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Anas Arfandi

anas.arfandi@unm.ac.id

Universitas Negeri Makassar

Saharuna Saharuna

Universitas Negeri Makassar

M. Syahid Nur Wahid

Universitas Negeri Makassar

Sudjani Sudjani

Indonesia University of Education

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RESEARCH ARTICLE

Social and technological factors explain artificial intelligence readiness among vocational high school students

Anas Arfandi*
Department of Civil Engineering and Planning, Universitas Negeri Makassar, Makassar, Indonesia
Email: anas.arfandi@unm.ac.id ORCID ID: https://orcid.org/0000-0002-2513-6786

Saharuna
Department of Automotive Engineering Education, Universitas Negeri Makassar, Makassar, Indonesia
Email: saharuna@unm.ac.id ORCID ID: https://orcid.org/0009-0001-7240-2178

M. Syahid Nur Wahid
Department of Informatics and Computer Engineering Education, Universitas Negeri Makassar, Makassar, Indonesia
Email: syahid@unm.ac.id ORCID: https://orcid.org/0009-0009-7766-2946

Sudjani
Department of Civil Engineering Education, Universitas Pendidikan Indonesia, Bandung, Indonesia
Email: sudjani@upi.edu ORCID: https://orcid.org/0009-0006-1461-7142

***Corresponding Author:** Anas Arfandi - Department of Technological and Vocational Education, Universitas Negeri Makassar, Makassar, Indonesia Email: anas.arfandi@unm.ac.id ORCID: https://orcid.org/0000-0002-2513-6786*

ABSTRACT

Artificial Intelligence (AI) has revolutionised professional settings, necessitating vocational students to cultivate new types of preparedness beyond traditional digital skills. This research seeks to analyse the factors influencing AI readiness as a novel aspect of job preparedness among vocational high school students by exploring the impacts of technological literacy, acceptance of technology, institutional backing, and technological infrastructure. A quantitative explanatory framework was utilised, focusing on vocational high school students in South Sulawesi, Indonesia. Data were gathered using structured questionnaires and examined using Partial Least Squares Structural Equation Modelling to assess both direct and indirect correlations among the research constructs. The findings indicate that institutional backing is the most significant factor influencing AI preparedness, succeeded by technological infrastructure. Institutional backing affects AI readiness both directly and indirectly via technology infrastructure, underscoring the significance of school-level environments in fostering pupils' technological competence. In contrast, technological literacy does not substantially forecast AI preparedness, revealing a disparity between fundamental digital abilities and sophisticated AI skills. Technological acceptability exhibits an inverse correlation with AI preparedness, contradicting traditional beliefs about sequential technological integration. The results suggest that students' preparedness for the workforce in the digital age relies on institutional capabilities, technological settings, and organised AI educational experiences, rather than solely on personal competencies. This research formulates a socio-technical framework elucidating AI preparedness as an integral element of vocational students' employment ready in technology-driven environments.

KEYWORDS

Preparedness for Artificial Intelligence; vocational learners; employment preparation; institutional assistance; technology framework

1. INTRODUCTION

The swift progression of Artificial Intelligence (AI) has radically altered modern educational frameworks, transitioning learning settings from traditional digitalisation to adaptable, intelligent, and data-centric ecosystems. Artificial Intelligence in Education (AIED) has progressed from being mere supplementary technological instruments to a vital element of educational innovation, facilitating personalised learning, automated feedback, learning analytics, and institutional decision-making processes (Mustafa et al., 2024; Song & Abdul Rabu, 2025). The incorporation of AI affects not only teaching methodologies but also wider systems of knowledge creation, evaluation, and educational administration (Pedro et al., 2019). The advent of generative AI tools, such ChatGPT, has significantly expedited this change by broadening the application of AI in educational settings, professional training, and academic research contexts (Ahadzadeh et al., 2026; Du Boulay, 2022; Holmes & Porayska-Pomsta, 2023). These advancements suggest that technological proficiency is now not merely an academic necessity but a crucial element of students' readiness for future job markets defined by automation, digitalisation, and AI-enhanced workflows.

The growing integration of AI in education presents significant prospects for elevating learning quality, boosting student involvement, and facilitating advanced cognitive growth. Prior research suggests that educational technologies powered by AI can enhance learning experiences when integrated into suitable pedagogical frameworks and bolstered by robust institutional measures (Kritandani et al., 2024; Nguyen et al., 2023). Nonetheless, the incorporation of AI presents intricate difficulties concerning algorithmic bias, openness, privacy safeguarding, and the maintenance of human agency in educational choices (Akgun & Greenhow, 2022; Lin et al., 2023). These opposing dynamics illustrate that effective AI deployment necessitates not only technological accessibility but also educational frameworks that cultivate human skills, institutional capability, and accountable governance structures to guarantee significant and fair AI integration (Alfredo et al., 2024; Holmes & Porayska-Pomsta, 2023). From the standpoint of vocational education, these competencies are progressively linked to students' preparedness for the workforce, as future alumni are anticipated to exhibit not only technical skills but also adaptability, digital proficiency, and the capacity to engage with emerging technologies in professional environments.

The significance of AI preparedness is especially apparent in vocational education, where educational establishments must equip students for job markets increasingly influenced by automation, digital evolution, and the advancements of Industry 4.0. Vocational High Schools (VHS) in Indonesia play a crucial role in generating graduates who are prepared for the workforce, possessing both technical skills and adaptability for technology-driven sectors (Kamal et al., 2025; Sudira, 2020). In this framework, preparedness for AI integration signifies an essential educational competency, since vocational learners must not only utilise digital technology but also comprehend, assess, and implement AI systems in real-world professional scenarios. Consequently, AI preparation transcends conventional technological literacy and embodies a multifaceted concept that includes knowledge, technological proficiency, psychological readiness, ethical consciousness, and contextual assistance. These dimensions are progressively acknowledged as crucial elements of student employability, as modern workplaces require graduates who can perpetually learn, adjust to technological advancements, and proficiently employ digital resources to address professional challenges (Arfandi et al., 2026).

Notwithstanding the increasing acknowledgement of AI preparedness as an essential educational competency, considerable obstacles persist concerning the disparity in prospects for AI implementation across various educational settings. Contemporary research on AI readiness has primarily concentrated on human characteristics such as digital literacy, technology acceptability, and perceived utility, while neglecting the wider social and institutional contexts that influence technical preparedness. In vocational education, students' proficiency in interacting with AI is affected by disparities in educational equity, variances in infrastructure access, variations in teacher expertise, institutional assets, and the effectiveness of policy execution (Jatmoko et al., 2023; Widana, 2020). Thus, AI preparedness should not be viewed merely as a personal competency but rather as a socially ingrained result shaped by institutional contexts and technological frameworks. This matter is especially pertinent to employment preparedness, as students could have vocational knowledge yet still be insufficiently equipped for technology-driven workplaces if educational settings do not offer necessary technological exposure and institutional assistance.

A primary study issue is that mere access to digital technology does not inherently lead to significant AI preparedness or enhanced employability among vocational learners. Despite the growing interaction of students with AI via online platforms, search engines, recommendation systems, and generative AI

tools, casual exposure does not inherently cultivate the cognitive, ethical, and practical skills essential for responsible AI utilisation (Alfredo et al., 2024; Burke & Crompton, 2024). This issue is especially pertinent in the evolution of educational institutions, where digital change frequently takes place amid infrastructural disparities and constrained institutional capabilities. In the absence of suitable institutional governance, teacher assistance, curriculum integration, and technological infrastructure, the implementation of AI may exacerbate current educational inequalities instead of enhancing students' preparedness for future job markets.

Prior research indicates that tackling AI preparedness obstacles necessitates a holistic strategy that combines personal competencies with organisational and technology factors. Readiness-focused frameworks highlight that successful technology implementation relies on the congruence between human skills and supportive environmental systems (Crompton & Burke, 2023; Eljasik-Swoboda et al., 2019b). In educational settings, this viewpoint emphasises that students' readiness for AI is contingent not solely on their technological competencies but also on institutional policies, learning environments, infrastructure accessibility, and social support systems. These factors are essential drivers of job preparedness, as the shift from education to employment for students relies on the interplay between personal skills and organisational settings that replicate professional requirements.

A significant recommendation found in earlier studies is the creation of AI literacy frameworks that go beyond mere digital skills to encompass thorough abilities for comprehending, assessing, and ethically utilising AI technologies. The AI literacy framework highlights that proficient interaction with AI necessitates users to identify AI systems, comprehend their functioning mechanisms, critically evaluate AI-generated results, and reflect on the ethical ramifications linked to AI usage (Miao & Holmes, 2021). The UNESCO AI competency framework also emphasises the necessity of amalgamating knowledge, skills, values, and ethical consciousness to facilitate responsible engagement in AI-centric contexts (Cukurova & Miao, 2024). These theories suggest that AI preparedness encompasses cognitive readiness, technological proficiency, psychological preparedness, ethical consciousness, and contextual assistance, rather than solely technical skill. In vocational education, these skills signify developing employability traits that enhance students' preparedness for effective performance in technology-driven environments.

An further answer arising from studies on technology adoption is the incorporation of social and organisational viewpoints into AI ready frameworks. The Technology Acceptance Model (TAM) elucidates how personal perceptions, namely perceived utility and perceived simplicity of use, affect attitudes and behavioural intentions around technology (Davis et al., 1989). In a similar vein, the Unified Theory of Acceptance and Use of Technology (UTAUT) enhances this discourse by highlighting conducive environments, social impact, and performance expectations as key factors in technology adoption (Venkatesh et al., 2003). Nonetheless, these person-focused frameworks offer insufficient insights into educational environments where the integration of technology is heavily influenced by institutional assets and governance systems. Consequently, a socio-technical viewpoint is necessary to elucidate how AI preparedness and occupational preparation develop through the interactions among students, institutions, and technology frameworks.

Socio-Technical Systems Theory offers a comprehensive theoretical framework for comprehending AI preparedness by highlighting that technological results arise from the congruence between social frameworks and technological infrastructures. This viewpoint contends that the deployment of technology is inextricably linked to organisational practices, institutional frameworks, and human competencies (Mustafa et al., 2024; Pedro et al., 2019). In academic settings, institutional assistance and technology frameworks serve as facilitating factors that influence students' ability to convert technological exposure into significant AI skills. Prior studies have shown that the accessibility of infrastructure, the preparedness of educators, and the backing from organisations markedly affect the results of digital transformation in vocational education (Ayanwale et al., 2022; Granström & Oppi, 2025; Prasetya et al., 2025). These elements are intricately linked to employment preparedness, since vocational graduates engage in environments that demand advanced technical systems, organisational assistance, and ongoing professional development.

Prior investigations have significantly enhanced comprehension of AI implementation and digital evolution; yet, some research deficiencies persist. Initially, empirical studies about AI preparedness have predominantly concentrated on higher education environments and the viewpoints of educators, whereas vocational high school students are notably absent from the discourse (Burke & Crompton,

2024; Crompton & Burke, 2023). Secondly, current research frequently investigates singular determinants, like technological proficiency or institutional backing, without formulating a cohesive structural model that concurrently addresses individual, institutional, and infrastructural elements. Thirdly, investigations into AI preparedness in developing areas, especially within Indonesian vocational education settings, are scarce, notwithstanding the critical role of vocational institutions in equipping future digital labourers. These constraints are significant as research on work readiness increasingly highlights that employability is influenced not solely by personal competencies but also by educational settings that offer genuine technological learning opportunities and institutional readiness for workplace evolution.

Moreover, current literature offers inadequate elucidation on how institutional capability and technology infrastructure influence the connection between person ready variables and AI adoption results. While technological literacy is often deemed essential for AI readiness, recent findings indicate that digital proficiency by itself may not lead to substantial AI preparedness without the backing of institutional frameworks and conducive technological environments. Likewise, technology acceptance frameworks may inadequately account for AI preparedness in vocational settings where students' interaction with technology is significantly shaped by institutional resources and educational administration. These constraints suggest the necessity for a cohesive framework that perceives AI preparation as a multifaceted and socially developed competence, enhancing students' overall employability in the context of digital change.

This research explores the preparedness for AI among vocational high school students in South Sulawesi, Indonesia, by analysing the correlations between technology literacy, acceptance of technology, institutional backing, technological infrastructure, and AI readiness. The innovation of this research resides in the creation of a socio-technical structural model that situates technology infrastructure as a mediating factor linking individual and institutional influences with AI ready results. The research enhances theoretical frameworks by broadening AI adoption studies from individual-focused viewpoints to a system-oriented comprehension of technology preparedness and its effects on vocational students' employment preparation. The research employs Partial Least Squares Structural Equation Modelling (PLS-SEM) to substantiate the suggested correlations, while also offering practical insights to enhance AI integration strategies, digital ecosystems, and workforce development initiatives in vocational education. The research examines perceived AI readiness as a novel aspect of work preparation, highlighting the structural factors that influence students' fitness for AI-enhanced educational settings and future technology-driven careers.

2. LITERATURE REVIEW

2.1. The Preparedness for Artificial Intelligence as a Multifaceted Concept in Vocational Education

The concept of Artificial Intelligence (AI) preparedness has become a significant framework for elucidating how individuals and educational entities prepare to embrace, incorporate, and ethically employ AI-driven technology. In contrast to traditional digital literacy, which focuses mostly on operational competencies and access to digital resources, AI readiness encompasses a wider range of abilities, including knowledge, skills, attitudes, ethical comprehension, and contextual factors that facilitate significant interaction with AI systems. In academic environments, AI readiness signifies students' capacity to comprehend AI principles, assess AI-produced content, engage proficiently with intelligent technologies, and use AI instruments in suitable educational and professional scenarios (Crompton & Burke, 2023; Miao & Holmes, 2021). Consequently, AI readiness ought to be understood as a multifaceted construct instead of merely a singular technological proficiency.

The advancement of AI preparedness has been significantly shaped by the AI literacy framework and the UNESCO AI competency framework. The AI literacy framework suggested by Miao and Holmes (Miao & Holmes, 2021) highlights the necessity for individuals to possess skills to identify AI applications, comprehend essential AI concepts, critically assess AI results, and reflect on the wider societal consequences of AI use. The UNESCO AI competency framework also emphasises that responsible AI involvement necessitates a blend of knowledge, technical expertise, values, and ethical consciousness (Cukurova & Miao, 2024). These frameworks illustrate that preparedness for AI

encompasses more than merely utilising AI tools; it necessitates the cultivation of cognitive, technological, psychological, ethical, and contextual competencies.

Cognitive readiness denotes the intellectual aspect of AI preparedness, indicating learners' capacity to comprehend AI principles, analyse algorithmic mechanisms, and assess AI-produced outcomes critically. In vocational education, cognitive preparedness is crucial as students must utilise AI knowledge in real-world professional settings instead of only absorbing technical products. Technological proficiency encompasses the practical aspect, involving the capability to utilise digital platforms, engage with AI systems, comprehend technological data, and incorporate AI technologies into educational tasks. While technological literacy establishes the basis for digital participation, preparedness for AI necessitates more sophisticated skills, including adaptive technology utilisation, data analysis, and critical assessment of AI efficacy (Casal-Otero et al., 2023; Kong et al., 2024).

Moreover, AI preparedness include psychological preparation, which signifies students' self-assurance, drive, trust, and eagerness to interact with AI technologies. Prior investigations on technology adoption indicate that beliefs regarding utility, user-friendliness, and individual self-efficacy affect technology-related actions (Davis et al., 1989; Venkatesh et al., 2003). Nonetheless, artificial intelligence presents more psychological difficulties concerning ambiguity, clarity, and the sense of agency over autonomous technologies (Holmes & Porayska-Pomsta, 2023). Ethical consciousness is a crucial aspect, since the implementation of AI necessitates that users comprehend matters concerning algorithmic bias, privacy, accountability, and the utilisation of human-centric technology (Akgun & Greenhow, 2022; Nguyen et al., 2023). Thus, the preparedness for AI in vocational education ought to be regarded as an all-encompassing capacity influenced by personal skills and the educational contexts that facilitate their growth.

2.2. Conceptual Framework: Socio-Technical Systems Theory, Technology Acceptance Model, and Unified Theory of Acceptance and Use of Technology in Elucidating AI Preparedness

Comprehending AI preparedness necessitates a theoretical framework that elucidates the interplay of personal competencies, organisational frameworks, and technical contexts. This research utilises Socio-Technical Systems Theory as its central theoretical framework, positing that the integration of AI in education is influenced not merely by the presence of technology or personal readiness, but rather by the congruence of social structures and technological infrastructures. Socio-technical viewpoints highlight that effective technology deployment necessitates the amalgamation of human skills, organisational methodologies, governance frameworks, and technological systems (Mustafa et al., 2024; Pedro et al., 2019). In the realm of vocational education, this viewpoint posits that students' preparedness for AI is influenced by their individual competencies as well as the institutional frameworks that facilitate or hinder technological involvement.

The socio-technical viewpoint is especially pertinent in vocational education as educational institutions serve as organisational settings that govern students' access to technological assets, learning prospects, and experiences connected to AI. Institutional backing, educator readiness, curricular incorporation, and infrastructure accessibility are essential factors that influence the sustainable implementation of AI adoption. Previous research indicates that educational technology transformation depends substantially on institutional capability, including leadership support, professional development, and digital governance systems (Ayanwale et al., 2022; Granström & Oppi, 2025). Consequently, AI preparedness ought to be perceived as a systemic result rather than simply a personal characteristic.

While Socio-Technical Systems Theory serves as the fundamental explanatory framework, theories of individual technology adoption continue to hold significance as supplementary viewpoints. The Technology Acceptance Model (TAM) elucidates the impact of perceived utility and perceived simplicity on users' attitudes and intentions on the adoption of technology (Davis, 1989). In a similar vein, the Unified Theory of Acceptance and Use of Technology (UTAUT) enhances this rationale by integrating facilitating conditions, social impact, and performance expectations as factors influencing technology acceptance (Venkatesh et al., 2003). These frameworks offer insightful elucidations concerning the psychological processes that drive technological involvement.

Nevertheless, TAM and UTAUT predominantly focus on personal views and behavioural intents, which may inadequately account for AI preparedness in educational settings marked by resource disparities and institutional variances. In vocational institutions, learners may have favourable dispositions toward AI yet struggle to interact proficiently with AI technology owing to inadequate infrastructure, insufficient institutional backing, or a lack of educational opportunities. Consequently, the amalgamation of TAM and UTAUT under a socio-technical paradigm offers a more thorough elucidation by linking personal psychological elements with wider institutional and technological contexts. This conceptual amalgamation bolsters the premise that AI preparedness arises from the interplay of individual proficiency, organisational capability, and technology frameworks.

2.3. Personal Factors Influencing AI Preparedness: Proficiency in Technology and Acceptance of Technology

Personal competences are crucial elements in elucidating AI preparedness, as learners need essential technological skills and favourable attitudes toward AI-driven systems. technology literacy constitutes an essential skill set that empowers individuals to navigate digital technologies, assess the quality of information, and employ technology instruments for educational and problem-solving purposes (Rahmah, 2015; Zulkarnain et al., 2024). In vocational education, technological proficiency holds strategic significance as students are equipped for professional settings increasingly shaped by automation, digitalisation, and the Industry 4.0 revolution. Prior research indicates that technological proficiency substantially influences the capacity of vocational students and educators to incorporate digital technologies into pedagogical methods (Saripudin et al., 2018; Widana, 2020).

Nonetheless, just technological literacy may be inadequate for achieving AI preparedness. Digital proficiency enables pupils to utilise technological systems, however interaction with AI necessitates further skills, such as comprehending AI reasoning, assessing algorithmic results, and employing AI judiciously in particular situations. Contemporary research indicates that learners could exhibit an awareness of digital technology yet possess insufficiently developed AI skills due to inadequate educational integration and institutional support (Casal-Otero et al., 2023; Fernández-Otoya et al., 2024). Consequently, technological literacy ought to be regarded as a fundamental yet insufficient factor in assessing AI preparedness.

Technological acceptability serves as a significant personal factor, as students' readiness to interact with AI is shaped by their views on its utility, user-friendliness, pertinence, and reliability. From the viewpoints of TAM and UTAUT, favourable attitudes toward technology typically enhance the desire to adopt and the behaviour of involvement (Davis, 1989; Venkatesh et al., 2003). Prior research suggests that both students and educators who possess favourable perceptions of AI are more inclined to explore AI applications and incorporate them into educational practices (Ayanwale et al., 2022; Burke & Crompton, 2024).

Nonetheless, the integration of AI diverges from traditional technology adoption due to the uncertainties associated with transparency, autonomy, and dependability. Learners could view AI as advantageous, while concurrently harbour apprehensions about its intricacies, precision, or moral ramifications. Consequently, the acceptance of technology ought not to be viewed as a direct measure of AI preparedness, but rather as a singular psychological component within a more extensive socio-technical framework. The correlation among technological literacy, acceptance of technology, and preparedness for AI may hinge on the extent to which educational institutions offer adequate support, infrastructure, and experiential learning opportunities that empower students to convert technological understanding into practical skills.

2.4. Organizational Assistance and Technological Framework as Fundamental Factors of AI Preparedness

Institutional backing serves as a vital structural factor in AI preparedness, as educational entities furnish the policies, resources, training, and cultural milieu essential for enduring technological assimilation. In the transformation of education through AI, institutional backing include leadership dedication, curriculum modification, educator professional growth, digital management, and availability of technical assets. Prior research indicates that institutional support markedly affects teachers' willingness to embrace AI technology, especially when accompanied by structured training and explicit implementation plans (Ayanwale et al., 2022; Granström & Oppi, 2025).

In vocational education, the significance of institutional assistance escalates as students' educational prospects are heavily shaped by the resources and organisational capabilities of their schools. Despite the widespread use of digital learning systems by numerous vocational schools, the integration of AI is inconsistent owing to variations in infrastructure accessibility, policy execution, and institutional readiness (Alam et al., 2026; Marienko et al., 2026). Consequently, institutional support serves not only as a facilitating element but also as a determinant of AI preparedness across various educational environments.

Technological infrastructure serves as an additional structural factor that establishes the material basis for AI involvement. Infrastructure include internet connectivity, hardware accessibility, software frameworks, digital learning environments, and availability of AI-driven applications. Prior research consistently recognises the availability of infrastructure as a crucial element affecting the effective integration of technology in educational settings (Choudhary et al., 2024; Duan, 2026; Made Sudana et al., 2019). In the absence of sufficient infrastructure, students' technological competencies and favourable dispositions may fail to result in significant AI integration.

Crucially, technology infrastructure constitutes a facet of educational disparity, as variations in infrastructure accessibility generate inequitable chances for students to cultivate AI skills. Educational institutions situated in underprivileged regions may have inadequate connectivity, a scarcity of devices, and limited access to digital resources, therefore hindering students' preparedness for AI irrespective of personal drive. Recent research indicates that infrastructure may serve as a mediating factor linking institutional support and individual skills to technology adoption results (Eljasik-Swoboda et al., 2019a; Jatmoko et al., 2023). Consequently, institutional backing and technical frameworks ought to be regarded as interrelated structural factors that influence the advancement of AI preparedness in vocational education systems.

2.5. Research Deficiency and Theoretical Integration

Despite the significant growth in research concerning AI in education, notable deficiencies persist in the formulation of AI preparation frameworks, especially within vocational education settings. Initially, current research has mostly focused on AI adoption within university students, educators, or higher education establishments, whereas vocational high school students have been comparatively overlooked (Burke & Crompton, 2024; Crompton & Burke, 2023). This constraint is crucial as vocational students embody the future workforce that necessitates AI-related skills in accordance with swiftly evolving industrial requirements.

Secondly, prior studies have often investigated the determinants of AI adoption in isolation, concentrating on either personal elements like digital literacy and technology acceptability or organisational aspects such as infrastructure and institutional support. Nonetheless, scant empirical data elucidates the interaction of these factors within a cohesive structural framework of AI readiness. Current research recognises that technological proficiency, organisational backing, and infrastructure impact technology adoption; nevertheless, the processes by which these elements jointly affect AI preparedness are not yet fully comprehended (Ayanwale et al., 2022; Jatmoko et al., 2023).

Thirdly, investigations carried out in educational settings, especially in Indonesia, are scarce, although the significance of vocational education in national digital transformation initiatives. Variations in infrastructure, institutional capability, and technology assets between regions may result in divergent levels of AI preparedness compared to environments with more developed digital ecosystems. Consequently, context-specific data is essential to comprehend the evolution of AI preparedness in vocational education systems facing digital transformation obstacles.

This research suggests a comprehensive conceptual framework that merges personal factors (technology literacy and acceptance) with structural factors (institutional support and technological infrastructure) to elucidate AI readiness in vocational high school students. The concept reframes technology infrastructure as a mediating factor, broadening current AI adoption studies from a focus on individuals to a socio-technical comprehension of preparedness development. This theoretical integration enhances the literature by elucidating AI readiness as a multifaceted and socially integrated competency influenced by the interplay of learners, institutions, and technological contexts.

3. MATERIAL AND METHODS

3.1 Research Design

This research utilised a quantitative explanatory framework to investigate the factors influencing Artificial Intelligence (AI) preparedness among vocational high school (SMK) students in South Sulawesi, Indonesia. The design was chosen for its appropriateness in examining proposed connections among various latent variables and for measuring both direct and indirect impacts within a structural framework. Consistent with previous research on the integration of AI in educational settings, this methodology facilitates a comprehensive assessment of the behavioural, institutional, and infrastructural factors affecting technological preparedness (Ayanwale et al., 2022; Granström & Oppi, 2025). The research employs a correlational framework to ascertain correlations between variables without experimental intervention, aligning with recognised methodologies in educational technology studies (Pedro et al., 2019; Widana, 2020).

The theoretical basis of this design is rooted in socio-technical viewpoints of AI incorporation in education, highlighting the interplay among personal skills, organisational contexts, and technology frameworks (Mustafa et al., 2024; Song & Abdul Rabu, 2025). This approach holds significant importance in vocational education settings, where the integration of AI is influenced by both student attributes and the preparedness of institutions along with the availability of infrastructure (Marienko et al., 2026; Sudira, 2020).

3.2 Context of the Study and Subjects

The research was carried out in vocational high schools (VHS) situated in South Sulawesi, Indonesia. These areas were chosen for their pivotal contribution to the advancement of vocational education and their continuous initiatives to enhance digital transformation within educational frameworks. Prior research suggests that variations in technological infrastructure and technology proficiency between regions markedly affect the success of educational technology deployment (Jatmoko et al., 2023; Tinmaz et al., 2022).

The study's population comprised students from public vocational schools. In South Sulawesi, there exist 168 public vocational high schools, of which 17 were chosen as a sample, representing both urban and rural regions across several regencies and cities. The aggregate count of students is 85,742. A preliminary statistical power analysis was conducted utilising G*Power 3.1 to ascertain the minimal sample size necessary for structural equation modelling. The examination utilised a medium effect size ($f^2 = 0.15$), a significance threshold of $\alpha = 0.05$, and an intended statistical power of 0.95. In accordance with Cohen's (2013) guidelines, the study utilised a linear multiple regression model featuring three predictors, a medium effect size ($f^2 = 0.15$), a significance threshold of $\alpha = 0.05$, and a statistical power of 0.95. The examination revealed that at least 119 participants were necessary to identify statistically meaningful outcomes. The study population included 85,742 vocational high school students, although the necessary sample size was dictated by the intended statistical power instead of the population size. Given that the research utilised Partial Least Squares Structural Equation Modelling (PLS-SEM), a considerably larger sample was gathered to augment estimation precision, bolster the stability of parameter values, and boost the generalisability of the results. The ultimate sample surpassed the minimum threshold indicated by the power analysis. Cluster stratified random sampling was utilised to guarantee proportional representation among various schools and educational clusters, thus reducing sample bias and improving external validity.

The research investigated four external variables and one internal variable. The external variables comprised Technology Literacy (X_1), Technological Acceptance (X_2), Institutional Support (X_3), and Technological Infrastructure (Z), whereas the internal variable was AI Readiness (Y). These concepts were established based on recognised literature regarding technology adoption, digital proficiency, and AI preparedness in education (Burke & Crompton, 2024).

3.3 Measurement and Instrument Development

Data were gathered utilising a standardised questionnaire formulated from validated constructs derived from previous research on technology literacy, technology acceptance, and AI preparedness. The tool was modified for the vocational education setting and enhanced via expert evaluation to guarantee content authenticity. This method aligns with recognised practices in educational measurement

research, utilising expert validation to guarantee coherence between theoretical notions and practical indicators.

The survey was disseminated to participants in chosen vocational institutions utilising both physical and online methods, contingent upon the availability of school infrastructure. This dual-mode distribution strategy was essential because of disparities in technical accessibility among institutions, a constraint frequently noted in vocational education studies. Participants were informed about the study's aims, and their involvement was optional to maintain ethical adherence to research protocols in educational environments.

3.3 1. Reliability-Validity Assessment

The research utilised evaluations of both content validity and construct validity. Content validity was confirmed via expert assessment, guaranteeing that all questionnaire items sufficiently reflected the targeted constructs. The construct validity was evaluated by Structural Equation Modelling utilising Partial Least Squares (SEM-PLS), a method commonly employed in educational technology studies for its strength in managing intricate models and non-normally distributed data.

Convergent validity was evaluated by examining outer loading values with a minimum threshold of $\geqslant$ 0.70, and the Average Variance Extracted (AVE) was mandated to surpass 0.50. Discriminant validity was assessed by the Fornell-Larcker Criterion and the Heterotrait-Monotrait (HTMT) ratio, with acceptable thresholds set below 0.90. The assessment of reliability was conducted by Cronbach's Alpha and Composite Reliability, with both metrics anticipated to surpass 0.70 to confirm the internal consistency of constructs. These statistical standards align with recognised protocols for SEM-PLS utilisation in educational studies.

3.4 Data Analysis Techniques

Data analysis was executed utilising Smart-PLS software to assess both the measurement model (outer model) and the structural model (inner model). The examination of the outer model encompassed evaluations of convergent validity, discriminant validity, and reliability, whilst the investigation of the inner model concentrated on assessing R-square, path coefficients, t-statistics, effect size (f^2), and predictive relevance (Q^2).
The structural model was created to evaluate both direct and indirect associations among variables, specifically investigating if Technological Infrastructure (Z) serves as a mediating variable between Technology Literacy, Technological Acceptance, Institutional Support, and AI Readiness. This mediation strategy aligns with socio-technical models of AI implementation, highlighting the interconnectedness of personal, organisational, and infrastructural elements.
The theoretical framework examined in this research is depicted in Figure 1, showcasing the proposed connections among technology literacy, technological acceptance, institutional support, technical infrastructure, and AI readiness. The framework posits that technological literacy, acceptance of technology, and institutional backing directly and indirectly affect AI preparedness via technological infrastructure as a mediating element.

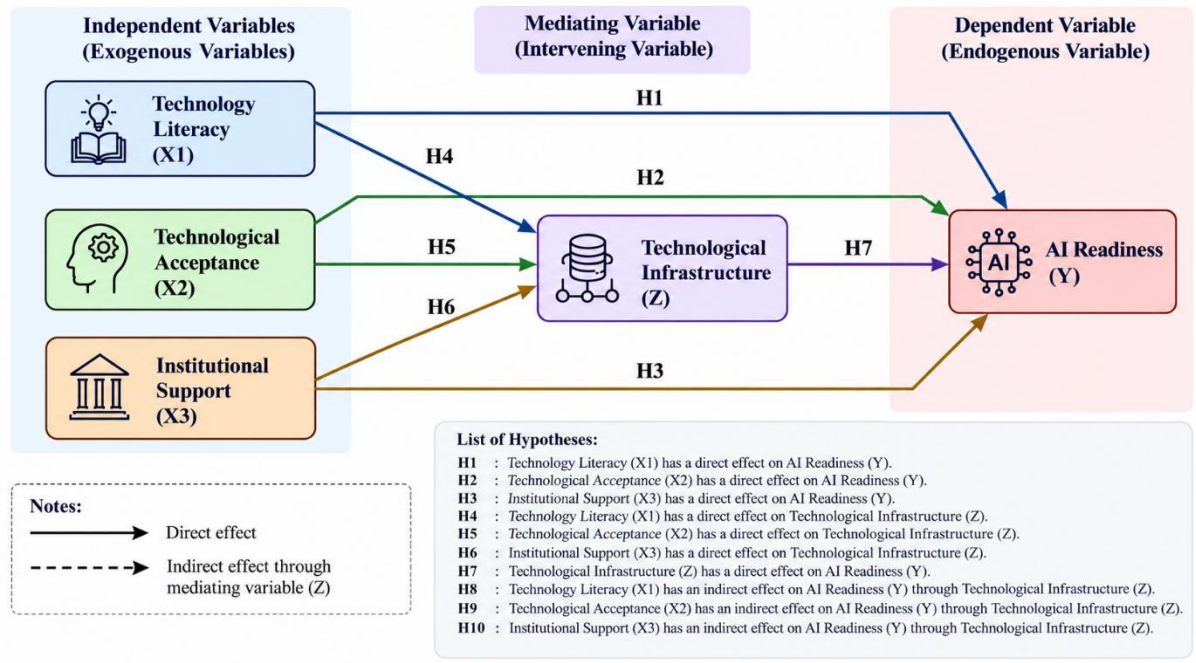


Figure 1. Research Model: Structural Framework of AI Readiness in Vocational Students

Figure 1 illustrates pathways from Technology literacy (X_1), Technological acceptance (X_2), and Institutional Support (X_3) toward Technological Infrastructure (Z), which subsequently influences AI Readiness (Y).

This structural framework is based on previous empirical evidence suggesting that technological infrastructure serves as a facilitating factor that enhances the influence of both individual and institutional variables on technology adoption results (Eljasik-Swoboda et al., 2019b; Jatmoko et al., 2023). The model advances prior studies by incorporating attitude as a psychological factor within a socio-technical framework, thereby offering a more thorough elucidation of AI ready development in vocational education settings.

3.8 Ethical Considerations

Ethical approval principles were observed throughout the research process. Participation was voluntary, and respondents were informed about the purpose of the study, confidentiality of responses, and their right to withdraw at any time. No personally identifiable information was collected. This research was reviewed and approved by the Research Ethics Committee of the Institute for Research and Community Service, Universitas Negeri Makassar under reference number: 3530/DST/UN36.12/TU/2026. This ethical approach aligns with international standards for educational research involving human participants and reflects the increasing emphasis on ethical considerations in AI-related educational studies.

Overall, the methodological design ensures robustness in examining the complex relationships between technology literacy, institutional factors, technological infrastructure, and AI readiness. By employing SEM-PLS and a multidimensional construct framework, the study provides a rigorous empirical basis for understanding AI readiness in vocational education settings within Indonesia.

4. RESULTS

4.1 Measurement Model Evaluation

Confirmatory factor analysis indicated that all indicators had factor loadings above the recommended threshold of 0.60, demonstrating acceptable convergent validity. The AVE values for all constructs exceeded 0.50, while composite reliability values were above 0.80, confirming adequate reliability.

Table 1. standardized loadings, internal consistency reliability, and convergent validity

Construct	Item	Loading Factor	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Technology Literacy	TL.1	0,800	0,819	0,872	0,631
	TL.2	0,700			
	TL.3	0,450			
	TL.4	0,712			
	TL.5	0,769			
	TL.6	0,854			
Technological Acceptance	TA.1	0,848	0,872	0,913	0,725
	TA.2	0,882			
	TA.3	0,894			
	TA.4	0,688			
	TA.5	0,754			
Institutional Supporting	IS.1	0,731	0,758	0,846	0,580
	IS.2	0,560			
	IS.3	0,777			
	IS.4	0,713			
	IS.5	0,797			
Technology Infrastructure	TI.1	0,403	0,802	0,884	0,717
	TI.2	0,629			
	TI.3	0,804			
	TI.4	0,892			
	TI.5	0,749			
AI Readiness	AI.1	0,878	0,906	0,930	0,727
	AI.2	0,833			
	AI.3	0,871			
	AI.4	0,821			
	AI.5	0,859			

Table 1 shows that all indicators exhibit acceptable standardized loadings (0.450–0.892), suggesting that each item contributes substantively to its respective construct. Internal consistency is also well supported, with Cronbach's alpha values ranging from 0.758 to 0.906 and composite reliability (CR) values from 0.846 to 0.930, both exceeding commonly accepted thresholds. Convergent validity is evidenced by AVE values above 0.50 for all constructs (0.580–0.727), indicating that, on average, each construct accounts for more than half of the variance in its indicators. Overall, these findings indicate that the measurement model satisfies standard requirements for indicator reliability, internal consistency, and convergent validity, thereby supporting the suitability of the instrument for subsequent structural model evaluation.

4.2 Structural Model Evaluation and Path Coefficient Overview

Structural equation modeling was conducted to test the causal relationships among latent variables—namely, technology literacy, attitudes toward technology, institutional support, technological infrastructure, and readiness to use AI (artificial intelligence)—among vocational high school students in South Sulawesi. The analysis, using a bootstrapping approach, yielded estimates of path coefficients (original sample), standard deviations, t-statistics, and p-values to determine the significance of the relationships among the constructs.

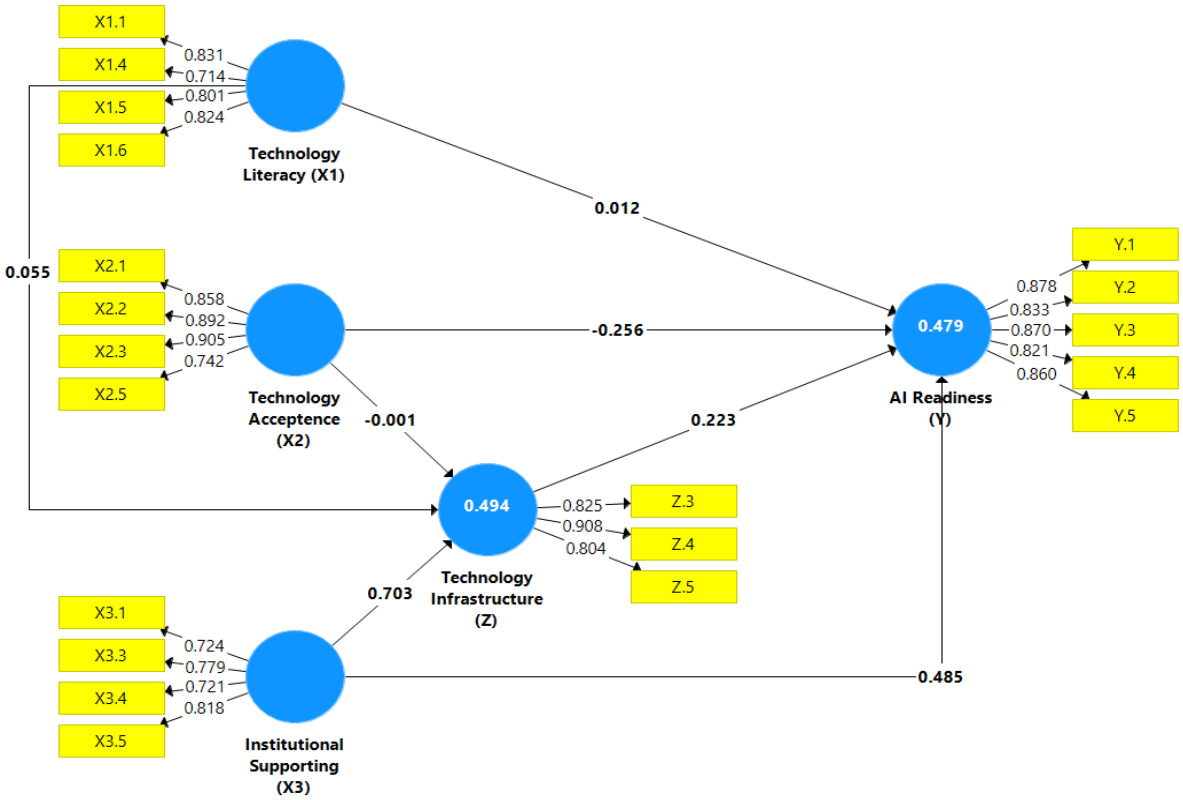


Figure 2. Framework Model

The overall results indicate that the model involves a combination of varying direct and indirect effects, with institutional variables and technological infrastructure having the most significant impact on readiness to use AI, while individual factors show a more limited contribution.

Table 2. Path Coefficient Model

Path	Coefficient (O)	Mean (M)	SD	t-statistic	p-value	Conclusion
Technology literacy → AI Readiness	0.012	-0.001	0.109	0.112	0.911	Not significant
Technology literacy → Technological Infrastructure	0.055	0.057	0.115	0.475	0.635	Not significant
Technological acceptance → AI Readiness	-0.256	-0.263	0.105	2.448	0.015	significant
Technological acceptance → Technological Infrastructure	-0.001	0.002	0.097	0.008	0.994	Not significant
Institutional Support → AI Readiness	0.485	0.494	0.085	5.695	0.000	significant
Institutional Support → Technological Infrastructure	0.156	0.158	0.072	2.187	0.029	significant
Technological Infrastructure → AI Readiness	0.223	0.223	0.098	2.263	0.024	significant

4.3 The Effect of technology literacy to AI Readiness

The results of the analysis show that technology literacy does not have a significant effect on the readiness of vocational high school students in South Sulawesi to use AI (β = 0.012; t = 0.112; p = 0.911). The very small coefficient value indicates that variations in technology literacy cannot explain

changes in the level of readiness to use AI. These findings suggest that technology literacy at the student level may not yet have translated into practical competencies in the context of artificial intelligence. In other words, students' technology literacy is more basic in nature (device operation) than advanced literacy, which encompasses the understanding, evaluation, and use of AI-based technologies.

4.4 The Effect of technology literacy to Technological Infrastructure

The relationship between technology literacy and technology infrastructure was also not significant (β = 0.055; t = 0.475; p = 0.635). These results indicate that improvements in students' technology literacy do not contribute to changes in perceptions of or the condition of technology infrastructure in the school environment. Conceptually, technological infrastructure is a systemic variable that is more influenced by institutional policies, funding, and school governance than by individual students' abilities. Therefore, the lack of significance in this relationship is consistent with the structural nature of the infrastructure variable.

4.5 The Effect of technological acceptance to AI Readiness

Technological acceptance had a significant effect on readiness to use AI, but the effect was negative (β = -0.256; t = 2.448; p = 0.015). These results indicate that higher scores on the Technological acceptance scale are actually associated with a decrease in readiness to use AI. These findings may indicate the presence of ambivalent or even resistant attitudes toward AI-based technology. In the context of vocational education, this can occur when students have high expectations of the technology but lack the practical readiness to use more complex AI-based systems.

4.6 The Effect of technological acceptance to Technological Infrastructure

technological acceptance do not have a significant effect on technology infrastructure (β = -0.001; t = 0.008; p = 0.994). These results indicate that individual psychological factors do not contribute to the development or improvement of school technology infrastructure. Theoretically, this confirms that technological infrastructure falls within the domain of the organization, not the individual. Thus, changes in students' attitudes will not directly affect the availability of devices, networks, or digital systems at school.

4.7 The Effect of Institutional Support to AI Readiness

Institutional support was found to have a positive and significant effect on readiness to use AI (β = 0.485; t = 5.695; p = 0.000). The magnitude of the coefficient indicates that this variable is a major predictor of readiness to use AI among vocational high school students. These findings indicate that school policies, teacher support, training, and the digital learning ecosystem play a crucial role in enhancing students' readiness to adopt artificial intelligence technology. Institutional support serves as a key catalyst in fostering technological readiness in vocational education settings.

4.8 The Effect of Institutional Support to Technological Infrastructure

Institutional support also has a positive and significant effect on technological infrastructure (β = 0.156; t = 2.187; p = 0.029). Although the coefficient is smaller than that of the direct effect on readiness, these results indicate that institutions play a role in providing and improving the quality of technological infrastructure. This reinforces the role of institutions as structural variables that not only influence individual readiness but also shape the technological ecosystem that supports competency-based learning.

4.9 The Effect of Technological Infrastructure to AI Readiness

Technology infrastructure was found to have a positive and significant effect on students' readiness to use digital learning tools (β = 0.223; t = 2.263; p = 0.024). These results indicate that the availability of devices, internet access, and school digital systems directly contribute to increasing students' readiness to use digital learning tools. Empirically, these findings confirm that technological readiness is determined not only by cognitive factors or attitudes, but also by the physical and digital environments that support the learning process.

4.10 Summary of the Relationship Model and Significant Paths

Overall, the model shows that there are three main significant pathways influencing readiness to use AI: technological acceptance, institutional support, and technological infrastructure. However, only institutional support has both a direct and an indirect influence (through technological infrastructure), and can therefore be categorized as the most dominant variable in this model.

Table 2. Summary of Significant Paths in the Model

Variable	Direct effect	Undirect effect	Strength of effect
technology literacy	Not significant	Not significant	Low
Technological acceptance	significant (negative)	Not significant	Medium
Institutional Support	significant	significant (via infrastructure)	High
technological infrastructure	significant	–	Medium

4.11 Interpretation of Structural Model

Theoretically, the results of this study indicate that vocational high school students' readiness to use AI is influenced more by structural factors than by individual factors. Institutional support serves as a key variable that shapes both the technological infrastructure and students' direct readiness.

Technology infrastructure serves as a partial mediator that strengthens the influence of institutional support on readiness to use AI. Meanwhile, technology literacy does not play a significant role in the model, suggesting a gap between basic digital skills and the need for more complex AI competencies.

4.12 Implication of Statistic Model

Statistically, the model shows consistent significance in the institutional and infrastructure pathways, with t-statistic values above the threshold of 1.96 at a 5% significance level. This model indicates that organization-based exogenous variables have stronger explanatory power than individual-based variables.

5. DISCUSSIONS

5.1 The Main Driver of AI Readiness and Work Readiness of Students: The Institutional Architecture

The empirical results of this study show that the main determinants of the AI preparedness of vocational high school pupils are the institutional and infrastructural arrangements and not the individual competencies. As shown in Table 1, the most important indicator of AI readiness is institutional support ($\beta = 0.485$; $p < 0.001$), followed by technological infrastructure ($\beta = 0.223$; $p = 0.024$). This structural dominance points to a paradigmatic shift in the theoretical understanding of AI adoption in vocational education: readiness is not just an individual's cognitive quality but an institutionalised capacity generated through the interplay of educational systems, technological resources and learning environments.

This discovery also contributes to the socio-technical systems theory, which posits that technological outputs are a function of the alignment between social structures and technological systems. The scale of the institutional impacts found in this study, however, suggests a higher institutional influence in situations of vocational education, in which schools are not just facilitators but also makers of students' technical preparation. This approach resonates with recent literature in artificial intelligence in education highlighting that the integration of AI is integrated in institutional governance, curriculum structures, teacher competencies and resource allocation mechanisms (Mustafa et al., 2024; Pedro et al., 2019).

This finding has an important impact from students' work preparation perspective. The traditional focus of vocational education has been on occupational competence and practical skills; however, Industry 4.0 workplaces increasingly demand graduates who can adapt to technological change, interact with intelligent systems and continuously acquire new digital competencies (Benešová & Tupa, 2017; Van Laar et al., 2020). Thus, institutional assistance should not only be considered as a factor impacting AI adoption but also as a vehicle to increase students' broader employability preparation. Schools with AI-oriented curriculum, teacher assistance, technical facilities and authentic digital learning experiences generate settings that enable students to transit more efficiently from educational contexts into technology-intensive jobs.

This study theoretically extends the UTAUT framework (Venkatesh et al., 2003), specifically the concept of enabling conditions. The conditions facilitating in this study include not only contextual aspects that enable technology acceptance but also structural mechanisms via which students build abilities necessary for future work. This means that modern vocational education work readiness is increasingly dependent on the ability of educational institutions to create technology-supported learning ecosystems.

5.2 AI Readiness Paradox – The Digital Literacy vs the Competence for Future Work Gap

The main conceptual contribution of the work is the identification of an AI readiness contradiction in designing vocational systems. However, the impact of technology literacy on AI preparedness is insignificant ($\beta = 0.012$; $p = 0.911$), but exposure to digital technologies increases. This research questions the common assumption that sophisticated technical preparedness will inevitably evolve from widespread digital ability.

The study reveals a structural gap between basic technological literacy and AI-specific competences. Technology literacy equips students with the ability to operate digital devices, find information, and engage with digital platforms, but AI readiness involves additional, more sophisticated competencies such as comprehending algorithmic processes, critically assessing outputs generated by AI, applying AI responsibly, and incorporating AI tools into problem-solving tasks (Cukurova & Miao, 2024; Miao & Holmes, 2021). Similar issues have been raised to the fore in recent AI literacy research demonstrating that being familiar with digital technology does not necessarily translate into the ability to engage critically and ethically with artificial intelligence systems (Casal-Otero et al., 2023; Kong et al., 2024).

This study has important consequences for the work preparation of students. Traditional vocational training has concentrated largely on technical abilities related to certain occupational sectors, but the jobs of the future demand flexible digital skills that enable workers to engage with constantly changing technologies. The digital transformation demands that employees have not only digital technical abilities, but also higher-order talents, such as critical thinking, creativity, problem-solving, and flexibility (Van Laar et al., 2020). This means that vocational students who have general technological literacy but lack AI-related cognitive and ethical competences may be unprepared for forthcoming work contexts.

The present results show that vocational institutions need to rethink the path from digital proficiency to work ready. Digital competence should not be seen as a destination but as a starting point for learning more complex technology skills. AI literacy should therefore be included in vocational curriculum as part of the development of employability and not as an additional technological issue.

5.3 Attitudinal Inversion and Complexity of Technology Work Readiness

Theoretically, this investigation revealed a substantial negative association between the technology acceptance and AI readiness ($\beta = -0.256$; $p = 0.015$). This result is contrary to the assumptions of the Technology Acceptance Model (TAM) which generally suggests that good views of usefulness and ease of use boost technology adoption intentions (Davis, 1989). Instead, the data suggest that vocational students' positive sentiments about technology may not necessarily translate into increased AI readiness.

This phenomenon may manifest as an attitudinal inversion whereby students who view technology positively may simultaneously experience feelings of uncertainty, lack of confidence, or lack of practical capacity when faced with advanced artificial intelligence (AI) systems. This creates an extra level of complexity around questions of autonomy, transparency, reliability and ethics (Holmes & Porayska-Pomsta, 2023) that is not the case with traditional digital technology. So, students might appreciate what AI could do for them, but lack the skills to use it well.

Regarding work readiness, this research underlines the difference between the willingness to use technology and ready to perform in technology-mediated workplaces. Employers increasingly seek graduates who are not only accepting of technology change, but also those who are able to critically assess and apply innovations in a professional setting. Thus, vocational education should not only promote favourable attitudes to technology, but also cultivate technological confidence, practical experience and reflective digital judgement.

This research also extends the ideas of technology adoption by demonstrating that the preparedness to adopt AI involves more than simple acceptance. Readiness in vocational settings occurs when students have the knowledge, experience, institutional support and infrastructure to channel technology attitudes into workplace-relevant competences.

5.4 Institutional Support: A Two-Channel Approach to AI and Employment Readiness

Institutional support has a direct effect on AI preparedness and an indirect effect through technological infrastructure (β = 0.156; p = 0.029). This dual approach makes institutional support a configurational determinant of the AI ready system. Institutional support is not only a passive environmental feature; it actively influences students' possibilities to interact with artificial intelligence (AI) tools through curriculum development, teacher preparation, digital regulations, and resource management.

These findings align with socio-technical approaches that emphasise the interdependence of organisational and technological aspects in successful digital transformation (Mustafa et al., 2024). The fate of AI as an accessible learning resource or an abstract technological concept of limited practical importance will be determined by educational institutions.

In vocational education, the linkage of institutional assistance and preparedness for work is very significant. Individual efforts are not the only means to develop work readiness, but also structured educational experiences that mimic work environments such as availability of the appropriate technologies, industry-related learning activities and professional guidance (Caballero et al., 2011; Jackson, 2015). Thus, the institutional assistance is a bridge between educational preparedness and employment requirements.

The indirect influence via technology infrastructure also highlights that institutional commitment should be enacted in actual learning settings. The poor technological implementation of policies has had a limited effect on students' practical preparation. In contrast, supportive institutions that provide infrastructure, training, and digital ecosystems open stronger avenues for students to gain AI-related employability competencies.

5.5 Technological Infrastructure as Material Boundary Condition for Future Workforce Development

Technological infrastructure is identified as a major predictor of AI readiness (β=0.223; p=0.024) further strengthening its significance as a key enabling factor. Students' ability to use AI apps, engage in digital learning activities, and gain hands-on experience with new technologies is determined by infrastructure availability.

Apart from its direct impact, infrastructure also acts as a boundary condition, which limits and shapes the possibilities of AI engagement in vocational schools. Students may be interested and technically motivated, but poor connectivity, lack of gadgets, or access to AI platforms can impede the growth of technological competence.

This condition is directly relevant to job preparedness, as the digital infrastructure and AI-supported procedures increasingly underlie the modern workplace. Graduates entering technology demanding businesses need to be familiar with the digital systems as they will be met in professional situations. Hence, differences in the availability of infrastructure might lead to differences in the work readiness of vocational students.

These findings corroborate earlier studies that suggest digital inequality remains a significant issue in the transformation of educational technology, particularly in developing environments (Jatmoko et al., 2023; Tinmaz et al., 2022). Thus, addressing infrastructural gaps is not only an educational issue but also an important approach to enhancing worker competitiveness.

5.6 Theoretical Implications: Reframing AI Readiness as Part of Work Readiness

Overall, the findings imply that AI preparedness among vocational students should be viewed as an emergent dimension of job readiness, which is influenced by institutional capacity, technology infrastructure, and human competencies. The dominance of institutional and infrastructural variables challenges the traditional belief that employability preparation is more a matter of students' own skills.

Instead, it promotes a systemic perspective on work preparation as constructed through interactions between learners, educational institutions and technological surroundings. This moves the literature on vocational education further by conceptualising AI competency as part of modern employability development, rather than as a digital talent in its own right.

The contribution of the findings theoretically is to synthesise the socio-technical systems theory and perspective of technology adoption to explain how vocational students are prepared for AI-supported work environment. Future study could extend this model to investigate other aspects of work preparation such as industry exposure, internship experience, teacher AI competency, vocational curriculum alignment and real AI use in the workplace. Longitudinal studies are also needed to explore the development of AI readiness across students' educational paths and its impact on transition to employment.

5.7 Implications for Theory Expansion

Overall, the results show that AI readiness in vocational education has to be reconceptualised as a structurally created and institutionally mediated phenomenon. The dominance of institutional and infrastructural impacts and the non-significance of individual variables dispute the concept of linear progression from digital proficiency to AI readiness.

Instead, the evidence suggests a multi-layered approach, where readiness is shaped by institutional governance, infrastructural access and only secondarily by individual dispositions. Such a structure-oriented view adds to ongoing discussions in AI-in-education research that demand post-individualistic frameworks of technology adoption.

From this approach, AI readiness is not an individual trait but a systemic property that arises from the interplay of institutional ability and material infrastructure within certain contextual restrictions as demonstrated in the SMK environment.

6. CONCLUSION

The results of this study indicate that the AI preparedness of vocational high school students is mostly built through institutional and technological ecosystems, rather than the individual technological aptitude. Results show that institutional support is the most significant factor of AI readiness, suggesting that school policies, teacher guidance, curriculum integration, training opportunities, and organisational commitment are vital to equipping students for AI-supported learning and workplaces of the future. Technological infrastructure also becomes a key enabling mechanism as students' access to digital materials, connectivity, and AI-based learning environments enable them to translate institutional support into tangible technological experiences.

The study also highlights a significant restriction of traditional assumptions on the development of digital competence. The impact of technology literacy on AI readiness was not substantial, indicating that basic digital abilities are not enough to prepare vocational students for AI-driven professional contexts. Students need higher-order skills such as AI literacy, critical evaluation, ethical consideration, and flexible technological application. The negative link between technological acceptance and AI readiness also indicates that positive views toward technology do not automatically lead to technologically relevant expertise in the job.

This research adds to the current body of knowledge by extending AI adoption studies toward a socio-technical approach and framing AI readiness as an emergent characteristic of vocational students' employment preparedness. The findings indicate that the preparation of the workforce for the AI future requires integrated strategies that encompass institutional capability, technical infrastructure, and competency-based learning methodologies. Additional work preparedness variables such as industry engagement, internship experience, teacher AI expertise, curriculum alignment, and real-world AI use in workplace settings should be examined in future research.

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CONFLICTS OF INTEREST

The author declares that no conflicts of interest are associated with this study.

DATA AVAILABILITY

The datasets utilized and/or analyzed during this research are available from the corresponding author upon reasonable request.

CLINICAL TRIAL NUMBER

Clinical trial number: not applicable.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This study was approved by the Research Ethics Committee of the Institute for Research and Community Service, Universitas Negeri Makassar, under approval number

3530/DST/UN36.12/TU/2026. All procedures involving human participants were conducted in accordance with the World Medical Association Declaration of Helsinki.
All participants were older than 16 years at the time of data collection. Freely given informed consent to participate was obtained from all participants before questionnaire administration. Participants received information about the study purpose, procedures, potential risks and benefits, and confidentiality. They were informed that participation was voluntary and that declining participation or withdrawing would not affect their grades or school standing.

CONSENT FOR PUBLICATION
Consent for publication was not applicable because this manuscript does not contain identifiable personal information or individual data.

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AUTHOR STATEMENT

Author 1 (A) contributed to the conceptualization of the study, development of the research framework, methodology design, and overall supervision of the research process.

Author 2 (Sah) contributed to data collection, data curation, formal analysis, and interpretation of the research findings.

Author 3 (Sy) contributed to literature review, validation of the results, visualization, and preparation of the initial manuscript draft.

Author 4. (Sud) contributed to manuscript review and editing, refinement of the theoretical discussion, project administration, and final approval of the manuscript.

All authors have read and agreed to the published version of the manuscript and are accountable for all aspects of the work, ensuring the integrity and accuracy of the research.

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