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Data Analytics Capabilities And Organisational Performance At An Emerging Economy's Local Government Assembly: The Roles Of Top-Management Support And Data Driven Decision Making

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Abstract

This study examines the impact of Data Analytics Capability on organisational performance within an emerging economy's local government assembly, with particular focus on the mediating role of Data-Driven Decision Making and the influence of Top Management Support. Grounded in the Organisational Information Processing Theory and the Upper Echelons Theory, the study adopts a cross-sectional survey explanatory design. Data was collected from 127 employees of the local assembly through structured online questionnaire and analysed using Partial Least Squares Structured Equation Modelling. The results reveal that DAC has no significant direct effect on organisational performance but exerts a strong positive effect on DDDM. In turn, DDDM significantly enhances organisational performance and mediates the relationship between DAC and performance. Additionally, TMS support significantly and directly influences organisational performance, although it does not moderate the DAC-performance relationship. The study concludes that DAC alone do not guarantee improved performance, rather, their value is realized through integration into decision-making processes. To the best of the authors' knowledge, this study is among the first to provide empirical evidence from an emerging economy's local government context demonstrating that DDDM is the critical pathway through which DAC translate into performance outcomes, while TMS operates as a direct driver rather than a conditional enhancer. This study contributes theoretically by refining the application of the OIPT and the UET in public sector analytics contexts and offers practical insights that performance improvements depend more on the use of data in decision-making than on the mere possession of analytics infrastructure.

Introduction and background

In many developing country contexts, including Ghana, weaknesses in administrative data systems and analytical capacity constrain the effective use of evidence in operational decisions (UNDP, 2022; MLGDRD, 2021). Local governments operate in increasingly complex environments where sound decisions must be made regarding revenue mobilisation, expenditure allocation, and service delivery, often under conditions of limited, fragmented, and low-quality information (World Bank, 2022; OECD, 2023). In such local governance contexts, organisational performance is closely tied to the quality of managerial decisions. Precisely, how revenues are mobilised, how scarce resources are prioritised, and how public programmes are monitored and evaluated (Chen et al., 2016). Weak information systems and delayed or incomplete records can therefore translate directly into revenue leakages, inefficient spending, and suboptimal service delivery outcomes.

Over the past decade, digitisation and administrative reforms within Metropolitan, Municipal, and District Assemblies (MMDAs) in Ghana have significantly expanded the volume of administrative data generated across functions. However, the public value of these records does not lie in their accumulation alone but rather through data analytics capabilities (DAC). This capability includes employees and the organisation's ability to organise, process, analyse, and interpret data to support planning, control, and service delivery outcomes (Chen et al., 2016; Popovič et al., 2018; Batistič & van der Laken, 2019).

Without such capabilities, data remain underutilised assets that do little to improve organisational performance.

Nevertheless, the presence of analytics capabilities alone may not automatically guarantee improved outcomes. From a dynamic capabilities perspective, the performance benefits of analytics are realised only when analytical insights are actively embedded in routine organisational choices through data-driven decision-making (DDDM) (Ghasemaghaei & Calic, 2019). DDDM reflects the extent to which evidence from data analysis informs prioritisation, resource allocation, performance monitoring, and corrective action. When data are systematically used to guide decisions, decision quality improves and operational risks are reduced (Shamim et al., 2020; Li et al., 2022). Conversely, when analytical outputs are produced but not used, their potential value is lost (Gupta et al., 2018).

The relevance of DAC in this context can be explained through the Organisational Information Processing Theory (OIPT), which posits that organisational effectiveness depends on the ability to process information at a level that matches environmental complexity and uncertainty. Explicitly, the Cape Coast Metropolitan Assembly's (CCMA) multifaceted mandate ranging from revenue administration and spatial planning to sanitation and social services creates high information-processing demands. As such, when the assembly lacks the analytical capacity to transform raw administrative records into actionable insights, uncertainty persists and coordination across departments weakens, ultimately constraining performance.

That notwithstanding, within public sector organisations, the effectiveness of both DAC and DDDM is highly dependent on the quality and completeness of administrative and financial records (Ghasemaghaei, 2019). Weak record-keeping systems, fragmented reporting structures, and inconsistent data standards can undermine analytical credibility and reduce trust in evidence-based decisions (Aladejebi & Oladimeji, 2019; Prempeh et al., 2022). As a result, even well-designed analytics systems may fail to influence practice if underlying data quality problems persist.

Crucially, the institutionalisation of analytics and DDDM within a local government setting depends on top management support (TMS). Drawing on Upper Echelons Theory (UET), organisational priorities, resource allocations, and control mechanisms reflect the values and orientations of senior leaders. At the CCMA, metropolitan and departmental leadership determine whether data use is encouraged, funded, enforced, and embedded in daily administrative routines. Empirical evidence suggests that without strong top management commitment, analytics initiatives often remain peripheral, under-resourced, and weakly adopted across departments (Lai et al., 2018; Maroufkhani, 2023; Shafique et al., 2024). This study argues that the missing link is DDDM.

Drawing on OIPT, CCMA faces high information-processing requirements because its activities are interdependent and uncertainty is high. Performance improves only when the assembly's information-processing capacity matches these requirements and is embedded in decision routines. In other words, analytics affects performance mainly when it becomes part of budgeting, revenue management, project tracking, and corrective action, not when it remains as periodic reporting. At the same time, leadership

shapes whether analytics is taken seriously and consistently used. The UET again, suggests that organisational priorities and outcomes reflect top managers' attention, values, and choices. In CCMA, top leadership determines whether resources are committed to data systems and staff capacity, whether data quality is enforced, and whether managers are held accountable for using evidence. This makes TMS a likely boundary condition that strengthens the impact of analytics and DDDM on performance.

Empirically, two gaps remain. Studies do not consistently test the mechanism through which DAC improve performance in public-sector settings, DDDM is often assumed rather than modelled and measured as a mediating process. Again, the boundary condition of leadership commitment is frequently discussed but under-tested as a moderator in explaining why analytics improves performance in some organisations but not others. These gaps are especially pronounced in Ghanaian local governance contexts, where institutional constraints and capacity limitations may shape the analytics-decision-performance pathway. Without this empirical clarity, the CCMA and other local government institutions will bear the brunt of persistent informational inefficiencies and sub-optimal resource allocation, with adverse implications for performance.

Against this backdrop, this study focuses on the CCMA to examine whether DDDM mediates the relationship between DAC and organisational performance, and whether TMS moderates the direct relationship between DAC and performance. By integrating insights from OIPT and UET, the study seeks to explain not only whether analytics matter in local government performance, but how and under what conditions they translate into tangible public sector outcomes. Hence the study.

The remaining sections of the study are organised as follows. The Section two presents the literature review, where the OIPT and the UET are expanded to provide the theoretical base to explain the various relationships the study investigates. Section three develops the research hypotheses. The research methods employed to gather and analyse data is presented in the Section four under Research Methods. The Section five presents the results and discussion. Flowing from which conclusions, implications and recommendations are presented.

Literature review

The literature review section of the study presents the theoretical foundation of the study. The Organisational Information Processing Theory and the Upper Echelons Theory are expanded in the context of this study. A review of the key concepts in the study is explained which is followed by a review of the empirical literature on these relationships as well as the development of the various hypotheses the study seeks to investigate.

Theoretical review

Organisational information process theory propounded by Jay Galbraith (1973) offers a robust explanation for the role of DDDM in the nexus between DAC and performance. The theory posits that organisations operate as information-processing systems and that performance improves when an

organisation's information processing capacity matches the information demands of its environment (Premkumar et al., 2005). Precisely, possessing information resources alone may be insufficient for performance improvement and as such organisations must be able to process, interpret, and use information effectively in decision making (Blenkinsop, 1993). Consequently, DAC primarily enhances organisational capacity to generate and analyse volumes of data and information (Huynh et al., 2023). However, these capabilities only contribute to improved performance when the insights produced are actively embedded into DDDM processes.

Explicitly, DAC enable the collection and analysis of high-quality data, but it is through DDDM that these analytical insights are translated into informed choices, strategic actions, and operational improvements (Abdul-Azeez et al., 2024; Tiwari, 2024; Riipa et al., 2025). Thus, when managers and decision makers rely on evidence generated from analytics rather than intuition or routine practices, the organisation's information processing capacity is effectively utilised, leading to enhanced efficiency, service delivery, and overall performance (Badmu et al., 2024). Conversely, in the absence of DDDM, DAC may have limited or no impact on performance (Mikalef, & Pateli, 2017). Even when sophisticated analytics systems are available, performance gains will not materialise if decision makers fail to trust, interpret, or apply data insights in policy formulation and operational decisions (Tushman & Nadler, 1978). Ultimately, DDDM acts as the transmission channel through which analytics capabilities influence organisational outcomes

Further, the moderating role of management support in the relationship between data analytics capabilities and performance is also robustly explained by the Upper Echelons Theory (UET), advanced by Donald Hambrick and Phyllis Mason (1984). The theory opines that organisational outcomes are reflections of the values, priorities, and strategic choices of top executives (Carpenter et al., 2004). Consequently, the extent to which organisational resources and capabilities translate into performance outcomes depends significantly on the commitment and actions of top management. Thus, DAC may not automatically lead to improved performance as its effectiveness may be heavily contingent upon the level of support provided by top management. When the management of CCMA actively champion data-driven initiatives, allocate adequate resources, enforce the use of analytics in decision-making, DAC may be more likely to be fully utilised and embedded into organisational processes. Under such conditions, the positive effect of DAC on CCMA's performance is strengthened. Conversely, when TMS is weak, DAC may remain underutilised or fragmented, regardless of existing technical sophistication consequently weakening the underlying nexus.

Empirical review

The current empirical literature on the nature of DAC, DDDM, TMS and the performance of institutions can be summarized in Table 1 of the study.

Table 1
Summary of empirical literature

Study	Methodology	Key Findings	Research Gap
Chen et al. (2016)	Survey, quantitative	Data analytics capability enhances operational efficiency and value creation	No consideration of leadership support or public sector applicability
Awan et al. (2021)	Survey, SEM	Big data analytics improves performance through enhanced insights	Limited attention to decision-making processes and governance
Li et al. (2022)	Econometric modelling	Analytics improves decision quality and firm outcomes	Excludes top management support
Ghasemaghaei and Calic (2019)	Survey	Data quality improves decision-making effectiveness	Weak linkage to organisational performance in public sector
Franke and Hiebl (2023)	Survey	Managerial analytics skills improve decision outcomes	Focuses on individuals, not organisational systems
Shafique et al. (2024)	SEM	Top management support enhances analytics adoption and performance	Limited integration with decision-making as mediator
Shamim et al. (2020)	Survey, SEM	Analytics capability improves decision-making performance	Limited role of leadership examined
Popovič et al. (2018)	Quantitative	Analytics improves performance via better decision-making	Lack of developing country context
Nisar et al. (2021)	Quantitative	Decision-making mediates analytics and performance	No inclusion of top management support
Marfo and Boateng (2015)	Mixed methods	Constraints exist in developing analytics capabilities	No linkage to performance or decision-making
Dlamini (2024)	Survey	Big data improves decision-making	No direct link to organisational performance
Kalema and Busobozi (2020)	Case/quantitative	Analytics improves data quality and decisions	Sector-specific, limited generalisability
Shamim et al. (2019)	SEM	Analytics improves decision quality and performance	Limited relevance to public sector

Source: Authors' Construct (2026)

Study	Methodology	Key Findings	Research Gap
Lai et al. (2018)	Survey	Top management support influences analytics adoption	Does not directly examine performance
Al-Dmour et al. (2023)	Quantitative	Big data analytics improves financial performance	Sector-specific focus
Source: Authors' Construct (2026)			

Hypotheses development

The growing importance of data as a strategic resource has intensified scholarly interest in how DAC, DDDM and TMS influence organisational performance. Drawing on the OIPT and the UET, this study conceptualizes DAC as a critical resource that enables organisations to transform their data into actionable insights, thereby enhancing decision-making quality and performance outcomes.

The direct relationship between DAC and organisational performance is grounded on the premise that organisations that effectively collect, process and analyse data are better positioned to optimise operations and achieve strategic goals. Chen et al. (2016) and Awal et al. (2021) find that analytics capabilities significantly improve operational efficiency and firm performance. Similarly, Al-Dmour et al. (2023) demonstrate that big data analytics enhances financial performance in banking institutions. In the Ghanaian context, although studies such as Ameyaw (2022) and Prempeh et al. (2022) focus more broadly on financial practices and record keeping, they underscore the relevance of information quality in improving performance outcomes. However, limited empirical evidence has examined DAC within public sector institutions such as MMDAs across the globe and in the Ghanaian context. This study therefore hypothesizes that:

H1: DAC has a statistically significant effect on the organisational performance at the CCMA.

DAC also play a critical role in enhancing DDDM by enabling organisations to extract meaningful insights from large and complex datasets. Conceptually, DAC provides the technological infrastructure, human expertise, and analytical tools necessary for informed decision-making. Empirical evidence supports this relationship. Ghasemaghaei and Calic (2019) find that data quality and analytical capabilities significantly influence decision effectiveness, while Shamim et al. (2020) demonstrate that analytics capability enhances decision-making performance in emerging markets. Similarly, Dlamini (2024) reports that big data analytics improves decision-making processes in financial institutions in South Africa. Within Ghana, studies on digital accounting systems such as Otchere et al. (2022) suggest that improved data characteristics contribute to better strategic decisions, although direct examination of DAC and DDDM remains limited. This gap is particularly evident in local government settings where decision-making processes are often constrained by limited analytical capacity. Therefore, it is hypothesised that:

H2: Data Analytics Capabilities (DAC) have a statistically significant effect on data-driven decision-making (DDDM) at the CCMA.

The relationship between DDDM and organisational performance is well established in the literature. DDDM enhances performance by reducing uncertainty, improving accuracy, and enabling timely responses to organisational challenges. Popovič et al. (2018) find that organisations that rely on data-driven insights achieve superior performance outcomes, while Nisar et al. (2021) show that decision-making capability significantly improves environmental and operational performance. Similarly, Li et al. (2022) demonstrate that data-informed decisions lead to improved organisational outcomes. In developing economies, Adegboyegun et al. (2020) and Senzu and Ndebugri (2018) highlight the importance of structured decision processes and reliable information systems in improving performance, although they do not explicitly conceptualise these as DDDM. Despite this, there remains limited empirical evidence on DDDM and its role in shaping organisational performance outcomes within public sector institutions. Therefore, it is hypothesised that:

H3: DDDM has a statistically significant effect on organisational performance at the CCMA.

Beyond direct effects, the literature suggests that DDDM mediates the relationship between DAC and organisational performance. From a theoretical perspective, DAC alone does not create value unless it is effectively utilised in decision-making processes. Thus, DDDM serves as the mechanism through which analytics capabilities translate into performance gains. Empirical studies support this mediating role. Nisar et al. (2021) find that decision-making capability mediates the relationship between big data management and performance, while Awan et al. (2021) report that data-driven insights act as an intermediary between analytics capability and organisational outcomes. Similarly, Shamim et al. (2019) confirm that decision quality mediates the impact of analytics on firm performance. However, such mediation has not been extensively tested in Ghanaian public sector contexts, particularly within metropolitan assemblies. Therefore, it is hypothesised that:

H4: DDDM mediates the relationship between DAC and organisational performance at the CCMA.

TMS is widely recognised as a critical organisational factor influencing performance. Conceptually, TMS ensures the allocation of resources, strategic direction, and institutional commitment necessary for achieving organisational goals. Empirical studies confirm its importance. Shafique et al. (2024) find that TMS significantly enhances organisational performance through improved analytics adoption. Similarly, Lai et al. (2018) show that managerial support is crucial for successful technology implementation, which ultimately affects performance outcomes. In the African context, leadership commitment has been identified as a key determinant of organisational effectiveness, particularly in resource-constrained environments. However, in Ghana, most studies focus on SMEs and private sector organisations, with limited attention to public institutions. This gap justifies further investigation in the context of local governance. Therefore, it is hypothesised that:

H5: TMS has a statistically significant effect on organisational performance at the CCMA.

Again, the effectiveness of DAC in improving organisational performance depends on the extent to which top management provides strategic guidance, fosters a data-driven culture, and supports the use of analytics in decision-making. Without such support, analytics initiatives may fail to yield desired outcomes. Empirical evidence supports this role. Studies such as Shafique et al. (2024) and Shamim et al. (2020) indicate that leadership support strengthens the impact of analytics capabilities on organisational outcomes. Similarly, research on technology adoption suggests that managerial commitment enhances the effectiveness of organisational capabilities (Lai et al., 2018). Despite these insights, there is little or no empirical evidence examining this interacting effect in the context of public sector institutions in Ghana. Therefore, it is hypothesised that:

H6: TMS moderates the relationship between DAC and organisational performance at the CCMA

Conceptual framework

The conceptual framework of the study is depicted in Fig. 1 as shown below. In Fig. 1, the various relationships that the study hypothesises are shown.

Research methods

This study adopts the post-positivism because it seeks to test theory-based relationships in a way that treats reality as measurable but not perfectly knowable (Fox, 2008). Post-positivism is suitable as the key constructs are latent and captured through indicators (survey items), meaning results are subject to measurement error and contextual influences. Consequently, the study adopts the explanatory research design to identify and clarify the causal links between the variables (Adam, 2015). This design is justified by the study's intent to go beyond merely describing the state of analytics adoption to explaining the underlying mechanisms that drive performance.

The area of interest to the study is the CCMA in the Central Region of Ghana. Cape Coast is a coastal metropolis known for its historical sites and a local economy driven by commerce, education, public services, tourism and hospitality, fishing, and small-scale manufacturing, with active formal and informal business activities. The CCMA is responsible for local governance and development, including planning and budgeting, land-use and building regulation, provision and maintenance of basic infrastructure, sanitation and environmental health services, local revenue mobilisation, public safety and disaster preparedness, and support for social services. These responsibilities are carried out through 20 specialised departments that manage administration, planning, regulation, sanitation, and social programmes.

Sample and Sampling Procedure

The population for this study comprises all employees of the CCMA. In total, the assembly has approximately 560 staff members distributed across its 15 departments, supporting both administrative functions and day-to-day service delivery within the metropolis (Cape Coast Metropolitan Assembly Annual Report, 2025). The population includes 392 employees who are Government of Ghana staff and the remaining 168 are Internally Generated Funds (IGF) staff, whose remuneration is supported through the assembly's IGF and who often provide additional operational and support services. Given a population of 560 employees, the study's sample size was determined using an a priori power analysis. The analysis was set at a 95% confidence level ($\alpha = 0.05$, two-tailed) and 80% statistical power ($1 - \beta = 0.80$) to ensure the study could reliably detect meaningful effects in the data. The study also assumes a medium effect size ($d = 0.50$), the minimum sample size required for the study was first estimated as $n_0 = 126$ using standard power-analysis calculations. Since the population is finite, a finite population correction was applied, which reduced the minimum required sample to $n = 103$. Again, to cater for non-responses and incomplete questionnaire items, the study adds 30% to the sample. Therefore, the study targets a minimum of 134 employees. The simple random sampling was then applied within each department to select the required number of respondents, ensuring that each eligible staff member had an equal chance of selection and reducing selection bias.

Data collection instruments

Following the formal approval of the research proposal, an introductory letter was obtained from the Head, Department of Data Science and Economic Policy, University of Cape Coast, and served to the Metropolitan Chief Executive (MCE) of the CCMA. An approval from the MCE through the Human Resource and Ethics Department of the CCMA was obtained thereafter. This approval granted the permission to proceed with the actual fieldwork and administration of the research instruments. Further, the entire process was done in accordance to the recommendations proposed by the Ethics Department. Throughout the research process, all prescribed ethical principles were strictly adhered to. Participation in the study was entirely voluntary, and respondents were also informed of their rights to withdraw at any stage without any adverse consequences. The principles of confidentiality, anonymity, and respect for participants' autonomy were scrupulously upheld during the data collection process. To further safeguard respondents, no identifying information such as names or official identification numbers were requested. Data was collected in-person but through the KoboToolbox data collection platform. This approach is considered appropriate as it allows the researchers to clarify questionnaire items where necessary, ensure a higher response rate, and retrieve completed online questionnaires promptly. The CCMA was visited and the online questionnaires distributed directly to respondents during working hours, with minimal disruption to their normal duties. The entire data collection phase last about 5 weeks.

Operationalization of variables

The study operationalises the variables in the study by adapting empirically proven scales of measurements for the variables of interest. Table 2 presents the various variables, their operational definition and empirical evidence supporting the basis for these measurements.

Table 2
Operationalisation of variables

Variable	Operational definition	Empirical evidence
Data Analytics Capabilities	5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree) Measured with • use of advanced analytics • data integration, visualization • data cleaning and preparation • spreadsheet functions use • data access and retrieval • communication of insights • statistical analysis	(Akter et al., 2016; Ghasemaghaei, 2019; Tetteh & Attah, 2025)
Data Driven Decision Making	5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree) Measured with • reliance on data over intuition • evaluation of alternatives • data quality assessment • trust in data over experience • decision updating, data seeking • use of reports/dashboards	(Brynjolfsson et al., 2011; Ghasemaghaei, 2019; Nisar et al., 2021; Sharda et al., 2014)
Top Management Support	5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree) Measured with • budget and resources • risk-taking in analytics adoption • staff training • evidence-based decision requirements • investment in data quality/systems	(Amoako et al., 2022; Chen et al., 2012; Shafique et al., 2024; Wixom & Watson, 2010)

Source: Authors' Summary (2026)

Variable	Operational definition	Empirical evidence
	• removal of organisational barriers	
Organisational Performance	5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree) Measured with • IGF growth, budget execution • image, revenue efficiency • employee turnover • absenteeism, productivity • complaints, service quality • implementation effectiveness • service timeliness	(Jyoti & Rani, 2017; Kumar & Singh, 2023; Popovič et al., 2018)
Source: Authors' Summary (2026)		

Data processing and analytical technique

Given the quantitative nature of the study, the completed questionnaires were organized to ensure accuracy, consistency, and completeness of the dataset. The cleaned data were then imported into SmartPLS software for advanced statistical analysis. The choice of PLS-SEM is justified by its suitability for predictive research, complex models involving multiple constructs, and its robustness in handling non-normal data distributions and relatively small to medium sample sizes (Hair et. al, 2021). All the study objectives and hypothesized relationships were analysed using the structural equation modelling (SEM) approach, following a two-stage procedure. First, the measurement model was assessed to establish the reliability and validity of the constructs using indicators such as factor loadings, composite reliability, Cronbach's alpha, average variance extracted (AVE), and discriminant validity (Hair et al., 2021; Hair et al., 2017). This step ensures that the measurement items adequately capture the latent constructs of the study. Subsequently, the structural model was evaluated to examine the hypothesized relationships among the constructs (Edwards & Lambert, 2007). The bootstrapping procedure will be employed to test the statistical significance of the path coefficients, allowing for the estimation of t-values, p-values, and confidence intervals (Hair & Sarstedt, 2019).

In addition, key diagnostic measures such as the Variance Inflation Factor (VIF) will be assessed to detect potential multicollinearity issues, while coefficients of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2) will be used to evaluate the explanatory and predictive power of the model as shown in Table 3 of the study and according to Hair (2014) and Hair and Sarstedt (2019). The results generated from the SmartPLS analysis will then be interpreted and presented using tables and figures, in

line with standard reporting practices for PLS-SEM studies. These results will provide empirical evidence to support or reject the study's hypotheses and address the research objectives comprehensively.

Table 3
Model indices

Measurement Model	**Indices**
Reliability	rho_A ≥ 0.7 (Henseler et al., 2015)
Convergent validity	Average variance extracted ≥ 0.5 (Hair et al., 2021)
Discriminant validity	Heterotrait-Monotrait Ratio ≤ 0.9 (Hair et al., 2021)
Composite reliability	Composite reliability ≥ 0.7 (Benitez et al., 2020)
Structural Model	**Indices**
Indicator reliability	Indicator loading > 0.7; p ≤ 0.05 (Benitez et al., 2020)
Coefficient of determination	R^2: Results above 0.67 (Substantial), 0.33 (Moderate) and 0.19 (Weak) (Benitez et al., 2020).
Source: Authors' Construct (2026)	

Results

Demographic characteristics

The results on the demographic characteristics of the respondents used in this study are presented in Table 4. The sample is comprised of about 55.12% males, with most of them falling within the 41 to 50 age bracket (35.43%). Most of these individuals have bachelor's degrees (56.69%), with 15 of these employees having master's degrees (11.81%). A significant proportion have qualifications less than bachelor's, comprised of SHS/High School/Vocational qualification (13.39%) and Higher National Diplomas (18.11%). About 14% of the respondents were from the works department whiles revenue, records and stores departments had 13.39%, 11.02% and 10.24% representation in the sample respectively.

Table 4
Demographic Characteristics of Respondents

	Frequency	Percentage
Gender		
Male	70	55.12
Female	57	44.88
Age		
41 to 50	45	35.43
31 to 40	32	25.20
20 to 30	24	18.90
51 to 60	26	20.47
Educational level (Completed)		
Bachelor's degree	72	56.69
Diploma/Higher National Diploma (HND)	23	18.11
Secondary/High school (SHS/Tech./Voc.)	17	13.39
Master's degree	15	11.81
Department		
Works	18	14.17
Revenue	17	13.39
Records	14	11.02
Stores	13	10.24
Internal Audit	12	9.45
Central Administration	11	8.66
Human Resource	11	8.66
Budget	7	5.51
Planning	6	4.72
Waste	5	3.94
Procurement	5	3.94
Source: Field Survey (2026)		

	Frequency	Percentage
Gender		
Legal	4	3.15
IT	4	3.15
Total	**127**	**100.00**
Source: Field Survey (2026)		

Measurement model

The study evaluated the structural model using PLS-SEM to assess how DAC influences operational performance at the CCMA, with TMS as the potential moderating variable and DDDM as the mediating pathway. However, before the structural relationships were assessed, we assessed the measurement model to establish construct validity and reliability (Henseler et al., 2015). The reflective measurement approach was employed which aided the assessment of indicator reliability, convergent validity, discriminant validity and internal consistency (Hair & Sarstedt, 2019). This ensured the measured accurately reflected the theoretical constructs while adhering to the study's key objectives.

Construct reliability and validity

From Table 5, all constructs show high internal consistency, as Cronbach's alpha values for all the measures were well above the threshold of 0.7. For rho_a, all measures scored well above 0.7 as well, indicating constructs' composite reliability (Henseler et al., 2015). Also, convergent validity was achieved since AVE scores was more significant than 0.5 for every construct measure. This confirms that the indicators represented sufficiently what they were supposed to measure (Benitez et al., 2020).

Table 5
Construct reliability, validity and Outer VIF

DAC	Loadings	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
		0.780	**0.816**	**0.852**	**0.590**
DAC2	0.809				
DAC5	0.763				
DAC6	0.726				
DAC8	0.773				
DDDM		0.911	0.919	0.938	0.790
DDDM1	0.914				
DDDM3	0.910				
DDDM5	0.912				
DDDM6	0.816				
OP		0.908	0.923	0.927	0.646
OP1	0.732				
OP10	0.825				
OP2	0.805				
OP4	0.705				
OP5	0.884				
OP6	0.837				
OP7	0.826				
TMS		0.838	0.840	0.903	0.757
TMS2	0.903				
TMS4	0.809				
TMS5	0.895				

DAC- data analytics capabilities; OP-organisational performance; TMS-top management support; DDDM-data driven decision making

Source: Field Survey (2026)

Discriminant validity

With evidence from the Heterotrait-Monotrait (HTMT) ratio, the results also indicate that all construct pairs achieve discriminant validity, since all HTMT values are well below the threshold of 0.85 (Hair et al., 2021; Henseler et al., 2015). The highest HTMT ratio is 0.595 between TMS and organisational performance, which is well below the threshold value of 0.85. All other construct pairs exhibit even lower HTMT ratios, confirming significant differences between the constructs in the study. These results provide strong evidence for the discriminant validity of the constructs, confirming that they measure distinct phenomena and are not correlated. This confirmation supports the appropriateness of the constructs and their measures for subsequent structural model analysis. The HTMT results are in Table 6.

Table 6
Discriminant validity

DDDM <-> DAC	**HTMT**
	0.554
OP <-> DAC	0.461
OP <-> DDDM	0.497
TMS <-> DAC	0.411
TMS <-> DDDM	0.401
TMS <-> OP	0.595

The values are below the threshold of 0.85 suggesting no discriminant validity issues.

Source: Field Survey (2026)

Multi-collinearity Statistics

To test for any possible collinearity issues, the study reports the Outer VIF values in Table 7. The multi-collinearity assessment results confirm all outer VIF values are below the threshold of 10, confirming the absence of collinearity in the measurement model. Several indicators showed moderate VIF values (DDDM1: 3.384, DDDM2: 3.927, DDDM5: 3.605, OP5:4.241), however, these remained within acceptable limits (Hair et al., 2021). This indicates each indicator uniquely contributes to the construct it measures, ensuring measurement distinctiveness. See Table 7.

Table 7
Outer VIF

DAC2	VIF
	2.210
DAC5	1.670
DAC6	1.838
DAC8	1.262
DDDM1	3.384
DDDM3	3.927
DDDM5	3.605
DDDM6	2.024
OP1	2.046
OP10	3.019
OP2	2.439
OP4	2.263
OP5	4.241
OP6	2.835
OP7	2.563
TMS2	2.747
TMS4	1.536
TMS5	2.748
Top Management Support x Data Analytics Capabilities	1.000

This proves that there are no issues of multicollinearity within the model as the VIF values are below 10.

Source: Field Survey (2026)

Common Method Bias

To reduce the prevalence of CMB, several ex-ante principles were applied. The pre-qualification of the respondents ensured that they had the necessary familiarity with the study's contents. Respondents were assured of the anonymity of the responses before the participants were given the items. Since the questions were written simply and unambiguously, respondents could not react to items on the structured scales using systematic response tendencies like extreme or moderate replies (Podsakoff et

al., 2012). Additionally, negative wording strategies and psychological separation were used. However, to fix the discrepancies in the data file about the negatively phrased elements, reverse coding was used.

CMB was quantified statistically using the inner VIF of the estimated model. This was done to determine whether CMB was present in the study or not. From the recommendations of Kock (2015), VIF values should be below 3.3 to confirm a lack of CMB issues in the model. In our model, all constructs exhibit VIF values well below 3.3, with 1.491 for the relationship between DAC and organisational performance being the highest. Our findings demonstrate that there are no CMB concerns for the estimated model. With these results, the true effects of the predictors on the outcome variables will not be obscured by path coefficient inflation and deflation (Kock, 2015). See Table 8.

Table 8
VIF

DAC -> DDDM	**VIF**
	1.000
DAC -> Organisational Performance	1.491
DDDM -> Organisational Performance	1.457
TMS -> Organisational Performance	1.255
TMS x DAC -> Organisational Performance	1.109
Source: Field Survey (2026)	

Structural model

After the validation of the measurement model, the structural model of the study was evaluated to systematically assess the hypothesized relationships between DAC, DDDM, TMS and organisational performance at the CCMA. The structural model in Fig. 2, represents the direct and indirect pathways through which DAC, DDDM and TMS influences organisational performance at the CCMA. The structural model assessment included key parameters such as path coefficients, significant levels (p-values), coefficient of determination (R^2) and effect sizes (f^2) to establish the strength and practical significance of each relationship. This analysis in this section focuses primarily on testing the five hypotheses: the relationship between DAC and organisational performance, the relationship between DAC and DDDM, the relationship between DDDM and organisational performance, the relationship between TMS and organisational performance, the mediating role of DDDM as well as the role of TMS.

Path coefficient

DAC has no significant effect on organisational performance ($\beta = 0.180$, $p > 0.05$). Thus, H1 is not supported, which means DAC does not in itself influence or have an effect on organisational performance. DAC however has a large, positive and highly significant effect on DDDM ($\beta = 0.518$, $p < 0.001$). Therefore, H2 is supported, implying that DAC positively influences DDDM at the CCMA as

employees DAC are able to translate into DDDM outcomes. The results also confirms that DDDM has a strong, positive and statistically significant effect on organisational performance (β = 0.230, p < 0.05). With this, sufficient evidence is tabled in support of H3. This indicates that DDDM does positively influences performance outcomes at the CCMA as employees who make data-driven decisions are able to influence performance. TMS also has a large, positive and highly significant effect on organisational performance (β = 0.402, p < 0.000). This finding also provides evidence in support of H4. This confirms that TMS does influences organisational performance outcomes. See Table 9.

Table 9
Structural Model assessment (Direct)

DAC -> OP	**Original sample (O)**	**T statistics**	**P values**	**Lower 2.5%**	**Upper 97.5%**
	0.180	**1.709**	**0.087**	**-0.044**	**0.367**
DAC -> DDDM	0.518	9.322	0.000***	0.396	0.618
DDDM -> OP	0.230	2.308	0.021*	0.037	0.43
TMS -> OP	0.402	4.374	0.000***	0.206	0.563
Note: *** p-value < 0.001, ** *p* < 0.01, * *p* < 0.05.					
Source: Field Survey (2026)					

Mediation

From Table 10, the results confirm that DDDM mediates the relationship between DAC and organisational performance at the CCMA (β = 0.119, p < 0.05), providing evidence in support of H5. This result confirms that DDDM is a vital channel through which DAC can translate into improved organisational performance outcomes.

Table 10
Structural Model assessment (Indirect)

	Original sample (O)	T statistics (|O/STDEV|)	P values	Lower 2.5%	Upper 97.5%
DAC -> DDDM -> OP	0.119	2.087	0.037*	0.017	0.244
Note: *** p-value < 0.001, ** *p* < 0.01, * *p* < 0.05.					
Source: Field Survey (2026)					

Moderation

TMS does not moderate the relationship between DAC and organisational performance at the CCMA ((β = 0.045, p > 0.05), providing no support for H6. This indicates that, for the CCMA, the level of TMS does not influence how DAC influences organisational performance. See Table 11.

Table 11
Structural Model assessment (Moderation)

	Original sample (O)	T statistics (|O/STDEV|)	P values	Lower 2.5%	Upper 97.5%
TMS x DAC -> OP	0.045	0.682	0.495	-0.081	0.178
Note: *** p-value < 0.001, ** $p < 0.01$, * $p < 0.05$.					
Source: Field Survey (2026)					

Coefficient of determination and Predictive relevance

The findings of the study demonstrate moderate explanatory power for the key constructs of interest. From the results, DAC explains 26.3% (moderate) of the variation in DDDM. For the endogenous variable, organisational performance, the exogenous variables (DAC, DDDM and TMS) combine to explain 37.4% of the variation in organisational performance. Further, the Q^2 also complements this assertion in terms of predictive relevance as it scores are above zero. Further, the f^2 shows the individual contribution of each exogenous variable with DAC exhibiting the highest effect on DDDM. TMS also exhibits a notable influence on organisational performance. These measures confirm the model's predictiveness and further robustness. See Table 12.

Table 12
Coefficient of Determination and Predictive Relevance

DDDM	**R^2**	**Adj-R^2**	**f^2**	**Q^2**
	0.269	**0.263**		**0.248**
OP	**0.394**	**0.374**		**0.293**
DAC -> DDDM			0.368	
DAC -> OP			0.036	
DDDM -> OP			0.060	
TMS -> OP			0.212	
TMS x DAC -> OP			0.005	
Source: Field Survey (2026)				

Robustness tests

The study conducted several robustness tests to validate the model's stability and predictive power, ensuring the reliability and validity of our findings. These tests confirms that results as reported are not

abstract in themselves but reflect genuine relationships in the data. These robustness tests included an assessment of the model's predictive relevance through f^2 and Q^2.

Discussion of Results

This study sort to establish the relationship between DAC, DDDM, TMS and organisational performance, using evidence from an emerging economy's local government assembly. Grounded in the OIPT and the UET, the study conceptualized DAC as a critical information processing capability, DDDM as a mechanism for reducing uncertainty and improving decision quality and TMS as a reflection of leadership influence on organisational outcomes. The results present a nuanced understanding of how these constructs interact within a public sector context.

The first hypothesis (H1) posited that DAC has a significant effect on organisational performance. However, the findings revealed that DAC has no statistically significant effect on organisational performance at the CCMA. This suggest that possessing DAC alone does not automatically translate into improved performance outcomes. This finding contrasts with several empirical studies including Chen et al. (2016), Awan et al. (2021) and Al-Dmour et al. (2023), which found a direct positive relationship between analytics capabilities and performance. We argue that bureaucratic processes, limited autonomy and structural rigidities at the CCMA may inhibit the direct conversion of DAC into performance gains. Also, from the perspective of OIPT, while DAC enhances an organisation's capacity to process information, performance improvements are contingent on how effectively this information is utilized in decision-making processes. This finding highlights a critical gap between capability possession and capability utilization, particularly in developing country public sector institutions. Therefore, the lack of support for H1 underscore the importance of complementary mechanisms, in translating DAC into performance.

The second hypothesis (H2) examined the relationship between DAC and DDDM. The results indicate a strong, positive and highlight significant effect of DAC on DDDM, supporting H2. This finding aligns with Ghasemaghaei and Calic (2019) and Shamim et al. (2020), which demonstrate that analytics capabilities enhance the quality and effectiveness of decision-making. Similarly, Dlamini (2024) found that big data analytics significantly improves decision-making processes in African financial institutions. Within the CCMA, this suggests that investments in analytics infrastructure, tools, and skills are effectively enabling employees to make more informed, data-driven decisions. From the lens of OIPT, this finding confirms that DAC strengthens the organisation's information processing capacity, thereby reducing uncertainty and improving decision quality.

The findings provide strong support for third hypothesis (H3), indicating that DDDM significantly enhances performance outcomes at the CCMA. This is consistent with studies such as Popovič et al. (2018), Nisar et al. (2021), and Li et al. (2022), which establish that data-driven decisions lead to improved efficiency, effectiveness, and overall organisational performance. In line with OIPT, organisations that utilise data in decision-making are better able to align their actions with environmental demands, thereby improving outcomes. In the Ghanaian context, the adoption of DDDM

can significantly enhance service delivery and operational efficiency. This finding reinforces the central role of decision-making as a driver of performance rather than merely the availability of data or analytics tools.

The mediating role of DDDM (H4) was also confirmed, indicating that DDDM serves as a critical pathway through which DAC influences organisational performance. This finding is consistent with prior empirical evidence from Nisar et al. (2021), Awan et al. (2021), and Shamim et al. (2019), which highlight the mediating role of decision-making in the analytics-performance relationship. The implication is that DAC does not directly improve performance but does so indirectly by enhancing decision-making processes. From an OIPT perspective, this reinforces the notion that information processing capabilities create value only when they are embedded in organisational decision-making routines. This finding also explains the non-significant direct effect observed in H1, suggesting a full mediation effect where DDDM fully channels the impact of DAC on performance. In the context of the CCMA, this underscores the need to prioritise the integration of analytics into decision-making processes rather than merely investing in data infrastructure.

The findings on the fifth hypothesis (H5) indicates that TMS has a strong, positive, and highly significant effect on performance. This result is consistent with empirical studies such as Shafique et al. (2024) and Lai et al. (2018), which emphasise the critical role of leadership in driving organisational outcomes. From the perspective of Upper Echelons Theory, organisational performance is a reflection of the values, priorities, and decisions of top management. At the CCMA, this finding suggests that leadership commitment, resource allocation, and strategic direction significantly influence performance outcomes. In public sector settings, where hierarchical structures are prominent, the role of top management becomes even more critical in shaping organisational effectiveness.

The results sixth hypothesis (H6) confirms that TMS does not play a moderating effect in the DAC-organisational performance relationship. This suggests that the level of TMS does not significantly influence how DAC translates into performance outcomes at the CCMA. This finding contrasts with studies such as Shamim et al. (2020) and Shafique et al. (2024), which found that leadership support strengthens the impact of analytics capabilities on performance. This means within the CCMA, TMS is directly linked to overall organisational functioning rather than specifically enhancing the effectiveness of analytics capabilities. From a UET perspective, this implies that while leadership plays a direct role in influencing performance, it may not necessarily shape the effectiveness of specific organisational capabilities such as DAC. This finding highlights a contextual nuance in public sector organisations, where formal structures and processes may limit the moderating influence of leadership.

The overall model demonstrates moderate explanatory power, with DAC explaining 26.3% of the variance in DDDM and the combined effects of DAC, DDDM, and TMS explaining 37.4% of the variance in organisational performance. The positive Q^2 values further confirm the model's predictive relevance, while the effect size (f^2) results indicate that DAC has the strongest influence on DDDM and that TMS has a notable effect on organisational performance. These findings suggest that while the model is

robust and predictive, a significant proportion of variance in organisational performance remains unexplained, pointing to the potential influence of other organisational, institutional, or environmental factors not captured in this study.

Conclusion

This study examined the influence of DAC, DDDM and TMS on organisational performance at an emerging economy's local government assembly, drawing on the OIPT and the UET. The findings show that DAC does not directly improve organisational performance but significantly enhances DDDM, which in turn drives performance outcomes. This confirms that the value of analytics capabilities lies in their effective use within decision-making processes rather than their mere existence. The results further show that DDDM plays a significant mediating role in the relationship between DAC and organisational performance, highlighting it as a key pathway through which DAC translate into tangible outcomes. In addition, TMS emerged as a strong determinant of organisational performance, underscoring the critical role leadership plays in shaping organisational success. However, TMS does not significantly moderate the relationship between DAC and performance at the CCMA, suggesting that leadership influence operates more directly rather than by strengthening analytics-performance linkages.

Theoretical contribution

This study makes important theoretical contributions by extending the application of the OIPT and UET within the context of data analytics and public sector performance in emerging economies. Especially, the first to provide evidence on these dynamics from an emerging economy's local government assembly perspective. The study refines OIPT by demonstrating that DAC, while enhancing an organisation's information processing capacity, do not directly translate into improved organisational performance. Instead, their value is realised through DDDM, which fully mediates the relationship between DAC and performance. This finding advances OIPT by empirically confirming that the mere availability of information processing capabilities is insufficient; what matters is how effectively such capabilities are embedded in decision-making processes to reduce uncertainty and improve outcomes. The study further contributes to the information processing literature by positioning DDDM as a critical organisational mechanism through which information is transformed into actionable outcomes. By establishing the significant mediating role of DDDM, the research highlights that decision-making quality is the true conduit through which data resources generate value. This adds nuance to existing theoretical perspectives by shifting emphasis from technological capability to its utilisation, particularly in public sector contexts.

In addition, the study extends UET by providing empirical evidence on the direct role of TMS in influencing organisational performance. The findings reinforce the central premise of UET that organisational outcomes are shaped by the values, priorities, and actions of top executives. In the context of the CCMA, TMS emerges as a dominant driver of performance, underscoring the importance of leadership commitment in resource allocation, strategic direction, and organisational effectiveness.

However, the study also introduces an important nuance by showing that TMS does not significantly moderate the relationship between DAC and organisational performance. This suggests that while leadership is critical for overall performance, it may not necessarily enhance the effectiveness of specific organisational capabilities such as data analytics. Also, the study contributes to the growing body of literature on data analytics in emerging economies by providing context-specific insights from a Ghanaian public sector institution. It challenges the often-implicit assumption in prior studies that analytics capabilities inherently lead to improved performance, instead demonstrating that contextual factors play a crucial role in shaping outcomes. This highlights the need for theoretical models to better account for organisational context, particularly in public sector and developing country settings.

Managerial implication

This study offers clear managerial implications for the CCMA and similar local government and public sector institutions. The management of local government assemblies should not assume that merely investing in data analytics tools, systems, or technical capacity will automatically improve organisational performance. The findings show that DAC does not directly drive performance; its value is realised only when it is translated into DDDM. Consequently, managers must move beyond technology acquisition and ensure that data is actively embedded in planning, budgeting, service delivery, monitoring, and administrative decision processes. Again, management should prioritise building a strong decision culture around data use. Staff should be trained not only to generate and analyse data but also to interpret and apply it in solving operational and strategic problems. This suggests that capacity-building efforts in local government assemblies should focus less on technical analytics alone and more on converting analytics outputs into actionable decisions. Regular performance review meetings, departmental dashboards, and evidence-based reporting systems would help institutionalise this process.

Also, senior managers at the assembly must provide direction, allocate resources, and signal the strategic importance of data use across departments. They must champion performance improvement efforts, enforce the use of evidence in decision-making, and create an environment where data is treated as a managerial asset rather than a compliance requirement. However, because TMS does not moderate the DAC-performance relationship, management support should not be limited to endorsing analytics initiatives; it should directly strengthen organisational systems, supervision, coordination, and performance management.

Limitations and future research

While this study provides useful evidence on these relationships, some limitations should be noted. The cross-sectional design restricts strong causal inference, even though the structural model shows significant paths. Future studies should adopt longitudinal designs to test whether these relationships remain stable over time. Also, because the study was conducted within a single public sector institution, the findings may not be fully generalisable to other local government or public sector organisations

operating under different institutional conditions. Comparative studies across multiple public institutions would strengthen external validity. Again, although the model showed moderate explanatory power and predictive relevance, a substantial share of organisational performance remains unexplained, suggesting that other factors such as organisational culture, data literacy, technological readiness, structure, and environmental uncertainty should be integrated into future models to provide a fuller explanation of performance in public sector settings.

Ethical Statement and Informed Consent

This study was appropriately conducted in reference to accepted ethical standards in research and recommendations by the Human Resource and Ethics Department of the CCMA. Participation was voluntary and respondents were informed of the study's goals prior to participation. Further, no respondent was coerced or forced to partake in the process. These respondents were also assured of their strict confidentiality and anonymity and their rights to withdraw from the research at any time without consequence. The information solicited were used only for academic purposes.

Declaration of competing interests

The authors state that there are no known competing financial or personal interests that could have influenced this study in any form or direction.

Data Availability Statement

The data that support the findings of this study are not publicly available due to privacy and ethical restrictions governing the participants who took part in the survey. However, the data may be made available upon request to the corresponding author, subject to applicable ethical and institutional guidelines.

Declarations

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Author Contributions

A.N.K.A. conceptualised the research, prepared main manuscript, reviewed literature, designed data collection instruments and analysed the results. M.F. conceptualised the research, prepared main manuscript, designed the research methods, supervised data collection and analysed the results. B.B. prepared main manuscript, supervised data collection and formatted tables and figures. E.E.A. reviewed the manuscript, validated instruments, reviewed research methods and results. J.A. reviewed the manuscript, reviewed and validated the results. E.A. reviewed the results, validated research instruments, edited and formatted the manuscript. All authors reviewed the manuscript.

Declaration of AI-assisted technologies use

As authors, we declare that no Generative AI tools were used in the design, data collection, statistical analysis or interpretation of findings. All analytical work was conducted by the authors using PLS-SEM via the SMARTPLS software. Generative AI tools such as the premium versions of ChatGPT and Claude Sonnet 4.6 were used in a limited and assistive capacity for proofreading and improving the grammatical fluency of selected sections of the manuscript. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article. All intellectual content, arguments, theoretical framing and conclusions are entirely the original work of the authors.

References

1. Adam AM (2015) Statistics for business research. Global Research
2. Akter S, Wamba SF, Gunasekaran A, Dubey R, Childe SJ (2016) How to improve firm performance using big data analytics capability and business strategy alignment? Int J Prod Econ 182:113–131. https://doi.org/https://doi.org/10.1016/j.ijpe.2016.08.018
3. Aladejebi O, Oladimeji JA (2019) The Impact of Record Keeping On the Performance of Selected Small and Medium Enterprises in Lagos Metropolis. J Small Bus Entrepreneurship Dev 7(1). https://doi.org/10.15640/jsbed.v7n1a3
4. Amoako DK, Zakuan N, Dwomoh A, Tetteh F, Effah IA (2022) The Effect of Top Management Support on Environmental Sustainability. Does Supplier Development Matter in the Ghanaian Cocoa Industry? Int J Acad Res Bus Social Sci 12(4):1135–1150. https://doi.org/10.6007/IJARBSS/v12-i413198
5. Assembly C-CM (2025) *Annual Report 2024*

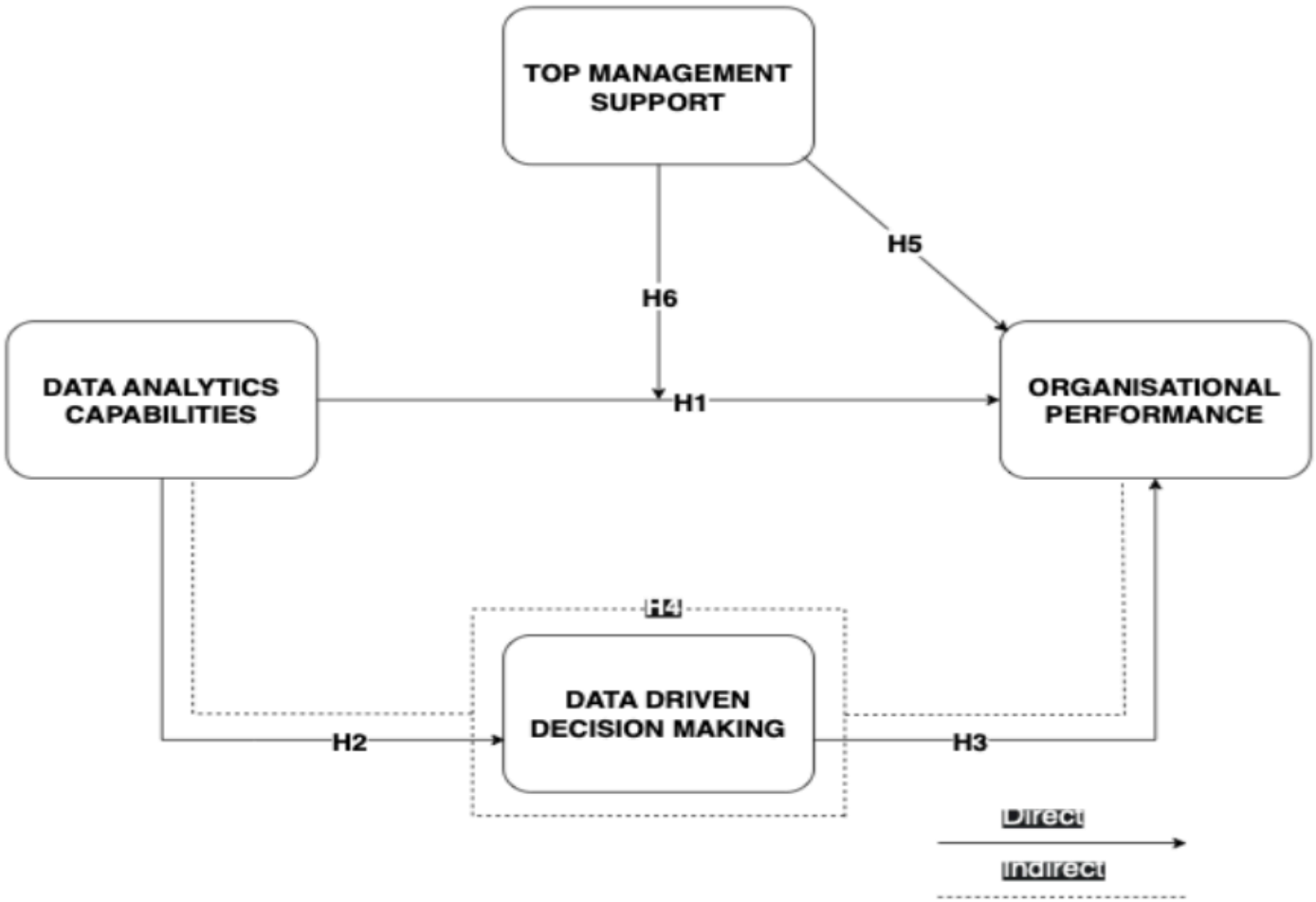
6. Awan U, Shamim S, Khan Z, Zia NU, Shariq SM, Khan MN (2021) Big data analytics capability and decision-making: The role of data-driven insight on circular economy performance. Technol Forecast Soc Chang 168:120766. https://doi.org/https://doi.org/10.1016/j.techfore.2021.120766
7. Batistič S, van der Laken P (2019) History, Evolution and Future of Big Data and Analytics: A Bibliometric Analysis of Its Relationship to Performance in Organizations. Br J Manag 30(2):229–251. https://doi.org/10.1111/1467-8551.12340
8. Blenkinsop SA (1993) Organisational aspects of information processing systems. Loughborough University
9. Bose S, Dey SK, Bhattacharjee S (2023) Big data, data analytics and artificial intelligence in accounting: An overview. In *Handbook of Big Data Research Methods* (Eds., Vol. 61, Issue 2, pp. 1–34). Forthcoming. https://doi.org/10.4337/9781800888555.00007
10. Brynjolfsson E, Hitt LM, Kim HH (2011) Strength in numbers: How does data-driven decisionmaking affect firm performance? *Available at SSRN 1819486*
11. Cape Coast Metropolitan Assembly (2025) Annual Internal Audit Report on the Assembly. Internal Audit Department Records
12. Chen DQ, Preston DS, Swink M (2016) Creation in Supply Chain Management. J Manage Inform Syst 32(4):4–39. https://doi.org/10.1080/07421222.2015.1138364. How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management How the Use of Big Data Analytics Affects Value
13. Chen H, Chiang RHL, Storey VC (2012) Business intelligence and analytics: From big data to big impact. MIS Q, 1165–1188
14. Deniswara K, Handoko BL, Mulyawan AN (2020) Big data analytics: Literature study on how big data works towards accountant millennial generation. Int J Manage 11(5):376–389. https://doi.org/10.34218/IJM.11.5.2020.037
15. Dlamini Z, Dlamini Z (2024) Influence of Big Data Analytics on Decision-Making Processes in Financial Firms in South Africa Influence of Big Data Analytics on Decision-Making Processes in Financial Firms in South Africa. Am J Data Inform Knowl Manage 5(1):14–15
16. Edwards JR, Lambert LS (2007) Methods for integrating moderation and mediation: a general analytical framework using moderated path analysis. Psychol Methods 12(1):1
17. Franke F, Hiebl MRW (2023) Big data and decision quality: the role of management accountants data analytics skills. Int J Acc Inform Manage 31(1):93–127. https://doi.org/10.1108/IJAIM-12-2021-0246
18. Ghasemaghaei M (2019) Does data analytics use improve firm decision making quality? The role of knowledge sharing and data analytics competency. Decis Support Syst 120:14–24. https://doi.org/https://doi.org/10.1016/j.dss.2019.03.004
19. Ghasemaghaei M, Calic G (2019) Can big data improve firm decision quality? The role of data quality and data diagnosticity. Decis Support Syst 120:38–49. https://doi.org/https://doi.org/10.1016/j.dss.2019.03.008

20. Grossi G, Kallio KM, Sargiacomo M, Skoog M (2020) Accounting, performance management systems and accountability changes in knowledge-intensive public organizations: A literature review and research agenda. Acc Auditing Account J 33(1):256–280. https://doi.org/10.1108/AAAJ-02-2019-3869
21. Gupta A, Deokar A, Iyer L, Sharda R, Schrader D (2018) Big Data & Analytics for Societal Impact: Recent Research and Trends. Inform Syst Front 20(2):185–194. https://doi.org/10.1007/s10796-018-9846-7
22. Hair JF (2014) A primer on partial least squares structural equation modeling (PLS-SEM). sage
23. Hair JF, Hult GTM, Ringle CM, Sarstedt M (2017) A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), 2nd edn. SAGE
24. Hasan AR (2022) Artificial Intelligence (AI) in Accounting & Auditing: A Literature Review. Open J Bus Manage 10(01):440–465. https://doi.org/10.4236/ojbm.2022.101026
25. Henseler J, Ringle CM, Sarstedt M (2015) A new criterion for assessing discriminant validity in variance-based structural equation modeling. J Acad Mark Sci 43(1):115–135. https://doi.org/10.1007/s11747-014-0403-8
26. Joubert A, Murawski M, Bick M (2023) Measuring the Big Data Readiness of Developing Countries – Index Development and its Application to Africa. Inform Syst Front 25(1):327–350. https://doi.org/10.1007/s10796-021-10109-9
27. Jyoti J, Rani A (2017) High performance work system and organisational performance: role of knowledge management. Personnel Rev 46(8):1770–1795. https://doi.org/10.1108/PR-10-2015-0262
28. Kalema BM, Busobozi VV (2020) *Big Data Analytics for Data Quality Improvement to Enhance Evidence-Based Health Care in Developing Countries BT - Performance Management of Integrated Systems and its Applications in Software Engineering* (M. Pant, T. K. Sharma, S. Basterrech, & C. Banerjee, Eds.; pp. 29–42). Springer Singapore. https://doi.org/10.1007/978-981-13-8253-6_4
29. Kumar A, Singh RK (2023) Supply chain management practices, retail outlets attributes and organisational performance : a case of organised food retailers in India. J Global Oper Strategic Sourc 16(2):568–589. https://doi.org/10.1108/JGOSS-12-2021-0107
30. Kumi CA, Andoh-baidoo FK, Asamoah D, Agyei-owusu B, Asamoah D, Andoh-baidoo FK, Agyei-owusu B (2024) Leveraging Big Data Analytics to Improve Supply Chain Robustness: A Dynamic Capabilities Perspective. *Association for Information Systems AIS Electronic Library*
31. Lai Y, Sun H, Ren J (2018) Understanding the determinants of big data analytics (BDA) adoption in logistics and supply chain management An empirical investigation. Int J Logistics Manage 29(2):676–703. https://doi.org/10.1108/IJLM-06-2017-0153
32. Li L, Lin J, Ouyang Y, Luo X (2022) Evaluating the impact of big data analytics usage on the decision-making quality of organizations. Technol Forecast Soc Chang 175:121355. https://doi.org/https://doi.org/10.1016/j.techfore.2021.121355

33. Marfo SJ, Boateng R (2015) Developing big data capabilities in developing countries: Evidence from a cross industry study in Ghana. *2015 Regional Conference of the International Telecommunications Society (ITS): The Intelligent World: Realizing Hopes, Overcoming Challenges*.
34. Maroufkhani P (2023) Determinants of big data analytics adoption in small and medium- sized enterprises (SMEs). Industrial Manage Data Syst 123(1):278–301. https://doi.org/10.1108/IMDS-11-2021-0695
35. Mikalef P, Pateli A (2017) Information technology-enabled dynamic capabilities and their indirect effect on competitive performance: Findings from PLS-SEM and fsQCA. J Bus Res 70:1–16. https://doi.org/https://doi.org/10.1016/j.jbusres.2016.09.004
36. Nisar QA, Nasir N, Jamshed S, Ali M, Ali S (2021) Big data management and environmental performance: role of big data decision-making capabilities and decision- making quality. J Enterp Inform Manage 34(4):1061–1096. https://doi.org/10.1108/JEIM-04-2020-0137
37. Ofori WO (2024) *Unlocking the potential: A systematic analysis of big data applications in Ghanaian academic libraries*. https://doi.org/10.1177/02666669241227912
38. Otchere SK, Nyamewaa EB, Hammond F (2022) Big Data Characteristics and Innovation Performance in Ghanaian Manufacturing Firms: The Role of the Big Data Team? *Open Access Library Journal*, *9*. https://doi.org/10.4236/oalib.1108378
39. Popovič A, Hackney R, Tassabehji R, Castelli M (2018) The impact of big data analytics on firms' high value business performance. Inform Syst Front 20(2):209–222. https://doi.org/10.1007/s10796-016-9720-4
40. Prempeh A, Osei B, Osei F, Kuffour EO (2022) Accounting Records Keeping and Growth of Small and Medium Enterprises in Kumasi Metropolitan. Open J Social Sci 10(13):184–207. https://doi.org/10.4236/jss.2022.1013015
41. Saleh I, Marei Y, Ayoush M, Abu Afifa MM (2023) Big Data analytics and financial reporting quality: qualitative evidence from Canada. J Financial Report Acc 21(1):83–104. https://doi.org/10.1108/JFRA-12-2021-0489
42. Shafique MN, Yeo SF, Tan CL (2024) Roles of top management support and compatibility in big data predictive analytics for supply chain collaboration and supply chain performance. Technol Forecast Soc Chang 199:123074. https://doi.org/https://doi.org/10.1016/j.techfore.2023.123074
43. Shamim S, Zeng J, Khan Z, Zia NU (2020) Big data analytics capability and decision making performance in emerging market firms: The role of contractual and relational governance mechanisms. Technol Forecast Soc Chang 161(1):120315. https://doi.org/10.1016/j.techfore.2020.120315
44. Shamim S, Zeng J, Shariq SM, Khan Z (2019) Role of big data management in enhancing big data decision-making capability and quality among Chinese firms: A dynamic capabilities view. Inform Manage 56(6):1–12. https://doi.org/10.1016/j.im.2018.12.003
45. Sharda R, Delen D, Turban E, Aronson J, Liang T (2014) Business intelligence and analytics. *System for Decesion Support*, *398*, 2014

46. Tetteh FK, Attah J (2025) Big data analytics capability and dimensions of business model innovation: the mediating role of strategic orientations under varying conditions of market dynamism. J Enterprising Communities: People Places Global Econ 1750–6204. https://doi.org/10.1108/JEC-09-2024-0180
47. Tushman ML, Nadler DA (1978) Information Processing as an Integrating Concept in Organizational Design. Acad Manage Rev 3(3):613–624. https://doi.org/10.5465/amr.1978.4305791
48. Wixom B, Watson H (2010) The BI-based organization. Int J Bus Intell Res (IJBIR) 1(1):13–28

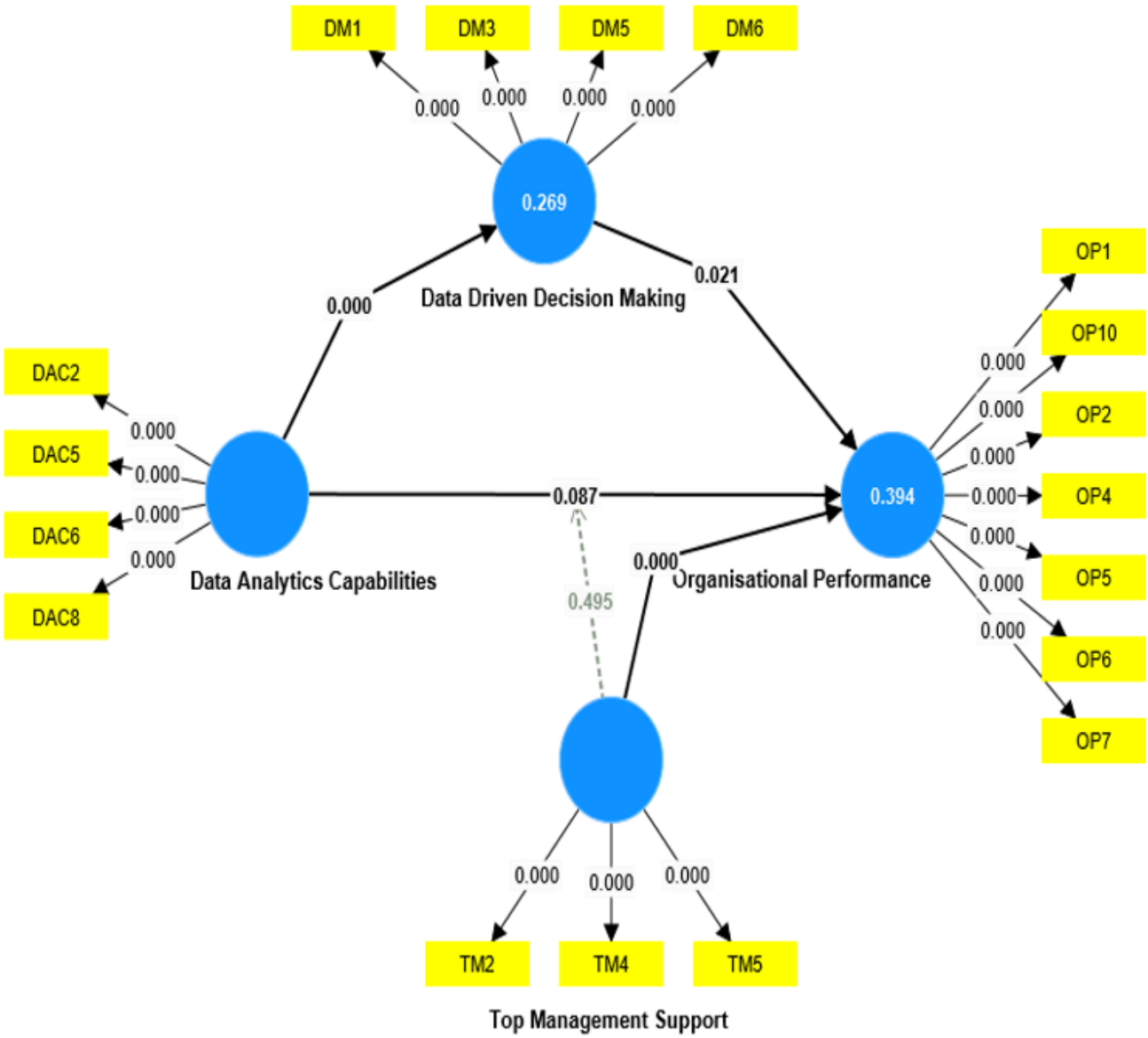
Figures



Source: Authors' Construct (2026)

Figure 1

Conceptual framework



PLS Bootsrapp image
Source: Field Survey (2026)

Figure 2

PLS Bootsrapp image