

Factors Influencing the Procurement Officers' Intention to Adopt AI. The Mediating Role of Organisational Support

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Abstract

This study examined the factors influencing procurement officers' intention to adopt AI, with organisational support as a mediating variable. This study employed a quantitative research strategy and adopted a cross-sectional survey design, supported by elements of an explanatory research design. The target population were supply chain personnel, logistics managers, and operations officers at cocoa-producing firms in Ghana. The sampling technique used was purposive sampling to select 300 respondents involved in supply chain processes. The primary data for this study were collected through a structured questionnaire administered to employees within the selected firms. Statistical Package for the Social Sciences (SPSS) version 26 was used for descriptive analysis, including means and standard deviations. International Business Machines Corporation (IBM) Amos was also employed to test the study's hypotheses.

The findings showed that performance expectancy, effort expectancy, social influence, digital literacy, and training all shape organisational support, which in turn has a powerful effect on workers' intention to adopt AI. The results revealed that organisational support plays a significant mediating role in employees' adaptation to AI. Thus, without sufficient organisational support, positive employee perceptions and attitudes alone may not translate into adoption behaviour.

However, the results of the study revealed that the effect of social influence on organisational support was not significant. It is therefore recommended that future research consider expanding the sample to include respondents from other sectors, such as manufacturing, banking, public procurement, and healthcare, to enhance generalizability.

Keywords: *Performance expectancy, procurement officers, organisational support, effort expectancy, social influence, digital literacy, AI adoption, Unified Theory of Acceptance and Use of Technology*

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1.0 INTRODUCTION

With the pace of digitisation of the contemporary economy increasing in recent times, there is no doubt that tech-driven innovation is constantly changing conventional business operations such as procurement. In pursuit of efficiency, swiftness, and strategic procurement

operations, Artificial Intelligence (AI) is becoming an important component of procurement operations. For instance, AI technologies, including predictive analytics, chatbots, robotic process automation, and intelligent sourcing tools, are being leveraged to enhance decision-making, supplier assessment, risk management, and cost reduction in procurement operations (Gunasekaran, Mghili & Saravanakumar, 2022; Dwivedi et al., 2021). Despite these benefits of AI in procurement operations, its adoption by procurement professionals in developing countries, including Ghana, remains low (Yevu et al., 2022). Procurement officers are crucial in deciding whether digital innovations such as AI are adopted within their organisations. Their intentions are often influenced by a mix of personal factors, including performance expectancy, effort expectancy, social influence, digital literacy, and training (Al-Emran et al., 2023). While earlier studies have mostly focused on technology acceptance at a broader organisational level, using models such as the Unified Theory of Acceptance and Use of Technology (UTAUT), there is limited research specifically targeting the procurement context, particularly regarding how organisational support affects the relationship between these influence factors and the intention to adopt AI.

However, in many procurement departments, especially in public institutions and mid-sized enterprises in Africa, resistance to digital transformation is a major issue. This resistance is often driven by fear of job loss, limited understanding of AI, and a lack of institutional support (Ahmed et al., 2021; Dwivedi et al., 2023). Procurement officers might consider adopting AI if they perceive their organisation as ready to support such adoption (Dwivedi et al., 2023). The use of Artificial Intelligence (AI) technologies is a major driver of organisations' competitive advantage across different domains (Horani et al., 2023). AI can offer significant benefits to procurement functions through predictive analytics, supply risk management, contract optimisation, and decision-making (Gunasekaran, Mghili & Saravanakumar, 2022). Procurement professionals are not embracing AI technologies to the expected extent.

The scenario is even bleaker in developing countries and public-sector organisations, where bureaucratic hurdles, limited infrastructure, and lack of organisational support are major hindrances to the implementation of AI (Dwivedi et al., 2023). Existing research has explored overall technology acceptance using models such as the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). Little research has examined procurement officers' decision-making regarding AI, especially in contexts where organisational support is an important variable. Although various studies emphasise factors such as perceived usefulness, ease of use, and personal attitudes, the effect of organisational support, training, commitment, and IT infrastructure is not examined comprehensively, especially in procurement contexts (Ahmed et al., 2021). This study seeks to bridge the gap by investigating the main factors that influence procurement officers' intent to adopt AI, which are performance expectancy, effort expectancy, social influence, digital literacy, and training, and how organisational support influences the relationship between these factors and procurement officers' intent to adopt AI.

2.0 ADOPTION OF ARTIFICIAL INTELLIGENCE AND ROBOTICS

The rapid spread of artificial intelligence systems, along with robotic machinery, has triggered concerns about workplace efficiency that could lead to job losses and mass layoffs (Smith & Anderson, 2014). Researchers who studied human capital operations in the past examined how employees would lose their jobs due to automation and the implementation of AI systems. For example, Frey and Osborne (2013) used a Gaussian process classifier to estimate that nearly 50% of all U.S. jobs could be automated in the coming decades. The approach Bowles (2014) used for Europe showed that automation would lead to the disappearance of 54% of European work positions. Lee et al. (2017) applied Frey and Osborne's job automation risk assessment to Asian countries, showing that Singapore's workforce faced computerisation threats in about 25% of their employment positions.

Smith and Anderson (2014) surveyed 1,900 experts who predicted that AI-operated machines and networked applications would replace multiple blue-collar and white-collar

positions by 2025. The research conducted by Chui, Manyika, and Miremadi (2015) shows that AI and robotics systems will perform 45% of the tasks which American workers used to do in their previous roles. The study by Acemoglu and Restrepo (2017) demonstrated that each new industrial robot that operated with 1,000 American workers would reduce the national employment share by 0.18 to 0.34 percentage points. The rapid growth of robotics and AI technology creates two main problems that affect employees' work habits and feelings about their jobs. The research by Chui et al. (2015) demonstrated that modern technology would create greater workforce instability, affecting all business sectors.

Brougham and Haar (2017) found that workers often feel undervalued because their organisations prioritise smart technology systems, AI, robotics, and algorithmic solutions over human worker involvement. The research established that workers who understand STARA experience negative effects which reduce their dedication to their company and their satisfaction with their professional path. The research revealed that workers who understood STARA at an advanced level were more likely to develop plans to leave their current employment. The research indicates that employees decide to leave their current jobs because advanced technology systems raise concerns about employment security and future career opportunities.

2.1 Theoretical Framework

Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) serves as the theoretical foundation for this research project because it helps researchers identify which elements influence technology adoption. UTAUT posits that people will adopt new technology based on three main factors: perceived effort, social interactions, and the support they receive for implementing the technology (Dwivedi et al., 2019). The research extends its existing model by adding organisational support as a mediating factor, which researchers use to examine how procurement officers decide to use Artificial Intelligence (AI) in their professional activities. The extension shows that technology adoption occurs because people make technology decisions based on their beliefs, and because organisations provide environments that either promote or block technology adoption.

Users assess AI systems based on their personal experiences, which determine how difficult or easy they will find system operation (Rezvani, Heidari, Roustapisheh & Dokhanian, 2022). Procurement officers are more willing to use AI tools when they believe the tools are easy to operate and do not involve complex tasks. Organisations can enhance this perception through their training programs, technical guidance, and process simplification activities, which help users master operational tasks (Chen, Gascó-Hernandez & Esteve, 2024)—the social influence metric measures how AI usage receives support from coworkers and higher-level managers, as well as organisational practices. A digital transformation initiative receives stronger support from an organisation when its staff and managers back it, leading to increased technology adoption (Chen, Gascó-Hernandez & Esteve, 2024).

Another important element of this process requires procurement officers to demonstrate their ability to use AI systems through their knowledge of digital literacy. Officers with higher digital literacy can better understand AI advantages and implement those benefits into procurement processes. Organisations can improve this ability through skills development programs and by giving their staff access to artificial intelligence technologies. Training directly helps procurement officers gain confidence and competence by teaching the essential skills needed to work with AI tools and to understand how these tools enhance procurement processes (Singh, Mittal & Sinha, 2025).

The study uses organisational support as a mediating variable that connects individual-level factors to effort expectancy, social influence, and digital literacy and training needs, and to their AI adoption intention. The support system consists of three components: leadership commitment, resource provision, and a workplace atmosphere that promotes technology development. Organisational support has two distinct impacts on adoption processes: it

eliminates obstacles and establishes a suitable foundation for technological adoption, making other factors more effective. The theoretical framework of this study identifies key adoption factors that organisational support mediation affects, providing an extensive understanding of AI adoption patterns among procurement officers.

2.2 Research Framework

The framework provides a visual representation of predicted relationships among variables that affect procurement officers' decisions to use Artificial Intelligence (AI) technology, given organisational support. The framework identifies five key factors, including performance expectancy, effort expectancy, social influence, digital literacy, and training, as independent variables that shape organisational support. The factors define the advantages organisations perceive from AI adoption, the simplicity of implementation, the impact of colleagues and supervisors, the officers' ability to handle technology, and the availability of educational opportunities. Organisational support acts as a mediator, enhancing the connection between these elements and procurement officers' intention to adopt. The evidence shows that organisational resources and leadership commitment, together with organisational support policies, form the main requirements for organisations to achieve their goals, while individual competencies and organisational resources can contribute to their work.

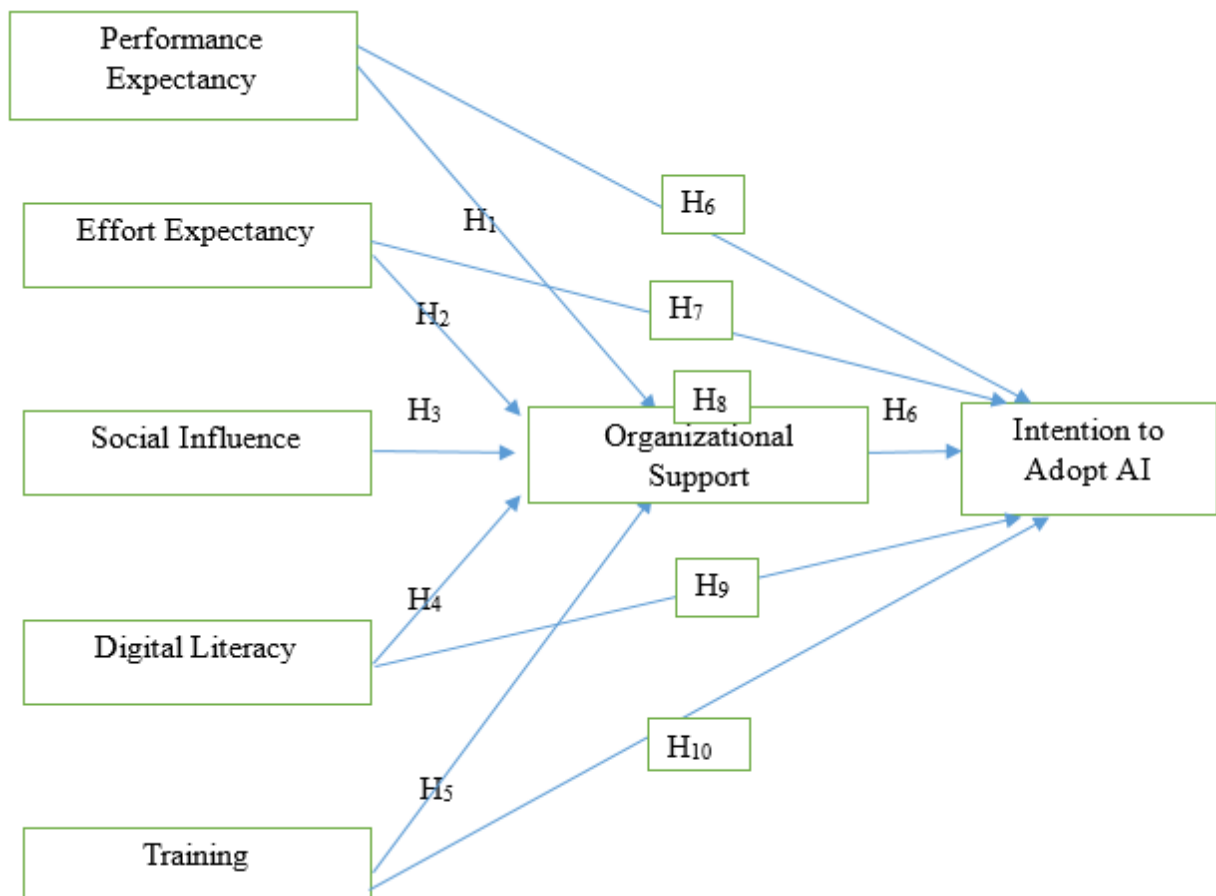


Figure 1: Research model

2.3 Hypothesis Development

Performance Expectancy and Organisational Support

According to Venkatesh et al. (2003), the Unified Theory of Acceptance and Use of Technology (UTAUT) identifies performance expectancy (PE) as one of four essential factors that determine when people will use technology. Performance expectancy has been defined as the degree to which an individual believes that using a system will enhance their job performance (Venkatesh et al., 2003). Employees who expect AI technologies to enhance procurement processes can expect their organisation to provide the necessary training, infrastructure, and managerial backing to ensure successful implementation (Al-Sadhan & Bhatti, 2023). The connection between performance expectancy and organisational support is a two-way relationship: organisations allocate resources based on high perceived usefulness, while organisational support increases users' perceived system value (Al-Sadhan & Bhatti, 2023). Research studies have established performance expectancy as a critical factor driving technology adoption across various settings.

Venkatesh et al. (2003) showed that PE functioned as the primary UTAUT element, explaining user technology acceptance behaviour through its capacity to produce different outcomes. The later study by Venkatesh et al. (2012) confirmed PE as a key factor in users' reactions to revolutionary technologies. Shayo et al. (2021) found that performance expectancy positively affected e-procurement system usage in Tanzanian public institutions, with organisational support as the main enabling factor. Song, Ma and Ran (2025) discovered that users who anticipate high performance advantages from AI applications will see their organisations use support elements such as training programs, infrastructure investments and leadership commitment more frequently.

The performance expectancy of a system determines how employees view its ability to enhance procurement results through improved supplier selection accuracy, reduced costs, and better risk assessment. Higher performance expectancy signals to procurement officers that the institution is more likely to support AI adoption by providing technical support, simplifying policies, and making the environment more favourable for adoption. UTAUT demonstrates that performance-related beliefs form the core foundation that determines both behavioural patterns and the organisational requirements needed for technology use. The UTAUT model, together with supporting empirical research, demonstrates that procurement officers who perceive AI as highly beneficial for their work will expect their organisation to provide stronger backing for its implementation. Thus, the study hypothesises that:

H₁: Performance expectancy positively influences organisational support for procurement officers to adopt AI.

Effort Expectancy and Organisational Support

According to Venkatesh et al. (2003), effort expectancy refers to users' perceived difficulty in using a new technology. AI adoption for procurement activities depends on how convenient procurement officers find it to operate AI systems. Employees at organisations with technology systems that require less effort to operate will experience better organisational support because they perceive these systems as more efficient and better suited to their needs. Organisations that adopt user-friendly technologies provide essential support services, including training, technical assistance, and documented operational procedures, to help users navigate the system (Dwivedi et al., 2021). Previous studies have demonstrated that employees' intention to use new technologies is affected by their effort expectancy, as it reduces perceived system complexity and increases their ability to use the system (Venkatesh et al., 2012; de Oliveira et al., 2022).

The organisation improves its perceived support by providing capacity-building and system-design enhancements to address expected usability issues (Tarhini et al., 2017). AI solutions become user-friendly when procurement officers adopt them, believing their

organisation has made adoption easier through its high-level priorities. The study presents the following hypothesis:

H₂: Effort expectancy positively influences organisational support for AI adoption among procurement officers.

Social Influence and Organisational Support

Social influence explains how much people believe that their authority figures, like managers, coworkers, and industry leaders, expect them to adopt specific technologies (Venkatesh et al., 2003). In organisational settings, influence will extend from individual attempts at persuasion to stronger institutional force, organisational standards, and the requirements of essential decision-making authorities. When procurement officers experience high levels of support from important people, they are likely to perceive organisational dedication to AI implementation through resource allocation. The research findings demonstrate that social influence affects technology adoption behaviour through its positive effects on three factors: perceived organisational readiness, legitimacy, and credibility (Ifinedo, 2014; Martins et al., 2020).

The existence of peer communities, supported by senior management, creates a procurement system that reduces uncertainty and builds trust in artificial intelligence systems. The public statements made by organisational leaders about AI's strategic value, together with their demonstration of AI use, create a situation in which employees perceive organisational backing that supports their work (Dwivedi et al., 2021). Social influence demonstrates its power to create collective responsibility across various sectors through organisational backing, which manifests as technology investment programs, training opportunities, and ongoing support for technology use (Tarhini et al., 2016). The procurement officers in the organisation perceive AI advocacy from key internal and external influencers as a demonstration of organisational support that they observe throughout their work. The study proposes the following hypothesis:

H₃: There is a positive relationship between social influence and organisational support for AI adoption among procurement officers.

Digital Literacy and Organisational Support

The definition of digital literacy describes a person's ability to use digital technologies for their intended purposes, to understand digital content, and to adapt to new technological developments (Siddiq et al., 2017). Officers with advanced digital literacy skills possess the fundamental knowledge to use AI systems with confidence, understand how these systems respond, and leverage that understanding to improve their operational performance. The two abilities help people accept AI more easily by creating a tendency to use it in their daily procurement work. Organisations understand that employees with computer skills will utilise AI technologies to their full potential, which motivates them to establish supportive systems that include specialised training programs, improved digital resources, and assistance with process integration (Carretero et al., 2022).

The organisations can direct their efforts toward providing complete support and ongoing educational programs, as their digitally skilled employees need only basic implementation assistance. The theory of self-efficacy links organisational support and digital literacy by explaining how people develop technology skills through employment support and resource availability (Eastin & LaRose, 2000). The digital literacy of procurement officers will create better career alignment with their expertise through organisational support and technological resources, leading to continuous progress between institutional backing and their acquired abilities. This study anticipates that;

H₄: There is a positive relationship between digital literacy and organisational support for AI adoption among procurement officers.

Training and Organisational Support

Procurement officers require training to develop their knowledge and skills, as this training enables them to build their self-confidence in AI technologies (Alshehhi, Cheaitou & Rashid, 2024). Organisations that provide formal training programs demonstrate their commitment to developing human capital while showing that employees can handle advanced digital technologies (Noe et al., 2014; Salas et al., 2015). Training develops technical skills while teaching employees to solve problems and use systems with increased confidence and decreased fear of technological advancements. Organisations that implement complete training programs demonstrate their capability to support innovation and maintain digital transformation activities (Sung & Choi, 2021). Employees at the organisation develop new technology skills through training programs, creating a learning environment they trust will support their professional development.

Organisational behaviour creates a perception of support, which becomes stronger when training includes mentoring, demonstrations, and follow-up training to support learning. Training receives organisational backing through the essential role of leadership, which connects training efforts to organisational support. Top management demonstrates trust and commitment to employees by establishing continuous skill development programs, thereby linking strategic goals to employee development (Hameed et al., 2022). The procurement officers believe that the company shows genuine dedication to their development and the success of AI adoption initiatives. This study presents the following hypothesis:

H₅: There is a positive relationship between training and organisational support for AI adoption among procurement officers.

Organisational Support as Mediator

Organisational support refers to how organisations assist and motivate employees as they learn to use new technologies (Chen et al., 2020). The organisation provides employees with leadership backing, necessary resources, and training programs, and establishes a corporate environment which helps employees adopt new practices. The organisation demonstrates its dedication to employee success by providing backing throughout the transformation process, which helps employees understand their value to the organisation (Eisenberger, Rhoades-Shanock & Wen, 2020; Caesens & Stinglhamber, 2020). Organisational support functions as a link between various factors affecting employee performance and their decision to implement AI technology. The research shows that employees in organisations with support systems demonstrate greater confidence in using technology, higher motivation to use it, and lower resistance to new technological advancements (Brock et al., 2022).

The research demonstrates that organisational support creates an environment that allows employees to apply their knowledge and skills, thus improving organisational performance (Newman et al., 2022). The research demonstrates that organisational support helps organisations translate their initial positive expectations into successful long-term technology implementation (Brock, 2022). The study delivers the following expected outcomes:

H₆: Organisational support mediates the relationship between performance expectancy, effort expectancy, social influence, digital literacy, training, and procurement officers' intention to adopt AI.

3.0 METHODOLOGY

3.1 Instrumentation

The study used a structured questionnaire to collect data in a quantitative format, enabling empirical testing of theoretical concepts. The questionnaire used closed-ended questions (Sanchez, 2024) to capture information across five key areas. The first section of the

study collected demographic information about participants, including their age, gender, job title, and work experience. Section B focused on factors that influence procurement officers' intention (Performance Expectancy, Effort Expectancy, Social Influence, Digital Literacy, and Training). Section C comprised questions on intention to adopt AI, while Section D explored the presence of Organisational Support. The study used a 5-point Likert scale, which measured all questions from strongly disagree (1) to strongly agree (5)

Measures

Intention to adopt Artificial Intelligence (AI) in procurement is defined as the degree to which an individual is willing to use AI technologies in procurement activities. The items used to measure the dependent variable, intention to adopt AI, were adapted from Venkatesh et al. (2003) with a sample item such as: "I intend to use AI technologies in my procurement activities in the future." Performance expectancy is defined as the degree to which an individual believes that using AI will enhance job performance in procurement activities. The items used to measure performance expectancy were adapted from Venkatesh et al. (2003), with a sample item such as: "Using AI will improve my efficiency in procurement activities." Organisational support is defined as the extent to which an organisation provides the necessary resources, commitment, and infrastructure to support AI adoption. The items used to measure organisational support were adapted from Tornatzky and Fleischer (1990), with a sample item such as: "My organisation provides adequate support for adopting AI technologies."

Effort expectancy is defined as the degree of ease associated with the use of AI systems in procurement activities. The items used to measure effort expectancy were adapted from Venkatesh et al. (2003), with a sample item such as: "Learning to use AI for procurement would be easy for me." Social influence is defined as the degree to which an individual perceives that important others believe they should use AI in procurement. The items used to measure social influence were adapted from Venkatesh et al. (2003), with a sample item such as: "People who influence my work think I should adopt AI in procurement." Digital literacy is the ability to use digital tools and technologies to perform work-related tasks effectively. The items used to measure digital literacy were adapted from Gilster (1997), with a sample item such as: "I am comfortable using digital tools and platforms for work." Training is defined as the extent to which employees are provided with opportunities to acquire the knowledge and skills necessary to use AI systems. The items used to measure training were adapted from Noe (2017), with a sample item such as: "My organisation provides training on emerging technologies like AI."

3.2 Data Collection

Based on purposive sampling technique, Three hundred (300) questionnaires were distributed to supply chain experts who worked at Cargill and Armajaro Ltd. and Federated Commodities Limited and Nananom Buyers Company Limited and Kuapa Kooko Co. Ltd. and CJ Commodities Ltd. and ELIHO Ltd. and Adikanfo Commodities Ltd. and Olam Ghana Ltd. and Unicom Commodities Gh Ltd. All three hundred (300) questionnaires distributed were retrieved, resulting in a 100% usable response rate.

4.0 DATA ANALYSIS

Out of the three hundred (300) questionnaires obtained, 166 respondents (55.3%) were male, while 134 respondents (44.7%) were female. The results show that male participants slightly outnumbered their female counterparts. The findings showed that Master's degree holders made up the largest educational group (27.3%), while 80 respondents (26.7%) chose a Bachelor's degree. A further 65 respondents (21.7%) possessed a Diploma, while 53 respondents (17.7%) fell under the "Other" category, representing professional certificates and other qualifications. Additionally, 20 respondents (6.7%) had 68 years of experience in their field, while 59 respondents had 11-15 years of experience. The group included 58 respondents with less than 1 year of work experience and 45 respondents with 6 to 10 years of work experience. The

results on working positions further illustrate the organisational distribution of the respondents. Top-level Managers made up 72 respondents, representing 24.0% of the total, while Procurement/Logistics Managers and Supply Chain Officers followed with 65 and 59 respondents, representing 21.7% and 19.7%, respectively. Operations Managers made up 50 respondents (16.7%) of the total, while 54 respondents (18.0%) were classified as "Others" because they worked in positions that did not fit into the main job categories.

Table 1: Demographic profiles (N = 300)

Category	Frequency	Percentage (%)
Gender		
Female	134	44.7
Male	166	55.3
Educational Level		
Bachelor's Degree	80	26.7
Diploma	65	21.7
Doctoral Degree	20	6.7
Master's Degree	82	27.3
Other	53	17.7
Work Experience		
Less than 1 year	58	19.3
1-5 years	70	23.3
6-10 years	45	15.0
11-15 years	59	19.7
Above 15 years	68	22.7
Working Position		
Operations Manager	50	16.7
Procurement/Logistics Manager	65	21.7
Supply Chain Officer	59	19.7
Top-level Manager	72	24.0
Others	54	18.0

4.1 Factor Analysis

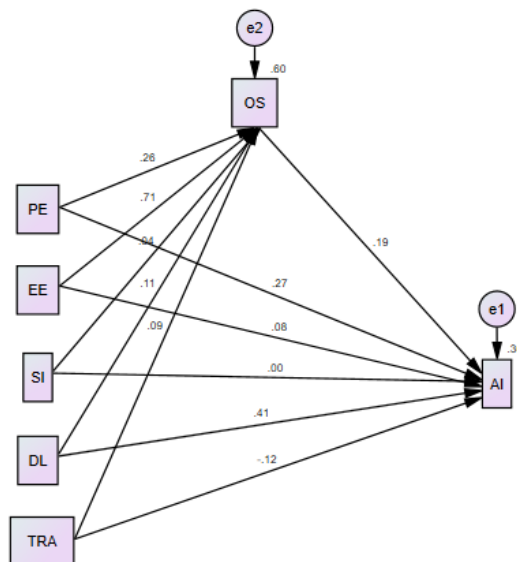
Factor analysis was conducted using principal component analysis (PCA) to identify patterns and reduce the dimensionality of the items in the research instrument. The use of the varimax method ensured that the dimensions were uncorrelated, improving the interpretation of the results. To test the significance of the factor loadings, Hair *et al.* (1998) and Field (2000) have suggested that, in the interpretation of the factor matrix, factor loadings greater than + or -0.40 are significant predictors. Norusis (1993) also indicates that factor loadings greater than or equal to 0.50 are very significant predictors. This met the criteria for factor loadings, all factors having loadings above or below 0.50 (see Table 2). A correlation matrix from the factor analysis was used to check for the pattern of relationships. Variables were examined using significance values equal to or greater than 0.05. For this study, most correlation values were greater than 0.5.

These loadings indicate that the underlying constructs loaded well on one another. The factor analysis yielded four factors, with a Kaiser-Meyer-Olkin value above the recommended minimum of 0.6 (Kaiser, 1974). Bartlett's test of sphericity was significant ($p < 0.05$), indicating good factorability of the correlation matrix. Table 2 indicates that all items loaded well on their respective factors, with Cronbach's Alpha values above 0.80 (see Table 2).

Table 2: Factor loadings

Variable	Item	Loading	CA
Performance Expectancy	PE1	.761	.864
	PE2	.676	
	PE3	.694	
	PE4	.671	
Effort Expectancy	EE1	.743	.874
	EE2	.675	
	EE3	.716	
	EE4	.644	
Social Influence	SI1	.694	.886
	SI2	.785	
	SI3	.732	
	SI4	.727	
Digital Literacy	DL1	.767	.845
	DL2	.714	
	DL3	.759	
	DL4	.729	
Training	Tr1	.758	.879
	Tr2	.696	
	Tr3	.725	
	Tr4	.710	
Organizational Support	OS1	.573	.854
	OS2	.590	
	OS3	.695	
	OS4	.730	
Intention to Adopt AI	AI1	.795	.870
	AI2	.811	
	AI3	.694	
	AI4	.605	

Figure 1: Structural Equation Model



NB: Performance Expectancy (PE); Effort Expectancy (EE); Social Influence (SI); Digital Literacy (DL); Training (TRA); Organisational Support (OS)

Source: *Field Survey (2025)*

Table 1: Structural Equation Modelling (Sem) Results

Hypothesis	Estimate	S.E.	t	P	Decision
Direct					
H ₁ : PE--->OS	0.210	0.030	6.987	0.000	Significant
H ₂ : EE---> OS	0.576	0.030	19.446	0.000	Significant
H ₃ : SI---> OS	0.031	0.027	1.142	0.254	Not significant
H ₄ : DL---> OS	0.084	0.028	2.979	0.003	Significant
H ₅ : TRA---> OS	0.070	0.029	2.440	0.015	Significant
Mediator/ Indirect					
H ₆ : OS---> AI	0.219	0.084	2.619	0.009	Significant

NB: Performance Expectancy (PE); Effort Expectancy (EE); Social Influence (SI); Digital Literacy (DL); Training (TRA); Organisational Support (OS)

5.0 DISCUSSION AND IMPLICATIONS

The results showed that expected performance expectancy has a positive effect on organisational support. Procurement officers who believe AI will improve their work efficiency, accuracy, and productivity tend to view organisational support for them as more extensive. The Unified Theory of Acceptance and Use of Technology (UTAUT) framework demonstrated that positive performance expectations lead management to fund technological adoption through training, necessary tools, and essential leadership support. Organisations need performance expectancy to assess their AI system readiness, as it establishes their technological operational capability for AI implementation. The findings support Venkatesh et al.'s (2003) claim that employee performance expectations determine how organisations support the adoption of new technologies. The organisation needs performance expectancy because it helps management staff decide whether to fund digital technologies which improve their operations. Organisations need to provide support through resources and tools, as well as incentives, to encourage their staff members to adopt AI technology.

The relationship between social influence and organisational support was not significant. Social pressure from colleagues and supervisors encourages AI adoption, yet fails to create higher levels of organisational support. Organisations increase their support systems after supervisors, colleagues, and external stakeholders promote AI adoption, according to research conducted by Horani et al. (2025). Venkatesh and Bala (2008) discovered that social pressures lead to greater management participation during technology deployment. Dwivedi et al. (2019) show that social norms force professional groups to adopt new digital technologies, which have become common practice. The research found that social pressure does not affect organisational support, yet earlier studies found that social influence drives organisations to develop AI implementation methods.

The results further showed that digital literacy provides a positive and significant effect on organisational support. The results demonstrate that procurement officers with higher digital skills tend to select work environments that provide organisations with support for their AI implementation efforts. Park, Oh, and Sang (2024) found that digital literacy enhances organisational readiness by developing employees' skills, helping organisations overcome implementation obstacles. Ameen and Willis (2018) demonstrated that organisations with digital capabilities are more likely to integrate new technologies into their business activities. Organisations tend to allocate more resources to artificial intelligence when their staff members demonstrate proficiency with digital technologies.

The findings again demonstrate that training, together with organisational support, creates a significant positive relationship. Organisations that provide training create an

environment which helps employees adopt artificial intelligence technology. Procurement officers gain confidence in using AI through training, which provides them with essential knowledge and practical skills. Organisations support current and future AI adoption initiatives by providing their employees with training on AI tools. Training enables staff members to deal with technological advancements more effectively, according to research by Amoako-Gyampah and Salam (2004). Training increases user confidence, according to Tarhini et al. (2017), which leads organisations to enhance their support for technology adoption. Training establishes employee readiness while organisations become more willing to allocate resources toward artificial intelligence implementation.

Finally, the research found that organisational support acts as a substantial mediator between the identified factors, including performance expectancy and effort expectancy, and digital literacy and training, and the intention to adopt AI. The organisation provides strong support, leading officers to develop higher adoption intentions for AI technology because they already hold positive expectations and the necessary skills. The study established that organisational support is essential to enhance performance expectancy, effort expectancy, social influence, and digital literacy and training, which people use to decide whether to adopt new technologies. The research conducted by Rho et al. (2021) established that organisational support functions as the primary mechanism that links individual beliefs to organisational outcomes during technology adoption. The research by Teo, Bentley and Nguyen (2020) demonstrated that organisational support enhances the influence of personal factors on behavioural intentions in public-sector technology adoption contexts. The present study, therefore, confirms that organisational support is a critical pathway through which technological, social, and individual factors translate into a willingness to use AI in procurement operations.

6.0 CONCLUSION

The main aim of the study was to examine the factors that affect procurement officers' decisions to use Artificial Intelligence (AI) technology in cocoa production companies throughout Ghana, and to examine how organisational support functions as a mediating element. This study concludes that both individual perceptions and organisational actions strongly influence the adoption of AI among procurement officers. The findings showed that performance expectancy, effort expectancy, social influence, digital literacy, and training all shape organisational support, which in turn has a powerful effect on workers' intention to adopt AI.

The results revealed that organisations play a vital mediating role. Thus, without sufficient organisational support, positive employee perceptions alone may not translate into adoption behaviour. The results of the study also revealed that social influence has no significant impact on organisational support. The study further showed that organisations must create supportive environments for the successful integration of AI into procurement operations. Organisational support acts as a bridge connecting individual readiness to actual adoption intentions. Therefore, enhancing digital literacy, increasing performance awareness, improving ease of use, strengthening social encouragement, and delivering training are important for motivating organisations to invest in AI and for enabling procurement officers to embrace these technologies.

6.1 Limitations and Future Research

Although the study contributes significantly to the understanding of AI adoption in procurement, certain limitations were acknowledged. Firstly, the research focused only on cocoa-producing companies in Ghana, limiting generalizability to other industries. Also, the study employed a cross-sectional design, which restricts the ability to track changes over time. Furthermore, the variables used, such as performance expectancy, effort expectancy, social influence, digital literacy, training, and organisational support, may not capture all determinants of AI adoption. Additional factors, such as organisational culture, technological infrastructure, and regulatory conditions, could be considered by other researchers.

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