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The Effects of Universal Design for Learning and AI-AT on the Engagement and Academic Outcomes of Students with Disabilities

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Abstract. Challenges to inclusive educational practice in Indonesia remain significant in addressing the responsive learning needs of students with special needs. The partial adaptive learning, the differing preparedness of educators, and their limited use of AI-based assistive technology reveal a mismatch between what is being done with respect to inclusivity goals. Specifically, it is our goal to empirically evaluate the validity and strength of UDL and AI-AT effectiveness and impact on student engagement and academic outcomes for students with disabilities. This study employed a quasi-experimental pretest–posttest design on students with disabilities in an inclusive elementary school in Central Java (purposive sampling; control n=69, experimental n=74). Data were collected through pretest–posttest tests, interaction observations, and AI-AT usage logs. Analysis was conducted using descriptive statistics and ANCOVA, followed by PLS-SEM to examine the relationship between UDL–engagement–academic outcomes and AI-AT moderation. Findings revealed that the combination of UDL, AI-AT, and Engagement as a single model can predict academic success for students with disabilities in an inclusive educational setting (R^2=0.830). The strongest predictor is AI-AT ($\beta = 5.67$, $p < 0.001$), followed by UDL, which shows significant predictive strength ($\beta = 3.27$, $p < 0.001$). UDL and AI-AT significantly contribute to learning involvement and academic outcomes in inclusive schools. The integration justifies the development of technology-enhanced inclusive pedagogical practices based on empirical evidence. The integration of UDL and AI into learning models practically has implications for active student engagement and forms the basis for measurement indices needed in inclusive learning assessments.

Keywords: AI; engagement; inclusive; outcomes; people with disabilities; UDL

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1. Introduction

Inclusive education for students with disabilities is crucial for equal access to learning, but challenges of teacher preparedness and the lack of adaptive pedagogy in developing countries like Indonesia demand the integration of Universal Design for Learning (UDL) with AI-based assistive technology (AI-AT) to improve engagement and academic achievement. In Indonesia, Law No. 8 of 2016 concerning Persons with Disabilities and national regulations on inclusive schools require learning practices that effectively respond to student diversity. However, the needs analysis of 150 inclusive practitioners from the Solo Raya region indicated that teacher readiness remains low, only 40% are confident in using adaptive strategies, 20% have inadequate skills, and the majority (60%) are willing to implement new approaches but still require further guidance. These findings demonstrate the need for an adaptive, applicable, and culturally informed pedagogical model.

Learning variability arises from differences among three learning systems related to engagement, representation, and action/expression as developed by CAST (McKenzie & Dalton, 2020). UDL encourages representation, engagement, and action - expression in various forms to accommodate the learning needs of diverse learners. Supporting the principle of immediacy, AI-enabled assistive technology takes this further with interactive feedback and responses, individualized multimodal access to content, and embedded communication support for students.

International research consistently shows that when UDL is implemented well, the gains are enormous. A comprehensive meta-analysis of 52 worldwide studies found that UDL promotes engagement (31%), motivation (29%), and academic performance (22%) (Almeqdad et al., 2023). In the US, UDL adoption can increase by 18–22% in engagement, learning experience, belonging, and persistence (Nance, 2022). In Finland, qualitative research found that students with disabilities had increased engagement in discussions and collaborative activities during UDL (Millett, 2023; Nieminen, 2025). UDL increases students with disabilities' persistence and engagement. It can improve learning retention and support learning differentiation in heterogeneous classrooms (Tas & Minaz, 2024). AI-based devices also show high potential for inclusive educational practices.

Holmes et al. (2019) found that AI tutoring and adaptive learning for students with cognitive disabilities increased learning accuracy by 47%. For school-age and adult Deaf/Hard of Hearing students, speech-to-text systems increased comprehension by 35–45% (Nance, 2022). Eye-tracking and emotion recognition devices increased engagement in students with ADHD by up to 38% (Bozkurt et al., 2024; Chauhan et al., 2020; Wang et al., 2025). Recent studies have shown that AI enhances UDL by dynamically responding to users' cognitive and sensory parameters (Sheejamol et al., 2025), with real-time adaptive instruction quadrupling STEM engagement (Leon et al., 2025).

Student diversity is seen as natural and expected in UDL. According to this theory, learning has to be customized to account for variations in perception, motivation, and expression (Priyadharsini & Mary, 2024). UDL and AI-AT also align with the theoretical perspective of the Zone of Proximal Development (ZPD), which is defined as gradual learning that occurs between independent and supported skills. AI enables real-time scaffolding with adaptive feedback and supports students with special needs in stretching beyond the ZPD in ways traditional teaching does not. AI-AT is informed by Human-Computer Interaction (HCI) theory and learning analytics, suggesting that technology can be used to enhance learning through the analysis of user actions and real-time feedback. AI personalizes content to student profiles in inclusive contexts and supports learning through multiple modes (Ayeni et al., 2024).

Dewantara's philosophy serves as a distinctive foundation for education in Indonesia. His approach supports differentiated, contextualized learning, which aligns with the core principles of UDL, particularly in promoting self-directed learning. According to *Ing Ngarsa Sung Tuladha*, modeling uses UDL structured scaffolding. *Ing Madya Mangun Karsa* encourages facilitation (e.g., through different learning approaches). *Tut Wuri Handayani* supports student independence (in harmony with UDL expressions). Further, collaboration with UDL and the implementation of Dewantara philosophies emphasize that the pedagogical approach should be in accordance with local cultures (in Indonesian schools).

UDL and AI-AT synthesis with student variability theory, Cognitive Load Theory (CLT), ZPD, and Self Determination Theory (SDT), as well as Dewantara's philosophy, provides a comprehensive framework for inclusive education. UDL offers a pedagogical approach to content, AI-AT promotes technological access and flexibility, cognitive theories ensure learning effectiveness, motivation theory ensures engagement, and Dewantara's philosophy determines cultural relevance. Together, these theories elucidate how a combined framework of UDL and AI-AT can promote student engagement as well as learning achievements among students with disabilities. in a country like Indonesia.

Based on the study literature, several gaps were identified that are useful not only for Indonesian but also for international analysis. There is no integrated model of UDL and AI-AT that has been tested empirically. Moreover, no UDL framework has been contextualized within Indonesian educational philosophy, despite evidence that cultural adaptation will improve motivation for learning (Salmiah et al., 2025). Quantitative data on the effectiveness of UDL and AI-AT in inclusive schools in Indonesia is scarce. Most research is descriptive/qualitative, and no empirical studies have examined the relationship between UDL practices, AI-AT adoption, student engagement, and academic outcomes. Quantitative evaluation of educational outcomes for students with disabilities in adaptive instructional or technology-based models is also very limited.

Despite Indonesia's progressive inclusive education policies, teaching practices in primary and secondary schools still do not adequately address the specific requirements of students, largely because of a lack of adaptive pedagogy, low teacher preparedness, and limited use of AI-based assistive technology. The combination of UDL and AI-AT has also not been empirically studied to improve academic engagement and performance in the Indonesian cultural context.

Therefore, this research is important for several reasons. Theoretically, this article introduces a new model that integrates UDL with AI-based assistive technology and Dewantara's educational philosophy, a combination that has not been discussed in local or international literature. Empirically, this article provides explanatory evidence on the influence of UDL and AI-AT integration on student engagement and academic outcomes. Practically, this article offers an operational approach for inclusive teachers and schools. At the policy level, the results of this study can form the basis for formulating standards for the implementation of UDL and assistive technology in Indonesia.

This research is related to (1) How effective is Artificial Intelligence-Assisted Technology (AI-AT) in increasing the engagement of students with disabilities?; (2) What is the impact of the use of UDL and AI-AT on academic outcomes among students with disabilities?; (3) What is the causal relationship between UDL, AI-assisted technology, student engagement, and academic outcomes?; and (4) What are the recommendations for empirically validated UDL and AI-based learning models? Meanwhile, this research aims to: 1) analyze the effectiveness of Artificial Intelligence-Assisted Technology (AI-AT) in increasing the engagement of students with disabilities; (2) test the impact of the implementation of Universal Design for Learning (UDL) and AI-AT on the academic outcomes of students with disabilities; (3) identify and explain the causal relationship between UDL, AI-based assistive technology, student engagement, and academic outcomes; and (4) develop recommendations for empirically validated UDL and AI-based inclusive learning models.

2. Literature Review

2.1 Inclusive Education and Theoretical Foundation

Inclusive education refers to an educational approach grounded in a human right–based perspective and contemporary understandings of disability that emphasize the role of structural, pedagogical, and social barriers, rather than viewing disability solely as an individual limitation. In recent literature, inclusive education is conceptualized as a systematic effort to promote equitable opportunities for all learners, including students with disabilities, to have equitable access, active participation, and meaningful opportunities to achieve learning outcomes within mainstream schools (OECD, 2023; UNESCO, 2020).

UNESCO conceptualizes inclusive education as a continuous process of addressing and removing the barriers experienced by all learners through changes in curricula, teaching methods, evaluation, and learning environments (UNESCO, 2021). Consistent with this view, Ainscow contends that inclusion necessitates systemic-level policy and school-practice change to ensure that all students are there, attending and participating meaningfully in learning in typical classroom environments (Ainscow & Ainscow, 2020).

However, realizing inclusivity in education still confronts chronic, interrelated challenges in teacher capacity, instructional support, and systemic resourcing. The international evidence is overwhelming that inclusion will not occur simply by placing students in regular class settings; sustained system and school changes are needed to mobilize professional capacity, leadership, and classroom practices so that barriers to participation and learning can be eliminated (Ainscow & Ainscow, 2020).

From an inclusive pedagogy point of view, Alam & Mohanty (2023) argue that successful inclusion requires teachers to be professionally able to broaden access to learning opportunities available for all students while challenging deterministic practices, such as fixed ability grouping, which inherently positions some children, including those with disabilities, as inherently limited in their capacity to learn. This emphasizes that the lack of teacher preparedness and confidence is not a sidebar but a primary impediment, as it directly influences teachers' capacity to plan for accessible instruction and ensure fair participation, particularly when ongoing professional development and school-site supports are inadequate.

Empirically, it is shown that teachers' attitudes and instructional self-efficacy, as well as the classroom climate more generally, mediate the enactment of inclusive practices in particular ways for students with a disability. Research indicates that teachers' positive beliefs and greater instructional self-efficacy for inclusion are associated with the implementation of inclusive instructional practices and the quality of instructional support provided to students with disabilities (Saloviita, 2020). In addition to the presence of teachers, social dynamics among students in the classroom are also important; meaningful contact in inclusive settings has shown a strong correlation with children's positive attitudes toward peers with disabilities (Farmer et al., 2019), and, in turn, affect participation, peer acceptance, and engagement.

Teachers' self-efficacy beliefs are also influenced by the school context and mastery experiences, which shape classroom processes that may facilitate or inhibit students' opportunities to participate meaningfully (Wilson et al., 2018). At the systemic level, a lack of access to adaptive, accessible learning materials can create scale-up gaps, especially in education systems with uneven capacity-building and resource constraints. As a result, policy reviews of this kind from around the world highlight that successful inclusive education relies on comprehensive investment in governance, professional capacity development and educational resourcing – rather than over-relying on teachers to compensate for systemic weaknesses (UNESCO, 2020).

2.2 Universal Design for Learning

UDL emerged as a pedagogical framework grounded in the science of learning and the principle of learner differences. Instead of pursuing "one-size-fits-all" solutions, UDL posits that learner variability is not the exception but the rule. Developed by CAST, the framework is based on research on three core learning systems—engagement, representation, and action/expression—that are translated into the UDL guidelines to support learner motivation, information processing, and learning expression (Boysen, 2024). The principles that undergird UDL comprise multiple means of engagement, representation, and action/expression—designed from the outset to be inclusive of diverse learners, including students with disabilities, in classrooms.

Emerging empirical evidence suggests positive overall effects of UDL on students' engagement, accessibility, participation, and academic achievement (Guo & Wang, 2025). Research on inclusive education environments has found that UDL fosters students' cognitive and affective engagement by providing multiple, flexible learning options and diverse representations of content or instruction (Espada-Chavarria et al., 2023). In addition, UDL helps enable participation of students with disabilities by removing curricular obstacles and improving access to learning resources, which, in turn, improve academic performance more than mainstream instruction (Rusconi & Squillaci, 2023). These findings suggest that UDL is ultimately a pedagogical approach aligned with the goals of inclusive education and equitable educational opportunities.

The literature does emphasize the limitations of practicing UDL, however. UDL is only as effective as teachers' capacity to develop content and instruction that is responsive, or flexible, by design, that is, significant variability exists in the quality of instruction and consistency of practice across different settings. (Unal et al., 2020). Moreover, without adaptive tools, the practice of UDL itself leads to relatively static changes that cannot keep up with learners' variation over time and across contexts—especially for students with disabilities, who may have highly individual needs. Several studies suggest that UDL alone is insufficient without technologies for automating adaptation, personalization, and continuous support (Bray et al., 2024). It is therefore necessary to embed the UDL framework into adaptive technological solutions, thereby increasing its relevance within initiatives aimed at supporting an inclusive learning environment.

2.3 AI-Based Assistive Technologies in Inclusive Learning

AI-AT is a shorthand term for AT that leverages computer-based AI—machine learning, natural language processing, and computer vision—to revolutionize access, personalisation, and adaptation in learning for learners with diverse educational needs. Compared to traditional AT, which is mainly static, AI-AT can dynamically adjust its response based on user-specific data, interaction behaviors, and personal training progress. In inclusive education environments, AI-AT includes diverse applications such as speech-to-text/text-to-speech intelligent tools, adaptive learning systems, intelligent tutors, and predictive analytical tools supporting self-regulation and content accessibility (Kothari & Cruikshank, 2022). AI's capability to represent learning actions and provide personalized feedback means that, in principle, AI-AT is a technology developed in accordance with inclusive pedagogical principles that account for learner diversity.

Increasing empirical evidence and policy work have suggested that AI-AT exerts a beneficial effect on student academic outcomes, especially among students with disabilities in inclusive educational settings. AI in education research has demonstrated that AI-based adaptive systems can improve cognitive and affective engagement through personalized feedback, flexible learning pace, and sustained support adapted to the individual needs of each (Holmes, W. & M., Fadel, 2019). These systems augment multimodal supports (UNESCO, 2021; Wang et al., 2024), automate text conversion, and provide adaptive learning recommendations, enabling more equitable participation than non-adaptive instructional approaches. Therefore, AI-AT does not function solely as compensation but rather as a pedagogical process that enhances both engagement and learning in inclusive classrooms.

While the potential is vast, the literature also notes that AI-AT adoption raises questions about ethical and institutional preparedness. Among the key concerns are: the safeguard of learner data and privacy; the danger that algorithmic bias could perpetuate existing inequalities; and deficits in teachers' competences to integrate AI pedagogically, not just technically (Bulathwela et al., 2024; Zawacki-richter et al., 2019). Finally, in the absence of a clear pedagogical frame, AI implementation would become fragmented and unsustainable. Thus, AI-AT should not be taken as a substitute for pedagogy, but rather as an enabler of inclusive pedagogy, a technology that can adaptively and responsively enact the principles of inclusion at scale in real-world learning environments.

2.4 Student Engagement and Academic Outcomes

Student engagement is commonly recognized as a complex multidimensional concept with behavioural, affective, and cognitive dimensions that reflect learners' involvement in learning activities (Wong & Liem, 2021). Behavioral engagement consists of visible involvement (e.g., effort, persistence, and on-task behavior); emotional engagement targets students' affective reactions (e.g., interest, belonging, and value applied to learning), whereas cognitive engagement refers to strategic learning behavior, self-regulation skills, and investment in deep understanding (Gomes et al., 2023). Engagement is a particularly relevant variable for students with disabilities in inclusive settings because it serves as a conduit through which these individuals can gain access to learning opportunities previously restricted by curricula, pedagogy, or environment.

Research (Espada-Chavarria et al., 2023) demonstrates the effectiveness of UDL in engaging students with disabilities by providing a range of options for how to become engaged in the representation of content and in participation around learning tasks that lead to ongoing motivation and sustained active engagement. Likewise, AI-enhanced assistive technologies (AI-AT) have been found to enhance engagement with personalized information and adaptive pacing, along with multimodal supports that cater to individual learning needs, particularly for learners who may need more scaffolding (Holmes, W. & M., Fadel, 2019; OECD, 2023). Taken together, this evidence places engagement as a proximal or mediating outcome that moderates the impact of inclusive pedagogical frameworks and adaptive technologies on more distant learning outcomes.

Academic results of inclusive education mainly refer to what students attain, progress toward, and master curricular goals, as measured by performance indicators (e.g., standardised test scores, grades) and learning development over time. Consistent evidence indicates that learning gaps are often not attributable to learners' inabilities but rather to unequal access to high-quality instructional delivery and responsive supports (Chand, 2024; Zawacki-richter et al., 2019). To address outcome disparities, instructional design and technologically rich instruction are particularly important.

The research indicates that UDL-embedded learning helps minimise curricular barriers and maximise affordances, enabling students to express their understanding in a variety of ways (Ng et al., 2026). Analogous efforts in AI and education suggest that AI-AT can be used to improve learning outcomes through personalized learning pathways, increased access to content and assessments, and support for sustained learner engagement over time (Holmes, W. & M., Fadel, 2019; UNESCO, 2021). The combination of UDL and AI-driven assistive technologies (AI-AT) can impact educational outcomes in several interconnected ways. The simultaneous application of UDL and AI-based ATs can impact educational outcomes in several interconnected ways.

Theoretically, the model proposes sound links between variables, suggesting that UDL and AI-AT directly influence the academic outcomes of diverse learners through student engagement. Collectively, these findings support the premise that engaging students through inclusive pedagogies, supported by their personal beliefs and values, can strengthen learning engagement and promote adaptive behavior.

3. Methodology

3.1 Research Design

Quantitative data were obtained through a quasi-experimental design to analyze the relationships among UDL, engagement, academic outcomes, and AI-AT moderation variables.

3.2 Research Sample

The population of this study comprised all students with disabilities studying in inclusive elementary schools that implement UDL and AI-AT in Central Java Province. The quantitative sample consisted of 69 students with disabilities assigned to the control group and 74 to the experimental group. Students with disabilities included those with physical disabilities, intellectual disabilities, slow learners, learning disabilities, visual impairments/blindness, autism, and hearing impairments/deafness. The sampling technique used was purposive sampling (Etikan et al., 2016), with the criterion that schools be inclusive and have implemented UDL and AI-AT in learning.

3.3 Data Collection

Data collection was conducted in stages through pretest–posttest, observation, and AI logs in a quasi-experimental design, for quantitative triangulation of student engagement and academic outcomes. Next, quantitative data were analyzed using descriptive and inferential statistics—including normality tests, pretest–posttest score differences between groups, and moderation analyses (e.g., moderated regression/PROCESS)—to ensure that changes in student engagement and academic outcomes could be attributed to the implementation of UDL and were influenced by the degree of AI-AT implementation.

3.4 Research Validity

Validity was established through construct validity, Confirmatory Factor Analysis (CFA), member checking, data triangulation, and peer debriefing. Internal consistency reliability was evaluated using Cronbach's alpha. Composite reliability coefficients at or above 0.7 confirmed adequate reliability. Subsequently, data analysis was conducted using PLS-SEM to test the effects of UDL and AI on student engagement and academic outcomes, the effect of engagement on academic outcomes, and the moderating role of AI-based assistive technology on the influence of UDL. Further tests were also conducted to measure Predictive relevance (Q^2), effect size (f^2), and multi-group analysis by disability type.

3.5 Data Analysis

Data analysis was conducted in a structured, phased manner. The initial stage included data editing and screening, including coding by group (control/experimental) and measurement time (pretest/posttest), checking for completeness of responses, handling missing data, detecting outliers, and checking relevant assumptions such as normality and multicollinearity as needed. Descriptive analysis was then conducted to describe sample characteristics and the distribution of scores for the main variables (UDL, engagement, academic outcomes, and AI-AT) in the pretest and posttest using means, standard deviations, and score ranges. To ensure balance in the initial conditions of the quasi-experimental design, a baseline test was conducted between the control and experimental groups using pretest scores.

The effectiveness of UDL implementation was then tested by comparing changes in pretest and posttest scores between groups, using either a gain score approach (posttest–pretest difference.) or ANCOVA and regression analysis, controlling for pretest scores as a covariate, and incorporating effect sizes to facilitate practical interpretation of the magnitude of impact Engagement observation data and AI logs were described to support quantitative triangulation by assessing consistency across data sources or integrating them as indicators of engagement measurement.

The inter-variable relationship testing was conducted comprehensively using PLS-SEM through measurement model evaluation (reliability and construct validity) and structural model evaluation (path coefficients and significance through bootstrapping, R^2, effect size f^2, and predictive relevance Q^2). The moderating effect of AI-AT was tested by forming an interaction construct (UDL × AI-AT) to examine whether AI-AT strengthens the influence of UDL on engagement and/or academic outcomes. Finally, a multi-group analysis was conducted based on disability type to identify differences in the pattern of relationships between variables in different student groups to ensure that the interpretation of results is sensitive to the diverse needs of inclusive learners.

4. Results and Findings

4.1 AI-AT is effective in increasing student engagement

The study was conducted on the experimental and control groups to obtain engagement scores before and after the intervention, thus obtaining a difference (gain score). The calculation results obtained a mean gain value of 1,917 for the experimental group, in contrast to 1,215 for the control group. The t-test (independent samples t-test) obtained a t-value of 6.122 with a p-value of 1.40×10^{-8} (very significant). The effect size value was 1.04, which is considered large. Students with disabilities attending inclusive educational settings demonstrated an increase in engagement that was almost 2 times that of the control group. This can be seen in the results: the experimental group had a gain value of +1.92, while the control group had +1.21. The statistical significance test also yielded a p-value of 0.000000014 (<0.001). Therefore, it can be concluded that the groups differed significantly in the increase in student engagement between the groups that use UDL and AI-AT and those that do not.

Table 1: Independent samples t-test results and effect sizes

Analysis Components	Value	Interpretation
Test Type	Independent Samples t-Test	Compares the means of two groups
T-value	6.122	Very strong difference in means
P-value	1.40×10^{-8}	Very significant ($p < 0.001$)
P-value	0.000000014	Strengthens statistical significance
Effect Size (Cohen's d)	1.04	Very large effect
Conclusion	H_0 rejected	There is a significant difference with strong practical impact

These findings demonstrate that learning with engaging, interactive, and accessible media, such as AI-AT, provides an effective solution for students with disabilities across all types and degrees. In inclusive schools, more than one type of disability can be present in the same class. This presents a challenge and a potential obstacle to effective learning. Teachers must be able to accommodate all students, both those with and without disabilities. AI-AT can help teachers more easily and quickly transfer knowledge to students with disabilities according to each learner's potential and learning style.

4.2 The Effect of UDL and AI-AT on Academic Outcomes among Students with Disabilities

A regression analysis was conducted on the independent variables (X), including the implementation of UDL, the use of AI-AT, and academic scores before the intervention, as a baseline control for the dependent variable (Y), which represents academic outcomes after the intervention. The researchers conducted the regression analysis and interpreted each variable to obtain more in-depth and unbiased results, as presented below.

Table 2: Results of regression analysis

Variable	β (Coefficient)	t	p	Interpretation
UDL_latent	3.27	5.30	0.000	Significant and positive effect
AI_latent	5.67	15.73	0.000	Significant and positive effect
Academic_pre	-0.0037	-0.12	0.902	Not significant
R2= 0.830				Very strong model (83% of the Academic Outcomes variation is explained by the model)

Based on Table 2, the results of the regression analysis indicate that the model has very strong explanatory power with an R^2 value of 0.830, meaning that 83% of the variation in academic outcomes can be explained by the variables in the model (UDL and AI-AT). Partially, the AI-AT variable has a positive and highly significant influence on academic outcomes ($\beta = 5.67$; $t = 15.73$; $p = 0.000$), and is the strongest predictor in the model. This indicates that the use of AI-based assistive technology provides the most dominant contribution to improving student academic achievement in the context of inclusive learning.

Meanwhile, UDL also shows a positive and significant influence ($\beta = 3.27$; $t = 5.30$; $p = 0.000$), confirming that the UDL-based adaptive learning framework substantially supports improved learning outcomes. In contrast, the academic pre-score variable did not have a significant effect ($\beta = -0.0037$; $t = -0.12$; $p = 0.902$), indicating that differences in students' initial abilities were not a determining factor in this model Overall, these findings confirm that the integration of UDL and AI-AT is a key factor in improving academic outcomes in inclusive classrooms, with AI-AT being the most dominant contributor.

4.2.1 The Impact of UDL on Academic Outcomes

Table 3: Effect of UDL implementation on academic outcomes

Predictor Variable	Dependent Variable	β (Coefficient)	t-value	p-value
UDL Implementation	Academic Outcomes	3.27	5.30	< 0.0001

The analysis obtained a coefficient value of 3.27 ($p<0.0001$) and a t-value of 5.30. It means that every one-point increase in UDL implementation increases academic outcomes by 3.27 points. This demonstrates that UDL functions as an effective instructional foundation for supporting learning among students with disabilities within inclusive educational settings. UDL offers a flexible, accessible, multimodal learning environment oriented toward the needs and potential of students with disabilities in inclusive learning environments, ultimately supporting and improving their academic outcomes in inclusive schools.

4.2.2 The Impact of AI-AT

Table 4: Effect of AI-Assistive Technology (AI-AT) on academic outcomes

Predictor Variable	Dependent Variable	β (Coefficient)	t-value	p-value	Interpretation
AI-Assistive Technology (AI-AT)	Academic Outcomes	5.67	–	< 0.001	Significant positive effect; each 1-point increase in AI-AT usage increases academic outcomes by 5.67 points

The table shows that the use of AI-based assistive technology (AI-AT) has a positive and significant impact on academic outcomes. A coefficient value of 5.67 with $p < 0.001$ indicates that every one-point increase in AI-AT use contributes to a 5.67-point increase in academic scores. This finding indicates that AI-AT makes a very strong contribution to supporting student learning outcomes in inclusive learning contexts. Several AI-based assistive technologies used by students with disabilities, such as speech-to-text, JAWS, voice assistants, and sign language recognition, have provided greater personalization than UDL alone. In fact, the effect was almost double that of UDL alone.

4.2.3 Initial Value (Pre-Academic)

The pre-academic score analysis showed a coefficient of -0.0037, accompanied by a p-value of 0.902. This clearly demonstrates that the results are not significant. This means that students' pre-academic scores do not determine the increase in academic outcomes of students with disabilities in inclusive educational settings. The research subjects consisted of students with disabilities of various types and degrees of severity This test shows that students with severe, moderate, and mild disabilities receive equal benefits from implementing UDL and AI-AT in the learning process. Although the differences are not significant, this finding reflects the success of inclusive education, as the interventions used can further reduce the gap.

Table 5: Initial value analysis results

Analysis Components	Value	Interpretation
Coefficient (β)	-0.0037	Very weak negative relationship (approaching zero)
P-value	0.902	Not significant ($p > 0.05$)
Statistical Significance	Not significant	There is no significant effect/difference

4.2.4 Model Interpretation

The R^2 value of the model is 0.830, an acceptable level for educational research. UDL and AI-AT explain 83% of the variance in academic outcomes. The model is demonstrated to be stable, accurate, and robust. UDL and AI-AT can work together to support the learning roles and functions for students with disabilities in an inclusive educational setting. This model allows teachers to maximize students' potential by helping them achieve already-established instructional and educational goals. This successful intervention is expected to positively influence the learning trajectory of students with disabilities in inclusive schools.

Table 6: Direct effects of UDL and AI-AT on academic outcomes

Predictor Variable	Dependent Variable	Path Coefficient (β)	p-value	Significance Level	Strength of Effect
AI-AT	Academic Outcomes	5.67	< 0.001	Highly Significant	Strongest
UDL	Academic Outcomes	3.27	< 0.001	Highly Significant	Strong

Based on the reported test results, it is possible to deduce that UDL and AI-AT have a significant effect on academic outcomes among students in an inclusive learning context. The strongest influence is AI-AT ($\beta = 5.67$, $p < 0.001$), followed by UDL, which also demonstrates a strong influence ($\beta = 3.27$, $p < 0.001$). UDL offers an adaptive and accommodating framework for students with disabilities, supported by AI-AT that creates an accessible, inclusive, productive, equitable, and disability-friendly learning environment.

4.3 Causal relationship between UDL, use of AI-AT, engagement, and academic

4.3.1 Inter-Construct Correlation

Table 7: Correlation matrix between constructs

Construct	UDL	AI-AT	Engagement	Outcomes
UDL	1.00	0.66	0.59	0.73
AI-AT	0.66	1.00	0.68	0.89
Engagement	0.59	0.68	1.00	0.70
Outcomes	0.73	0.89	0.70	1.00

AI-AT has a strong correlation with academic outcomes ($r = 0.89$). These results indicate several things, including: 1) The implementation of AI-AT has a strong association with supporting improved academic outcomes for students with disabilities, 2) The higher the implementation of AI-AT, the greater the tendency for improved learning performance among students with disabilities, and 3) AI-AT is the most dominant predictor of learning outcomes when compared to other variables.

Through interactive, accessible features and fast feedback, AI-AT increases the engagement of students with disabilities. At this point, engagement plays a role in improving learning outcomes. Engagement is a psychological mechanism that can explain the contribution of AI-AT to enhanced learning outcomes. UDL makes a significant contribution to the academic outcomes of students with disabilities ($r = 0.73$). Overall, AI-AT is a quick and suitable assistive technology tool, while the UDL framework provides pedagogical support to create an inclusive, flexible learning environment that helps people with disabilities achieve learning goals.

The correlation between UDL and AI-AT has a correlation coefficient of 0.66. This figure reflects a strong relationship. The three main core principles of UDL, namely multiple means of action, expression, and representation, as well as engagement, align with the role of AI-AT in personalizing learning. AI-AT further strengthens the UDL framework by enabling easier differentiation of materials, greater accessibility, and the adaptation of learning styles for students with disabilities in inclusive classrooms. Based on the statistical analysis, no extreme correlations are approaching 1.00, indicating no construct redundancy, with all relationships falling in the moderate-to-very-strong range, which supports discriminant validity and the theoretical relationships among constructs.

4.3.2 The Influence of UDL and AI-AT on Student Engagement

Table 8: The influence of UDL and AI-AT

Predictor	β (coefficient)	p-value	Interpretation
UDL_latent	2.880	$p<0.001$	Significant
AI_latent	5.224	$p<0.001$	Very significant
$R^2=0.495$			49.5% of engagement variation is explained by the model

The findings from the regression analysis highlight several important points in this study. The learning engagement of students with disabilities was successfully improved through the use of AI-AT. 49.5% of the variation in engagement was explained by the learning model that implemented UDL and AI-AT. The remaining 50.5% was explained by factors outside the model, such as unexamined variables, learning experience, social support, self-efficacy, a conducive learning environment, psychological factors, and others. Therefore, the construct model used was appropriate for predicting students' engagement in an inclusive educational setting.

4.3.3 The Influence of UDL, AI-AT, and Engagement on Academic Outcomes

Table 9: The influence of UDL, AI-AT, and engagement on academic outcomes

Predictor	β (Coefficient)	p-value	Interpretation
UDL_latent	2.880	$p<0.001$	Significant
AI_latent	5.224	$p<0.001$	Very significant
ENG_latent	1.703	$p<0.021$	Significant
$R^2=0.830$			83% of outcomes variation is explained by the model

These results demonstrate that integrating UDL, AI-AT, and engagement is an effective combination for improving academic outcomes for students with disabilities in inclusive schools ($R^2=0.830$). Engagement had a smaller effect than UDL and AI-AT. However, as a psychological determinant of learning, the results continued to show a statistically significant effect. Each variable has indicators. These indicators are used to measure and identify causal relationships between variables. The following are the indicators of each variable that have been coded (table 9) and the causal relationship is presented in the following SEM diagram (figure 1).

Table 10: Indicators for Each Research Variable

UDL	AI-AT	Engagement	Academic Outcomes
UDL 1 Clarity of representation	AI 1 Ease of use	ENG 1 Behavioral engagement	OUT 1 Assignment performance
UDL 2 Multiple means of engagement	AI 2 Usefulness	ENG 2 Emotional engagement	OUT 2 Test results
UDL 3 Flexibility of assessment	AI 3 Accessibility	ENG 3 Cognitive engagement	OUT 3 Classroom performance
UDL 4 Accessibility of material	AI 4 Frequency of use	ENG 4 Participation	OUT 4 Overall academic perception
UDL 5 Teacher adaptation	AI 5 Perceived impact	ENG 5 Persistence	
UDL 6 Learner support			

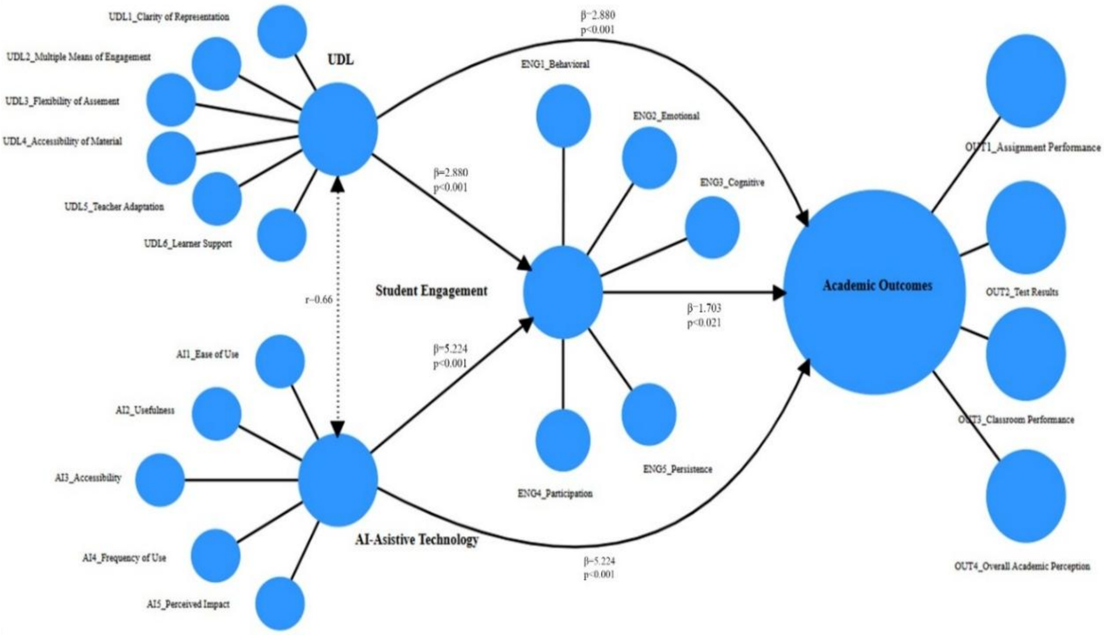

Figure 1: SEM Diagram (SMARTPLS)

The results of the structural analysis showed that AI-AT had the strongest influence on student engagement ($\beta = 5.224$, $p < 0.001$) and academic outcomes ($\beta = 5.224$, $p < 0.001$), followed by UDL, which also had a significant influence on engagement and academic outcomes. Student engagement significantly mediated the relationship ($\beta = 1.703$, $p = 0.021$), indicating that student engagement is an important mechanism in explaining the effectiveness of UDL and AI-AT implementation in inclusive classrooms.

The PLS-SEM analysis results confirm that AI-AT and UDL have a significant influence on student engagement and academic achievement. Therefore, an operational model was needed to explain how these findings could be translated into learning practices. The following figure presents an implementation framework that illustrates how the integration of UDL and AI-AT can be systematically implemented through the planning, learning implementation, and assessment and feedback stages in an inclusive classroom.

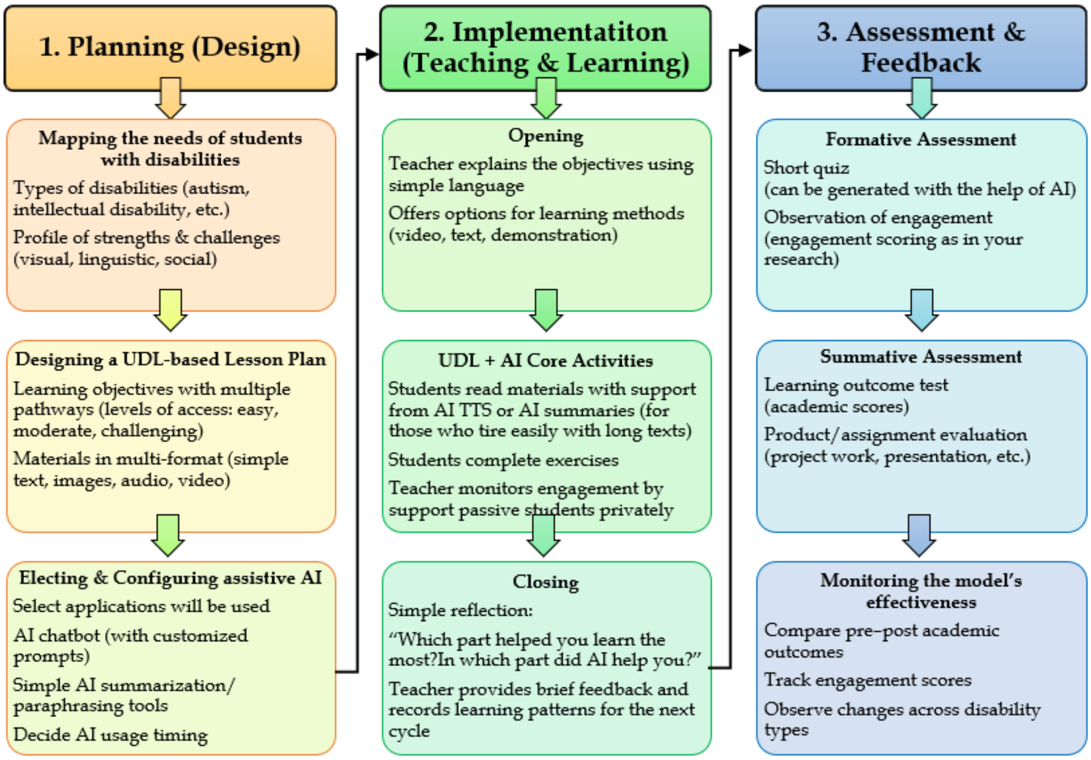

Figure 2: Inclusive learning model based on UDL and AI technology

Figure 2 represents the integrative implementation framework for UDL and AI-Assisted Technology (AI-AT) in an inclusive classroom, structured into three main stages: planning, implementation, and assessment and feedback. In the planning stage, teachers begin by mapping the needs of students with disabilities, including the type of disability and the profile of their strengths and learning challenges. Based on this mapping, teachers design UDL-based lesson plans by providing various learning pathways and materials in multiple formats (text, images, audio, and video). They then selected and configured appropriate AI applications, such as educational chatbots or text summarization tools, and determined the timing of their use.

The implementation stage emphasizes the active integration of UDL and AI into the learning process. In the opening section, teachers explain learning objectives in simple language and offer various learning method options. In the core activities, AI is used to support learning differentiation, for example, assisting students who have difficulty reading long texts through text-to-speech or automatic summarization, while teachers continue to monitor student engagement and provide one-on-one individual support. The closing stage includes a simple reflection on the benefits of learning and the use of AI, as well as teacher feedback for improvement in the next learning cycle.

The assessment and feedback phase emphasizes ongoing evaluation through formative assessment (AI-assisted quizzes and engagement observations) and summative assessment (learning outcome tests and assignment/project evaluations). The model's effectiveness is monitored by comparing pre- and post-intervention academic outcomes, tracking student engagement scores, and observing changes based on disability type. Overall, this figure demonstrates that the integration of UDL and AI-Assisted Technology (AI-AT) is not simply an instructional strategy, but a systematic cycle linking design, implementation, and evaluation to improve accessibility, engagement, and academic outcomes in an inclusive education context.

Overall, this implementation model confirms that the systematic integration of UDL and AI-Assisted Technology (AI-AT) in the planning, implementation, and assessment stages of learning can create an inclusive classroom ecosystem that is more adaptive, structured, and responsive to the diverse needs of students. Through flexible learning design, personalized technology support, and ongoing evaluation, this approach not only increases student engagement but also strengthens the effectiveness of learning and the quality of teachers' pedagogical decision-making in an inclusive school context.

5. Discussion

This research confirms that AI-AT significantly improves the degree of accessibility as well as the effectiveness of learning for students in an inclusive classroom. Inclusive classes in Indonesia present a real challenge with the presence of various disabilities (sensory, cognitive, physical, and communication) within a single learning environment. Rather than merely functioning as assistive supplements, AI-ATs in this study operate as structural enablers that reduce systemic inequities in access to instructional content and participation. Several AI-ATs (such as text-to-speech technologies, adaptive content, screen-reading tools, and related applications) can provide personalization for students, making it easier for them to access learning resources according to their needs.

The findings of this study align with those of Al-Azawei et al. (2016), who demonstrated that AI-based technology can enhance the participation and engagement of students with diverse learning needs through content personalization. Another study, by Holmes et al. (2019), emphasized that AI in education has the potential to reduce learning barriers by providing immediate feedback and learning pathways aligned with students' cognitive profiles. In the context of inclusive classrooms, AI-AT has been shown to act as a structural mechanism that reduces inequities in access to learning materials. This is consistent with the UDL framework, with its crucial emphasis on providing diverse representations, expressions, and engagement to ensure equal access (CAST, 2018). In contrast, other researchers in developed countries emphasize the readiness of digital infrastructure as a key prerequisite for AI effectiveness

(Luckin et al., 2016). This study demonstrates that despite limited resources, AI-AT can still be utilized significantly through pedagogical and contextual integration.

Furthermore, these findings demonstrate that AI-AT operates as a structural driver, expanding the discourse that views assistive technology as a mere compensatory tool. Previous research has criticized inclusive education practices that only position technology as a supplementary tool without systemic change. This study demonstrates that the integration of AI-AT can shift the paradigm from support-based inclusion to equity-driven inclusion. This technology becomes a medium for redistributing equitable learning opportunities. In other words, AI-AT not only improves learning comfort but also intervenes in the structures of unequal academic access. These findings contribute to previous research on inclusive education by showing that AI-AT not only rhetorically aids inclusion but also has material effects on the shaping of technology access conditions in resource-deprived environments like Indonesia.

AI-AT does offer a fast and fairly accurate response. However, this does not mean that AI-AT can replace teachers' roles in inclusive schools. Teachers still play a crucial role in inclusive classes, namely as pedagogical decision-makers. Teacher competence in mediating, directing, and controlling the use of AI-AT is also essential to accommodate the needs and potential of each student with disabilities. AI-AT plays a greater role in increasing teachers' adaptive capacity in the learning process. As is known, teachers in inclusive schools face a high burden because they must accommodate both regular students and students with disabilities in the same class. The results of this study expand on previous literature, which generally positions assistive technology as a support tool for students. Research by Trust et al. (2016) and Holmes et al. (2019) confirms that integrating AI into learning can help teachers plan differentiation, provide automated feedback, and monitor student progress.

This research reconceptualizes AI-AT not as a replacement for teaching labor, but as a magnifier of teachers' adaptive capabilities amid instructional overload. Moreover, the majority of inclusive schools in Indonesia do not yet have assistant teachers or special education teachers who collaborate with class teachers or subject teachers. As a result, class teachers have a dual role in accommodating learning needs and achieving predetermined learning objectives. As a result, AI-AT augments and supports teachers in expediting knowledge transfer, determining appropriate strategies, personalizing material, and fostering learning.

Previous studies have confirmed that collaboration between teachers and AI enhances teacher engagement in the learning process, including selecting appropriate teaching methods and optimizing pedagogical decisions (Ding & Li, 2025). AI serves as an external resource that helps teachers map student needs and reduces mental and administrative burdens, enabling better personalization and differentiation of learning. AI is used in learning and assessment systems that provide real-time data analysis, strategy recommendations, and material adjustments, providing teachers with immediate feedback that can be applied to accelerate knowledge transfer and improve the effectiveness of their teaching strategies (Tan et al., 2025).

AI-AT serves as compensatory support to promote material adjustment, pacing decisions, and differentiated instruction for teachers by reducing cognitive load and managerial burden. An experimental study shows that an AI-based recommendation system can complement teachers' decision-making processes, monitor students' learning paths, and reduce cognitive workload through dashboards and automated recommendations (Machado et al., 2025). This systematic review found that AI technology in education, including adaptive learning models, adapts content to individual student needs in real time (Hariyanto et al., 2025). These results are consistent with AI-AT's function of helping teachers choose appropriate learning strategies and adapting materials based on students' learning profiles, thus making knowledge transfer more effective and relevant.

Significant effects were observed for AI-AT compared to UDL. As a result, real-time adaptive technological interventions directly impact learning outcomes and are not solely based on pedagogically inspired design principles. AI-AT can create real-time and differentiated accessibility, reduce communication and sensory barriers, and provide fairer access to materials for students with disabilities Deaf students could communicate and understand messages delivered by teachers using speech-to-text applications. Blind students were able to engage in learning and read digital copies of teaching materials using text-to-speech applications. People with dyslexia could read more easily with the help of adaptive reading applications and similar tools.

This contribution, which is aligned with and predictive of prevailing models of inclusive education, also provides empirical support for the claim that adaptive technology is a proximal predictor of learning gains in challenging instructional environments. These results are consistent with SDT, in which autonomy, competence, and relatedness explain motivation for engagement. The concept of the ZPD focuses on the gradual transition between independent and assisted abilities. AI tools offer real-time scaffolding through immediate feedback as students with disabilities move further into the ZPD than traditional instructional models allow. AI individualizes resources through student profiling in inclusive environments and enhances learning outcomes through multimodal support (Ahmed et al., 2025).

The synergy between UDL and AI-AT has indeed fostered a more viable, inclusive learning system than would have been achieved by either approach in isolation. UDL functions as a pedagogical model, while AI-AT serves as an operational tool to put UDL (multiple ways of representation, engagement, and expression) into practice in inclusive teaching classrooms. This synergy facilitates an important theoretical distinction: UDL is a definition of what to seek in inclusive pedagogy, not how it can be accomplished under realistic classroom circumstances, that domain belongs to AI-AT.

The study also integrated UDL, AI-AT, and student engagement. Therefore, in this combination, student engagement was a psychological variable that could foster improved learning effort among students with disabilities. After the analysis, student engagement was the least influential among UDL and AI-AT, yet it still resulted in a statistically significant effect. This suggests that the cognitive dimension of learning is a key factor for students with disabilities. Instead of signaling deficits in engagement, these findings demonstrate that in inclusive educational contexts for students with disabilities, structural accessibility and cognitive scaffolding might drive motivation. The simultaneous integration of UDL, AI-AT, and student engagement can be a promising approach to increasing the effectiveness of inclusive classrooms in Indonesia, as it is more adaptive to respond to the learning needs of student with disabilities and enable teachers to deliver higher quality educational support for both regular students and students with disabilities, although their schools do not have a teacher assistant or special education teacher.

Other studies support these findings, discussing the convergence of UDL and AI principles as an approach that can create inclusive and autonomous learning spaces by strengthening the three UDL principles and optimizing AI in providing learning content (Saborío-Taylor et al., 2024). This integration is considered to empower students to adapt to their learning needs without having to rely on teachers. The potential of UDL, adaptive learning, and AI-AT supports students with specific learning disabilities. AI-AT can complement the UDL framework by automatically presenting personalized content, making learning more responsive to student needs in inclusive classrooms (Li et al., 2025; Pontillo & Oliva, 2025; Stelea et al., 2025).

This research also has limitations. The study's design was quasi-experimental rather than experimental; therefore, some confounding factors, such as school atmosphere, teacher quality, and parental support, cannot be entirely ruled out. Moreover, a suboptimal distribution of disability types was observed. As the proportion of disability types in our dataset was imbalanced and because UDL and AI-AT may have different effects depending on the type of disability, the sample may not be fully representative across all disability types. Future studies may consider using cluster-randomized or multigroup designs to explore differences in the effects of AI-AT and UDL across disability profiles, thereby improving internal validity and theoretical specificity.

This learning design can integrate UDL with AI-AT to promote student engagement that leads to academic achievement. Furthermore, the model establishes new structural relationships as illustrated in Figures 1 and 2 as follows: This model also addresses the typical challenges faced by inclusive schools in Indonesia, which serve students with heterogeneous disability needs while facing a shortage of teachers and an imbalance between general and special education services. The model extends both constructivist and variability-based learning theories by providing empirical evidence on how pedagogical designs and adaptive technologies, together, target learner diversity within systemic constraints. Education needs to be accessible to different perceptions, motivations, and expressions (Mayer et al., 2014). Rose & Dalton's (2009) student variability theory posits that students differ in cognitive, affective, perceptual-motor, and cultural background factors. These results suggest a theory-based, empirically tested model that could inform future inclusive education policies in other resource-limited environments.

The findings of this study strengthen the inclusive education framework by integrating UDL and AI-AT as a unified model. The findings demonstrate that AI-AT is an adaptive technology and a key mediator that operationalizes UDL principles in practice, not merely a support system. Furthermore, empirically, this study provides concrete evidence that the integration of UDL and AI-AT can improve student engagement and academic outcomes, evidence of this kind has historically been minimal. The identification of the most influential predictors provides a new understanding that the effectiveness of inclusive classes is largely determined by the capacity of technology to bridge the heterogeneous learning needs of students. This study also offers policy direction and concrete implementation for inclusive schools in Indonesia. Furthermore, these findings provide an evidence base for policymakers to design teacher training, procure adaptive technology, and formulate digital ecosystem-based inclusion policies.

6. Conclusion

An AI-AT integrated UDL model has not been empirically tested in developing countries, nor has a UDL framework been contextualized within Indonesian educational philosophy. The findings of the research confirmed that UDL and AI-AT are suitable approaches to enhance students' engagement and academic achievement in inclusive education classes in the Indonesian context. PLS-SEM results indicate that AI-AT has the strongest influence on student engagement and academic outcomes, followed by UDL, which also demonstrated significant predictive strength, indicating that adaptive technology serves as the primary enhancer of accessibility and learning effectiveness in diverse inclusive classrooms.

By integrating principles of pedagogical foundations and adaptive technologies, the model offers a practical approach to inclusive education in areas with limited teacher capacity and unequal access to special education support. This represented a theoretical advance in the field that extended the literature on inclusive education beyond normative recommendations toward technology-supported, evidence-based instructional models. More specifically, it positions AI-AT not only as a supporting tool but also as a structural enabler that makes inclusive pedagogy feasible within real-world classroom constraints. From a practical and policy-oriented perspective, these results provide evidence-based guidance for schools and policymakers in low-income countries seeking scalable solutions to inclusive education challenges, especially given the limited supply of special educators.

Additionally, this work laid the groundwork for future developments in assistive technologies and inclusive instructional design by demonstrating how pedagogical frameworks and AI-driven tools can be systematically harmonized to improve learning equity.

7. Conflict of Interest

The authors report no conflict of interest. The research was conducted independently, free from any influence from funding bodies, institutions, or commercial organizations. The authors certify that the manuscript accurately represents the data and referenced sources. Known confounding variables were identified and controlled to the extent possible within the study design.

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