

Realizing Adaptive Learning with Living Intelligence: The Role of AI, Biotechnology, and Smart Sensors in Education

Nia Mariyani¹, Do Intan Putri Anum², Rista Adhani Restiawati³, Harun Fitrawan⁴,
Dafyar Eliadi Hardian⁵

^{1,2,3,4,5} Universitas Islam Syekh Yusuf Tangerang, Indonesia

Abstract

The 21st century demands an education system that is adaptive, personalized, and responsive to the diversity of learners. The integration of Artificial Intelligence (AI), biotechnology, and smart sensors within the concept of living intelligence offers a transformative solution for realizing dynamic, evidence-based learning. AI utilizes real-time analytics, knowledge tracing, and multimodal modeling to map students' cognitive, affective, and contextual states, allowing for prescriptive and anticipatory learning interventions. Biotechnology and smart sensors enrich the system with biometric indicators such as heart rate variability (HRV), electrodermal activity (EDA), brain waves (EEG), and sleep quality, which are analyzed synchronously to monitor learning readiness in real time. This approach combines cognitive, affective, and physiological dimensions within a single, interconnected ecosystem. Challenges such as algorithmic bias, data privacy, concept drift, and infrastructure limitations are addressed through privacy-by-design governance, federated learning, and explainable AI. The role of the teacher shifts to that of a curator of meaning and a data-driven decision-maker, while the open learner model provides space for student participation. Through multidisciplinary collaboration and ethical policies, living intelligence becomes a new paradigm for education that is inclusive, sustainable, and capable of forming lifelong learners who are relevant to future demands.

Keywords : Artificial Intelligence; Biotechnology; Smart Sensors

Citation :

Prayoga et al. 2025. Analysis of the Effect of Food Prices, GDP, Inflation, and Exchange Rate on Poverty in 4 ASEAN Countries. *MSJ: Majority Science Journal*, 3(2), 135-146

Corresponding Author:

Nia Mariyani
2407010189@students.unis.ac.id



1. Introduction

21st-century education faces multidimensional challenges that require learning systems to be more adaptive than uniform, adapting to the diversity of student characteristics. This transformation is driven by massive technological developments, changes in social structures, and the demands of 21st-century competencies that prioritize personalized learning. Adaptive learning models offer the answer to accommodate individual needs, tailoring materials, methods, and learning rhythms to each student's capacity. However, the realization of this model cannot rely solely on educator intuition; it requires the support of intelligent, data-driven systems capable of responding quickly and accurately to changing student needs. Without technological innovation capable of managing this diversity, education risks experiencing an effectiveness gap, with some students being left behind due to a lack of learning differentiation. In this context, the role of Artificial Intelligence (AI), biotechnology, and smart sensors is crucial for creating a dynamic and responsive learning ecosystem (Judijanto et al., 2025).

AI's ability to process large-scale data in a short timeframe opens up opportunities for precise, adaptive learning. Through machine learning algorithms, AI can map learning patterns, identify academic obstacles, and recommend learning strategies tailored to students' cognitive profiles (Puspitawati et al., 2024). This process relies not only on exam or assignment data but also includes student interaction with the material, time spent working, and concentration levels. This allows teachers to focus their energy on fostering students' social-emotional skills, rather than solely relying on technical monitoring. AI integrated into education also fosters the concept of living intelligence, a system capable of learning from interactions and continuously improving its performance (Strielkowiaki et al., 2025; Bhardwaj et al., 2022). This concept makes learning more dynamic, where materials and methods can continuously adapt to students' development.

However, optimizing adaptive learning relies not only on cognitive data but also on understanding students' physiological and psychological states. This is where biotechnology and smart sensors play a vital role in collecting biometric information relevant to learning. Wearable devices and biometric sensors can monitor indicators such as heart rate, brain activity, stress levels, and even sleep quality. Integrating this biological data with AI allows for real-time adjustments in learning intensity and strategies based on students' physical and mental readiness. This approach not only maximizes learning effectiveness but also protects students' mental and physical health. This way, the learning process becomes more holistic, combining cognitive, affective, and physiological dimensions within a single, interconnected system (Allam et al., 2025; Kshirsagar, 2025).

Modern wearable technology makes it easier to collect such data without compromising user comfort. For example, sensors integrated into smart bracelets or head-mounted devices can transmit continuous data to learning platforms for real-time analysis. If the system detects decreased focus or increased stress levels, learning materials can be adjusted by slowing down the pace, changing methods, or inserting interactive breaks. This creates a constantly adaptive learning cycle, not just at the beginning of planning, but throughout the process. This approach can also prevent learning burnout, which often occurs due to a mismatch between academic demands and individual capacity. Thus, biotechnology and smart sensors not only enrich data but also act as a protective mechanism for students' learning health (Nasution et al., 2024).

Beyond the individual level, smart sensors can also provide significant benefits in collective classroom management. Data collected from all students allows for analysis of classroom dynamics, such as detecting patterns of collective fatigue or decreased learning engagement. This information can be used by teachers to implement strategic interventions, such as modifying schedules, changing teaching methods, or adding restorative physical activities (Strielkowski et al., 2025). These decisions are more objective because they are based on real-time data, rather than subjective observations that are prone to bias. With a feedback loop between technology and teachers, classroom management can be adaptive, efficient, and evidence-based. This concept strengthens the position of technology not as a

substitute for teachers, but as a collaborative partner in achieving inclusive and effective educational goals.

The concept of living intelligence, a combination of AI, biotechnology, and smart sensors, marks the birth of a continuously evolving learning paradigm. This system not only stores and processes data but also interprets, learns, and predicts future learning needs. The advantage of living intelligence lies in its ability to continuously adapt based on a combination of cognitive, emotional, and biological data (Bhardwaj et al., 2022). This continuous adaptation ensures that learning materials and methods remain relevant despite changes in student profiles or needs. Thus, learning is no longer reactive to problems but proactive in anticipating challenges. This makes living intelligence a strategic solution for maintaining educational relevance amidst rapid social and technological change.

Nevertheless, the implementation of living intelligence requires robust, ethically grounded multidisciplinary integration. Collaboration between information technology, biotechnology, sensory science, educational psychology, and pedagogy is necessary to ensure that the resulting system remains aligned with human values. Issues of privacy, data security, and potential technological dependency must be carefully managed through clear and transparent policies. Teachers and students also need technological literacy to optimally utilize the potential of living intelligence. With proper management, this technology can be a driver of educational inclusivity, not a source of new inequalities. This approach ensures that technological advancement is always accompanied by commensurate social responsibility.

The transformation towards adaptive learning based on living intelligence is ultimately a strategic agenda that goes beyond mere technology adoption. It is an effort to create an education system capable of responding to change at the same pace as the global environment (Sagdic et al., 2022). Successful implementation depends on the readiness of all stakeholders government, educational institutions, teachers, students, and the community to collaborate in building supportive infrastructure, policies, and a learning culture. With a clear vision and a well-thought-out strategy, the integration of AI, biotechnology, and smart sensors can become a key driver of the 21st-century educational revolution. Adaptive education will lay the foundation for the birth of a generation of lifelong learners who are resilient, creative, and relevant to future challenges. At this point, living intelligence is not just a technological concept, but a new paradigm for the sustainability of educational quality.

2. Method

This research uses a qualitative approach with a systematic literature review to explore the concept of living intelligence in adaptive learning and the integrative role of Artificial Intelligence (AI), biotechnology, and smart sensors in education. The qualitative approach was chosen because the research focuses on conceptual exploration, theoretical synthesis, and critical analysis of the findings of various scientific studies. Through this method, the researchers seek to identify recent developments, map research gaps, and formulate potential implementations of multidimensional data-based adaptive learning that are relevant to future educational needs.

The data sources used were credible scientific publications, including Scopus-indexed international journals, Sinta-accredited national journals, conference proceedings, academic books, and official reports from research institutions or global educational organizations such as UNESCO, the OECD, and the World Bank. The primary focus was on publications from the last five years (2020–2025) to ensure relevance to the latest technological developments, although older sources were still used if they had significant conceptual contributions. The literature search was conducted through major databases such as Scopus, Web of Science, IEEE Xplore, SpringerLink, ScienceDirect, and Google Scholar.

Data collection was conducted using a systematic literature review (SLR) procedure that includes keyword identification, initial selection, feasibility evaluation, and the application of strict inclusion and exclusion criteria. Keywords used included "adaptive learning," "living intelligence," "artificial intelligence in education," "biotechnology in learning," and "smart sensors education," including their Indonesian equivalents. Initial selection was based on titles and abstracts to eliminate irrelevant articles, followed by a thorough reading to ensure

suitability for the research focus. Inclusion criteria included peer-reviewed articles, relevant to the topic, having a clear methodology, and discussing the implementation or potential of related technologies. While exclusion criteria applied to non-scientific publications, product promotion articles, and articles lacking adequate data or analysis.

Data analysis was conducted using a thematic synthesis approach, beginning with a data extraction process that included the research objectives, methods, key findings, and implications of each source. The collected data were then categorized into key themes, such as the concept of living intelligence in learning, the role of AI in adaptive learning, the contribution of biotechnology in monitoring learning readiness, and the function of smart sensors in education. The next stage was a comparative analysis to identify similarities, differences, and development trends across various studies, which were then integrated through a comprehensive synthesis to build a coherent conceptual framework.

The validity of the findings was ensured through source triangulation, which involves comparing information from various sources and authors to ensure consistent interpretation. Additionally, peer debriefing with experts in educational technology and biotechnology was conducted to verify the accuracy of the analysis. This procedure ensures that the research results have a high level of reliability and credibility.

This research design aims to yield a scientific synthesis that illustrates the close relationship between AI, biotechnology, and smart sensors in shaping a living intelligence-based adaptive learning ecosystem. The research findings serve not only as a theoretical contribution but also as a basis for formulating strategic recommendations for developing educational policies and implementing inclusive, personalized, and sustainable learning practices in the digital age

3. Results and Discussion

Integration of Artificial Intelligence in Adaptive Learning Based on Living Intelligence

The integration of Artificial Intelligence (AI) into living intelligence-based adaptive learning can be understood as an algorithmic orchestration process that continuously updates learners' knowledge representations, learning contexts, and the quality of pedagogical interactions. Living intelligence refers to a "living" system because its model is co-evolutionary: adaptation parameters and policies are updated in real time as the system receives new signals, such as clicks, pauses, errors, reading speed, revision patterns, and affective indicators.

Conceptually, this system maps students' learning states, containing cognitive, affective, and contextual information, into pedagogical actions, such as question recommendations, feedback, or scaffolding. These actions are selected based on policies designed to maximize learning outcomes, as measured by increased conceptual mastery, knowledge retention, and reduced cognitive load (Sodikin, 2024). This approach allows the system to adapt within microseconds to students' current performance, while simultaneously establishing medium-term learning pathways.

The real-time data analysis capabilities of this system rely on a learning analytics pipeline that transforms event streams into meaningful temporal features. Knowledge tracking is performed using probabilistic techniques such as Bayesian Knowledge Tracing, Deep Knowledge Tracing, Neural Item Response Theory (Neural-IRT), or memory networks, which estimate the level of mastery of each concept and update it after each student interaction. These estimates are enriched with affective models, such as levels of engagement, confusion, or mind-wandering, identified through interaction rhythms, response time lags, and revision patterns. Thus, adaptation policies consider not only "what material has not been mastered" but also the student's "readiness" for a particular intervention. Detecting changes in error patterns due to new topics triggers model adjustments, ensuring that personalization remains relevant even if the curriculum or class characteristics change (Demartini et al., 2024).

Prediction of learning needs in living intelligence is done through two main channels:

1. Projected future mastery: Knowledge transition models predict the likelihood of a learner mastering a concept at a specific point in the future. This information allows the system to prescriptively schedule spaced practice and interleave material across concepts.
2. Intervention readiness estimation: Policy models, such as multi-armed bandit, contextual bandit, or reinforcement learning, balance exploration and exploitation to select interventions with the highest potential for improving learning outcomes, while minimizing saturation and cognitive load.

The combination of these two pathways produces recommendations that are anticipatory, not merely reactive. Automatic adjustments to the material are made using semantic representations of knowledge through knowledge graphs and document-item embeddings aligned with competency taxonomies. Large Language Models (LLMs) can be used to generate content variations, such as paraphrasing, adjusting difficulty levels, or constructing contextual analogies. However, this process is protected by retrieval-augmented generation, validity screening based on trusted sources, and verification of the difficulty level and discriminatory power of questions through item calibration. Thus, living intelligence determines not only “when” and “for whom” a material is provided, but also “which version” of the material is most effective for a particular learner profile.

The benefits of AI integration include accelerating personalization on a large class scale, increasing the efficiency of learning time through recommendations that reduce unproductive activities, and strengthening metacognitive skills through understandable diagnostic feedback (Gligorea et al., 2023). At the institutional level, mapping conceptual gaps facilitates remedial planning and evidence-based curriculum development. For learners, the learning experience becomes more aligned with their personal rhythms, from pacing to media preferences to the need for repetition, contributing to an increased sense of agency and sustained engagement.

However, the challenges faced are also significant. Bias and inequity can arise from historical data (e.g., sampling bias and labeling bias) as well as from model design (e.g., spurious correlations), potentially leading to unfair recommendations between groups. Transparency in decisions is often limited, especially when the models used are black-box, making pedagogical accountability difficult (Nisa et al., 2025). The risk of privacy breaches and data misuse requires strong governance regarding data collection, storage, processing, and sharing, including the implementation of data minimization, encryption, federated learning, and differential privacy. From a technical perspective, challenges such as cold-start issues (limited initial data), concept drift, and limited infrastructure in schools require robust and resource-efficient system design, for example through on-device distillation, quantization, and inference techniques.

Optimization strategies require an integrated socio-technical approach. At the model layer, ensembling various knowledge tracking techniques, policy models, and affective models, as well as weighting predictive uncertainty, can improve recommendation reliability. At the data layer, item curation with stable psychometric parameters, consistent annotation, and the addition of prerequisite information to the knowledge graph will improve the quality of learning signals. At the evaluation layer, controlled field tests, off-policy evaluations, and causal analysis are needed to ensure that improvements in system metrics actually impact learning outcomes, rather than simply correlational relationships.

The role of teachers remains crucial and irreplaceable; their role has shifted to that of designers of learning experiences and guardians of data ethics. Teachers play a key role in interpreting model outputs into understandable pedagogical language, for example, identifying “fraction misconception indicators” rather than simply displaying model coefficients, and then designing social-emotional interventions that cannot be automated. Living intelligence provides diagnostic dashboards and recommendations, but final decisions, particularly those concerning grades, motivation, and classroom relationships, still require the practical wisdom of teachers. Professional development programs focused on data literacy, model

interpretation, and AI-assisted activity design are prerequisites for preventing personalization from devolving into mere, rigid automation.

Students' learning experiences will be optimal if technical adaptations are accompanied by transparency and collaboration. An accessible open learner model that displays concept maps of what has and hasn't been mastered, the rationale for recommendations, and future achievement targets will encourage self-regulation and more internalized learning goals. A contestability mechanism allows students to correct system assumptions, for example, when errors stem from non-cognitive factors. Thus, living intelligence truly becomes a dynamic ecosystem that interacts and negotiates with its users, not simply a recommendation engine.

The Contribution of Biotechnology and Smart Sensors to Monitoring Student Learning Readiness

Biotechnology and smart sensors offer transformative opportunities in monitoring student learning readiness by utilizing biometric indicators that reflect physiological, affective, and physical conditions in real time. Learning readiness, previously measured subjectively, can now be operationalized through the collection of objective data such as heart rate variability (HRV), electrodermal activity (EDA), brain waves (EEG), and sleep quality obtained from actigraphy. HRV, specifically the RMSSD and SDNN parameters, have been shown to correlate with autonomic nervous system regulation and stress levels, while EDA, through its tonic (SCL) and phasic (SCR) components, maps the dynamics of arousal and attention. EEG, although often associated with laboratory research, can now be implemented through lightweight wearable devices such as headbands, with theta/beta ratio (TBR) and alpha activity as indicators of cognitive engagement. Sleep quality estimated from PPG or movement sensors is an important predictor of students' alertness and energy levels the following day (Wulandari et al., 2021).

The accuracy of these measurements is enhanced by a multimodal data fusion approach that synchronously combines PPG, EDA, EEG, and motion sensor signals. The technical steps include anti-artifact preprocessing to eliminate movement interference, short-time window feature extraction, normalization against a personal baseline, and feature fusion at both early and late stages before classification. State-space models and Kalman filters enable continuous latent state estimation, while machine learning algorithms such as Support Vector Machines or Random Forests predict conditions such as overload, underload, or optimal load. This inferred data serves as the basis for an adaptive learning system to automatically adjust cognitive load, rest duration, or material difficulty (Judijanto et al., 2025).

Within a closed-loop adaptive learning framework, detecting a significant decrease in HRV and increase in EDA can trigger interventions such as micro-breaks or breathing exercises to restore physiological homeostasis. Conversely, when EEG and EDA indicators indicate an underload condition leading to boredom, the system can increase the complexity of the material or change the learning stimulus to maintain engagement. Monitoring learning readiness applies not only intra-session but also inter-session, where daily sleep indices are used to plan short-term learning strategies, such as prioritizing retrieval practice on days with optimal readiness and reducing new material on days with low readiness.

While this technology holds promise, ethical and privacy challenges remain central. Biometric data is highly sensitive and potentially misused if not managed with strict governance. Data minimization principles should be upheld, with only relevant indicators collected and data stored encrypted. Distributed learning models such as federated learning can be used to train algorithms without transferring raw data, while differential privacy protects individual identities (Shen et al., 2022). Usage policies should limit the application of this technology to pedagogical purposes only, prohibit the use of data for disciplinary assessments, and provide opt-out rights for students and parents.

From a scientific validity perspective, meta-analyses indicate that physiological indicators such as HRV, EDA, and sleep quality are significantly associated with students' academic performance and well-being, although generalization across contexts requires specific calibration based on age, gender, and culture. Initial testing should be conducted on a small scale with a single-case or N-of-1 design to calibrate personal thresholds before mass

implementation. Data triangulation through a combination of physiological measures, self-reports, and behavioral indicators will enhance construct validity and minimize bias.

The technical feasibility of implementation also needs to consider the limitations of devices in the field, such as sensitivity to motion artifacts and signal quality variability. Device selection should be based on independent validation evidence and on-device processing capabilities to mitigate the risk of data leakage. Furthermore, a mechanism for regular data access audits accessible to authorized parties such as teachers and parents is needed to ensure transparency. Strategically, the application of biotechnology and smart sensors in education can create a more responsive and personalized learning ecosystem. By combining physiological monitoring and adaptive algorithms, learning can shift from a uniform approach to a learning experience that considers the dynamics of each individual's readiness. This aligns with the principles of precision education, which borrows concepts from precision medicine to optimize interventions based on a student's unique profile.

Moving forward, the research agenda should focus on developing explainable AI inference models to increase user trust, standardizing signal preprocessing protocols for school environments, and developing open benchmarks that link physiological data to long-term learning outcomes. With a sound scientific approach, rigorous governance, and stakeholder participation, the integration of biotechnology and smart sensors could be a milestone in building adaptive, ethical, and sustainable learning systems.

A Multidisciplinary Collaborative Model for the Implementation of Living Intelligence in Education

A multidisciplinary collaborative model for implementing living intelligence in education requires close synergy between information technology, biotechnology, sensory systems, educational psychology, and pedagogy, thus forming an adaptive, integrated, and sustainable learning ecosystem. This collaboration is not sufficient at the level of technical coordination alone; it must be realized through transdisciplinary co-design that combines a shared framework, aligned cross-disciplinary terminology, and decision-making protocols that prioritize the role of pedagogy as a direction-setter, while technology serves as an implementation enabler. Within this framework, the development of boundary objects such as learning journey maps, learning design patterns, and data architecture is key to aligning perceptions among stakeholders, while a cross-functional operating cadence enables classroom experiments, psychometric analysis, and AI model testing to run simultaneously in a measurable cycle (Siregar & Nurazizah, 2025).

Multidimensional data integration forms the technical foundation that ensures living intelligence can generate targeted pedagogical decisions. Data generated from LMS interactions, natural language feedback, IoT-based classroom sensors, wearables that record physiological parameters, and science laboratory devices need to be managed through an architecture that ensures semantic interoperability, for example with the xAPI or IMS Caliper standards connected in a student profile knowledge graph (Widarti et al., 2025). A lakehouse architecture for historical data is combined with real-time event streaming and edge computing that processes sensitive data locally, thereby reducing the risk of leakage. Furthermore, a multimodal fusion model combines Bayesian knowledge tracing-based knowledge estimation, cognitive load detection from interaction patterns, and physiological signal analysis using a Kalman filter. These are then connected to a policy engine to generate interventions such as material adjustments, micro-break scheduling, or referrals to counseling services, all with the principle of explainability and teacher involvement as the final decision-maker (Ritonga & Sofiyah, 2024).

The use of analytics and AI within this framework is only meaningful if anchored in sound learning theory, where educational psychology ensures the construct validity of the measured indicators, while pedagogy guides appropriate response strategies such as mastery learning, spaced practice, or metacognitive prompting (Amalia et al., 2025). Generative AI can enrich narrative feedback with language styles tailored to student profiles, but requires rubric-based oversight, guardrails to prevent bias and hallucinations, and model fairness audits using metrics such as equalized odds or predictive parity. Policy governance should be grounded in

the principles of privacy-by-design and inclusion-by-default, encompassing layered security through zero-trust architecture, end-to-end encryption, role-based access control, and clear data retention; while ensuring inclusivity through WCAG accessibility testing, multi-language support, offline-first for low-connectivity areas, and reasonable adjustments for students with special needs.

The government, educational institutions, and the community have complementary roles in ensuring the sustainability of this innovation (Nasir et al., 2023). The government establishes national interoperability standards, develops a regulatory sandbox, and provides sustainable funding schemes; educational institutions establish data stewardship units, train teachers in data literacy and AI ethics, and integrate the Plan–Do–Study–Act cycle for continuous evaluation; the community is engaged through participatory design, community data trusts, and public forums that monitor the transparency of impact reports. Social and ethical sustainability is reinforced through Green AI principles to reduce carbon footprints, right-to-repair policies to reduce e-waste, and subsidies for low-bandwidth devices and content to address the digital divide. Regular evaluations measure not only learning outcomes but also indicators of well-being, inclusion, perceptions of fairness, and ethical accountability. Thus, this multidisciplinary collaborative model forms a complete value cycle from learning theory, data integration, adaptive inference, to inclusive interventions—so that living intelligence technology in education is not only technically effective but also socially, ethically, and sustainably tested.

4. Conclusions and Suggestions

The integration of Artificial Intelligence (AI) into adaptive learning based on living intelligence, powered by biotechnology, smart sensors, and a multidisciplinary collaborative model, represents a systemic transformation from uniform education to dynamic, personalized, and evidence-based education. This system utilizes real-time analytics, knowledge tracing, and multimodal inference from physiological signals and learning behaviors to continuously map students' cognitive, affective, and contextual states. Adjustments to materials, learning rhythms, and pedagogical interventions are carried out prescriptively through adaptive policies that balance exploration and exploitation, while managing cognitive load and student engagement. The role of AI is not merely reactive but anticipatory, supported by large language models and knowledge graphs for the differentiation of relevant, valid, and calibrated content. The integration of biotechnology enables monitoring of learning readiness based on objective indicators such as HRV, EDA, EEG, and sleep quality, which are diffused multimodally to improve the accuracy of inferring learning conditions. The multidisciplinary collaborative model ensures that the development and implementation of this technology aligns with learning theory, pedagogical principles, and ethical data use. Challenges such as algorithmic bias, concept drift, data privacy, and infrastructure limitations are addressed through privacy-by-design governance, federated learning, explainable AI, and resource-efficient system design. Teachers act as curators of meaning, interpreters of analytical results, and final decision-makers on values, motivation, and socio-emotional interactions. Transparency through an open learner model and contestability mechanisms provides space for students to actively participate in the adaptation process. Ethical governance includes data charters, bias audits, and balanced performance indicators covering academic achievement, equity, well-being, and AI literacy. Governments, educational institutions, and communities collaborate to provide regulation, infrastructure, funding, and ongoing public oversight. Thus, living intelligence is not simply the integration of advanced technologies, but a responsive, accountable learning ecosystem oriented toward meaningful learning. The combination of technical adaptation, human participation, and strong governance makes it a transformative milestone for the future of education.

Bibliography

- Allam, H. M., Gyamfi, B., & AlOmar, B. (2025). Sustainable Innovation: Harnessing AI and Living Intelligence to Transform Higher Education. *Education Sciences*, 15(4), 398.
- Amalia, S., Adawiyah, S. R., Septilia, W., & Marinda, Z. (2025). Integrasi Kebutuhan Akademik dan Keterampilan Hidup di Sekolah Dasar. *Jurnal Multidisiplin Ilmu*, 1(1).
- Bhardwaj, A., Kishore, S., & Pandey, D. K. (2022). Artificial intelligence in biological sciences. *Life*, 12(9), 1430.
- Demartini, C. G., Sciascia, L., Bosso, A., & Manuri, F. (2024). Artificial intelligence bringing improvements to adaptive learning in education: A case study. *Sustainability*, 16(3), 1347.
- Gligorea, I., Cioca, M., Oancea, R., Gorski, A. T., Gorski, H., & Tudorache, P. (2023). Adaptive learning using artificial intelligence in e-learning: A literature review. *Education Sciences*, 13(12), 1216.
- Judijanto, L., Hartati, T., Apriyanto, A., Pamangin, W. W., & Haluti, F. (2025). *Pendidikan Abad 21.: Menyambut Transformasi Dunia Pendidikan di Era Society 5.0*. PT. Sonpedia Publishing Indonesia.
- Kshirsagar, K. P. (2025). The Role of Artificial Intelligence in Advancing Applied Life Sciences: An Introduction. *The Role of Artificial Intelligence in Advancing Applied Life Sciences*, 1-48.
- Nasir, M., Mahmudinata, A. A., Ulya, M., & Firdaus, F. A. (2023). Strategi pemberdayaan sekolah sebagai upaya peningkatan manajemen pendidikan. *Journal of International Multidisciplinary Research*, 1(2).
- Nasution, J. N., Putri, A. E., Lubis, Y., Siagian, R. T., & Umar, A. T. (2024). Membangun pendidikan 4.0: Peran vital teknologi dalam meningkatkan kualitas pembelajaran. *NUSRA: Jurnal Penelitian Dan Ilmu Pendidikan*, 5(3), 985-997.
- Nisa, S. F., Ginting, F. B., & Ananda, A. D. (2025). Kurikulum Pendidikan Agama Islam Adaptif untuk Menyongsong Era Artificial Intelligence. *Mesada: Journal of Innovative Research*, 2(1), 311-325.
- Puspitawati, R. P., Afnan, M. Z., Abrizal, H. P., Anjani, G. A. D. K., & Adisatria, B. (2024). Artificial Intelligence dalam Artikel Pendidikan Biologi pada Rentang Tahun 2003-2024. In *Seminar Nasional Inovasi Penelitian dan Pembelajaran Biologi* (Vol. 8, pp. 44-60).
- Ritonga, L. A., & Sofiyah, K. (2024). Tantangan dan Inovasi Dalam Pendidikan Matematika Melalui Pendekatan Multidisiplin Dapat Membangun Keterampilan Berpikir Kritis. *Calakan: Jurnal Sastra, Bahasa, dan Budaya*, 2(2), 88-92.
- Sagdic, K., Eş, I., Sitti, M., & Inci, F. (2022). Smart materials: rational design in biosystems via artificial intelligence. *Trends in biotechnology*, 40(8), 987-1003.
- Shen, S., Zhu, T., Wu, D., Wang, W., & Zhou, W. (2022). From distributed machine learning to federated learning: In the view of data privacy and security. *Concurrency and Computation: Practice and Experience*, 34(16), e6002.
- Siregar, R. D., & Nurazizah, N. (2025). Peran Pendekatan Multidisipliner Dalam Pengembangan Ilmu dan Teknologi. *Citizen: Jurnal Ilmiah Multidisiplin Indonesia*, 5(3), 879-885.
- Sodikin, S. (2024). Transformasi Pendidikan Agama Islam Melalui Artificial Intelligent (AI): Upaya Meningkatkan Kemampuan Berpikir Kritis Mahasiswa. *Academicus: Journal of Teaching and Learning*, 3(2), 78-89.
- Strielkowski, W., Grebennikova, V., Lisovskiy, A., Rakhimova, G., & Vasileva, T. (2025). AI-driven adaptive learning for sustainable educational transformation. *Sustainable Development*, 33(2), 1921-1947.

- Widarti, E., Efitra, E., Juansa, A., Adhy, D. R., Anwar, N., Prasetya, L. A., & Rianty, E. (2025). *Smart Life With Internet of Things (IoT): Optimalisasi & Pemanfaatan IoT untuk Kehidupan Modern*. PT. Star Digital Publishing, Yogyakarta-Indonesia.
- Wulandari, I. Y., Silalahi, L. M., Indroasyoko, N., Ema, E., & Muhtar, M. (2021). Studi literatur review: Integrasi kurikulum pembelajaran cerdas biosensor menggunakan teknologi internet of things. *Jurnal Tiarsie*, 18(3), 97-102.