023; Holmes et al., 2022). For example, during the denial phase, faculty members may reject ChatGPT due to concerns about plagiarism or the loss of academic integrity, similar to the concerns of researchers at BRIN about technological dependence; the implication is the need for university policies emphasizing ethical guidelines for AI use to prevent initial rejection (Selwyn, 2022). In the anger and depression phase, faculty frustration with AI complexity can lead to demotivation, which can be addressed through Grief Cycle-based training, such as workshops that facilitate ethical negotiations for using AI as an aid, not a replacement (UNESCO, 2023). Finally, in the acceptance phase, this framework supports the integration of AI to enhance personalized learning in higher education, such as the use of ChatGPT for adaptive virtual tutors, which can increase student engagement by up to 30% (Zhai et al., 2021). The overall implication is that higher education institutions can adopt an approach similar to BRIN's, combining TAM with the Grief Cycle to design holistic training programs, ensuring sustainable and ethical AI adoption in the digital age (Lund & Wang, 2023).

This framework makes a significant theoretical contribution by expanding the Technology Acceptance Model (TAM) through the integration of the Grief Cycle as an emotional moderator, which is rarely applied in AI technology adoption literature (Davis, 1989; Kübler-Ross, 1969). Specifically, this framework explains why AI adoption, such as ChatGPT, remains low despite high perceived usefulness (PU) ($\beta = 0.399$, $p < .001$), due to ethical barriers and the depression phase in the Grief Cycle, which weaken behavioral intention (BI) to an R^2 of only 14.6% (Setiawan, 2025). This approach adds a psychological dimension to AI adoption literature, where traditional models like TAM often overlook emotional factors such as frustration or demotivation, which have proven crucial in knowledge-intensive organizational contexts like BRIN (Friedrich & Wüstenhagen, 2015; Budiansyah et al., 2024). Additionally, this framework enriches our understanding of how ethical concerns such as dependency risks and scientific integrity interact with the Grief Cycle phase to moderate the entire adoption process, thereby filling a gap in previous studies that have focused more on technological aspects than emotional ones (Jobin et al., 2019; Lund & Wang, 2023). Thus, this contribution not only extends TAM to the realm of generative AI in developing countries like Indonesia but also paves the way for interdisciplinary research combining organizational psychology with information technology, as recommended in recent literature on digital transformation (Selwyn, 2022; Tlili et al., 2023). Finally, this framework offers a new perspective for understanding the adoption of disruptive technology, where emotions are not only barriers but also catalysts for sustainable innovation.

The practical implications of this framework are particularly relevant for the R&D and education sectors, where the adoption of AI such as ChatGPT can be managed through strategies based on the Grief Cycle and TAM. In R&D, such as at BRIN, AI ethics training can be designed to reduce initial resistance and anger, for example, through modules that discuss the risks of technological dependence while emphasizing the benefits of efficiency, thereby helping researchers move through the negotiation phase more quickly (Budiansyah et al., 2024; Setiawan, 2025). Additionally, transparency policies, such as AI usage guidelines requiring disclosure of automatically generated content, can support full acceptance, prevent organizational depression, and enhance cross-team collaboration (Romadona & Setiawan, 2021; Jobin et al., 2019). In the education sector, particularly higher education, this framework suggests Grief Cycle-based training for teachers or lecturers to address resistance to AI, where lecturers can be guided to recognize their anger phase toward the complexity of technology and transition to ethical negotiation through interactive workshops (Tlili et al., 2023; Selwyn, 2022). Ethical guidelines for using ChatGPT in personalized learning, such as recommending student assignments or synthesizing lecture materials, can be applied to ensure academic integrity, thereby encouraging the acceptance of technology as an aid rather than a replacement (Chen et al., 2023; Holmes et al., 2022). Overall, these implications encourage institutions to integrate emotional training with technology policies, not only to enhance AI adoption in R&D and education but also to create more

adaptive and sustainable work and learning environments in the digital age (UNESCO, 2023; Lund & Wang, 2023).

Limitations

- The dominance of senior researchers (36.59% born between 1981 and 1990) may exaggerate PU (Budiansyah et al., 2024).
- Findings specific to BRIN require testing in other contexts (Romadona & Setiawan, 2021).

CONCLUSION

This study integrates the Grief Cycle with the Technology Acceptance Model (TAM) to explore the emotional dynamics of adopting ChatGPT, a deep learning-based technology, at Indonesia's National Research and Innovation Agency (BRIN). By synthesizing data from three secondary studies: quantitative analysis using TAM, qualitative topic modeling from a 2023 survey, and Grief Cycle analysis of BRIN's organizational changes from 2016 to 2019, this research maps researchers' emotional responses, from denial to acceptance, toward AI adoption. Perceived usefulness emerges as a primary driver of adoption intent, yet ethical concerns, such as risks of dependency and threats to scientific integrity, significantly limit adoption rates. Initial denial and anger, driven by fears of losing research autonomy, mirror challenges in higher education, where faculty resist AI due to concerns about plagiarism and technological complexity. The framework reveals that negotiation and acceptance phases, supported by efficiency and collaboration benefits, pave the way for successful adoption. In BRIN, researchers' early resistance, rooted in ethical dilemmas, transitions to selective use of ChatGPT for tasks like literature synthesis, reflecting a pragmatic approach to balancing benefits and risks. This dynamic parallels higher education, where faculty negotiate AI use for personalized learning tools, such as adaptive virtual tutors and tailored course materials, to enhance student engagement. The framework uniquely bridges emotional dynamics with deep learning technologies, offering novel insights into managing resistance in Indonesia's public R&D context and beyond.

In higher education, this framework provides actionable strategies to overcome faculty resistance, enhancing personalized learning. For instance, ethics-focused training can address early denial by clarifying AI's role as a supportive tool, while transparency guidelines build trust to mitigate anger and depression phases. These strategies enable universities to leverage ChatGPT for adaptive learning systems, fostering student-centered education. Similarly, in R&D, holistic programs combining emotional and technical training can accelerate AI adoption, ensuring sustainable innovation. With this framework provides actionable strategies for managing AI resistance in higher education, enhancing personalized learning through adaptive technologies

Despite its contributions, the study faces limitations. The reliance on secondary data restricts real-time insights into emotional dynamics, and the BRIN-specific context limits generalizability to other R&D or educational settings. The dominance of senior researchers in the 2023 survey may overemphasize perceived usefulness, potentially skewing findings. Future research should pursue primary studies in educational settings, particularly universities, using longitudinal approaches to track emotional changes over time. Incorporating real-time AI usage data could further refine the framework, ensuring its applicability to diverse contexts. By addressing these gaps, the framework can support inclusive and ethical AI adoption, revolutionizing both R&D and higher education in the era of deep learning.

ACKNOWLEDGEMENT

Data was obtained from LIPI research conducted between 2016 and 2019 and BRIN research conducted in 2023. AI was used to process the data (Grok, Deepseek, and ChatGPT) and to translate it into English (DeepL).

REFERENCES

Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., ... & Amodei, D. (2020). Language models are few-shot learners. *Advances in Neural Information Processing Systems*, *33*, 1877–1901.

Budiansyah, A., Alamsyah, P., Isnasari, Y., Asmara, I. J., Setiawan, S., & Romadona, M. R. (2024). Unraveling Indonesian public R&D institutions' perspectives on ChatGPT: An analytical approach to decoding open-ended surveys through topic modeling. *Journal of STI Policy and Management*, *9*(1), 15–32. https://doi.org/10.14203/STIPM.2024.386

Chen, X., Zou, D., Xie, H., & Wang, F. L. (2023). AI-based personalized learning: A systematic review of opportunities and challenges. *Educational Technology & Society*, *26*(2), 45–60.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Friedrich, P., & Wüstenhagen, R. (2015). The emotional dynamics of organizational change. *Journal of Change Management*, *15*(3), 220–240.

Grimaldi, G., & Ehrler, B. (2023). AI in scientific production: Opportunities and challenges. *Journal of Artificial Intelligence Research*, *76*, 123–145.

Holmes, W., Bialik, M., & Fadel, C. (2022). *Artificial intelligence in education: Promises and implications for teaching and learning*. OECD Publishing.

Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence*, *1*(9), 389–399. https://doi.org/10.1038/s42256-019-0088-2

Kübler-Ross, E. (1969). *On death and dying*. Macmillan.

Lund, B. D., & Wang, T. (2023). Chatting about ChatGPT: How may AI and GPT impact academia and libraries? *Library Hi Tech News*, *40*(3), 26–29. https://doi.org/10.1108/LHTN-01-2023-0009

OpenAI. (2023). *ChatGPT: A generative AI model for conversational tasks*. https://openai.com/research/chatgpt

Romadona, M. R., & Setiawan, S. (2021). Researchers' view on R&D organizational change using the grief cycle. *Journal of STI Policy and Management*, *6*(2), 157–171. https://doi.org/10.14203/STIPM.2021.313

Selwyn, N. (2022). The future of AI and education: Some cautionary notes. *European Journal of Education*, *57*(4), 620–631. https://doi.org/10.1111/ejed.12532

Setiawan, S. (2025). *Structural equation modeling of ChatGPT adoption in Indonesian public R&D institutions* [Unpublished manuscript].

Tlili, A., et al. (2023). What if the devil is in the details? A case study of ChatGPT in education. *Computers & Education*, *200*, 104–120.

UNESCO. (2023). *Artificial intelligence in education: Challenges and opportunities for sustainable development*. UNESCO Publishing.

Zhai, X., Chu, X., Chai, C. S., Jong, M. S. Y., Istenic, A., Spector, M., ... & Li, Y. (2021). A review of artificial intelligence (AI) in education from 2010 to 2020. *Complexity*, *2021*, Article 8812542. https://doi.org/10.1155/2021/8812542