Policy Perspective on Proposed Framework of NLP AI to Bridge the Inclusive Support in Higher Education with a Mixed Methods Approach in Indonesia and Malaysia

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Manuscript received July 8, 2025; revised July 28, 2025; accepted August 11, 2025; published December 12, 2025

***Abstract*—Despite inclusive education policies in Southeast Asia, disabled students still face barriers and difficulties. Mainly due to the limited individual support and institutional readiness. This study addresses this issue by proposing a policy-aligned Natural Language Processing (NLP) AI framework that uses a dual theoretical foundation (Digital Inclusion and Technology-Organization-Environment (TOE)). This approach could help to bridge the gap between policy and its implementation, especially in low-resource environments. Policymakers play a pivotal role in shaping the future of education by creating an environment to support inclusion and ensuring equity for students with disabilities. This research emphasizes strategic policy for the implementation of the NLP AI framework to support disabled students in increasing their academic activities, particularly in developing countries. The framework itself uses sentiment analysis, entity recognition, and conversational agents from the NLP component to facilitate real-time and context-based responses. The research approach is mixed method, with disability students from Indonesia and Malaysia for the qualitative interview participants, and disability students across universities in Indonesia for the quantitative data SEM analysis. Unlike previous studies that focus on either technology or policy in isolation, this research presents an integrative NLP AI framework validated through the policy change perspective. The proposed framework is one of the first that highlights the alignment of the NLP AI implementation with the institutional-level policy readiness. It is designed with a user-centered approach using the Digital Inclusion Model, shifting from a function-based approach in existing studies to drive improvement and access to an equitable learning environment.**

***Keywords*—inclusive support policy, artificial intelligence, natural language processing, inclusive education, disability support**

I. Introduction

The integration of AI technologies into education presents an opportunity to address disparities experienced by disabled students. Despite advances in inclusive education policies, many students continue to face challenges due to the lack of individualized support and accessible learning environments. Policymakers must harness the capabilities of Artificial Intelligence (AI), particularly in Natural Language Processing (NLP) systems, to bridge these support gaps and promote true educational equity.

The problem that motivates this study is how persistent the gap between inclusive education policy and its actionable application is. While digital tools exist, their adoption is often hindered by institutional constraints and unclear policy direction. This research aims to develop a scalable framework that directly maps NLP capabilities to cater to disability needs within the limitations of institutional and environmental readiness. This can be seen from the observations that reveal many of the involvement from students with disabilities in campus activities is very low, indicating the need not only for inclusive technology-based solutions [1, 2] but also for supporting policy. Currently, supporting policy for inclusive learning is still lacking in real-world, actionable implementation strategies. A large amount of resources and cost is needed for an adequate, inclusive support environment, which many academic entities don't have. The standard of general public education today for inclusive learning still remains lacking, even within large-scale organizations. With the advent of Large Language Model (LLM) AI, there is potential to address this matter. The problem is how to utilize the Large Language Model (LLM) AI to create standards for providing inclusive environments and program materials that are accessible to students with disabilities during the implementation of campus activities [3–8].

There is a variety of research already in this field. From Information and Communication Technologies (ICT) in helping people with disabilities [9, 10], the need for universities to provide more support for disability students for academic and non-academic activities [11], or those specific that dwell on the importance of inclusive programs for non-academic activities [12]. There is also research from Neumann that stated the need for more educational technologies in higher education that could also support inclusive education [13]. As much of the research today is more focused on AI readiness [4, 14], this study brings newness by addressing the policy barrier in higher education institutions through an NLP AI design. That is because the study is not only focusing on the availability of AI tools, but also on how institutional policy can enable or hinder their adoption. The research highlighted the gap between technological potential and current actual implementation, shaped by the inclusive policies. The proposed framework will be validated using the qualitative method, using interviews with thematic analysis, and also by using quantitative SEM analysis. The proposed framework that is built with the Digital Inclusion Model for Assistive Technologies [15] in combination of the Technology-Organization-Environment (TOE) framework [16] aims to bridge the direct application of inclusive policy support practicality changes into development, while provide a cost friendly, modular, and adaptable framework, a novelty that still rarely addressed in prior studies that assume abundant resources that is seldomly found on developing countries.

II. Literature Review

A. Disability Types

Before we dwell on the inclusive support in academics for disabilities, the definition and types of disabilities should be defined first.

To categorize the various types of disabilities, the World Health Organization (WHO) developed the classified system known as the International Classification of Functioning, Disability, and Health (ICF). ICF has a combined model that defines and categorizes the disability into 15 types, which consist of physical impairment, brain Injury, visual, hearing, speech and language, facial deformities, kidney, heart, liver, respiratory, ostomy, epilepsy, intellectual, autism, and mental disabilities [15, 16].

In this research, we grouped the disability into three main groups.

1) The first is a disability with visual impairment, which refers to ICF classification number 3.
2) The second is disability with hearing impairment, which refers to ICF classification number 4.
3) The last is a disability that has a physical impairment or difficulty communicating with normal means without assistive tools, which refers to ICF classification numbers 1 and 5.

The reason we divide disability into those three groups is that the resource data we gathered is mainly from those three groups. Other disabilities, like mental and other health-related disabilities, are excluded because of resource and time limitations.

B. Natural Language Processing (NLP) for Disabilities

In the current era, technology is an integral part of life, but people with disabilities often lack access to it, even though they could benefit the most from its use.

The research by Naneetha [17] shows that ICT could allow impaired disabled persons to read the text without braille tools, hence helping to bridge the scarcity of braille-type resources. This shows the importance of technology to improve the education and life of people with disabilities.

Many types of assistive technologies for disabled person have been used to help them in their daily activities. This assistive technology has different functions with different people and will cater to their specific needs. And the assistive tools are becoming easier to implement and use [18]. The struggle to develop machines that could communicate like people, known as Natural Language Understanding (NLU) systems, is considered the pinnacle of Artificial Intelligence (AI). Previous-generation NLU systems had a common architecture where deep artificial neural networks were initially trained on large amounts of unlabelled text data, which were later modified for specific applications.

The presence of Big Data and increased computational power has revolutionized Natural Language Processing (NLP) and Artificial Intelligence (AI), shifting from rule-based systems to more dynamic and adaptive models [19]. The integration of NLP AI makes it possible to transform how we interact with technology. These intelligent systems could understand, interpret, and respond to human language, thus providing more personalized and contextual interactions and adding them to their algorithm [20]. In education, it has been proven to increase student engagement and learning outcomes [20]. Its further advancement also makes them capable of understanding complex questions and detecting emotional nuances in text or voice input [21]. In this context, NLP bridges the Natural Language Understanding (NLU) systems and makes communication easier between normal individuals and those with disabilities or impairments, as NLP simplifies the NLU process in general communication.

The proposed framework aims to leverage NLP to assist students with disabilities. While AI includes many NLP components, this framework utilizes the following three NLP components to support the communication of students with disabilities [3]:

1) Sentiment Analysis. This component helps interpret the emotional intentions in the communication of students with disabilities. This helps understand the emotional state and needs of students with disabilities.
2) Entity Recognition. This component helps identify key messages from students in communication and the meaning of the conversation.
3) Conversational Agent. This component, also known as a chatbot, enables real-time communication and responses. This allows for flexible communication with other students and faculty. The component can also support tasks such as controlling devices and enhancing linguistic expression through speech recognition.

These NLP components, along with the digital inclusion model for assistive technologies, served as the foundation for building the proposed framework to support students with disabilities.

Although NLP tools like ChatGPT and sentiment analysis have been discussed, for example, in the Lalwani studies [21], their categorization and alignment with specific disability types and their real-time campus policy implications are still underexplored. This study proposes a three-part disability through NLP AI mapping that enables direct application of policy changes into development, a gap that is still rarely addressed in prior studies.

To bring out the NLP-AI framework implementation, the Bidirectional Encoder Representations from Transformers (BERT) engine is the ideal choice. Its strength lies in capturing even the subtle meaning of words in their full context, making it ideal for tasks like sentiment analysis and Named Entity Recognition (NER) [22]. These capabilities are essential when used to engage with disabled student, as the system needs to understand their emotional state and identify important information in their responses. Unlike traditional models such as LSTMs, BERT handles those things better and is also more manageable to configure. This is important for educational institutions with limited technical resources. A recent study combining BERT with FastText embeddings in an educational context demonstrated notably improved sentiment understanding compared to conventional approaches [23]. Additionally, BERT supports multilingual modeling, an advantage in areas with diverse regions and languages. While standard multilingual BERT (mBERT) covers over 100 languages, studies show its performance still benefits from targeted adaptation to local dialects. For instance, as Indonesia and Malaysia have many different language dialects, BERT could handle the differences and variations very well [24]. So, BERT's contextual intelligence, ease of management, and multilingual adaptability make it a great, resource-efficient engine that aligns with the needs of inclusive education frameworks in developing-country settings.

C. Institutional Policy Perspective on Supporting Disabilities

The study from Indonesia and Malaysia found that while legal regulations and directives for disability support exist at the institutional level, there are significant challenges in their practical application and strategic implementation.

In Indonesia itself, universities are currently required to support disabled students through the foundational laws on Persons with Disabilities and the Ministry of Education, Culture, Research, and Technology (MoECRT) Regulation from 2017. The law itself mandates universities to provide reasonable accommodation and support, but doesn't give details on how the implementation should be. Still, currently, there are ongoing commitments to develop National Digital Accessibility Guidelines to improve digital inclusion, as previous laws are more focused on physical accessibility. There is also growing encouragement and efforts to implement Universal Design for Learning (UDL) principles in Indonesian higher education to create more flexible and accessible learning environments for all students, including those with disabilities, but still, disabilities are not the main priority of this program.

In Malaysia, there has been a proactive attempt to update its policy to increase the technology-driven support for students, with disabilities as one of the targets in higher education. The Digital Education Policy, which launched in November 2023, aims to equip students with digital skills and integrate digital technology across the learning ecosystem. It would increase the digital competency for educators and also improve the infrastructure, which could boost the foundation in supporting students with disabilities. There is also the Malaysia Digital Economy Blueprint (MyDIGITAL) that includes initiatives aimed at ensuring digital inclusivity by promoting accessible digital infrastructure and services.

Nevertheless, the studies found several barriers to supporting disabilities.

1) Existence of Policies. The legal regulations and directives for disability support were generally in place at the institutional level in both countries. However, a significant gap was observed between the existence of these policies and their practical, strategic implementation in higher education institutions [25].
2) Symbolic Initiatives. Initiatives to support students with disabilities were often perceived as mostly symbolic, lacking follow-through or reasonable planning. There is a need for more concrete policies and implementation to support disabled students, particularly those who are resource-friendly [26].
3) Technological Prioritization. Specifically concerning advanced technological support, the support for disabled students was not yet an institutional priority. Most of the technology deployments are still focusing on general academic efficiency because of the budget and resource constraints [26].

Although the updates show a trend in both nations to recognize and support more disabled students through technology, it still shows how common the disconnect is between policies in place and their actual implementation. They rarely truly give the benefit that a disabled student hopes for. Since many of the implementations are poorly implemented, that is broken down in a structured way. By linking the gaps we observed directly to specific types of technology through the proposed framework, it offers a new perspective on why many well-intentioned policies fall short in practice, and how AI tools could help turn those policies into real, workable solutions.

To ensure that the proposed NLP-AI framework is in line with regulatory ecosystems, this study references national and international legislation related to inclusive education and maps them to the NLP-AI framework component. The mapping can be seen in Table 1 as follows:

Table 1. Policy mapping to the proposed NLP-AI framework

Policy / Legislation	Framework Dimension	Relevant Component	Alignment / Gap Identified
Indonesia: Law No. 8/2016 on Persons with Disabilities	Environmental (TOE)	Institutional Culture, Regulatory Compliance	Mandates inclusive education, but lacks specific provisions for ICT/NLP tools or digital accessibility. Implementation gap in higher education.
Indonesia: Permendikbud No. 46/2017	Organizational (TOE), Motivation (Digital Inclusion)	Campus Policy Support, Student Motivation	Requires inclusive learning access but does not specify technological tools or funding mandates. Motivation exists among students, but policy lacks operational clarity.
Indonesia: National Digital Literacy Movement (2021–2025)	Technological (TOE), Access (Digital Inclusion)	Infrastructure Readiness, Accessibility	Supports digital literacy broadly, but lacks specific targeting of students with disabilities. Opportunity to link NLP-AI tools here.
Malaysia: Persons with Disabilities Act 2008 (Act 685)	Environmental & Organizational (TOE)	Legal Foundation, Inclusion Mandate	Recognizes the rights of students with disabilities, but has weak enforcement mechanisms for AI/tech integration. Alignment exists, but with poor execution.
Malaysia: Malaysia Education Blueprint 2015–2025 (HE)	Environmental Fit (TOE), Motivation	Inclusive Vision, Student Agency	Prioritizes inclusion but lacks detail on digital/AI tool usage. Useful to justify motivation for using NLP-AI tools.
Malaysia: Digital Education Policy (2023–2030)	Technological (TOE), Access & Skills	Technology Readiness, AI Integration	Strong alignment. Emphasizes digital infrastructure for higher education, offers a direct entry point for the NLP-AI framework.
UNCRPD - Article 24	Environmental (TOE) & Motivation	Global Norms for Accessible Education	Both countries ratified. Strong external alignment. Failure to meet this standard highlights institutional and regulatory gaps that the framework addresses.
UNESCO Guidelines on Inclusion in Education (2009)	Environmental & Organizational (TOE)	Institutional Strategy, Interdepartmental Support	Provides international legitimacy. Supports the call for cross-unit coordination and inclusive digital design strategies.

The policy mapping table above is used as one of the references for the proposed NLP AI framework.

D. Comparison with Related Studies

Despite growing attention to inclusive education technologies, especially in AI-supported learning environments, most existing studies either emphasize technological development without institutional considerations or remain theoretical. This research contributes uniquely by integrating the Digital Inclusion Model and the Technology–Organization–Environment (TOE) framework into a policy-aligned NLP-AI design. The framework focuses on institutional policy readiness and directly mapping NLP components (Sentiment Analysis, Entity Recognition, Conversational Agents) to grouped disability types, thus giving a scalable implementation that is resource-friendly.

Table 2 below compares the state-of-the-art studies in current inclusive AI education with the contributions of the research.

Table 2. Comparison with related studies in inclusive AI for education

Study	Focus Area	Framework / Approach	AI/NLP Engine	Methodology	Context	Limitation
Song *et al.*, 2024 [27]	UDL-based inclusive AI in K-12	Universal Design for Learning (UDL)	Not specific to NLP	Conceptual/theoretical	Developed K–12	No empirical validation; K-12 only
Togni, 2025 [11]	Assistive tech platform using ML/NLP	Practical accessibility tools	Speech recognition, TTS, OCR	Case study (system demo)	Higher Ed	No policy or TOE framing
Balza *et al.*, 2025 [28]	Simulated adaptive inclusive pedagogy	Computational adaptation model	Custom simulation models	Experimental (ab-based)	Not disability-specific	Focused on model behaviour, not user validation
Neumann, 2023 [13]	GPT in inclusive higher education	Policy/pedagogy discussion	GPT-based AI	Policy review	Higher Ed	Lacks empirical user data
This study	NLP-AI for inclusive higher ed policy design	Digital Inclusion + TOE	BERT (NLP: NER, SA, CA)	Mixed-methods (interviews + SEM)	Indonesian & Malaysian universities	Limited disability types; focused on student-side input

The table above shows how this research offers a new practical contribution by bringing together the alignment of policy change with the Digital Inclusion Model and the Technology–Organization–Environment (TOE) on the proposed NLP AI framework for inclusive design, with the details as follows:

1) This study utilizes a dual framework integration that combines Digital Inclusion and TOE for inclusive technology readiness.
2) The study uses disability type to specific NLP Mapping that aligns NLP components like sentiment analysis, entity recognition, to grouped disability types for targeted intervention.
3) The Policy-Based Implementation Design. The study aligns the proposed system with institutional regulatory limitations and readiness, a dimension missing in most AI inclusion research.
4) The study uses Mixed-Methods Validation that combines qualitative thematic findings and SEM for a deeper validation across the targeted circumstances and policy landscape. This makes the proposed framework more realistic to implement, especially in settings with limited resources.

III. METHODS

A. Research Design

The research used a mixed method in the study. Mixed Methods Research (MMR) is an approach that integrates both qualitative and quantitative methodologies to generate more comprehensive and more insight than what an independent method could achieve [29, 30]. MMR gives analytical depth and quality of results as it highlights a well-designed method that is anchored by a combination and integration of both qualitative and quantitative strategies [29, 30]. The research flow is as follows:

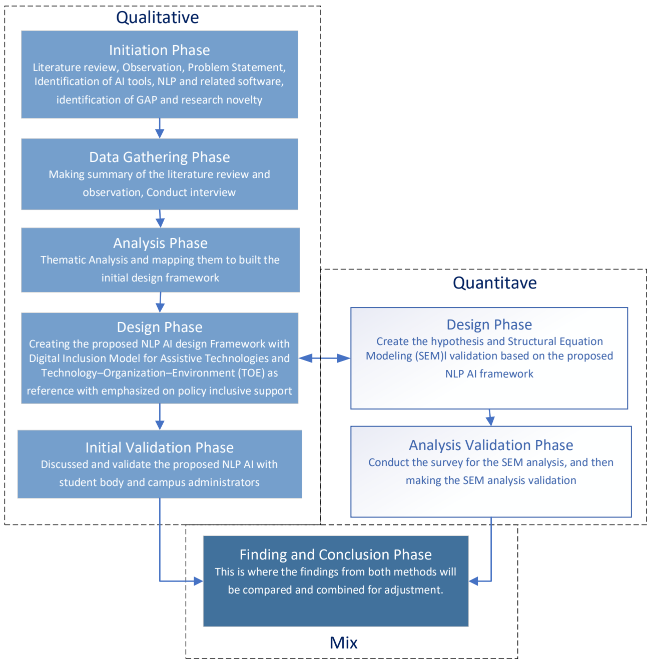

Fig. 1. Research flow.

As can be seen in Fig. 1 above, there are qualitative and quantitative parts of the study.

The study began with a qualitative part, with the data collected through the interview [31]. The interview is performed with the disabled student within the academic campus in Java, Indonesia, and also in the Selangor District, Malaysia. The interview results will then be analyzed using thematic analysis to understand and discover the reality perceived in the interview. After that, it will be used as the reference to create the proposed NLP AI framework [31]. The result is then presented to the student body and campus administrators' representatives. They were interviewed to give their opinion about the framework and findings to see how institutional policies and the current support mechanisms regarding disabled students are. The research object here focuses on how inclusive policies support the direct implementation of the proposed framework. The study uses purposive sampling, where several students with different types of disabilities are selected to fulfill the required data input. Purposive sampling involves researchers selecting samples based on the characteristics of the sample members that align with the purpose of the study [32]. In this study, a total of 21 people were interviewed. 15 disabled students (10 from Indonesia and 5 from Malaysia) were chosen for the interview. There are also four student body representatives interviewed for cross-reference. And the last is two campus administrators, also interviewed for model implementation viability validation. The 15 disabled students are chosen through selective purposive sampling to make sure they cover many types of disabilities that exist on the campus. Purposive sampling itself is a non-probability sampling technique that selects its participants based on specific characteristics [33]. In this case, the selected sample represents three groups of disabilities, which are visual impairment, hearing impairment, and Physical/Motor Impairment that require Assistive Communication Technologies. The disabled students chosen for the interview data are not disclosed in the research and are given aliases to replace their names. This is to protect their confidentiality. Although the sample is small, they are representative enough because of the diversity of its types of disability. The student representatives are interviewed for reference regarding the support for inclusive policies in the proposed framework.

For the quantitative part, there will be SEM analysis using a data survey to test the design framework created through the hypothesis that aligns with it [34]. The survey for SEM analysis data collection was conducted using Google Forms from April to June 2025. The survey data is gathered from disabled students across Indonesia with the help of the student body, to help alleviate their difficulty in filling out the survey form. There is are total of 83 data surveys used for this analysis from 92 survey participants, with 9 data were omitted. Due to time and resource constraints, the research participant was limited to disabled students in Indonesia only. The data was gathered with disability students representing various types of impairments. Most respondents came from state-owned universities. As it was challenging to reach and recruit students with disabilities for the survey, our student body organization collaborated with other university student bodies, which are primarily state institutions. They will help to identify and assist eligible participants in filling out the form.

B. Theoretical Framework

To build the proposed NLP-AI framework, the research used the combination of the Digital Inclusion Model with the Technology Organization–Environment (TOE) Framework. The combination of the dual framework strategy will allow the research to be a multi-dimensional validation as follows:

1) Digital Inclusion Model to assess user-centered inclusivity.
2) TOE assesses institutional readiness and systemic scalability.

In contrast, other models like UTAUT or TAM focus mostly on individual adoption without explaining organizational or environmental readiness, which is important when proposing assistive technology in education policy. The Digital Inclusion Model for Assistive Technologies emphasizes access, skill, and motivation in building assistive tools for the disability person which is in line with the research goals since the proposed framework aims for the availability of NLP AI tools for students with disabilities (Access), the ease of use of the assistive technology for the disability student (Skills), and how the NLP AI proposed framework could help the university to create more policy support regarding the inequality of disability student on academic activities (Motivation) [15]. The Technology-Organization-Environment (TOE) framework [16] will help to check the implementation feasibility of the proposed model, especially in the inclusive support policy. If the institutional support is in line and fits through TOE's three three-dimensional factors, then the proposed framework does have valid potential for its proper implementation.

IV. Result and Discussion

This section presents the findings and the discussion regarding the implications of Natural Language Processing (NLP) Artificial Intelligence (AI) tools to support disabled students from Indonesia and Malaysia. There is data analysis from qualitative analysis through the interview, and also SEM analysis from the quantitative data analysis. This was done to see how the current policy supports the proposed framework.

A. Interview for The Proposed Framework with Students

The proposed framework objective and the supporting tools are explained to the interview candidates before the interview takes place. We explain how the NLP AI could help them in their activities, and the plan for the possibility of incorporating them into the campus system in the future to help them. The result from the thematic analysis is as follows:

1) Interview results from Indonesia

The interviews were performed with ten disabled students from various universities in Indonesia, but mainly from UNESA, East Java. The interview summary from Indonesia reveals that while students with disabilities are eager to participate in organizational and extracurricular activities, they face consistent challenges related to communication, mobility, and environmental accessibility. Many emphasized that technology, particularly AI tools like image description software, voice commands, and platforms similar to ChatGPT, can play a transformative role in enhancing independence. For tasks involving navigation, communication, and information access, they show well in helping them. Students with low vision highlighted the usefulness of tools like OCR and Be My Eyes, while those with speech or cognitive impairments expressed hope for future features addressing dyslexia and supporting sign language translation. Despite their enthusiasm and active involvement, participants stressed that technological support alone is not enough. Institutional understanding, inclusive facilities, and disability aware campus organizations, with proper policy support, are essential to ensure equal opportunities and meaningful participation. Overall, these insights underscore the need for not just adaptive technology and systemic inclusion but also proper policy support to empower students with disabilities across diverse educational activities.

2) Interview results from Malaysia

The interviews were performed with five disabled students from Universiti Kebangsaan Malaysia (UKM It revealed how some of the students never participated in non-academic or organizational activities due to their dyslexia disabilities and had difficulties in communication and information processing. The other disabled student had some level of involvement but reported facing considerable challenges related to accessibility and communication barriers. They emphasized that the system's ease of use and affordability are important for campus-wide implementation. They hope that their university will adopt an inclusive NLP AI-based support system to improve learning and engagement opportunities for students with disabilities in the future.

3) Student interview summary result

From all of the thematic interview analyses from 15 of the interviewers, the Thematic Code Frequency and analysis obtained are as follows:

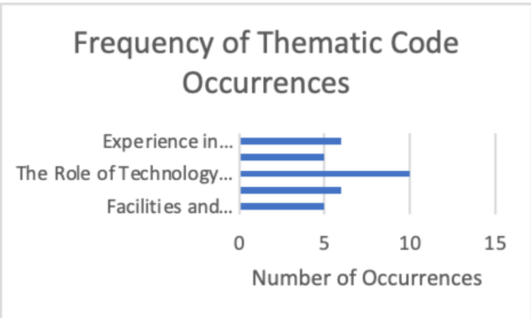

Fig. 2. Thematic code frequency.

From Fig. 2 above, we can see that the most dominant topic in the thematic analysis is "The Role of Technology in Helping the Disabled Student" because almost all the students talk about it. This shows that they understand the potential importance of technology in supporting the participation of disabled students. On the other hand, Challenges and Obstacles in Academic Activities and Expectations for Organizations and Campus Environments to support disability emerged in equal numbers, which means that the challenges and inclusive inequality are still major issues, mainly in the policy support. Also, here we can see that Facilities and Infrastructures have the lowest mention than other aspects, but are still an important aspect for those students with impaired mobility disability.

After the initial interviews and the development of the framework, follow-up interviews were conducted with four student body representatives for cross-reference. The student body representative added that there are currently no specific programs empowering students with disabilities in the student body. However, the institute does provide media content in audio, visual, and text formats to be accessible for students with disabilities. The student body wants to create programs that could involve more participants of disabled students in the future. Currently, at the university level, there are already sports events involving students with disabilities, but it is still sporadic. The interviewer stated that the main challenges are participation and the lack of knowledge and special training for communicating with students with disabilities. They also mentioned the limited availability of skilled human resources for sign language. And the campus didn't offer or provide help regarding this matter. There is still inadequate inclusive policy support from the institution. They hope that they can use the proposed framework to support disabled students. Additionally, they plan to use technologies to be more helpful to those with disability to participate more in their program.

B. The Proposed Framework for NLP AI-Based Inclusion Design and Tools

Based on the interview research, evidence shows that students with disabilities are underserved in higher education. This manifests as:

- Low participation in campus activities indicates a lack of true inclusion.
- Ceremonial policies that lack meaningful implementation and resource allocation.
- Insufficient resources and funding to provide adequate support.
- Accessibility barriers within the learning environment.
- These issues highlight the need for policy intervention to mandate and facilitate the use of innovative solutions like NLP AI.

The proposed framework in this research has two main objectives. The first is how to create standards for accessible program materials for students with disabilities using NLP AI Support. The second is how to create an Inclusive Environment and minimize risks faced by students with disabilities in student activities by using NLP AI Applications. Referring to the disability types from ICF, since there are too many disability types, we break down disability types to be as simple as possible, so that they can still fit the classification, but can cover many of the types of disabilities that exist on the campus. So, we design the proposed NLP AI tools and Applications into three group categories of disability, as they already represent most of the disabled students on the campus. This will also help with the time and resource constraints for the research.

As policymakers, the purpose of goals is clear. The policymaker needs to support a strategic policy that facilitates the ethical and equitable implementation of NLP systems to achieve better growth and foster inclusive learning environments. The framework highlights how it doesn't just organize NLP features by what they do, but also how they specifically support different types of disabilities with the help of the Digital Inclusion Model. This shift from a general, function-based approach to a more user-centered design from the existing studies on AI and inclusion. On top of that, the framework is built with real-world constraints, like limited budgets and the need for policies that can actually be put into practice, which is based on the TOE framework. This makes it more practical and scalable than many AI inclusion models, which often assume institutions have unlimited resources.

In response to the stakeholder, the research simplified and broke down the disability support and then mapped it with the dual framework as follows:

Table 3 shows how the Digital Inclusion Model shapes the inclusive design principles for the disability specific needs and NLP technology choices. This will ensure that the solutions are both human-centered and give proper results. With the dual framework references planned, the study also needs to map the TOE model into the proposed framework, which can be seen in Table 4 below.

Table 3. Mapping from the digital inclusion model to disability NLP AI framework

Digital Inclusion Dimension	Sub-Criteria	Non-Verbal Communication Tools (e.g., Pictograms)	Verbal-Based Communication Tools (for Visual Impairments)	Assistive Communication Technologies (Physical/Motor Disabilities)	NLP Component Used
1. Access	Personalized Interaction	Generates tailored symbols that reflect unique user expression styles.	Delivers audio descriptions customized to user preferences (e.g., speech rate, language).	Enables customized device control through voice commands and gesture-based interfaces.	Entity Recognition (NER), Conversational Agents
	Adaptability in Communication Abilities	Adapts pictographic output complexity (e.g., simple vs. advanced) to align with user capabilities.	Modulates verbal descriptions to suit the user's emotional context and reading level.	Accommodates a range of input modalities, including voice, touch, and eye-tracking.	
2. Skills	Automated Real-Time Support	Provides real-time generation of pictograms from typed or spoken input.	Offers real-time text-to-speech (TTS) or Optical Character Recognition (OCR) for material description.	Executes device commands via real-time voice recognition.	Sentiment Analysis, Entity Recognition (NER), Conversational Agents
	Lessen Communication Barrier	Facilitates the rapid expression of needs (e.g., health, academic requests) through visual cues.	Articulates descriptions of visual surroundings or text-based information for visually impaired students.	Transforms partial or limited speech into coherent, fully understandable output.	
3. Motivation	Enhance Engagement and Participation	Promotes independent interaction in group settings through the use of pictogram boards.	Fosters active participation in reading, navigation, and lectures via integrated audio support.	Enhances user autonomy in performing academic tasks, such as submitting assignments through voice commands.	Sentiment Analysis, Entity Recognition, Conversational Agents
	Institutional Incentive for Implementation	Features low-cost, scalable systems that permit straightforward integration across departments.	Encourages widespread adoption by ensuring high accessibility and a minimal learning curve.	Reduces the burden on support staff, thereby increasing the feasibility of implementation.	

Table 4. Mapping from Technology Organization–Environment (TOE) to disability framework

TOE Factor	Impact on Implementation	Non-Verbal Communication (Pictograms)	Verbal-Based Communication (Visual Impairment)	Assistive Communication Tech (Physical/Motor Impairment)
1. Technological Factors	Pertains to the availability and seamless integration of AI tools within existing institutional systems.	Simple pictogram tools are designed for straightforward integration with existing LMS and mobile platforms. Underlying NLP models (e.g., entity recognition) map text to images, facilitated by simple API integration.	Text-to-speech (TTS) and OCR applications integrate easily with digital content platforms. NLP components, such as sentiment and entity recognition, enhance the quality and context-awareness of generated audio.	Voice and gesture recognition tools are compatible with standard mobile and desktop operating environments. Core NLP technologies like chatbots and voice control protocols enable hands-free device operation.
2. Organizational Readiness	Concerns the level of institutional support, staffing capabilities, and interdepartmental coordination.	Disability support centers can manage and curate symbol libraries while assisting with user adoption. User training and support can be efficiently delivered through existing student support offices.	Library services and academic staff can collaborate to support visual-to-audio content conversion workflows. This promotes collaboration between faculty and content delivery teams to ensure accessibility.	Requires coordination with IT and facilities management to configure smart environments, such as voice-enabled classrooms. Fosters a team-based implementation model involving academic, IT, and disability service units.
3. Environmental Conditions	Relates to external regulations, internal policy alignment, and the prevailing institutional culture regarding inclusion.	Aligns directly with inclusive education mandates; low-cost options facilitate broader institutional adoption. Requires minimal infrastructural changes, which aids in achieving rapid policy compliance.	Supports compliance with accessibility laws by providing alternative formats for digital content. Encourages the development of accessible syllabus designs and the curation of inclusive digital libraries.	Visibly demonstrates institutional commitment to inclusivity through independence-enabling technologies. Reinforces national disability inclusion policies by empowering students through technology.

Table 4 above shows how the TOE framework aligns with the implementation needs of the three types of disability support tools within the proposed NLP-AI system. In this context, the Technological Factors reflect how the preparation and compatibility of the university's infrastructure are required to adopt the NLP AI solutions. Features such as pictogram-based communication and text-to-speech functionalities can be integrated into academic environments through NLP technologies like entity recognition. The voice command is particularly beneficial for students with visual or verbal impairments, allowing for smooth, intuitive interactions. The Organizational Readiness, on the other hand, relates to the availability of institutional resources, staff capacity, and interdepartmental collaboration. Successful implementation goes more than just having the right tools. It also requires active involvement from support units such as disability service centers, libraries, and IT teams to configure systems, manage content, and train users. This coordinated support structure will enable greater accessibility and promote an inclusive academic atmosphere. Lastly, the Environmental dimension focuses on how well the initiative aligns with existing policies, cultural values, and funding priorities. Institutions that incorporate digital accessibility educational policy regulations are more likely to implement NLP AI properly. A supportive environment not only encourages adoption but also ensures that these technologies give visible benefits for students with disabilities.

The detailed design classification of the assistive NLP tools by disability communication mode (non-verbal, verbal, assistive) will give a clear reference for the institutions. So, when the institution deploys the inclusive infrastructure, it could accompany it with proper policy regulations for better implications. Something that is missing in most AI deployment proposals.

C. Proposed NLP AI Framework Model Design and Validation

With the input from the thematic analysis and suggestions from the student body representative interview results, we finalize the proposed framework for Inclusive NLP AI as follows:

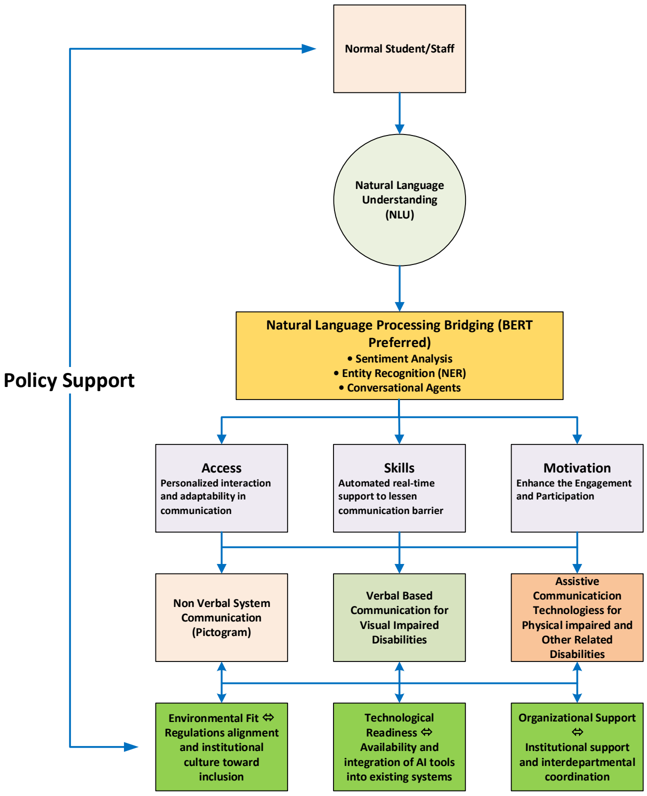

Fig. 3. Finalized proposed framework for inclusive NLP AI implementation.

Fig. 3 above shows the model framework implementation of NLP AI to support the involvement of students with disabilities in campus activities. Using these NLP components and tools within the framework can improve accessibility and facilitate the understanding of the needs of disabled students. Since disability itself is very broad, this framework limits the type mainly to three groups of disability types that could represent most disabled students on campus. This framework will bridge the use of NLP AI technology to help with this disability, according to the type of disability. In this model, NLP bridges existing Natural Language Understanding (NLU) systems, making communication easier between individuals with disabilities and non-disabled people, as NLP simplifies the NLU process to approximate general communication [35].

The proposed models are also in line with TOE's three dimensions of validation factors [16], which are Technological, Organizational, and Environmental Factors. Based on the interview results with the two campus administrators, we can see how the proposed framework could help with the shortcomings in the TOE's three existing dimensions. This design makes the framework more resource-reducing and time-friendly to develop, and makes it possible to be implemented alongside the general academic system development. This will give the university policymakers easier for university policymakers to issue regulations and policies that support inclusiveness. With the correct policy support, the framework has the potential to shorten the gap between disabled student activity and that of non-disabled students. The finalized proposed framework could help disabled students communicate and interact with other students in their academic activities. This study uses a triangulation model involving end-users (students), policy actors (administrators), and mediators (student body). This validation architecture gives practical legitimacy to the framework and reflects actual policy friction points with the implementation plan.

D. Interview for the Proposed Framework with System Administrators

The final Interviews were performed with two of the campus system administrators to see the take of the university policy support on the adoption of the NLP technology framework implementation. This is performed through the TOE framework with the result as follows:

1) Technology dimension implementation validation. How does the institute promote technology development to support the framework implementation? Currently, the NLP AI implementation to support disabled students is not a priority. They still focused on improving the general academic system and accessibility support. The current technology to support disabled students is still basic in functionality and doesn't cater to the needs of many disabled students.
2) Organizational dimension implementation validation. How the universities encourage the establishment of dedicated units and foster inter-departmental collaboration to support the use of NLP AI. Universities already have a special unit to support disability. However, the unit has limited resources and a lack of coordination with other units that supposedly help disabled student with their collaboration. Let alone adopt the NLP AI establishment.
3) Environmental Factors dimension implementation validation. The institute enacts policies that mandate accessibility, provide funding, and create incentives for institutions to prioritize inclusive practices. The Government and university regulations to support accessibility for the disabled already exist. However, their implementation on campus is still weak and not well-directed. It showed how disabled student still don't feel proper support in their academic activities and can't perform their activities properly in academics.

An interview regarding the inclusive support policy on the implementation of the proposed NLP AI framework shows that the current policy is still mainly limited due to the lack of funding, human resources, and priority. The unit that is supposed to handle disability support lacks coordination and a proper strategy to support the disabled student. More concrete policies and implementation to support disabled students are needed to be able to support them in inclusive academic activity and reduce inequality.

E. Proposed Framework for NLP AI-Based SEM Analysis

For validating the proposed framework, the SEM analysis is performed as follows:

1) Hypothesis building

For SEM analysis, the hypotheses that are aligned with the proposed framework design are created. The hypotheses will examine the relationship between the factors it was built and how they affect the disabled students and the institution, from the perceived effectiveness of each of the criteria, and also the intention to use. The hypothesis built is as follows:

H1: Access positively influences Perceived Effectiveness

Access enables students with disabilities to easily access the tools through their own devices or university facilities. Removing barriers, whether technical or procedural, gives students more independence and confidence, which directly shapes how effective they feel the technology is in supporting their academic work [36].

H2: Skills positively influence Perceived Effectiveness

Digital skills are essential because students who possess the ability to operate NLP-AI tools with confidence, or who find the tools intuitive and easy to learn, will tend to perceive the technology as more effective. When students know how to use NLP-AI tools or find them simple to learn, they tend to get more out of them. Tools that are designed to match students' skill levels, especially for those with disabilities, become more practical and easier to integrate into daily learning [14].

H3: Motivation positively influences Perceived Effectiveness

Motivation plays an important role in assistive tech. If they're motivated, they're more likely to try new tools and discover their benefits. This kind of active use helps students feel that the tools are making a difference in their academic experience [37].

H4: Technological Readiness positively influences Intention to Use

Technological readiness refers to the availability, compatibility, and capacity of the institution's IT infrastructure. Students are more likely to use NLP-AI tools when their university has the right tech infrastructure in place. If the systems are reliable and easy to connect with, it gives students the confidence to adopt the tools. But if the tech is outdated or hard to work with, students might avoid using it altogether [38].

H5: Organizational Support positively influences Intention to Use

Organizational support includes administrative backing, support services, and institutional policies that promote the use of assistive technologies. When students feel that their campus actively supports the use of assistive technologies through services, programs, or policies, they're much more likely to trust and use those tools. That kind of visible commitment shows students that inclusion is more than just talk, and it helps build long-term engagement [39].

H6: Environmental Fit positively influences Perceived Effectiveness

Environmental fit encompasses the alignment between external forces, particularly policies, with the implementation of inclusive technologies. Students are more likely to find assistive tools helpful when their surroundings, like campus culture, national policies, or even public attitudes, are inclusive and encouraging. These kinds of environments help break down stigma and reinforce the idea that the tools are relevant and valuable in both academic and social contexts [40].

H7: Environmental Fit positively influences Intention to Use

A supportive environment consists of supportive national regulations, institutional culture, and societal expectations. When students are part of a community where inclusion is prioritized through regulations, campus initiatives, or general awareness, they feel safer and more confident using assistive technologies. That kind of environment not only encourages adoption but also helps sustain long-term use [41].

H8: Perceived Effectiveness positively influences Intention to Use

Perceived effectiveness creates a bridge between experience and future behavior. If students believe that the tools are helping them, whether that's improving communication, understanding, or learning. They're far more likely to keep using them. This sense of effectiveness comes from their personal experience and is shaped by things like access, support, and ease of use [42].

2) SEM model

Based on the hypothesis and the framework model, the SEM model for analysis is then built as follows:

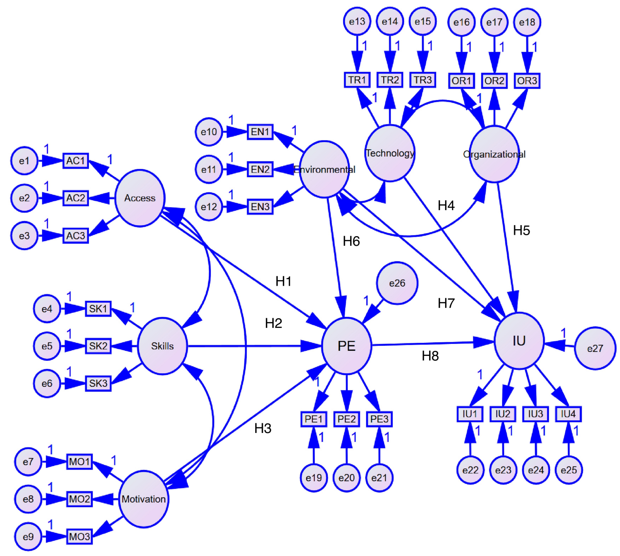

Fig. 4. SEM model from AMOS SPSS.

Fig. 4 above shows the structure of the SEM model, how the variables Access, Skills, and Motivation are linked to Perceived Effectiveness. Meanwhile, the Technology, Organizational, and Environmental factors from the TOE framework are connected to Intention to Use. Additionally, the Environmental factor also influences Perceived Effectiveness. Overall, the SEM model reflects the proposed NLP-AI framework, incorporating both the Digital Inclusion Model and the TOE framework, with each variable aligned with the hypotheses presented in the study.

The indicators used for the SEM data analysis are as follows:

Table 5. SEM indicator

No.	Variable Label	Indicator	Indicator Label
1	Access [36]	I can easily access NLP-AI tools for my academic activities.	AC1
		The NLP-AI tools are available to support my learning at any time I need	AC2
		I face no difficulty in finding or using assistive technology on campus.	AC3
2	Skills [14]	I feel confident in my ability to use NLP-AI tools effectively	SK1
		I can learn to use assistive technologies without much difficulty.	SK2
		The NLP-AI tools are user-friendly for someone with my level of skill.	SK3
3	Motivation [37]	I am motivated to use NLP-AI tools to enhance my academic participation.	MO1
		Using assistive technology helps me feel more included in campus life.	MO2
		I believe NLP-AI tools will help reduce the barriers I face in learning.	MO3
4	Technology [38]	My campus has the necessary infrastructure to support NLP-AI tools.	TR1
		Technological systems on campus are compatible with assistive tools.	TR2
		There are reliable technical resources to support the implementation of NLP-AI.	TR3
5	Organizational [39]	My university provides strong institutional support for disability tools	OR1
		There are policies and programs in place to help students with disabilities use technology.	OR2
		My academic institution actively promotes inclusion through technology	OR3
6	Environmental [40, 43]	University policies encourage the use of assistive technologies for disabled students.	EN1
		The campus culture supports digital accessibility and inclusion.	EN2
		There are national or local regulations that support inclusive technology use.	EN3
7	Perceived Effectiveness (PE) [41]	I believe that NLP-AI tools can improve my academic performance.	PE1
		Using NLP-AI tools helps me engage more effectively in academic activities.	PE2
		I find NLP-AI tools effective in overcoming my communication barriers.	PE3
8	Intention to Use (IU) [42]	I am willing to use NLP-AI assistive tools in my academic activities.	IU1
		I intend to use the NLP-AI tools when they are available at my university.	IU2
		I feel confident that NLP-AI tools will work effectively within my university's support system.	IU3
		I would continue using NLP-AI tools if they prove effective in supporting my learning needs.	IU4

Each of the variables and indicators in Table 5 above corresponds to the proposed hypothesis and the proposed NLP AI model framework.

3) SEM respondent demography

The data used for the SEM analysis were collected from a diverse group of students with disabilities enrolled in both public and private universities across Indonesia. Due to limitations in time and resources, the study focused solely on Indonesian participants. There are 83 valid survey entries obtained from students with various types of disabilities. The survey included both demographic questions and Likert scale items (ranging from 1 to 5). Most of the respondents came from state-owned universities because of the difficulty in getting data from disabled students. The student body organization collaborated with student bodies at other universities, especially public ones, to locate participants and assist them in completing the survey. Students with visual impairments were the least represented, as they often required additional help to respond to the questionnaire.

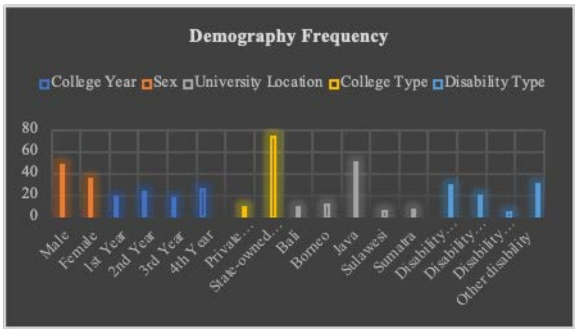

Fig. 5. Respondent demography frequency.

Fig. 5 above shows that many of the respondents are from state-owned universities and the Java area. It is because of the nature of the difficulty in obtaining data from disabled student due to their constraint. We can't just distribute questionnaires, but use the help of the student body to collect the responses, which mainly come from state-owned universities in Java. This is why the participation of disabled students is concentrated in those areas.

4) SEM analysis

From the SEM analysis, we can see the result as follows

a) Model validation

The Chi-Square, CFI (Comparative Fit Index), RMSEA (Root Mean Square Error of Approximation), and SRMR (Standardized Root Mean Square Residual) are used for the model validation, with the values as follows:

Table 6. Model Fit

No.	Variable Fit	Value
1	Chi-Square (simulated)	130.28
2	CFI (approx)	0.949
3	RMSEA (approx)	0.065
4	SRMR (approx)	0.076

From Table 6 above, the Chi-Square is roughly at ≈ 130, which is still the cut-off value of 165 ($df = 55$), which is an acceptable fit. For the CFI, it has a value of 0.949, which is over the acceptable threshold (≥ 0.90), so it is acceptable. The RMSEA value is below the threshold of < 0.08, which is acceptable. Whilst the SRMR value is still acceptable, just a bit below the acceptable range, which is below 0.08.

b) Variable construct validation and reliability

For the variable validation, we used the Factor loadings and t-values of factor loadings; Cronbach's α, C.R., and AVE for the variable used with each of the values can be seen in Table 7.

The values of the Access, Skills, and Motivation from the table above all have AVE value ≥ 0.5 and CR ≥ 0.7, showing strong convergent validity and reliable measurement. The Cronbach's Alpha analysis shows that all constructs exhibit acceptable to good reliability, which means consistency within each set of survey questions.

Table 7. Variable validation and reliability check

No	Variable	AVE	CR	AVE ≥0.5	CR ≥0.7	Cronbach's Alpha
1	Access	0.588	0.801	TRUE	TRUE	0.821
2	Skills	0.647	0.840	TRUE	TRUE	0.830
3	Motivation	0.514	0.738	TRUE	TRUE	0.756
4	Technological Readiness	0.571	0.706	TRUE	TRUE	0.735
5	Organizational Support	0.602	0.721	TRUE	TRUE	0.737
6	Environmental Fit	0.581	0.704	TRUE	TRUE	0.704
7	Perceived Effectiveness	0.587	0.714	TRUE	TRUE	0.732
8	Intention to Use	0.585	0.716	TRUE	TRUE	0.746

c) Regression and hypothesis validation

The regression analysis from the SEM model can be seen in Table 8 is as follows:

Table 8. SEM regression

No	Hypothesis	Estimate	S.E.	C.R.	P	Support	Loading Factor
1	H1: Access → Perceived Effectiveness	0.371	0.081	**4.589**	***	Supported	0.857
2	H2: Skills → Perceived Effectiveness	0.190	0.078	**2.426**	**0.0176**	Supported	0.864
3	H3: Motivation → Perceived Effectiveness	0.178	0.084	**2.133**	**0.0361**	Supported	0.821
4	H4: Technological Readiness → Intention to Use	0.283	0,085	**3.318**	**0.0014**	Supported	0.808
5	H5: Organizational Support → Intention to Use	0,184	0.089	**1.994**	**0.0456**	Supported	0.807
6	H6: Environmental Fit → Perceived Effectiveness	0.342	0.091	**3.726**	***	Supported	0.792
7	H7: Environmental Fit → Intention to Use	0.256	0.098	**2.408**	**0.0109**	Supported	0.792
8	H8: Perceived Effectiveness → Intention to Use	0.124	0.091	**1.985**	**0.0488**	Supported	0.816

Note: *** means that the p-value is lower than 0,01, thus indicating a strong significance

From the SEM analysis regression table results above shown that all standardized coefficient (β) values are greater than zero, which means it is positively influencing the variable. All the constructs show loading factor values above 0.7, which means that the indicators are reliable. The critical ratio (C.R.) value is exceeding 1.96, which means statistical significance at the 0.05 level ($p < 0.05$), and values above 2.56 mean significance at the 0.01 level ($p < 0.01$).

These SEM results are consistent and in line with the proposed NLP AI framework. As we can see from the findings, **Access (H1**) was strongly confirmed, determining the crucial role of ensuring students with disabilities have both physical and digital access to NLP-based tools, thus significantly shaping their perception of the tool's effectiveness.

The Skills (H2) is supported, showing the importance of user competence and ease of use, in line with previous studies that highlight usability as a key factor in technology engagement. **Motivation (H3**) was statistically supported, too, showing the idea that students' willingness to engage with assistive technologies is essential for consistent use, which is also shown in the interview result analysis.

From the TOE factors, the **Technological Readiness (H4)** is supported, suggesting that well-prepared and compatible campus infrastructure encourages adoption of the NLP-AI framework.

For the **Organizational Support (H5)**, it is supported and shows how the lack of consistent, visible, and actionable support from institutions led students to perceive organizational backing as just symbolic, reducing its influence on their willingness to adopt NLP-AI tools. And even though some support exists, their limited implementation renders them practically irrelevant.

The Environmental Fit (H6) is strongly supported. It played a significant role in shaping the perceived effectiveness. This is also in line with the interview results that highlight how inclusive institutional environments help reduce social barriers and promote adoption.

The Environmental Fit to Intention to Use (H7) from TOE is also supported. It shows how cultural and especially policy support will lead to an increase in usage intention, and directly help in the NLP AI implementation.

The last is **Perceived Effectiveness influencing Intention to Use (H8)**, which is also supported. It shows that while students recognized the potential effectiveness of NLP-AI tools, this perception did not translate into an intention to use without proper support from infrastructure, institutional readiness, and policy enforcement. This is also reflected in the interview results.

F. Discussion

The research result indicates that NLP AI tools have a high potential to improve the participation of disabled students in their academic activities by providing customized and accessible solutions.

Neumann's study emphasized that AI-powered tools (such as ChatGPT) can improve accessibility but require strong institutional implementation strategies [13]. The research result confirms this finding by showing that university policies are currently still mainly ceremonial rather than actively supportive.

Firaina [4] states that large-scale AI integration in higher education improves student engagement, but institutions often lack clear adoption models. The research result addresses this gap by offering a proposed NLP AI framework with structured implementation steps for universities.

There are also contrasting research results from studies in the same field. Zawacki [14] stated that AI's impact on education depends on pedagogical adaptability and digital literacy. However, this study found that this is not the case. The main barrier instead is the lack of a policy that properly supports disabled students, and also the limited supporting assistive tools to help disabled students in their academic activities.

The performance of the proposed NLP AI framework was assessed using SEM analysis, supported by 83 student responses. The Model fit indicators show CFI = 0.949, RMSEA = 0.065, and SRMR = 0.076, which fall within acceptable thresholds. Eight hypotheses were tested and supported, confirming the significant influence of Digital Inclusion (Access, Skills, Motivation) and TOE components (Technology, Organization, Environment) on perceived effectiveness and intention to use. These quantitative findings validate the framework's design logic and relevance in the target circumstances.

The SEM analysis reveals that access, skills, and motivation are supported in affecting students' perceptions of how effective NLP-AI tools are, confirming the core dimensions of the Digital Inclusion Model (H1, H2, H3). This finding aligns with the results from student interviews, where participants emphasized that having accessible tools, easy-to-use interfaces, and motivation-driven engagement are critical for participating in academic activities. Students with visual and speech impairments, in particular, showed enthusiasm for tools such as symbol-based systems and conversational agents, highlighting their potential to overcome communication barriers. These findings support Zawacki-Richter's study [14], which brings up the importance of digital literacy and inclusive design in strengthening student participation.

The analysis also shows that technological readiness, organizational support, and environmental fit are supported in influencing students' intention to use these tools (H4, H5, H7). This supports key aspects of the Technology–Organization–Environment (TOE) factor from the proposed NLP AI framework. It shows that even though many universities may possess the necessary infrastructure and regulatory frameworks to support inclusion, both students and staff acknowledge that these resources are often underutilized. Despite supportive policies, there remains a clear gap between intention and implementation.

The organizational support to affect intention to use (H6) is also found to be supported. This outcome is consistent with the interview results from the administrator and student body, who cited fragmented departmental coordination and weak policy enforcement as major obstacles. These challenges also have similarities with Arias's finding [44] that shows many Southeast Asian universities struggle with effective ICT implementation due to conflicting priorities and limited stakeholder involvement, although this study finding differs in that they still do so with enough ICT resources. This is resulting in fragmented and inconsistent support systems for the inclusive student.

A notable finding is that how Perceived Effectiveness affects the Intention to Use (H8) is also supported. It shows that even when students believe in the usefulness of NLP-AI tools, it doesn't always lead to adoption (H8). Institutional and systemic barriers often stand in the way. This highlights that, in reality, having the right technology is not enough. Without proper implementation from coordinated support structures, collaborative institutional action, and particularly strong policy alignment, the most promising innovations may go unused. Bervell [45] shows similar findings that disability policies often lack practical implementation, leading to low engagement with inclusive technologies.

Unlike previous AI-inclusive research that assumes adequate infrastructure and mature policy support, this model study is aimed at developing countries, where resource limitations are more common. It is also the first to propose a scalable NLP design that maps directly to regulatory frameworks using BERT as the NLP engine, thus allowing multilingual and culturally sensitive implementations. Furthermore, this study combines the triangulation of administrator, student, and institutional input that offers a multidimensional validation, that rarely found in prior research.

V. Conclusion

The study reveals that students with disabilities are willing to participate in extracurricular activities, but certain barriers arise that are linked directly to their kind of disability. The proposed NLP AI framework is are ideal solution for such problems because they have tools that can be tailored to the particular needs of each type of disability. The proposed NLP-AI framework is designed with user needs centered in mind. Using the Digital Inclusion Model as a reference, which highlights the importance of access, skills, and motivation in adopting new technologies. These elements are thoughtfully built into the framework to ensure it truly supports students with disabilities. To test how well it could work in practice, the framework was evaluated using the Technology–Organization–Environment (TOE) model.

While many universities already have AI-related policies, the findings show a clear gap when it comes to putting those policies into action, especially in providing substantial support for disabled students. This is largely due to weak institutional support, inconsistent implementation, and especially a disconnect between policy and practical execution. These findings suggest that the main challenges of digital inclusion for students with disabilities lie more in institutional governance and coordination rather than in technological limitations, mainly the alignment of the policy support and its actual effective implementation. Only with these foundational supports in place can students with disabilities fully engage and benefit from inclusive academic systems.

This study is limited to disabled students in selected universities in Indonesia and Malaysia, with a primary focus on state-owned institutions in Java and the Selangor district. Because of the limitations of time, resources, and participants, the research only includes three types of disabilities as described. Other types of disabilities, such as cognitive, mental health, or other related health conditions, are not included. The study's findings may not fully represent the situations in other regions or developing countries without further study and adaptation. In addition, the relatively small number of participants may limit the statistical generalization of the findings for wider populations. This study will give early insight and a basis for further research with a larger and more diverse disability types.

The current research results, in the form of an NLP AI framework implementation, could work well with many of the disabled students for their academic activities if supported with the proper policy. The study indicates that policymakers should go beyond just envisioning the inclusive into policy support. In the future, the follow-up research could involve more external views, like the Government and Legislative Support. Since those things also play a crucial role in helping the implementation of the NLP AI disability framework. The longitudinal research could further validate the policy change's impact on the inclusive support implementation. The research should also include more diverse disability spectrums, including cognitive and mental impairments. A pilot implementation phase using an NLP AI framework as a prototype within a university department is a great addition. Because it can be used to monitor usability, adoption, and learning impact. This pilot would also offer empirical data to validate the framework's real-world implementation impact and results.

Nevertheless, the current research carried some limitations. The first is that this study includes only five Malaysian students in its qualitative phase and no Malaysian participants in the SEM phase. As a result, generalizations to Malaysian higher education are preliminary and require confirmation in future studies. The second is that the type of disabilities included in the research is limited to just three groups of disability types, with health and mental disabilities excluded, since the majority of the sample found in this research can be grouped into these types. Since many of the mental disabilities are not disclosed or do not make it to the higher education level. This exclusion will result given might not be as rich and accurate as it could have been. The last is that the external views on the policy are omitted due to the lack of time and resources.

Declaration of Generative AI in Scientific Writing

Generative Artificial Intelligence and AI-assisted Technologies (such as ChatGPT, Gemini, Grammarly, etc.) were used to assist in the creation and refinement of the article. However, all conceptual content, analysis, framework design, and findings presented in this paper were developed solely by the authors.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Nanang Husin contributes with the Conceptualization (Lead), Formal analysis (Lead), Methodology (Equal), Writing—original draft, review, and editing (Equal); Ummu Ajirah Abdul Rauf contribute with the Data curation (Equal), Investigation (Equal), Resources (Equal), and Validation (Equal); Hujjatullah Fazlurrahman contribute with providing the Project administration (Equal) and Supervision (Equal); Anita Safitri contributes with the Project administration (Equal) and provides Resources (Equal); Riska Dhenabayu contributes with the Project administration (Equal) and Investigation (Equal); whilst Aldi Muhamad Fitrah contributes with the Data curation (Equal), Resources (Equal), Validation (Equal), and also Writing review and editing (Equal). All authors had approved the final version.

Funding

This paper is part of the Digital Business Department from the Faculty of Economics and Business, UNESA, RKI Research Output Grant in 2025 No. 542/UN38/HK/2025, Matching Grant between the Graduate School of Business, Universiti Kebangsaan Malaysia, and Universiti Surabaya (GSB-2024-026), and Research Grant under the Graduate School of Business, Universiti Kebangsaan Malaysia (GSB-2025-017).

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