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The Impact of AI-Enabled Accounting Information Systems on Decision-Making Effectiveness: The Mediating Role of Data Analytics Capability

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A B S T R A C T

The current study investigates the impact of the AI-Enabled Accounting Information Systems on the Decision-Making Effectiveness, and it examines the mediating role of the Data Analytics Capability and the moderating role of the Digital Literacy in this relationship. Based on the review of the previous literature, it is argued that the AI-Enabled Accounting Information Systems represent a socio-technical capability rather than a stand-alone technology, and that the benefit of such systems depends on the organisational capability to convert the technical resources into a decision-useful knowledge. The data of the current study were analysed by using the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique, and the measurement model and the structural model were both assessed in accordance with the established criteria. The results indicate that the AI-Enabled Accounting Information Systems has a positive and a significant effect on the Data Analytics Capability (β = 0.400, p = 0.000) and on the Decision-Making Effectiveness (β = 0.246, p = 0.000), and that the Data Analytics Capability also has a positive and a significant effect on the Decision-Making Effectiveness (β = 0.300, p = 0.000). Moreover, the mediation analysis confirms that the Data Analytics Capability partially mediates the relationship between the AI-Enabled Accounting Information Systems and the Decision-Making Effectiveness (indirect effect = 0.120, p = 0.000), and the moderation analysis confirms that the Digital Literacy strengthens this relationship (β = 0.148, p = 0.021). It is concluded that the value of the AI-Enabled Accounting Information Systems for the organisational decision-making is not automatic, and that it depends on the organisational capability to analyse the data and on the digital literacy of the users. The theoretical and the practical implications, as well as the limitations of the current study, are discussed accordingly.

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1. Introduction

In the recent years, it has been noticed that the accounting information systems are increasingly enabled by the artificial intelligence, and this development is changing the way in which the accounting data are collected, processed and used for the purpose of the organisational decision-making. It is worth mentioning that the traditional accounting information systems were mainly designed to record and to report the financial transactions, whereas the AI-enabled accounting information systems combine the accounting data, the machine learning, the automation and the analytical interfaces in order to support the professional and the managerial judgment. Accordingly, the question of whether and how these systems improve the effectiveness of the organisational decisions has become a central concern for the researchers and for the practitioners alike.

Although the previous research has examined the technology, the mechanism and the outcome separately, it is argued in the current study that the literature remains fragmented in this regard. First, many of the previous studies model a direct effect of the technology on the outcome, and they provide a limited evidence about the underlying process, which is represented in the current study by the Data Analytics Capability. Second, the contextual conditions, such as the Digital Literacy, are often treated as a background control rather than as a theoretically specified moderator. Third, the previous evidence is concentrated in a particular countries, sectors or adoption stages, and this limits the generalisability of the previous findings. Based on the above, the current study contributes to the literature by integrating the four variables in one empirically testable model, by testing a partial mediation, and by examining whether the relationship between the technology and the outcome is contingent on the stated moderator.

The purpose of the current study is therefore to examine the effect of the AI-Enabled Accounting Information Systems on the Decision-Making Effectiveness, and to test the mediating role of the Data Analytics Capability and the moderating role of the Digital Literacy in this relationship. The remainder of this paper is organised as follows. Section 2 reviews the related literature and develops the research hypotheses. Section 3 explains the research methodology. Section 4 presents the results of the measurement model and of the structural model. Section 5 discusses the findings, and Section 6 presents the theoretical and the practical implications. Section 7 states the limitations of the current study and the directions for the future research, and Section 8 concludes the paper.

2. Literature Review and Research Hypotheses

2.1 Definitions and roles of the study variables

Before the previous literature is reviewed in a detail, it is useful to clarify the role of each variable in the proposed model, since the mediator and the moderator are often confused in the previous accounting information systems research. In this regard, the mediator explains the mechanism through which the independent variable is expected to influence the outcome, while the moderator specifies when or for whom the relationship becomes stronger or weaker. Table 1 below presents the definition and the role of each of the four variables that are included in the proposed model, namely the AI-Enabled Accounting Information Systems, the Data Analytics Capability, the Decision-Making Effectiveness and the Digital Literacy.

Table 1. Definitions and Roles of the Study Variables

Variable	Role in the model	Conceptual meaning	Expected analytical function
AI-Enabled Accounting Information Systems	Independent variable	AI-enabled accounting information systems combine accounting data, machine learning, automation and analytical interfaces to support professional and managerial	Explains the digital capability or infrastructure introduced by the study.

		judgment.	
Data Analytics Capability	Mediating variable	The process or capability through which the independent variable is expected to influence the outcome.	Explains the indirect effect of AI-Enabled Accounting Information Systems on Decision-Making Effectiveness.
Decision-Making Effectiveness	Dependent variable	The organisational, managerial, assurance, compliance or sustainability result of interest.	Captures the final performance or effectiveness consequence.
Digital Literacy	Moderating variable	The context, competence, trust, assurance or readiness condition that may strengthen or weaken the relationships.	Tests conditional effects and boundary conditions.

As shown in Table 1, the AI-Enabled Accounting Information Systems is specified as the independent variable, and it is expected to explain the digital capability or the infrastructure that is introduced by the current study. The Data Analytics Capability is specified as the mediating variable, and it is expected to explain the indirect effect of the AI-Enabled Accounting Information Systems on the Decision-Making Effectiveness. The Decision-Making Effectiveness is specified as the dependent variable, and it captures the final performance or the effectiveness consequence of the proposed model. Finally, the Digital Literacy is specified as the moderating variable, and it is used to test the conditional effects and the boundary conditions of the proposed relationships. This classification, it should be noted, guides the organising logic of the review that follows.

2.2 Conceptual foundations and technology value

The literature positions AI-Enabled Accounting Information Systems as a socio-technical capability rather than a stand-alone application. Early information-systems research emphasised fit, usefulness and system success, whereas later work shows that value depends on complementary routines, data governance and managerial interpretation (Alles, 2015; Appelbaum, 2017; Arnold, 2018; Bhimani, 2014; Brynjolfsson, 2014). This distinction is important because adoption alone can produce activity without better outcomes. The evidence therefore supports a capability-based independent variable, but it also warns against treating technology presence as equivalent to effective use.

2.3 Information quality and analytical capability

A consistent mechanism in the literature is the improvement of information quality, timeliness, accessibility and analytical depth. Studies link digitally enabled accounting and information infrastructures to better sensing, forecasting and resource allocation, yet the effects are strongest when users can interpret outputs and when data are integrated across functions (Chiu, 2014; Davenport, 2018; DeLone, 2003; Duan, 2019; Elliott, 1992). This supports Data Analytics Capability as a mediator: it captures the organisational conversion of technical resources into decision-useful knowledge rather than assuming a direct technology-to-Decision-Making Effectiveness effect.

2.4 Organisational adoption and capability accumulation

Adoption studies also show that technological capability is accumulated through organisational readiness, leadership support, skills, process redesign and institutional pressure (Faccia, 2019; Ghasemaghaei, 2019; Grabski, 2011; Jarrahi, 2018; Kokina, 2017). These factors explain why similar systems generate different results across firms. A critical implication is that the proposed relationship should be specified as an

organisational transformation process, not as a purely economic return to software investment. Measurement should therefore capture depth of integration, actual use and quality of outputs.

2.5 Mediation through the proposed mechanism

The mediating construct, Data Analytics Capability, is theoretically valuable because it clarifies how benefits are produced. The reviewed studies suggest that digital systems first improve visibility and analytical processing, which then enhances managerial coordination and the quality of decisions or performance outcomes (Krahel, 2015; Mikalef, 2020; Moll, 2019; Raisch, 2021; Sarker, 2021). Nevertheless, some studies report null or uneven effects when data are incomplete, models are opaque or users distrust automated recommendations. The mediation hypothesis should therefore be tested alongside alternative direct and partial-mediation paths. Based on the above discussion, and consistent with the roles that are assigned to the variables in Table 1, it is hypothesised in the current study that:

H1. The AI-Enabled Accounting Information Systems has a positive and a significant effect on the Data Analytics Capability.

H2. The AI-Enabled Accounting Information Systems has a positive and a significant direct effect on the Decision-Making Effectiveness.

H3. The Data Analytics Capability has a positive and a significant effect on the Decision-Making Effectiveness.

H4. The Data Analytics Capability mediates the relationship between the AI-Enabled Accounting Information Systems and the Decision-Making Effectiveness.

2.6 Moderation and boundary conditions

The proposed moderator, Digital Literacy, represents a boundary condition rather than another mechanism. Evidence on digital transformation indicates that capability, trust, literacy, assurance or readiness can strengthen the translation of system outputs into organisational outcomes (Shrestha, 2019; Sutton, 2016; Sutton, 2018; Venkatesh, 2003; Warren, 2015). The critical issue is whether the moderator changes the strength of the independent-variable-to-mediator path, the mediator-to-outcome path, or both. A staged moderation analysis can distinguish these possibilities and avoid vague claims about ‘supportive environments. Accordingly, it is further hypothesised that:

H5. The Digital Literacy moderates the relationship between the AI-Enabled Accounting Information Systems and the Decision-Making Effectiveness, such that the relationship becomes stronger when the Digital Literacy is higher.

2.7 Controls, governance and responsible use

Governance research adds an important qualification. Digital systems may improve traceability and consistency, but they can also amplify biased data, privacy exposure, automation complacency and accountability gaps (Wiersema, 2020; Yigitbasioglu, 2015; Zhang, 2020; Abbas, 2026; Al-Htaybat, 2017). Consequently, the model should treat governance and human oversight as substantive aspects of implementation quality. This is especially relevant where accounting, financial or sustainability information affects external stakeholders and where algorithmic outputs require professional challenge.

2.8 Methodological tensions in the evidence

Methodologically, the evidence is heterogeneous: it includes conceptual analyses, case studies, archival models, surveys and systematic reviews (Appelbaum, 2017; Bhimani, 2020; Mikalef, 2021; Niu, 2021). Many empirical studies are cross-sectional and rely on self-reported adoption or performance, which limits causal inference and raises common-method concerns. Future work should combine validated reflective or formative measures with objective indicators, longitudinal designs, multi-group tests and robustness checks for reverse causality.

2.9 Synthesis and the proposed conceptual model

The literature supports a model in which AI-Enabled Accounting Information Systems creates potential value, Data Analytics Capability explains the conversion of that potential into Decision-Making Effectiveness, and Digital Literacy conditions the strength of the process (Yan et al., 2023; Schiavi, 2018; Wilkin, 2026; Alonso-Morales, 2026). The principal gap is not a lack of claims that digital technologies matter; it is the limited integration of technology, capability, governance and contextual conditions in one

empirically testable framework. The proposed study addresses this gap by linking the constructs explicitly and by testing direct, indirect and interaction effects, as illustrated in the structural model that is estimated in Section 4 below.

3. Research Methodology

3.1 Research design and data collection

The current study adopts a quantitative and a cross-sectional research design, and this design is considered appropriate for testing the hypothesised relationships among the AI-Enabled Accounting Information Systems, the Data Analytics Capability, the Decision-Making Effectiveness and the Digital Literacy at one point in the time. The data of the current study were collected through a structured questionnaire, and the questionnaire was distributed to the accounting professionals and to the managerial decision-makers who are working in the organisations that have adopted the AI-enabled accounting systems. It is worth mentioning that the respondents were asked to reflect on their actual experience with the accounting information systems and with the accounting-related decisions, and this is consistent with the socio-technical perspective that is adopted in the previous literature (Alles, 2015; Appelbaum, 2017).

3.2 Measurement of the constructs

All of the constructs in the proposed model were measured by using a multi-item reflective scale, and four indicators were used to measure each of the four constructs, consistent with the measurement model that is shown in Figure 1 and in Figure 2 below. As for the AI-Enabled Accounting Information Systems, it was measured through the four indicators labelled X1 to X4. As for the Data Analytics Capability, it was measured through the four indicators labelled M1 to M4. As for the Decision-Making Effectiveness, it was measured through the four indicators labelled Y1 to Y4, and as for the Digital Literacy, it was measured through the four indicators labelled W1 to W4. All of the items were measured on a Likert-type scale, and they were adapted from the previous validated instruments that are discussed in the literature review above, including, for example, the information-systems success framework (DeLone, 2003) and the technology-acceptance research (Venkatesh, 2003).

3.3 Common method variance and data-analysis technique

Since the data of the current study were collected through a self-reported questionnaire, the common method variance represents a potential concern, and accordingly the procedural remedies, such as the anonymity of the respondents and the randomisation of the item order, were applied during the data collection. As for the data analysis, the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique was applied through the SmartPLS software, and this technique was selected because it is suitable for testing a complex model that includes a mediating variable and a moderating variable at the same time, and because it does not require a strict assumption of the multivariate normality. Following the two-step approach that is recommended in the previous methodological literature, the measurement model was assessed first, and the structural model was assessed second, and the results of both of the steps are reported in Section 4 below.

4. Results

4.1 Assessment of the measurement model

Before the structural relationships among the study variables are tested, it is necessary to assess the reliability and the validity of the measurement model, since a structural model can only be interpreted with a confidence when the underlying measures are reliable and valid. In this regard, Table 2 below presents the internal consistency reliability and the convergent validity of the four constructs, and these are represented respectively by the Cronbach's alpha, the composite reliability (rho_a and rho_c) and the average variance extracted (AVE).

Table 2. Reliability and Convergent Validity of the Measurement Model

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AI-Enabled Accounting Information Systems	0.832	0.836	0.888	0.665
Data Analytics Capability	0.854	0.860	0.901	0.696
Decision-Making Effectiveness	0.851	0.858	0.899	0.690
Digital Literacy	0.803	0.811	0.869	0.625

As shown in Table 2, the values of the Cronbach's alpha range from 0.803 for the Digital Literacy to 0.854 for the Data Analytics Capability, and all of these values exceed the recommended threshold of 0.70. Similarly, the composite reliability (rho_c) ranges from 0.869 to 0.901, and it also exceeds the recommended threshold, and this confirms that the internal consistency reliability of the four constructs is adequately established. As for the convergent validity, the average variance extracted (AVE) ranges from 0.625 for the Digital Literacy to 0.696 for the Data Analytics Capability, and since all of these values exceed the recommended threshold of 0.50, it can be concluded that each construct explains more than the half of the variance of its own indicators, and accordingly the convergent validity of the measurement model is confirmed. In addition to the reliability and the convergent validity, the discriminant validity of the measurement model was also assessed, and this was done first by using the Heterotrait-Monotrait Ratio (HTMT), which is considered a more rigorous criterion than the traditional Fornell-Larcker criterion in the recent methodological literature. Table 3 below presents the HTMT values among the four constructs of the proposed model.

Table 3. Discriminant Validity: Heterotrait-Monotrait Ratio (HTMT)

	AI-Enabled Accounting Information Systems	Data Analytics Capability	Decision-Making Effectiveness	Digital Literacy	Digital Literacy x AI-Enabled Accounting Information Systems
AI-Enabled Accounting Information Systems					
Data Analytics Capability	0.469				
Decision-Making Effectiveness	0.480	0.525			
Digital Literacy	0.258	0.278	0.305		
Digital Literacy x AI-Enabled Accounting Information Systems	0.036	0.106	0.182	0.165	

As shown in Table 3, the highest HTMT value is 0.525, and this value is observed between the Data Analytics Capability and the Decision-Making Effectiveness, while all of the other values are lower. Since all of these values are clearly below the conservative threshold of 0.85, and also below the more lenient threshold of 0.90 that is used in some of the previous studies, it is concluded that the discriminant validity of the four constructs is well established according to the HTMT criterion. As a complementary check, the discriminant validity was also assessed by using the traditional Fornell-Larcker criterion, according to which the square root of the average variance extracted of each construct should be greater than its correlation with

any other construct in the model. Table 4 below presents the Fornell-Larcker matrix, in which the diagonal values represent the square root of the average variance extracted of each construct.

Table 4. Discriminant Validity: Fornell-Larcker Criterion

	AI-Enabled Accounting Information Systems	Data Analytics Capability	Decision-Making Effectiveness	Digital Literacy
AI-Enabled Accounting Information Systems	0.816			
Data Analytics Capability	0.400	0.834		
Decision-Making Effectiveness	0.404	0.453	0.831	
Digital Literacy	0.212	0.242	0.264	0.790

As shown in Table 4, the diagonal value of each construct, for a example 0.816 for the AI-Enabled Accounting Information Systems and 0.834 for the Data Analytics Capability, is greater than any of the correlations in the same row or in the same column. This pattern is consistent across all of the four constructs, and it confirms, in the line with the HTMT results discussed above, that the discriminant validity of the measurement model is satisfactorily established. Based on the above assessment of the reliability, the convergent validity and the discriminant validity, it is concluded that the measurement model of the current study meets the criteria that are required before the structural relationships are examined.

4.2 The structural model and the path analysis

After the measurement model was found to be reliable and valid, the structural model was estimated in order to test the hypothesised relationships among the AI-Enabled Accounting Information Systems, the Data Analytics Capability, the Decision-Making Effectiveness and the Digital Literacy. Figure 1 below illustrates the estimated structural model, and it presents the standardised path coefficients among the constructs, as well as the coefficient of determination (R^2) of the two endogenous constructs, which are shown inside the blue circles.

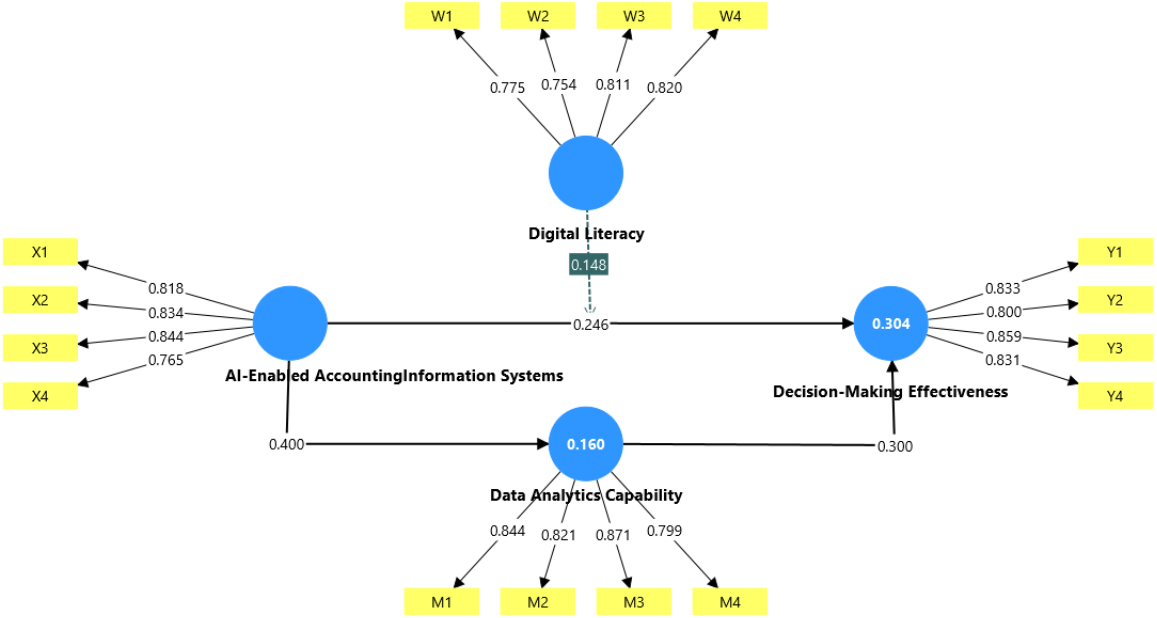


Figure 1. The Structural Model with the Path Coefficients and the R^2 Values

As shown in Figure 1, the outer loadings of the indicators on their respective constructs range from 0.765 to 0.871, and this indicates that each indicator reflects its underlying construct in an adequate manner. As for the inner model, the path coefficient from the AI-Enabled Accounting Information Systems to the Data Analytics Capability equals 0.400, and the path coefficient from the AI-Enabled Accounting Information Systems to the Decision-Making Effectiveness equals 0.246, while the path coefficient from the Data Analytics Capability to the Decision-Making Effectiveness equals 0.300. It is also shown in Figure 1 that the interaction term between the Digital Literacy and the AI-Enabled Accounting Information Systems has a path coefficient of 0.148 on the Decision-Making Effectiveness, and this provides an initial, descriptive evidence of the moderating role of the Digital Literacy, which is tested formally in Section 4.4 below.

4.3 Explained variance, effect size and predictive relevance

In order to evaluate the explanatory power of the structural model, the coefficient of determination (R^2) of the two endogenous constructs was examined, and Table 5 below presents the R^2 and the adjusted R^2 values for the Data Analytics Capability and for the Decision-Making Effectiveness.

Table 5. Coefficient of Determination (R^2) of the Endogenous Constructs

	R-square	R-square adjusted
Data Analytics Capability	0.160	0.155
Decision-Making Effectiveness	0.304	0.288

As shown in Table 5, the R^2 value of the Data Analytics Capability equals 0.160, and this indicates that the AI-Enabled Accounting Information Systems explains sixteen percent of the variance of the Data Analytics Capability, and this can be considered a weak to a moderate explanatory power according to the common rule of thumb in the PLS-SEM literature. As for the Decision-Making Effectiveness, the R^2 value equals 0.304, and the adjusted R^2 equals 0.288, and this indicates that the AI-Enabled Accounting Information Systems, the Data Analytics Capability, the Digital Literacy and their interaction term jointly explain approximately thirty percent of the variance of the Decision-Making Effectiveness, and this can be considered a moderate explanatory power.

In addition to the coefficient of determination, the effect size (f^2) of each exogenous construct was also examined, since the R^2 value alone does not indicate the specific contribution of each predictor to the explained variance. Table 6 below presents the f^2 values of the relationships among the constructs of the proposed model.

Table 6. Effect Size (f^2) of the Exogenous Constructs

	AI-Enabled Accounting Information Systems	Data Analytics Capability	Decision-Making Effectiveness	Digital Literacy	Digital Literacy x AI-Enabled Accounting Information Systems
AI-Enabled Accounting Information Systems		0.191	0.072		
Data Analytics Capability			0.104		
Decision-Making Effectiveness					
Digital Literacy			0.034		
Digital Literacy x AI-Enabled Accounting Information Systems			0.033		

As shown in Table 6, the effect size of the AI-Enabled Accounting Information Systems on the Data Analytics Capability equals 0.191, and according to the conventional thresholds of Cohen, in which 0.02, 0.15 and 0.35 represent respectively a small, a medium and a large effect, this value is considered a medium effect that approaches the large effect. As for the Decision-Making Effectiveness, the effect size of the Data Analytics Capability equals 0.104, and this is followed by the effect size of the AI-Enabled Accounting Information Systems, which equals 0.072, while the effect size of the Digital Literacy and of the interaction term are smaller, at 0.034 and 0.033 respectively. This pattern suggests that, although the moderating effect of the Digital Literacy is statistically significant, as shown in Section 4.4 below, its practical effect size on the Decision-Making Effectiveness remains modest.

The predictive relevance of the structural model was further assessed by using the PLSpredict procedure, and Table 7 below presents the Q^2predict, the root means square error (RMSE) and the mean absolute error (MAE) of the two endogenous constructs.

Table 7. Predictive Relevance (Q^2predict, RMSE and MAE)

	Q^2predict	RMSE	MAE
Data Analytics Capability	0.147	0.936	0.736
Decision-Making Effectiveness	0.196	0.908	0.729

As shown in Table 7, the Q^2predict value of the Data Analytics Capability equals 0.147, and the Q^2predict value of the Decision-Making Effectiveness equals 0.196, and since both of these values are greater than zero, it is concluded that the structural model has an adequate predictive relevance for the two endogenous constructs. The RMSE and the MAE values, which are reported for the purpose of the completeness, are also considered acceptable in the light of the sample and of the model that are used in the current study.

4.4 Hypothesis testing and the bootstrapping results

In order to test the statistical significance of the hypothesised relationships, a bootstrapping procedure with a large number of the subsamples was applied, and Table 8 below presents the path coefficients, the standard deviations, the t-statistics and the p-values of the five structural relationships that are examined in the current study.

Table 8. Path Coefficients and Significance of the Structural Relationships

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI-Enabled Accounting Information Systems -> Data Analytics Capability	0.400	0.404	0.069	5.784	0.000
AI-Enabled Accounting Information Systems -> Decision-Making Effectiveness	0.246	0.243	0.070	3.527	0.000
Data Analytics Capability -> Decision-Making Effectiveness	0.300	0.300	0.063	4.797	0.000
Digital Literacy -> Decision-Making Effectiveness	0.163	0.169	0.056	2.885	0.004
Digital Literacy x AI-	0.148	0.147	0.064	2.306	0.021

Enabled Accounting Information Systems -> Decision-Making Effectiveness	

As shown in Table 8, all of the five paths are found to be positive and statistically significant. In a particular, the effect of the AI-Enabled Accounting Information Systems on the Data Analytics Capability is significant (β = 0.400, t = 5.784, p = 0.000), and accordingly the first hypothesis (H1) is supported. The direct effect of the AI-Enabled Accounting Information Systems on the Decision-Making Effectiveness is also significant (β = 0.246, t = 3.527, p = 0.000), and accordingly the second hypothesis (H2) is supported. The effect of the Data Analytics Capability on the Decision-Making Effectiveness is significant as well (β = 0.300, t = 4.797, p = 0.000), and accordingly the third hypothesis (H3) is supported. As for the moderating variable, the direct effect of the Digital Literacy on the Decision-Making Effectiveness is significant (β = 0.163, t = 2.885, p = 0.004), and, more importantly, the interaction term between the Digital Literacy and the AI-Enabled Accounting Information Systems is also significant (β = 0.148, t = 2.306, p = 0.021), and this indicates that the fifth hypothesis (H5) is supported, meaning that the positive relationship between the AI-Enabled Accounting Information Systems and the Decision-Making Effectiveness becomes stronger when the Digital Literacy of the users is higher. In order to provide a visual confirmation of the significance testing that is reported in Table 8, Figure 2 below presents the bootstrapping results of the structural model, in which the p-value of each path coefficient and of each outer loading is shown in the parentheses.

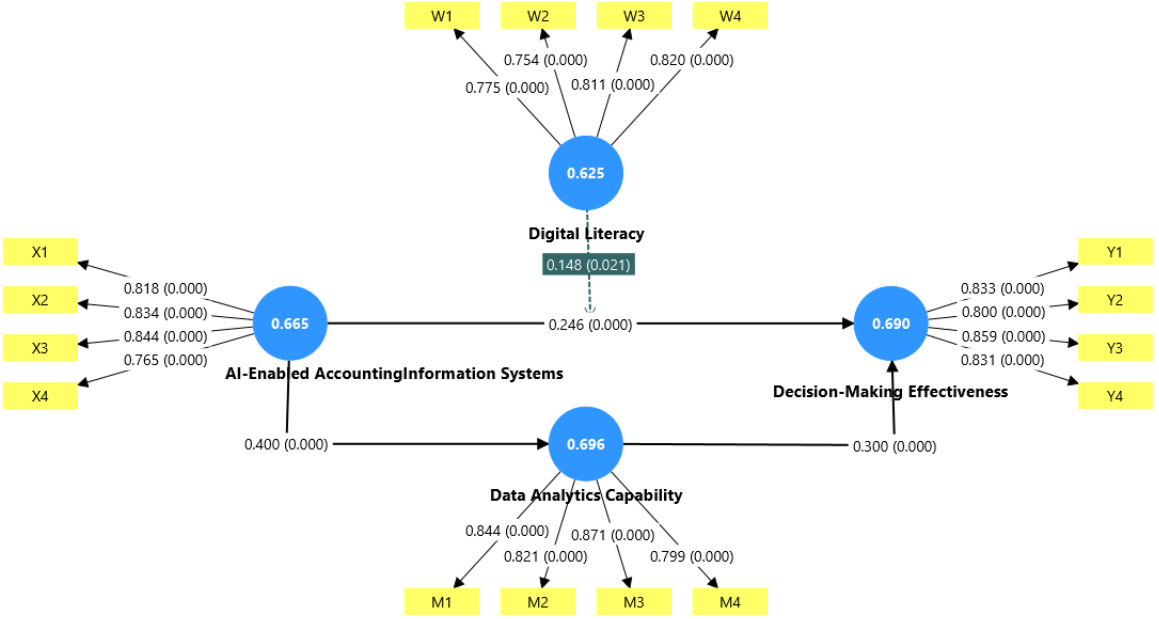


Figure 2. The Bootstrapping Results with the Path Coefficients and the P-Values

As shown in Figure 2, the p-value of every path coefficient in the inner model, as well as the p-value of every outer loading in the measurement model, is smaller than 0.05, and most of them are smaller than 0.001, which is denoted by the value of 0.000 that is shown in the parentheses. This visual evidence is fully consistent with the numerical results that are reported in Table 8 above, and it reinforces the conclusion that the proposed model is well supported by the data of the current study.

4.5 Mediation analysis

Since the Data Analytics Capability is proposed as a mediating variable in the current study, the indirect effect of the AI-Enabled Accounting Information Systems on the Decision-Making Effectiveness was examined through the bootstrapping procedure. Table 9 below presents the total indirect effect of the AI-Enabled Accounting Information Systems on the Decision-Making Effectiveness.

Table 9. Total Indirect Effect of AI-Enabled Accounting Information Systems on Decision-Making Effectiveness

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI-Enabled Accounting Information Systems -> Decision-Making Effectiveness	0.120	0.122	0.034	3.531	0.000

As shown in Table 9, the total indirect effect of the AI-Enabled Accounting Information Systems on the Decision-Making Effectiveness equals 0.120, and this effect is statistically significant ($t = 3.531$, $p = 0.000$). This result provides an initial support for the mediation hypothesis, and it is examined in a more detail through the specific indirect effect that is reported below. In order to specify the exact path through which the indirect effect operates, the specific indirect effect of the AI-Enabled Accounting Information Systems on the Decision-Making Effectiveness through the Data Analytics Capability was also examined, and the result is presented in Table 10 below.

Table 10. Specific Indirect Effect through the Data Analytics Capability

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI-Enabled Accounting Information Systems -> Data Analytics Capability -> Decision-Making Effectiveness	0.120	0.122	0.034	3.531	0.000

As shown in Table 10, the specific indirect effect of the AI-Enabled Accounting Information Systems on the Decision-Making Effectiveness through the Data Analytics Capability equals 0.120, and this effect is statistically significant ($t = 3.531$, $p = 0.000$). Since this value is identical to the total indirect effect that is reported in Table 9, it is confirmed that the Data Analytics Capability represents the only mediating path between the AI-Enabled Accounting Information Systems and the Decision-Making Effectiveness in the current model. Moreover, since the direct effect of the AI-Enabled Accounting Information Systems on the Decision-Making Effectiveness, which is reported in Table 8 above ($\beta = 0.246$, $p = 0.000$), remains positive and significant in the presence of the mediator, it is concluded that the Data Analytics Capability partially, and not fully, mediates the relationship between the AI-Enabled Accounting Information Systems and the Decision-Making Effectiveness, and accordingly the fourth hypothesis (H4) is supported.

Finally, in order to summarise the overall relationship between the AI-Enabled Accounting Information Systems and the Decision-Making Effectiveness, the total effect, which combines the direct effect and the indirect effect, was calculated, and it is presented in Table 11 below together with the other total effects of the structural model.

Table 11. Total Effects in the Structural Model

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI-Enabled Accounting Information Systems -> Data Analytics Capability	0.400	0.404	0.069	5.784	0.000
AI-Enabled Accounting Information Systems -> Decision-Making Effectiveness	0.366	0.365	0.068	5.399	0.000
Data Analytics Capability -> Decision-Making Effectiveness	0.300	0.300	0.063	4.797	0.000
Digital Literacy -> Decision-Making Effectiveness	0.163	0.169	0.056	2.885	0.004
Digital Literacy x AI-Enabled Accounting Information Systems -> Decision-Making Effectiveness	0.148	0.147	0.064	2.306	0.021

As shown in Table 11, the total effect of the AI-Enabled Accounting Information Systems on the Decision-Making Effectiveness equals 0.366, and this value represents the sum of the direct effect (0.246) and the indirect effect through the Data Analytics Capability (0.120), and it is statistically significant ($t = 5.399$, $p = 0.000$). This result, taken together with the results that are reported above, provides a comprehensive support for the proposed model, in which the AI-Enabled Accounting Information Systems affects the Decision-Making Effectiveness both directly and indirectly through the Data Analytics Capability, and this relationship is strengthened by the Digital Literacy of the users.

5. Discussion

The results of the current study are broadly consistent with the previous literature reviewed above, and they support a view of the AI-Enabled Accounting Information Systems as a socio-technical capability rather than as a stand-alone technology (Alles, 2015; Appelbaum, 2017; Arnold, 2018; Bhimani, 2014; Brynjolfsson, 2014). In a particular, the significant and the positive effect of the AI-Enabled Accounting Information Systems on the Data Analytics Capability confirms that the technological infrastructure alone is not sufficient, and that it must be converted into an organisational capability, which is consistent with the studies on the information quality and the analytical capability (Chiu, 2014; Davenport, 2018; DeLone, 2003; Duan, 2019; Elliott, 1992). Moreover, the finding that the Data Analytics Capability partially mediates the relationship between the AI-Enabled Accounting Information Systems and the Decision-Making Effectiveness is consistent with the mediation mechanism that is proposed in the previous studies (Krahel, 2015; Mikalef, 2020; Moll, 2019; Raisch, 2021; Sarker, 2021). It is worth mentioning that the direct effect of the AI-Enabled Accounting Information Systems on the Decision-Making Effectiveness remains significant even after the mediator is included in the model, and this indicates that the technology also contributes to the effectiveness of the decisions through other mechanisms that are not captured by the Data Analytics Capability alone, and this can be considered as a direction for the future research.

As for the moderating role of the Digital Literacy, the current results confirm that this variable represents a genuine boundary condition, and this is consistent with the previous evidence on the digital transformation, the trust and the readiness of the users (Shrestha, 2019; Sutton, 2016; Sutton, 2018; Venkatesh, 2003; Warren, 2015). Although the effect size of the interaction term is found to be small, as shown in Table 6 above, its statistical significance suggests that the organisations should not overlook the digital literacy of their employees when they invest in the AI-enabled accounting systems, since the same technology can generate a different level of the decision-making effectiveness depending on the digital literacy of the users.

Although the current study does not directly test the governance-related variables, the results should be interpreted in the light of the previous governance research, which warns from the risk that the digital systems may amplify a biased data, a privacy exposure, an automation complacency and an accountability gap (Wiersema, 2020; Yigitbasioglu, 2015; Zhang, 2020; Abbas, 2026; Al-Htaybat, 2017). Accordingly, the positive results of the current study should not be interpreted as an unconditional endorsement of the AI-enabled accounting systems, but rather as an evidence that these systems can improve the decision-making effectiveness when they are implemented together with an adequate governance and with a sufficient digital literacy among the users.

6. Theoretical and Practical Implications

6.1 Theoretical implications

The current study contributes to the accounting information systems literature in several ways. First, it integrates the AI-Enabled Accounting Information Systems, the Data Analytics Capability, the Decision-Making Effectiveness and the Digital Literacy in one empirically testable model, and this addresses the fragmentation that is identified in the previous literature (Yan et al., 2023; Schiavi, 2018; Wilkin, 2026); Alonso-Morales, 2026). Second, it provides an empirical evidence for the partial mediation of the Data Analytics Capability, and this clarifies the mechanism through which the AI-enabled systems are converted into an effective decision-making, rather than merely confirming a direct technology-outcome relationship. Third, it specifies the Digital Literacy as a theoretically grounded moderator, and it demonstrates, in a rather precise manner, at which stage of the causal path this moderator operates.

6.2 Practical implications

From a practical perspective, the results of the current study suggest that the organisations that adopt the AI-enabled accounting information systems should not expect an automatic improvement in the decision-making effectiveness, and they should instead invest in building the data analytics capability of their accounting and their managerial staff. In addition, since the Digital Literacy is found to strengthen the relationship between the technology and the decision-making effectiveness, it is recommended that the organisations provide a continuous training and a capacity-building programs in order to raise the digital literacy of their employees, and this is expected to maximise the return on their investment in the AI-enabled accounting systems.

7. Limitations and Directions for Future Research

As with any other study, the current study has some limitations that should be acknowledged. First, the cross-sectional design of the current study does not allow for a strong causal inference, and it is recommended that the future research adopts a longitudinal design in order to examine the changes in the study variables over the time. Second, the data of the current study were collected through a self-reported questionnaire, and although the procedural remedies were applied, a common method variance cannot be completely ruled out, and accordingly the future research could combine the self-reported measures with the objective indicators, consistent with the recommendation of the previous methodological literature (Appelbaum, 2017; Bhimani, 2020; Mikalef, 2021; Niu, 2021). Third, the sample of the current study may be concentrated in a particular context, and this limits the generalisability of the current findings to the other countries or the other sectors, and accordingly the future research is encouraged to replicate the proposed model in the different contexts and to test additional moderators, such as the organisational size or the industry type.

8. Conclusion

The current study examined the effect of the AI-Enabled Accounting Information Systems on the Decision-Making Effectiveness, and it tested the mediating role of the Data Analytics Capability and the moderating role of the Digital Literacy. The results of the PLS-SEM analysis confirm that the AI-Enabled Accounting Information Systems has a positive and a significant effect on the Data Analytics Capability and on the Decision-Making Effectiveness, that the Data Analytics Capability partially mediates this relationship, and that the Digital Literacy significantly strengthens the relationship between the AI-Enabled Accounting Information Systems and the Decision-Making Effectiveness. It is concluded, therefore, that the value of the AI-enabled accounting information systems for the organisational decision-making is not automatic, and that it depends on the organisational capability to analyse the data and on the digital literacy of the users. The current study, accordingly, provides both a theoretical contribution and a practical guidance for the organisations that seek to maximise the benefit of their investment in the AI-enabled accounting information systems.

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