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EXTENDING THE HOT-FIT MODEL WITH INFORMATION LITERACY TO EXPLAIN AI ADOPTION IN HIGH SCHOOLS

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Abstract— *Artificial Intelligence (AI) is increasingly transforming educational practices by enabling more adaptive and personalized learning experiences in secondary schools. Nevertheless, previous applications of the Human–Organization–Technology Fit (HOT-Fit) model have given limited attention to the roles of information literacy and trust in influencing AI adoption. To address this gap, the present study expands the HOT-Fit framework by incorporating three additional constructs: information literacy, perceived validity, and perceived trust, in order to better explain AI readiness and adoption in educational settings. A quantitative approach was employed involving 316 senior high school students from Kuningan Regency, Indonesia. Data were gathered using a structured questionnaire based on a five-point Likert scale and analyzed through Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS v3.0 to evaluate 29 proposed hypotheses. The findings revealed that 21 hypotheses were statistically supported. Information literacy demonstrated a strong positive effect on perceived trust ($\beta = 0.708$; $p < 0.001$), as well as on system use, organizational structure, environmental support, and user satisfaction. In addition, system quality significantly contributed to user satisfaction, whereas service quality affected both system use and satisfaction. Among all relationships, net benefit exerted the strongest effect on action to use ($\beta = 0.547$; $p < 0.001$). The R^2 results for several endogenous constructs were above 0.50, indicating acceptable explanatory capability of the proposed model. Practically, the findings offer implications for educators, policymakers, and system developers in designing AI-supported learning environments by emphasizing the enhancement of digital literacy, service support, and system effectiveness for sustainable AI integration in schools.*

Keywords: *Artificial Intelligence, Adoption, HOT-Fit Model, Information Literacy, Learning.*

Intisari— *Perkembangan pesat Artificial Intelligence (AI) telah membawa peluang baru dalam menciptakan proses pembelajaran yang lebih adaptif dan personal di tingkat sekolah menengah. Namun, sebagian besar penelitian yang menggunakan model Human–Organization–Technology Fit (HOT-Fit) masih memberikan perhatian yang terbatas terhadap peran literasi informasi dan kepercayaan dalam memengaruhi adopsi AI. Untuk mengatasi kesenjangan tersebut, penelitian ini mengembangkan model HOT-Fit dengan menambahkan tiga konstruk, yaitu literasi informasi, perceived validity, dan perceived trust, guna memberikan pemahaman yang lebih komprehensif mengenai kesiapan dan adopsi AI dalam pendidikan. Penelitian ini menggunakan pendekatan kuantitatif dengan melibatkan 316 siswa sekolah menengah atas di Kabupaten Kuningan, Indonesia. Data dikumpulkan melalui kuesioner terstruktur menggunakan skala Likert lima poin dan dianalisis menggunakan Partial Least Squares Structural Equation Modeling (PLS-SEM) dengan bantuan perangkat lunak SmartPLS v3.0 untuk menguji 29 hipotesis yang diajukan. Hasil penelitian menunjukkan bahwa 21 hipotesis dinyatakan signifikan. Literasi informasi terbukti memiliki pengaruh positif yang kuat terhadap perceived trust ($\beta = 0.708$; $p < 0.001$), serta terhadap penggunaan sistem, struktur organisasi,*

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lingkungan, dan kepuasan pengguna. Selain itu, kualitas sistem berpengaruh signifikan terhadap kepuasan pengguna, sedangkan kualitas layanan memengaruhi penggunaan sistem dan kepuasan pengguna. Di antara seluruh hubungan yang diuji, net benefit menunjukkan pengaruh paling kuat terhadap action to use ($\beta = 0.547$; $p < 0.001$). Nilai R^2 pada beberapa konstruk endogen berada di atas 0,50 yang menunjukkan kemampuan penjelasan model yang memadai. Dari sisi praktis, temuan penelitian ini memberikan implikasi bagi pendidik, pembuat kebijakan, dan pengembang sistem dalam merancang lingkungan pembelajaran berbasis AI melalui penguatan literasi digital, peningkatan kualitas layanan, dan optimalisasi efektivitas sistem guna mendukung integrasi AI yang berkelanjutan di sekolah.

Kata Kunci: *Kecerdasan Buatan, Adopsi, Model HOT-Fit, Literasi Informasi, Pembelajaran.*

INTRODUCTION

The rapid growth of information and communication technology (ICT) has long been regarded as a fundamental factor driving the transformation of education worldwide. Since the introduction of computer-based instruction (CBI) in the 1950s, ICT has increasingly supported teaching and learning activities. Early instructional theories illustrated how learning systems could deliver stimuli, generate learner responses, and provide immediate feedback, thereby laying the groundwork for computer-assisted learning. As computing technologies evolved, educational systems incorporated more interactive capabilities, such as multimedia features, problem-solving exercises, and adaptive tutorials. The COVID-19 pandemic further intensified the adoption of ICT, with digital platforms becoming indispensable for remote learning, communication, and access to information [1]. In the educational context, these technological developments have facilitated the emergence of smart learning environments that support flexible and location-independent learning [2]. In Indonesia, this transformation aligns with the implementation of Education 4.0, characterized by the widespread use of smartphones and digital learning applications at the secondary education level. Such conditions create opportunities for more interactive and engaging learning experiences [3], [4], [5].

Alongside ICT advancement, Artificial Intelligence (AI) has emerged as a transformative technology in education, enabling adaptive and personalized learning systems. In 2023, Indonesia ranked among the top countries in AI usage, with more than 1.4 billion visits to AI-based applications. Despite this rapid growth, several challenges remain, including concerns about plagiarism, limited development of critical thinking skills, and the need to ensure that AI complements rather than replaces teachers in shaping student character [6], [7], [8], [9], [10], [11]. These challenges highlight the need for further investigation into AI adoption, particularly in contexts where ICT infrastructure and digital literacy levels are uneven. Previous studies have examined factors influencing technology adoption in education. Information literacy has been shown to influence trust and technology acceptance [12], [13], as well as academic performance in blended learning environments [13]. Other studies emphasize the role of ICT infrastructure in supporting cognitive development [14], the importance of adaptive learning systems [15], and the need for innovation in developing students' information management skills [16]. However, most of these studies focus on higher education or blended learning, leaving limited empirical evidence in the context of secondary education.

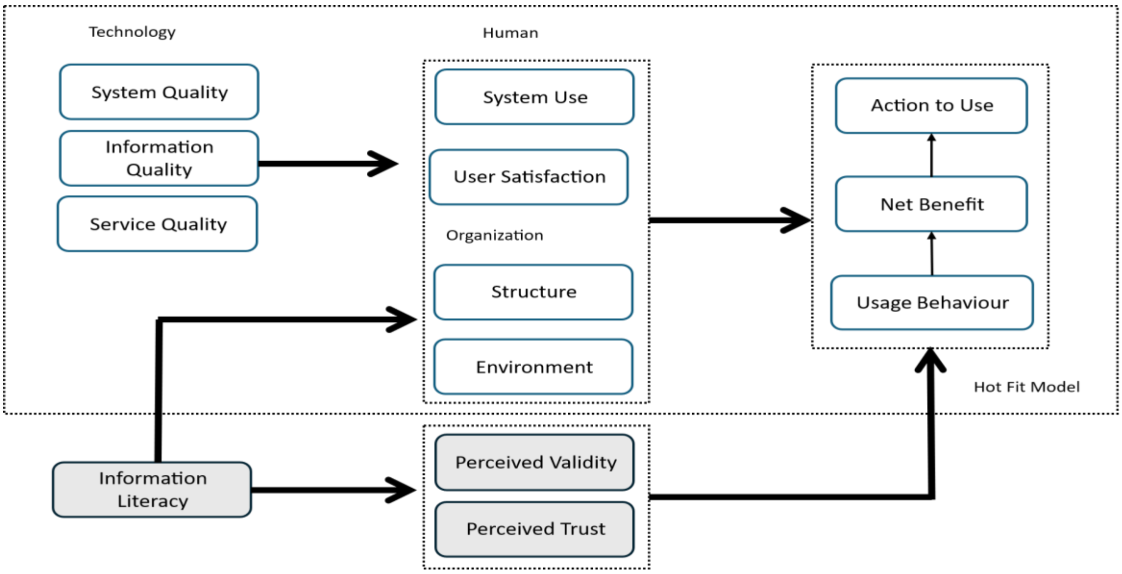
Various theoretical models have been developed to explain technology adoption, including the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). TAM primarily emphasizes perceived usefulness and perceived ease of use, whereas UTAUT extends this perspective by incorporating factors such as performance expectancy, social influence, and facilitating conditions [17], [18], [19], [20]. Although widely applied, these models primarily emphasize individual behavioral intention. In contrast, the Human–Organization–Technology Fit (HOT-Fit) model provides a broader perspective by integrating technological, organizational, and human dimensions in evaluating system success [21], [22]. This multidimensional approach is particularly relevant for analyzing AI adoption in educational environments, where institutional context and user readiness interact dynamically. Beyond technological and organizational factors, AI adoption in education also depends on users' cognitive ability to evaluate algorithm-generated information. In this context, information literacy plays an important role in shaping how students search, interpret, and use AI-generated content. Students with higher information literacy are more capable of evaluating the credibility of such information and are therefore more likely to develop trust in AI systems [12], [13]. In addition, perceived trust and perceived validity reflect users' evaluations of the reliability and consistency of AI-generated outputs. Given the complexity and limited transparency of AI systems, these cognitive evaluations are essential in shaping students' willingness to adopt AI-based learning tools. Integrating these constructs into the human dimension of the HOT-Fit model provides a more comprehensive framework for understanding AI adoption in educational contexts.

This research gap highlights the importance of investigating how information literacy, system quality, and service quality interact with perceived trust and perceived validity in shaping net benefits and the sustainable adoption of AI in secondary education. One of the most widely used frameworks for evaluating information system success (ISSM) is the HOT-Fit model, initially developed by [21], [22] to assess health information systems and later applied in education to evaluate e-learning success [23], [24]. The HOT-Fit model integrates three dimensions—human, organization, and technology—along with net benefits to provide a comprehensive assessment of system implementation. Beyond healthcare, the model has been adapted in various sectors, including education, to measure system effectiveness and user acceptance [4], [22]. However, its application in AI adoption at the senior high school level remains limited.

To fill this gap, the current study expands the HOT-Fit model by integrating perceived trust and perceived validity, while also exploring their mediating effects on the relationship between information literacy and net benefits in AI adoption. In addition, the study seeks to identify the main determinants influencing AI readiness and adoption among senior high school students. This model extension enriches the existing literature by providing a deeper understanding of AI adoption within educational settings. Furthermore, the study contributes empirical evidence from Indonesian senior high schools, a context that remains relatively underexplored, while also offering practical recommendations for implementing AI adoption strategies in secondary education.

MATERIALS AND METHODS

The development of this research model was initiated through a comprehensive review of relevant theories and conceptual frameworks, with particular emphasis on the HOT-Fit model, which has been extensively utilized to evaluate information system success in both healthcare and educational settings [21], [22], [25]. Based on the literature review and identified research gaps, the model was subsequently extended by incorporating three new constructs: *Information Literacy (INL)*, *Perceived Trust (PCT)*, and *Perceived Validity (PCV)*. The inclusion of these constructs aims to capture both the cognitive and affective dimensions of user experience in the context of Artificial Intelligence (AI) adoption within senior high school learning environments. This integration provides a more comprehensive framework for evaluating AI readiness and acceptance by combining technological, organizational, and human behaviour perspectives.



Source: (Research Results, 2025)
Figure 1. Extended HOT-Fit Conceptual Model Integrating Information Literacy, Perceived Trust, and Perceived Validity.

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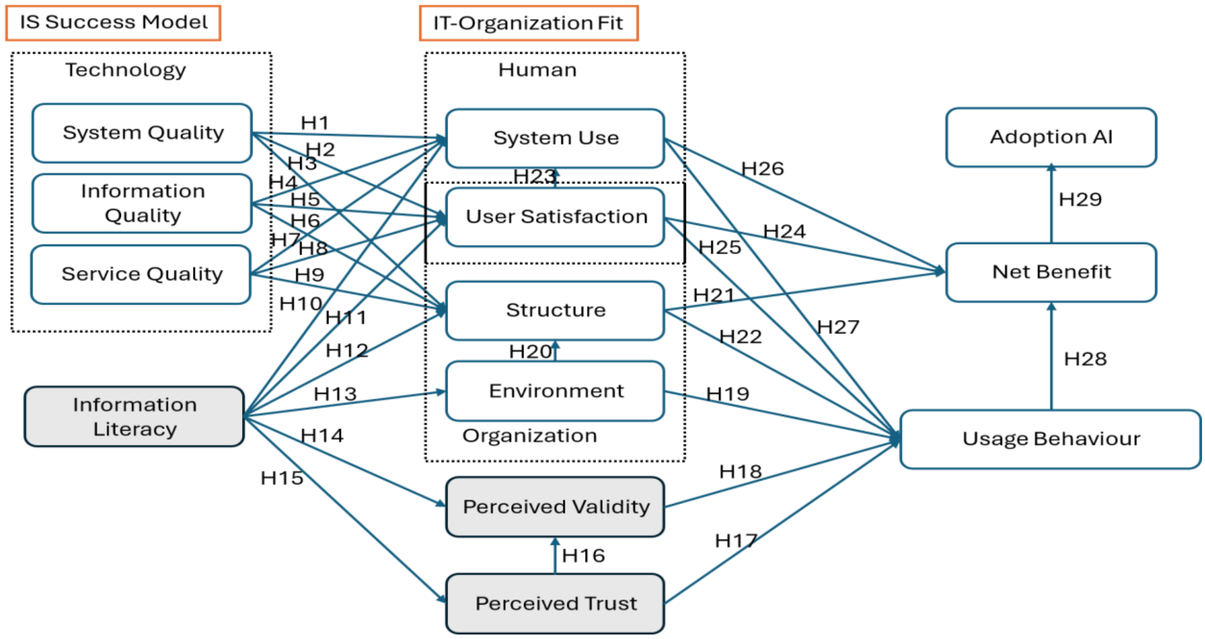
This study adopts a quantitative approach to examine the relationships among variables within the extended HOT-Fit model, with particular emphasis on evaluating AI readiness and adoption in secondary education. Figure 1 illustrates the conceptual basis of the proposed framework, which combines the original HOT-Fit dimensions human, organizational, and technological factors with additional constructs, namely information literacy, perceived trust, and perceived validity. By incorporating these constructs, the model captures the interaction between user readiness and trust in AI systems, thereby providing a more comprehensive evaluation framework compared to conventional system quality models.



Source: (Research Results, 2025)

Figure 2. Hypothesized Structural Relationships in the Extended HOT-Fit Model.

Figure 2 illustrates the proposed structural relationships among the variables, presenting the causal pathways tested empirically through the Partial Least Squares Structural Equation Modeling (PLS-SEM) method. The directional arrows represent the hypothesized causal effects derived from prior theoretical perspectives, including the impact of information literacy on perceived trust, system use, and organizational structure. Based on this framework, a total of 29 hypotheses were formulated to investigate both direct and mediating relationships among the constructs.

The development of these hypotheses is grounded in the theoretical logic that AI adoption in education is not a single-step process but a multi-stage interaction between technological performance, cognitive evaluation, and behavioral outcomes. Drawing from the HOT-Fit framework, technological quality is expected to shape users' experiences and satisfaction, which in turn influence system use and perceived benefits. At the same time, the inclusion of information literacy introduces a cognitive dimension that explains how students interpret and evaluate AI-generated information. This cognitive evaluation is further reflected in perceived trust and perceived validity, which function as key mediating mechanisms linking system characteristics to behavioral responses. Therefore, the hypothesized relationships are not formulated as isolated paths, but as an interconnected structure representing the dynamic process of AI adoption in educational environments.

Specifically, the hypotheses were grouped according to the three core dimensions of the extended HOT-Fit model—technology, human, and organization—along with the adoption and behavioral outcomes. Within the technological dimension, system quality, information quality, and service quality are hypothesized to positively influence system use, user satisfaction, and organizational structure (H1–H9), as higher system performance enhances usability, reliability, and user experience, which are essential for sustained interaction with AI systems.

Information literacy, as a critical human factor, is proposed to affect multiple constructs, including system use, user satisfaction, structure, environment, perceived validity, and perceived trust (H10–H15), as individuals with higher information literacy are better able to evaluate, interpret, and utilize AI-generated information in learning contexts [12], [13]. Perceived trust and perceived validity serve as mediating cognitive variables linking human and behavioral outcomes, where trust is expected to influence validity and usage behaviour, and validity in turn affects usage behaviour (H16–H18). This relationship reflects the role of cognitive evaluation in shaping users' willingness to rely on AI systems, particularly in environments where algorithmic processes are not fully transparent. From the organizational perspective, environment and structure are hypothesized to positively impact usage behaviour and net benefits (H19–H22), as institutional support and policy frameworks provide the necessary conditions for effective technology integration. Finally, user satisfaction and system use are expected to drive net benefits and AI adoption (H23–H26), while net benefit, usage behaviour, and AI adoption reinforce each other in reciprocal relationships (H27–H29), reflecting the iterative and reinforcing nature of technology adoption in educational settings.

Drawing upon the concepts, theoretical perspectives, and models outlined earlier, this study develops a research framework that is evaluated through reliability and validity assessments using a variance-based multivariate analysis technique, namely Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS version 3.0 software [26]. Previous studies indicate that PLS-SEM involves two primary stages of evaluation: the measurement model (outer model) and the structural model (inner model). The measurement model assessment is conducted to evaluate construct reliability and validity through procedures such as individual item reliability, internal consistency reliability, convergent validity, and discriminant validity [27].

A. Population and Sampling

The population targeted in this study comprised senior high school students in Kuningan Regency, West Java, Indonesia, who actively utilize AI technologies in learning activities. Kuningan Regency was chosen as the study area because it reflects a diverse educational environment, including both urban and rural schools with different levels of technological infrastructure and digital literacy. This diversity enables the study to capture a broader perspective on AI adoption in secondary education within a developing regional context. To ensure participant eligibility, the questionnaire incorporated screening questions to verify respondents' actual experience in using AI applications for learning purposes. Based on data from the West Java Provincial Education Office in 2023, the total number of senior high school students in Kuningan Regency reached 47,483, consisting of 18,156 students from public senior high schools, 1,601 from private senior high schools, 15,601 from public vocational schools, and 12,125 from private vocational schools.

To determine the research sample, this study applied a non-probability sampling approach using purposive sampling, as the respondents were specifically required to have prior experience in using AI technologies for learning activities. The initial sample size was calculated using Slovin's formula, which produced a minimum requirement of 276 respondents [28]. Nevertheless, because this study employs Partial Least Squares Structural Equation Modeling (PLS-SEM), the sufficiency of the sample size was further assessed in accordance with methodological guidelines recommended for PLS-SEM analysis. According to [26], PLS-SEM is suitable for studies with moderate sample sizes and does not require large samples compared with covariance-based SEM. In addition, the commonly applied 10-times rule suggests that the minimum sample size should be at least ten times the largest number of structural paths directed at any latent construct in the model. The final sample size in this study therefore satisfies both the Slovin-based estimation and the PLS-SEM sampling recommendations, ensuring sufficient statistical power for structural model estimation.

The recruitment process was conducted through coordination with several senior high schools in Kuningan Regency, where the questionnaire was distributed online with the assistance of teachers or school administrators to ensure that respondents were active students. To ensure eligibility, the questionnaire included screening questions asking whether respondents had previously used AI-based applications in their learning activities; only those who confirmed such use were allowed to continue the survey. A total of 340 responses were initially collected. After undergoing a data screening and cleansing process, including checking response completeness and consistency, 316 valid responses were retained for further analysis, which exceeds the minimum sample requirement and meets the recommended threshold for reliable PLS-SEM analysis. Moreover, considering the complexity of the proposed structural framework—which involves multiple latent variables and numerous structural relationships—the sample size was considered adequate to produce stable parameter estimations and reliable statistical conclusions. Hair et al.

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(2017) suggest that the recommended sample size in PLS-SEM analysis ranges from five to ten times the total number of indicators or questionnaire items included in the study.

B. Instrumentation

To ensure the construct validity of the instrument, all variables included in the questionnaire were derived from the extended HOT-Fit model, which integrates the dimensions of human, organization, and technology [21], [22], [24]. Each variable and indicator was carefully selected to align with the model's purpose of explaining AI adoption in secondary education contexts similar to Kuningan Regency. The technological dimension, represented by System Quality, Information Quality, and Service Quality, captures the technical effectiveness of AI systems and their influence on satisfaction and usage. The human dimension, consisting of Information Literacy, Perceived Trust, and Perceived Validity, emphasizes users' cognitive and affective readiness in interacting with AI systems, as supported by prior studies highlighting the role of trust and literacy in technology adoption [29], [30]. Meanwhile, the organizational dimension, reflected through Structure and Environment, represents institutional readiness and contextual factors that support AI integration [22]. Finally, Net Benefit, Usage Behaviour, and Action to Use serve as the outcome constructs that measure the overall impact and sustainability of AI use in learning.

Although System Use, Usage Behaviour, and Action to Use are all related to technology usage, this study distinguishes them based on their roles within the behavioral process of AI adoption. System Use refers to the actual interaction with AI systems, reflecting the frequency and extent of use in learning activities. Usage Behaviour represents users' evaluative and attitudinal responses toward the use of AI, indicating whether the technology is perceived as appropriate and beneficial. Meanwhile, Action to Use reflects the continuation and reinforcement of usage, capturing students' decisions to sustain or intensify the use of AI in the future.

This distinction aligns with well-established frameworks, including the ISSM by Delone and the TAM by Davis, which differentiate between actual system use, user responses, and behavioral intention. Therefore, these constructs represent sequential and complementary stages in the AI adoption process, rather than overlapping constructs. Although the constructs of System Use, Usage Behaviour, and Action to Use may appear conceptually similar, this study clearly distinguishes them based on their theoretical roles within the technology adoption process. System Use refers to the actual interaction with AI systems, reflecting the frequency and extent of system utilization in learning activities. Usage Behaviour represents users' evaluative and attitudinal responses toward the use of AI, indicating whether the technology is perceived as beneficial, appropriate, or desirable. Meanwhile, Action to Use reflects the continuation or reinforcement of usage behaviour, capturing students' decisions to sustain or intensify the use of AI in the future. This differentiation is in line with established frameworks, including the [31], [32] ISSM and TAM [17], [19], both of which distinguish actual system use from user responses and behavioral intentions. Therefore, each construct captures a different stage of AI adoption, reducing conceptual overlap and strengthening construct validity.

Although System Use, Usage Behaviour, and Action to Use are all related to technology usage, this study distinguishes them based on their roles within the behavioral process of AI adoption. System Use refers to the actual interaction with AI systems, reflecting the frequency and extent of use in learning activities. Usage Behaviour, in contrast, represents users' evaluative and attitudinal responses toward the use of AI, capturing whether the technology is perceived as appropriate, beneficial, or desirable. Meanwhile, Action to Use reflects the continuation and reinforcement of usage, indicating a more concrete decision to sustain or intensify the use of AI in the future. This distinction corresponds with established models, such as the ISSM by Delone and TAM Model by Davis, both of which separate actual system usage from user responses and behavioral intentions. Therefore, these constructs are not conceptually redundant but represent sequential and complementary stages in the AI adoption process.

Although several indicators within the Net Benefit construct, such as "job effects" and "work volume," were originally developed in organizational and workplace contexts, this study adapts their interpretation to fit the educational setting. In the context of student learning, these indicators are redefined to reflect learning-related outcomes, such as improved learning effectiveness, increased efficiency in completing academic tasks, enhanced understanding accuracy, and reduced errors in learning processes. This approach is consistent with prior studies that have successfully adapted the ISSM by DeLone and the HOT-Fit framework into educational contexts by contextualizing performance-related indicators into learning outcomes [21], [22], [31], [32]. Therefore,

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the Net Benefit construct in this study represents not occupational performance, but the perceived academic and cognitive benefits of using AI in learning, ensuring its contextual validity within secondary education.

The data for this study were gathered using a structured questionnaire employing a five-point Likert scale, where responses ranged from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). The questionnaire consisted of two main parts. The first part provided an introduction explaining the purpose of the research, ensuring the confidentiality and voluntary participation of respondents, and offering instructions for completing the questionnaire. The second part comprised the research items, including demographic questions to identify respondents' backgrounds and items related to the adoption and utilization of AI in learning activities. The questionnaire aimed to gain insights into how senior high school students in Kuningan Regency, West Java, Indonesia, perceive, adopt, and apply AI technology in their learning processes. The inclusion of an introductory explanation and ethical statement was intended to ensure transparency, encourage honest responses, and maintain research integrity throughout the data collection process. Table 1 (adapted from [12], [13], [21], [22], [31], [32]) lists the variables, indicators, and codes used in this study. This table serves to provide a clear picture of each variable studied, the indicators used to measure it, and the codes used in data analysis.

Table 1. Research Constructs, Indicators, and Measurement Sources

Construct	Indicators	Codes	Source
System Quality	Data Accuracy, Ease of Use, Reliability, Security, Response Time	SYQ1–SYQ5	[21], [22], [31], [32]
Information Quality	Relevance, Legibility, Accuracy, Completeness, Reliability	INQ1–INQ5	[31], [32], [33]
Service Quality	Quick Responsiveness, Assurance, Empathy, Technical Support	SRQ1–SRQ4	[31], [32], [33]
User Satisfaction	Overall Satisfaction, Perceived Usefulness, Software Satisfaction	UST1–UST3	[31], [32], [33]
System Use	Frequency of Access, Recurring Use, Knowledge/Expertise, Acceptance	SYU1–SYU4	[31], [32], [33]
Structure	Planning Strategy, Management, Leadership, Top Management Support	STR1–STR4	[21], [22]
Environment	Government Support, Policy/Politics, Inter-organizational Relationship	ENV1–ENV3	[31], [32], [33]
Information Literacy	Information Seeking, Information Verification, Information Sharing, Digital Literacy, Media Literacy	INL1–INL5	[12], [13]
Perceived Validity	Accuracy, Consistency, Easy to Describe, Retrievable	PCV1–PCV4	[30]
Perceived Trust	Clarity, Integrity, Systematization, Openness, Coherence	PCT1–PCT5	[31], [32], [33]
Net Benefit	Job Effects, Productivity, Work Volume, Efficiency, Effectiveness, Accuracy, Confidence, Error Reduction	NBT1–NBT8	[31], [32], [33]
Usage Behaviour	Bad/Good Idea, Foolish/Wise Idea, Dislike/Like, Unpleasant/Pleasant	UBV1–UBV4	[13], [17], [34]
Action to Use	Frequency of Usage, Duration of Use	ACU1–ACU2	[13], [17], [34]

Source: (Research Results, 2025)

Furthermore, the questionnaire items were adapted from previously validated instruments commonly used in information systems and educational technology research. The constructs of System Quality, Information Quality, Service Quality, System Use, User Satisfaction, Structure, Environment, and Net Benefit were adopted from the Information System Success Model introduced by [31], [32] and operationalized within the HOT-Fit model proposed by [21], [22]. The Information Literacy construct was adapted from prior studies examining digital information competencies in educational contexts, while Perceived Trust and Perceived Validity were adapted from research on trust and credibility in digital information environments. Example items include statements such as *"The AI system used in learning provides accurate information"* for System Quality, *"I feel satisfied when using AI tools in my learning activities"* for User Satisfaction, and *"I trust the information generated by AI systems used in learning"* for Perceived Trust.

Prior to the main data collection, the questionnaire was refined through contextual adaptation and language modification to ensure that the items were clear and appropriate for senior

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high school students. A pilot study was then conducted with a small sample of respondents to assess the clarity and understandability of the questionnaire items. Based on the feedback obtained, minor wording improvements were made to enhance readability while maintaining the original meaning of the measurement items.

In addition to statistical validation, particular attention was given to ensuring the conceptual alignment of measurement indicators with the educational context of AI-supported learning. The Perceived Validity construct in this study is interpreted as students' evaluation of the credibility, consistency, and interpretability of AI-generated information used in learning activities. Although the indicators such as accuracy and consistency are commonly applied in information system research, they are contextualized here to reflect how students assess the reliability and usefulness of AI outputs in supporting their understanding of learning materials.

Similarly, the Net Benefit construct, which was originally developed in organizational contexts, is redefined to represent learning-related outcomes. Indicators such as "job effects" and "work volume" are interpreted as improvements in learning effectiveness, efficiency in completing academic tasks, and reduction of errors in the learning process. This adaptation follows prior studies that apply the [31], [32] and HOT-Fit [21], [22] models in educational settings.

Therefore, although the indicators are derived from established instruments, their operational meaning in this study is fully grounded in the context of secondary education. This process ensured that the measurement instrument not only maintained theoretical consistency with the established model but also achieved contextual relevance for high school students, thereby strengthening the content validity and reliability of the measurement.

C. Reliability and Validity Test Result

Table 2 presents the results of the reliability and construct validity assessments for all variables examined in this study. The evaluation procedures comprised Cronbach's Alpha, rho_A, Composite Reliability, Average Variance Extracted (AVE), cross-loadings, the Fornell–Larcker criterion, and the Heterotrait–Monotrait Ratio (HTMT). All analyses were performed using SmartPLS version 3.0 software.

Table 2. Reliability and Validity Analysis Results

Variables	C. Alpha	rho_A	CR	(AVE)
Action to Use	0.751	0.756	0.889	0.800
Environment	0.791	0.794	0.878	0.705
Information Literacy	0.883	0.886	0.915	0.682
Information Quality	0.882	0.886	0.913	0.679
Net Benefit	0.943	0.944	0.953	0.716
Perceived Trust	0.923	0.923	0.942	0.765
Perceived Validity	0.869	0.869	0.911	0.718
Service Quality	0.861	0.871	0.906	0.709
Structure	0.881	0.881	0.918	0.737
System Quality	0.781	0.795	0.850	0.533
System Use	0.859	0.863	0.904	0.702
Usage Behaviour	0.893	0.897	0.926	0.757
User Satisfaction	0.831	0.831	0.899	0.747

Source: (Research Results, 2025)

According to Table 2, the analysis results indicate that the Average Variance Extracted (AVE) values for all thirteen constructs exceeded the recommended threshold of 0.5, while the Cronbach's Alpha values were all above 0.7 [28]. These findings demonstrate that the indicators satisfy the required convergent validity and reliability criteria, indicating that the constructs used in the research model are both valid and reliable.

Cross-loading analysis was first conducted to assess the discriminant validity of each indicator. Under this method, an indicator's outer loading on its designated construct must be higher than its correlations (cross-loadings) with other constructs [26]. The results indicated that all indicators fulfilled this criterion, as the factor loadings on their respective constructs were greater than the loadings on other constructs.

In addition, the Fornell–Larcker Criterion demonstrated that the square root of the AVE for each construct exceeded the correlations among constructs, confirming satisfactory discriminant validity. The final evaluation of discriminant validity employed the Heterotrait–Monotrait Ratio (HTMT), where values below 0.9 were regarded as acceptable indicators of discriminant validity [35].

Based on the three assessment procedures—cross-loadings, the Fornell–Larcker Criterion, and the Heterotrait–Monotrait Ratio (HTMT)—the findings indicate that the model does not present any discriminant validity concerns and therefore fulfills the required validity criteria [35]. In addition, the Heterotrait–Monotrait Ratio (HTMT), introduced by [35], was used as an additional measure of discriminant validity. The recommended HTMT threshold is below 0.85 or 0.90, depending on the research context. Since all HTMT values in this study were within the acceptable range, the discriminant validity of the research model can be considered satisfactory.

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D. Variance Inflation Factor (VIF)

To ensure that the findings were not affected by common method bias, a full collinearity assessment was performed by analyzing the Variance Inflation Factor (VIF) values for each indicator, following the recommendation of [35]. This procedure was considered necessary because all data were collected through self-reported questionnaires administered at a single point in time. As shown in Table 3, all VIF values remained below the recommended threshold of 3.3, with the highest value reaching 3.076, indicating that the proposed model was not affected by common method bias [35]. These results suggest that the explained variance of each construct was not substantially affected by the measurement method, thereby supporting the credibility of the structural relationships examined in this study.

Table 3. Outer VIF Value

Variables	VIF
ACU1	1.510
ACU2	1.510
ENV1	1.564
ENV2	1.642
ENV3	1.444
INL1	2.041
INL2	1.918
INL3	1.526
INL4	2.327
INL5	2.016
INQ1	1.790
INQ2	1.726
INQ3	2.356
INQ4	1.617
NBT1	2.367
NBT2	2.238
NBT3	2.573
NBT5	2.654
NBT7	1.779
PCT1	1.790
PCT3	1.790
PCV1	2.114
PCV2	2.114
SRQ1	1.530
SRQ2	1.510
SRQ4	1.952
STR1	1.817
STR2	1.882
STR3	2.229
STR4	2.348
SYQ1	1.512
SYQ2	1.369
SYQ3	1.335
SYQ4	1.269
SYU1	2.207
SYU2	2.148
SYU3	1.619
SYU4	1.860
UBV1	2.261
UBV2	2.117
UBV3	3.076
UBV4	2.757
UST3	1.000

Source: (Research Results, 2025)

E. Measurement Result of Structural Model

Tables 4 to 7 present the measurement results of the structural model, where the R^2 value indicates the proportion of variance in the dependent construct explained by the independent constructs; the f^2 value represents the effect size, or the strength of the influence of a predictor variable on the dependent construct; the Q^2 value reflects the model's predictive relevance for the dependent constructs; and the significance value shows the statistical significance of the relationships between variables in the model, as determined by the t-statistic and p-value tests.

Table 4. Coefficient of Determination (R^2) Values for Endogenous Constructs in the Extended HOT-Fit Model

R^2 Value	R^2 Value*	Model's Explanatory
ACU	0.299	Moderate
ENV	0.442	Moderate
NBT	0.693	Moderate
PCT	0.501	Moderate
PCV	0.494	Moderate
STR	0.624	Moderate
SYU	0.558	Moderate
UBV	0.531	Moderate
UST	0.514	Moderate

Source: (Research Results, 2025)
Note: R^2 values of 0.75, 0.50, and 0.25 are generally interpreted as indicating substantial, moderate, and weak explanatory power, respectively. [35]

The R^2 findings indicate that the structural model has adequate explanatory power for the endogenous constructs analyzed in this study. Among the examined variables, Net Benefit recorded the highest R^2 value (0.69), implying that the predictor constructs strongly account for students' perceived benefits of AI utilization in learning activities. This result suggests that variables such as information literacy, system use, and usage behaviour play an important role in influencing students' perceptions of the value and advantages of AI technology. Meanwhile, constructs such as System Use, Usage Behaviour, and User Satisfaction, which showed average R^2 values around 0.50, also demonstrated adequate explanatory capability, indicating that the human dimension within the HOT-Fit model plays an important role in influencing AI acceptance in learning environments. In contrast, the comparatively lower R^2 value for Action to Use (0.299) suggests that students' intentions to continue using AI are shaped not only by the variables included in the model but also by external influences, such as school regulations, teacher support, and access to technological resources. Overall, these findings suggest that the proposed

VOL. 11. NO. 4 MAY 2026
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model provides a reasonably strong explanation of the factors affecting AI adoption among senior high school students.

Table 5. Effect Size (f^2) Analysis for Relationships Among Key Variables in the Extended HOT-Fit Model.

Hypothesis	Relationship	f^2	Effect Size
H13	INL → ENV	0.791	Large Effect
H15	INL → PCT	1.002	Large Effect
H29	NBT → ACU	0.426	Large Effect
H10	INL → SYU	0.266	Medium Effect
H11	INL → UST	0.074	Medium Effect
H12	INL → STR	0.103	Medium Effect
H14	INL → PCV	0.085	Medium Effect
H16	PCT → PCV	0.213	Medium Effect
H17	PCT → UBV	0.063	Medium Effect
H19	ENV → UBV	0.033	Medium Effect
H2	SYQ → UST	0.062	Medium Effect
H20	ENV → STR	0.120	Medium Effect
H24	UST → NBT	0.061	Medium Effect
H26	SYU → NBT	0.086	Medium Effect
H27	SYU → UBV	0.059	Medium Effect
H28	UBV → NBT	0.320	Medium Effect
H7	SRQ → SYU	0.033	Medium Effect
H8	SRQ → UST	0.078	Medium Effect
H9	SRQ → STR	0.066	Medium Effect
H1	SYQ → SYU	0.001	Small Effect
H18	PCV → UBV	0.010	Small Effect
H21	STR → NBT	0.016	Small Effect
H22	STR → UBV	0.015	Small Effect
H23	UST → SYU	0.001	Small Effect
H25	UST → UBV	0.001	Small Effect
H3	SYQ → STR	0.000	Small Effect
H4	INQ → SYU	0.018	Small Effect
H5	INQ → UST	0.001	Small Effect
H6	INQ → STR	0.003	Small Effect

Source: (Research Results, 2025)
Note: f^2 values exceeding 0.02, 0.15, and 0.35 represent small, medium, and large effect sizes, respectively. [35]

The effect size (f^2) analysis presented in Table 4 shows that Information Literacy (INL) exerts the strongest influence on Perceived Trust (PCT), Environment (ENV), and Action to Use (ACU) through Net Benefit (NBT), highlighting its importance as a key determinant of AI adoption. Moderate effect sizes on System Use (SYU), Structure (STR), User Satisfaction (UST), and Perceived Validity (PCV) further suggest that information literacy contributes to both behavioral engagement and structural readiness in learning environments. In contrast, the comparatively lower effects of System Quality (SYQ) and Information Quality (INQ) indicate that technological factors alone are not sufficient to drive AI adoption without adequate human and organizational support. The practical implication is that AI adoption strategies in secondary schools should emphasize improving information literacy, building trust, and strengthening service quality and organizational support to ensure effective and sustainable AI integration.

Table 6. Q^2 Predictive Relevance Analysis for Key Constructs in the Extended HOT-Fit Model.

Variables	SSO	SSE	Q^2 (=1-SSE/SSO)
ACU	632,000	487,709	0.228
ENV	948,000	669,176	0.294
INL	1,580,000	1,580,000	0.000
INQ	1,264,000	1,264,000	0.000
NBT	1,580,000	830,134	0.475
PCT	632,000	371,263	0.413
PCV	632,000	366,593	0.420
SRQ	948,000	948,000	0.000
STR	1,264,000	717,079	0.433

Source: (Research Results, 2025)
Note: A Q^2 value greater than 0 indicates that the structural model possesses adequate predictive relevance. [35]

The Q^2 results shown in Table 6 suggest that the structural model possesses satisfactory predictive relevance for the endogenous constructs included in the study. Based on the Stone–Geisser criterion, a Q^2 value greater than zero indicates that the model has predictive capability for a given endogenous construct. In this research, multiple constructs produced positive Q^2 values, indicating that the model is able to predict the observed data with an acceptable level of accuracy. It should be noted that some constructs appear with Q^2 values equal to zero because they function as exogenous variables in the structural model and therefore are not predicted by other constructs. Consequently, Q^2 values are not applicable for these constructs, and their zero values should not be interpreted as an indication of weak predictive ability.

Table 7. Results of Structural Path Coefficients (β) and Hypothesis Testing

Hypo-thesis	Variables	β	T Statistics	P Values	Significant
H1	SYQ -> SYU	0,03	0,493	0,622	Rejected
H10	INL -> SYU	0,459	7.122	0	Accepted
H11	INL -> UST	0,245	3.846	0	Accepted
H12	INL -> STR	0,281	4.366	0	Accepted
H13	INL -> ENV	0,665	17.356	0	Accepted
H14	INL -> PCV	0,293	4.650	0	Accepted
H15	INL -> PCT	0,708	24.821	0	Accepted
H16	PCT -> PCV	0,464	7.425	0	Accepted
H17	PCT -> UBV	0,277	4.292	0	Accepted
H18	PCV -> UBV	-0,101	1.696	0,09	Rejected
H19	ENV -> UBV	0,199	3.330	0,001	Accepted
H2	SYQ -> UST	0,255	4.190	0	Accepted
H20	ENV -> STR	0,318	3.906	0	Accepted
H21	STR -> NBT	0,115	2.192	0,029	Accepted
H22	STR -> UBV	0,144	1.740	0,083	Rejected
H23	UST -> SYU	0,032	0,571	0,568	Rejected
H24	UST -> NBT	0,175	3.299	0,001	Accepted

Hypo-thesis	Variables	β	T Statistics	P Values	Significant
H25	UST -> UBV	0,024	0,463	0,643	Rejected
H26	SYU -> NBT	0,261	4.135	0	Accepted
H27	SYU -> UBV	0,272	3.663	0	Accepted
H28	UBV -> NBT	0,431	9.894	0	Accepted
H29	NBT -> ACU	0,547	11.207	0	Accepted
H3	SYQ -> STR	0,012	0,215	0,83	Rejected
H4	INQ -> SYU	0,144	2.195	0,029	Accepted
H5	INQ -> UST	0,032	0,417	0,677	Rejected
H6	INQ -> STR	0,054	0,907	0,365	Rejected
H7	SRQ -> SYU	0,199	3.069	0,002	Accepted
H8	SRQ -> UST	0,311	4.213	0	Accepted
H9	SRQ -> STR	0,255	4.237	0	Accepted

Source: (Research Results, 2025)
*Note: *significant at p < 0.05, t >1.96; [35],*

The significance test results in Table 7 indicate that most hypotheses in the research model were supported, highlighting the central role of *Information Literacy (INL)*, which significantly influenced *System Use (SYU)*, *User Satisfaction (UST)*, *Structure (STR)*, *Environment (ENV)*, *Perceived Validity (PCV)*, and *Perceived Trust (PCT)*. This confirms that information literacy is a key factor in building trust, validity, and readiness for AI adoption among students. Environmental and trust factors were also shown to affect usage behaviour, while *Service Quality (SRQ)* consistently influenced satisfaction, system use, and organizational structure, emphasizing the importance of technical and service support in strengthening adoption. Moreover, *Net Benefit (NBT)* emerged as a critical driver of *Action to Use (ACU)*, underscoring its role as an indicator of sustainable AI adoption in secondary education contexts similar to Kuningan Regency. Conversely, several paths such as *PCV → UBV* and *UST → SYU* were not significant, indicating that not all theoretical relationships were empirically validated. The practical implication is that AI adoption strategies in secondary schools should prioritize enhancing information literacy, fostering trust, and improving service quality to ensure that AI integration is effective, sustainable, and provides tangible benefits for students.

RESULTS AND DISCUSSION

The findings indicate that information literacy significantly influences students' readiness and acceptance of AI technologies in secondary education. Students with stronger abilities to search, evaluate, and interpret information demonstrate greater confidence in assessing the credibility of AI-generated outputs. This suggests that information literacy supports students' ability to engage critically with AI-supported learning environments. These results are consistent with prior studies [12], [13], while extending them to the context of secondary education. The effect-size (f^2) analysis in this study further highlights the dominant role of Information Literacy, particularly in shaping *Perceived Trust* and *Environmental Readiness*. This finding aligns with Information Literacy Theory [12], [13] and the assertion of [36] that *critical and participatory data literacy* forms the foundation of epistemic trust in AI-supported education. Likewise, [16] emphasized that teachers play a crucial role in scaffolding students' information-literacy skills to enable the *critical and ethical adoption* of emerging technologies in classrooms. Consistent with these perspectives, [37] conceptualized *AI literacy* as a multidimensional construct encompassing technical understanding, critical appraisal, and ethical use—factors that empower learners to make informed, responsible, and creative use of AI technologies. In this context, information literacy operates not merely as a technical skill but as a *cognitive instrument* that strengthens the trust relationship between learners and intelligent systems.

Results show that system quality and service quality significantly influence user satisfaction and system use. This indicates that successful AI adoption depends not only on system performance but also on the availability of responsive support and reliable services. These findings are consistent with the HOT-Fit framework [21], [22], [31], [32], which emphasizes the interaction between technological and human factors in determining system success. From an organizational perspective, structure and environment influence students' usage behaviour toward AI technologies. Institutional support and school policies contribute to shaping students' engagement with emerging technologies. Without adequate organizational support, the integration of AI may remain limited. These findings are consistent with previous studies [22], [25], while highlighting the role of institutional readiness in sustaining technology use.

Moreover, the mediating roles of Perceived Trust and Perceived Validity observed in this study demonstrate that students evaluate AI systems not solely on functionality but also on perceived *credibility* and *ethical reliability*. This finding aligns with the emerging Digital Trust Theory [30] and [38], who observed that *critical appraisal* can both enhance or reduce *self-efficacy* depending on users' trust in AI systems. The present study found that higher levels of perceived trust and validity enhanced students' behavioral intentions, confirming that *trust functions as a psychological*

VOL. 11. NO. 4 MAY 2026
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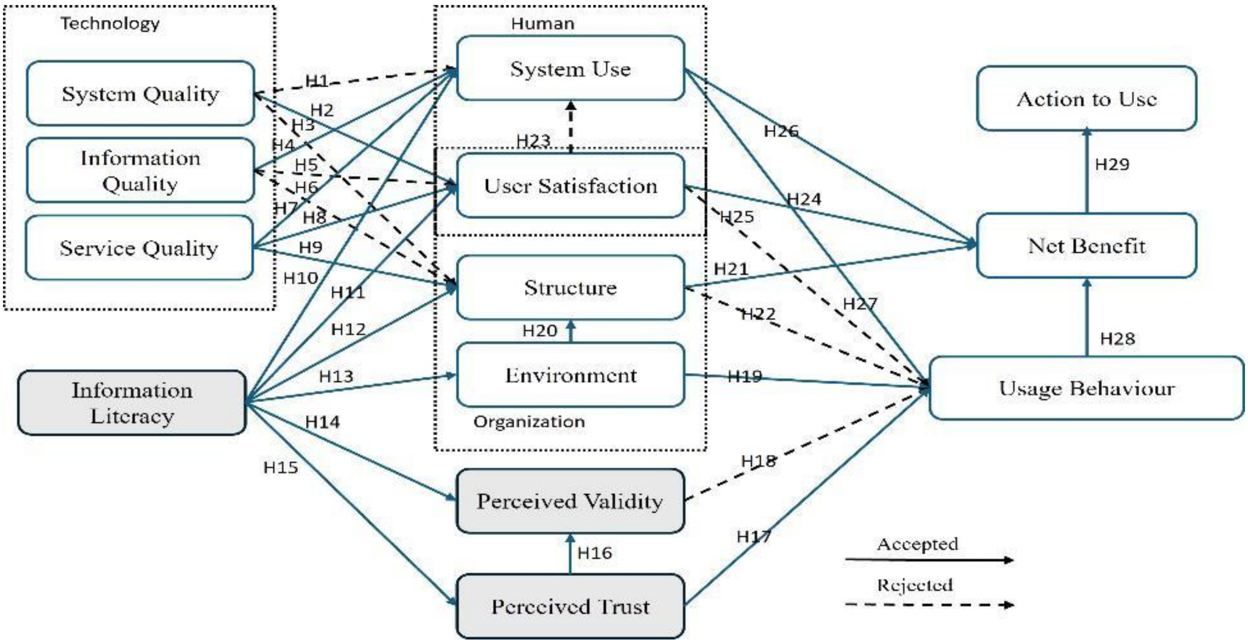
bridge connecting usability with sustained system use. Theoretically, this study extends the application of the HOT-Fit model into the educational sector by integrating *information literacy*, *perceived trust*, and *perceived validity* as additional constructs that reflect both cognitive and affective dimensions of technology use. This integrative approach bridges a gap identified in previous literature, which tended to emphasize technical or system-based determinants over socio-cognitive and institutional factors [22], [25]. Empirically, the findings corroborate multi-country evidence from Austria, Hungary, and Latin America, illustrating a convergent trend: students' engagement with AI tools is shaped simultaneously by individual literacy, trust, and institutional ecology.

Practically, these findings suggest a holistic strategy for AI adoption in secondary education contexts similar to Kuningan Regency—one that strengthens *information literacy* to build trust, ensures *service quality* to sustain satisfaction, and reinforces *organizational structures* to encourage innovation. Together, these dimensions ensure that AI integration in secondary education is not only technologically feasible but also pedagogically meaningful, ethically grounded, and aligned with institutional goals. In summary, this study extends the theoretical development of the HOT-Fit model by integrating cognitive trust, information literacy, and institutional readiness into a comprehensive framework for examining AI adoption in secondary education settings comparable to Kuningan Regency. The findings collectively affirm that successful AI adoption requires not only reliable technology but also *ethical literacy, trust-building mechanisms,* and *organizational alignment*—elements that empower students to become active, confident, and critical participants in the AI-driven learning ecosystem.



Source: (Research Results, 2025)

Figure 3. Final Structural Model after Hypothesis Testing.

The results of this study suggest that information literacy has a significant role in influencing students' readiness and acceptance of AI technologies in secondary education. Students with stronger abilities to identify, evaluate, and interpret information tend to show greater confidence in judging the credibility of AI-generated content. This finding indicates that information literacy extends beyond basic technical skills and functions as an advanced cognitive capability that supports students in critically engaging with AI-assisted learning environments. As a result, students who possess higher levels of information literacy are more likely to build trust in AI-based learning systems and incorporate these technologies into their educational activities. While previous studies [12], [13] have highlighted the role of information literacy in technology acceptance, this study extends these findings by demonstrating its critical function in shaping both trust and perceived validity within AI-driven learning contexts at the secondary education level, which has received limited empirical attention.

In addition, the results reveal that service quality and system quality significantly contribute to user satisfaction and system use. These findings indicate that technological performance alone is not sufficient to ensure successful adoption; the availability of responsive services, technical support, and reliable system functionality also influences students' experiences when interacting with AI tools. This observation aligns with the HOT-Fit model [21], [22], [31], [32]. However, the findings also show that not all technological factors consistently lead to behavioral outcomes, as reflected in the non-significant effects of system quality on system use and structure (H1 and H3), as well as information quality on user satisfaction and structure (H5 and H6). This suggests that the role of technology in AI adoption may be indirect and dependent on users' cognitive evaluation rather than purely on system performance.

From an organizational perspective, the findings suggest that organizational structure and educational environment influence students' usage behaviour toward AI technologies. Institutional support and school policies contribute to shaping students' engagement with emerging technologies. However, the non-significant effect of structure on usage behaviour (H22) indicates that organizational arrangements alone may not be sufficient to directly influence students' actions. This implies that organizational factors may operate through indirect mechanisms or require support from individual-level factors such as trust and information literacy. These results are consistent with previous studies [22], [25], while also highlighting the conditional role of organizational readiness in AI-supported learning.

Importantly, several non-significant relationships provide additional insights into the model. The limited influence of user satisfaction on system use and usage behaviour (H23 and H25) suggests that students' interaction with AI systems is not primarily driven by satisfaction. Similarly, the non-significant effect of perceived validity on usage behaviour (H18) indicates that students may not rely heavily on formal evaluations of information accuracy when deciding to use AI tools. Instead, behavioral engagement appears to be more strongly influenced by trust and perceived benefits. These findings highlight that AI adoption in secondary education is shaped more by cognitive and perceptual factors than by system or structural factors alone.

Overall, this study expands the application of the HOT-Fit model within the context of AI adoption in secondary education by integrating information literacy, perceived trust, and perceived validity into the framework. The findings offer a deeper understanding of the interaction among cognitive readiness, technological factors, and institutional support in influencing students' adoption and use of AI technologies. From a practical perspective, educational institutions should focus on strengthening students' information literacy, improving system service quality, and fostering supportive learning environments. At the same time, these efforts need to consider that improvements in system or organizational factors alone may not directly translate into behavioral change, emphasizing the importance of addressing students' perceptions and trust in AI systems.

CONCLUSION

This study advances the understanding of AI adoption in secondary education by demonstrating that information literacy is not merely a supporting skill but a key cognitive driver that shapes trust formation, perceived validity, and meaningful system use. By extending the HOT-Fit model with perceived trust and perceived validity, this research contributes theoretically by repositioning information literacy as a mechanism linking human readiness to organizational and technological outcomes. This extension addresses a limitation in prior HOT-Fit applications, which have predominantly emphasized technical performance while underrepresenting cognitive and affective user factors in educational AI adoption. From a practical standpoint, the findings suggest that successful AI integration in high schools cannot rely solely on system quality or technological availability. Instead, schools and policymakers should prioritize structured information literacy programs, strengthen trust in AI-generated content, and ensure responsive service support to maximize perceived net benefits. These insights provide guidance for designing AI adoption strategies that are technically feasible and pedagogically grounded.

Despite these contributions, several limitations should be recognized. First, the dependence on self-reported questionnaire data may introduce perceptual bias, although statistical procedures were implemented to minimize the risk of common method bias. Second, the cross-sectional design prevents the study from capturing potential changes in AI adoption behaviour over time. Third, the respondents were limited to senior high school students in Kuningan Regency, Indonesia, which may reduce the generalizability of the findings to other contexts with different technological infrastructures, institutional conditions, and cultural backgrounds. In addition, the proposed

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model may not fully capture all relevant factors influencing AI adoption, such as prior experience with AI or varying levels of digital competency. Future research is therefore encouraged to employ longitudinal and mixed-method approaches, involve more diverse samples across regions, and further refine the extended HOT-Fit framework by incorporating additional contextual, pedagogical, and ethical dimensions of AI use. Overall, this study offers both theoretical and practical contributions to understanding AI adoption in secondary education by emphasizing the role of cognitive readiness and trust in fostering meaningful and sustainable AI use within learning environments.

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