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Achieving High Performance through Artificial Intelligence-Enabled Effective and Efficient Work Habits: A Decision-Making Perspective in Higher Education in Malaysia

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Abstract

Artificial Intelligence (AI) within higher education has significantly transformed how decisions are made, work is performed, and performance is achieved, encompassing both academic faculties and administrative divisions. These indicate that the value of AI is not solely derived from technological advancement, but from how it enhances decision-making through effective and efficient work habits within organizational contexts. This study aims to examine how AI capabilities influence decision-making quality through effective and efficient work habits, and how these processes contribute to achieving high performance in higher institutions. It further investigates the role of organisational factors, namely teamwork, leadership, and culture, in shaping AI-enabled decision-making outcomes. A quantitative research approach was employed, with data collected from 312 respondents comprising academics, students, administrators, and other faculty members engaged in AI-supported work environments. The data were analysed using SPSS, including descriptive statistics, reliability analysis, correlation, and multiple regression analysis to examine the relationships among variables. The findings reveal that AI capabilities significantly enhance work efficiency and effectiveness, which in turn

improve decision-making quality and contribute to high performance. However, the results also indicate that ineffective teamwork and weak leadership practices limit the benefits of AI adoption, while culture negatively affects decision-making quality by reducing reliance on data-driven insights. This study contributes to theory and practice by demonstrating that achieving high performance in higher education institutions is not purely technology-driven but is fundamentally shaped by behavioural work habits and organizational dynamics that influence decision-making processes.

Keywords:
Artificial Intelligence; Machine Learning; Decision-Making; Work Habits; High Performance; Higher Education

Introduction:

Digital transformation (Vial & Verhoef et al., 2021) in the workforce precisely Artificial Intelligence (AI), is increasingly embedded within higher education institutions, transforming decision-making (Jarrahi et al., 2021) processes across to ensure a comprehensive institutional assessment, which in this study is operationalized to include both academic departments within faculties that focused on teaching and research and central administrative departments handling operations, student affairs, and registry functions.

AI technologies such as machine learning and predictive analytics enable institutions to improve data-driven decision-making (Makarius et al., 2020) and operational efficiency (Dwivedi et al., 2021). However, despite widespread adoption, many institutions struggle to achieve measurable improvements in management decision performance (Yamani & Mohammed et al., 2025). In the context of Malaysian higher education, institutions face intense pressure under the Malaysia Higher Education Blueprint to digitalize operations. However, a prominent gap exists: administrative departments are frequently bogged down by legacy bureaucratic workflows, while academic departments face extreme time constraints as they balance teaching, research, and compliance audits. This creates a critical bottleneck: AI tools are introduced, but the lack of accompanying 'efficient and effective work habits' prevents these tools from improving the quality of actual decision-making. Furthermore, empirical research in Malaysia has overlooked how micro-level organizational dynamics such as team silos, rigid hierarchical leadership, and a traditional risk-averse institutional culture actively counteract the data-driven insights provided by modern AI capabilities. Recent studies (Davenport et al., 2021)

highlight that AI implementation alone does not guarantee success; rather, its effectiveness depends on human (Jawad et al., 2025) and organizational factors (Davenport et al., 2023). High-performance work habits, specifically efficiency and effectiveness, serve as critical mechanisms through which AI influences decision-making (Okafor et al., 2025). AI enables faster processing and improved accuracy, but its value depends on how individuals integrate these tools into their daily practices (Jarrahi et al., 2023).

Organizational factors (Raisch et al., 2021) such as teamwork, leadership, and culture also play a significant role. A supportive organizational culture (Ranshotham et al., 2022) promotes innovation and data-driven (Provost et al., 2021) decision-making, whereas resistance to change can hinder AI adoption (Raisch & Krakowski, 2021). This study addresses these gaps by examining how AI capabilities influence decision-making (Shrestha et al., 2021) through work habits and how these processes contribute to achieving high performance within higher education.

Literature Review

AI Capabilities and Decision-Making

AI enhances decision-making (Binss, 2021) by enabling faster data processing, predictive (Shmueli et al., 2021) insights, and reduced uncertainty. Studies show that AI improves decision accuracy and efficiency (Zhu.C, 2025). in knowledge-based environments (Brynjolfsson & McAfee, 2017). However, its effectiveness depends on how individuals interpret (Bharadwaj et al., 2021) and apply AI-generated insights (Jobin et al., 2021).

Work Habits (Efficiency and Effectiveness)

Work efficiency refers to optimal use of time and resources (Kellogg et al., 2020), while effectiveness relates to achieving desired outcomes (Floridi et al., 2021). According to Drucker (2007), effectiveness is more critical than efficiency in knowledge work. AI enhances both by automating routine tasks and supporting complex decision processes.

Decision-Making and High Performance

High-quality decision-making (Jarrahi et al., 2023) is a key driver (Fosso et al., 2021) of organizational performance (Alrehili et, al.2025). Rational and data-driven decisions improve outcomes (Brynjolfsson et.al, 2021) and reduce risks (Simon, 1997). AI supports (Jussupow et al., 2021) this by providing evidence-based insights, but human judgment remains essential.

Teamwork and Leadership

Teamwork facilitates knowledge sharing and collaboration, enhancing the use of AI tools (Agarwal, 2025). Leadership plays a crucial role in promoting AI adoption and guiding organizational change (Yukl, 2013). Poor leadership can hinder implementation and reduce effectiveness.

Organizational Culture

Organizational culture shapes how individuals (Bag.S, 2021) perceive and adopt new technologies. A culture that supports innovation, learning, and data-driven decision-making enhances AI (Glikson et al., 2020) effectiveness, while resistant cultures limit its impact (Schein, 2010).

Underpinning Theories

The present study is underpinned by four complementary theories, namely the Resource-Based View (RBV), Sociotechnical Systems (STS) theory, the DeLone and McLean Information Systems Success model, and the Organizational Contingency Perspective. According to Barney (1991), the Resource-Based View explains that organizations achieve superior performance through valuable and strategic resources. In this study, AI capabilities are viewed as strategic resources that improve work efficiency and work effectiveness, which ultimately contribute to better organizational performance.

Sociotechnical Systems (STS) theory emphasizes the interaction between technology and human systems (Trist & Bamforth, 1951; Bostrom & Heinen, 1977). The theory suggests that organizational performance can be enhanced when technological tools and human work processes are properly aligned. Accordingly, AI capabilities are expected to improve work efficiency and work effectiveness, leading to better decision-making quality.

The DeLone and McLean Information Systems Success model (DeLone & McLean, 2003) explains that high-quality information and effective system use contribute to successful organizational outcomes. In the context of this study, AI-generated information is expected to enhance decision-making quality, which subsequently leads to institutional high performance. Furthermore, the Organizational Contingency Perspective argues that organizational effectiveness depends on contextual factors rather than a single best approach (Lawrence & Lorsch, 1967; Donaldson, 2001). Therefore, organizational factors such as teamwork, leadership, and organizational culture are proposed to moderate the relationships between AI capabilities, work habits, and decision-making quality. Overall, these theories provide a comprehensive foundation for explaining how AI capabilities improve work efficiency and effectiveness, enhance decision-making quality, and ultimately contribute to institutional high performance.

Theoretical Framework

This study utilizes the Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990) integrated with DeLone and McLean's Information Systems (IS) Success Model (DeLone & McLean, 2003) as its theoretical foundation. The technological dimension is represented by AI Capabilities, which directly shapes individual performance behaviors, namely Work Efficiency and Effectiveness (DeLone & McLean, 2003). The organizational dimension is captured through Teamwork, Leadership, and Organizational Culture, which act as environmental and institutional boundary conditions within the broader adoption context (Tornatzky & Fleischer, 1990). Together, these combined elements determine the quality of institutional Decision-Making and overall High Performance.

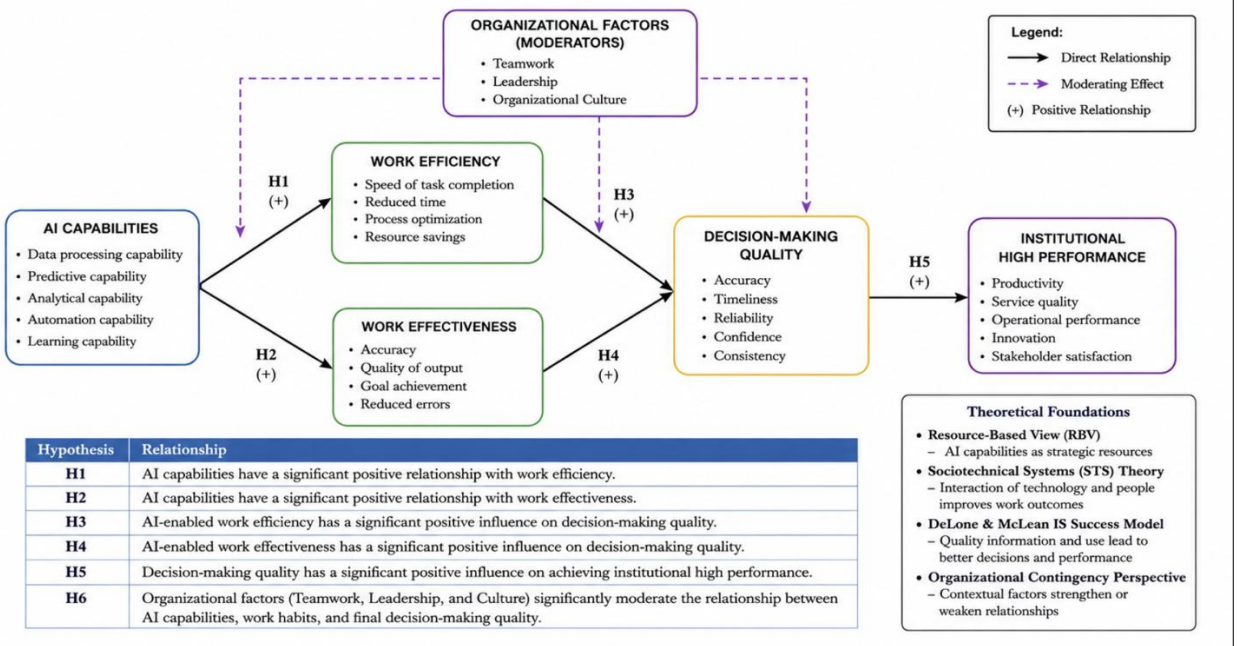
Hypotheses Development

Based on the figure 1 on proposed theoretical framework and reviewed literature, the following hypotheses are proposed for empirical testing:

- H1: AI capabilities have a significant positive relationship with work efficiency.
- H2: AI capabilities have a significant positive relationship with work effectiveness.
- H3: AI-enabled work efficiency has a significant positive influence on decision-making quality.
- H4: AI-enabled work effectiveness has a significant positive influence on decision-making quality.
- H5: Decision-making quality has a significant positive influence on achieving institutional high performance.
- H6: Organizational factors (Teamwork, Leadership, and Culture) significantly moderate the relationship between AI capabilities, work habits, and final decision-making quality.

Figure 1: Proposed Theoretical Framework

Impact of AI Capabilities on Decision-Making Quality and Institutional High Performance



Hypothesis	Relationship
H1	AI capabilities have a significant positive relationship with work efficiency.
H2	AI capabilities have a significant positive relationship with work effectiveness.
H3	AI-enabled work efficiency has a significant positive influence on decision-making quality.
H4	AI-enabled work effectiveness has a significant positive influence on decision-making quality.
H5	Decision-making quality has a significant positive influence on achieving institutional high performance.
H6	Organizational factors (Teamwork, Leadership, and Culture) significantly moderate the relationship between AI capabilities, work habits, and final decision-making quality.

Note: H6 represents moderation effects on the relationships in the model.

Source: Author, 2026

Methodology

Research Design

This study adopts a quantitative research design to empirically examine the relationships between Artificial Intelligence (AI) capabilities, work habits (efficiency and effectiveness), decision-making quality, and high performance within higher education institutional departments. A quantitative approach is considered appropriate as the

study aims to test theoretically grounded relationships and assess the strength and direction of associations among clearly defined constructs. This aligns with prior research emphasizing the suitability of quantitative methods for validating conceptual frameworks and establishing generalizable findings in organizational and technology adoption studies.

The research is grounded in a positivist paradigm, which assumes that relationships between variables can be objectively measured and statistically tested. This approach enables the study to move beyond exploratory insights and provide empirical evidence on the mechanisms through which AI capabilities influence performance outcomes (Keding. C, 2021). A cross-sectional survey design was employed, allowing data to be collected at a single point in time to capture respondents' perceptions of AI usage, work practices, and decision-making behaviours within their respective departments.

Data Collection

Data were collected using a structured questionnaire, designed based on established constructs from recent literature on AI adoption, work habits, and organizational performance. The questionnaire consisted of multiple sections measuring AI capabilities, work efficiency, work effectiveness, decision-making quality, teamwork, leadership, organizational culture, and high performance. All items were measured using a five-point Likert scale ranging from "strongly disagree" to "strongly agree" to ensure consistency and ease of response.

The survey was distributed to a target sample of 1,000 respondents across higher education institutions, focusing on individuals operating within AI-enabled or digitally supported environments. A total of 312 valid responses were obtained, representing a response rate sufficient for statistical analysis and consistent with recommended sample sizes for regression-based studies. The respondents comprised a diverse group of stakeholders, including academics, students, administrative staff, and other Faculty members.

Data Analysis

The analysis followed a structured, multi-stage procedure to ensure rigor and reliability using SPSS. First, descriptive statistics were employed to summarize the demographic profile of respondents and to provide an overview of the data distribution. This step helped in identifying any anomalies, missing values, or outliers.

Second, reliability analysis was conducted using Cronbach's Alpha to assess the internal consistency of the measurement scales. All constructs achieved values exceeding the recommended threshold of 0.70, indicating satisfactory reliability. Third, Pearson correlation analysis was performed to examine the strength and direction of relationships between variables. This provided preliminary insights into the associations among AI capabilities, work habits, decision-making, and performance.

Finally, multiple regression analysis was employed to test the hypothesized relationships and assess the predictive power of independent variables on dependent

outcomes. This technique enabled the identification of significant predictors of decision-making quality and high performance, as well as the evaluation of mediating relationships within the proposed framework. Overall, the analytical approach ensures methodological rigor and provides robust empirical evidence to support the study's objectives.

Results

Reliability Analysis

Descriptive analysis indicated that respondents generally reported moderate to high levels of AI usage within their respective departments. Reliability testing confirmed strong internal consistency across all constructs, with Cronbach's alpha values ranging from 0.85 to 0.91, well above the 0.70 threshold. Results are presented in Table 1.

Table 1: Reliability Test and Cronbach's Alpha Results

Variable	No. of Items	Cronbach's Alpha (α)	Interpretation
Ai Capabilities	5	0.87	Good Reliability
Work Efficiency	4	0.75	Acceptable
Work Effectiveness	6	0.94	Strong Reliability
Decision Making Quality	6	0.91	Strong Reliability
performance	5	0.83	Good Reliability
Teamwork	4	0.76	Acceptable
Leadership	4	0.75	Acceptable
Organisational Culture	5	0.81	Strong Reliability

Source: Author, 2026

Correlation Analysis

Pearson correlation analysis (one-tailed, N=312) revealed statistically significant, positive relationships among key variables. AI capabilities were strongly correlated with work efficiency ($r=0.612, p<0.01$) and work effectiveness ($r=0.589, p<0.01$). In turn, work efficiency ($r=0.664, p<0.01$) and work effectiveness ($r=0.651, p<0.01$) correlated strongly with decision-making quality. Decision-making quality displayed the highest correlation with institutional high performance ($r=0.721, p<0.01$).The detailed 1-tailed correlation coefficients are presented in Table 2.

Table 2 : Correlation Analysis Result

Variables	AI	Efficiency	Effectiveness	Decision Making	Performance
AI	1.000	0.721**	0.684**	0.632**	0.591**
Efficiency	0.721**	1.000	0.745**	0.701**	0.668**
Effectiveness	0.684**	0.745**	1.000	0.782**	0.851**
Decision Making	0.632**	0.701**	0.782**	1.000	0.729**
Performance	0.591**	0.668**	0.851**	0.729**	1.000

Source: Author, 2026

Regression Analysis

Multiple regression analysis was conducted and confirmed that AI capabilities significantly predict work efficiency (β=0.61, p<0.001) and work effectiveness (β=0.57, p<0.001), supporting H1 and H2. Combined work habits significantly predict decision-making quality (β=0.66,p<0.001), supporting H3 and H4. Decision-making quality emerged as the single strongest predictor of institutional high performance (β=0.72,p<0.001), supporting H5. Moderation testing supported H6, confirming that organizational factors (teamwork, leadership, culture) significantly condition these path relationships. Results are presented in Table 3.

Table 3: Regression Analysis Results

Predictive Effects	Beta (ß)	Significance	Interpretation
AI- Work Efficiency	0.61	P>0.001	Supported
AI-Work Effectiveness	0.57	P>0.001	Supported
Work habits -Decision Making	0.66	P>0.001	Supported
Effectiveness -performance	0.72	P>0.001	Supported

Source: Author, 2026

Discussion

The empirical findings provide strong support for explaining how AI capabilities translate into high performance within higher education institutional departments. Crucially, the results move beyond simplistic assumptions of direct technological impact, demonstrating that software adoption alone does not guarantee high performance. Instead, individual work habits (efficiency and effectiveness) serve as critical transformation mechanisms.

Efficient work habits reduce time waste and accelerate data processing, while effective work habits ensure that AI insights align with strategic organizational outcomes. Together, these work habits enhance decision-making quality, which proved

to be the single most influential determinant of high performance. Furthermore, the results highlight that organizational factors like teamwork, leadership, and culture are vital boundary conditions. Departments with strong collaborative practices and supportive leadership leverage AI capabilities effectively, whereas rigid hierarchies and risk-averse cultures experience restricted technological value realization.

Conclusion

Achieving high performance in higher education requires strategic alignment between AI capabilities, individual work habits, and organizational dynamics. AI enhances decision-making quality through work efficiency and effectiveness, but its ultimate success depends on supportive teamwork, transformative leadership, and an adaptive culture.

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