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El papel del liderazgo de servicio y del liderazgo del conocimiento en el análisis de grandes datos: Perspectivas de oficiales militares en la Escuela Superior de Guerra del Ejército del Perú.

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Resumen

Determinar la influencia del liderazgo servicial y del liderazgo del conocimiento en la adopción de la analítica de grandes datos dentro de la Escuela Superior de Guerra del Ejército. En particular, se analiza cómo el liderazgo impacta la toma de decisiones basada en datos y si dicha relación es mediada por el capital intelectual. El estudio adopta un enfoque cuantitativo, utilizando el modelado de ecuaciones estructurales mediante mínimos cuadrados parciales para analizar datos recopilados de 187 oficiales del Curso de Comando y Estado Mayor de la Escuela Superior de Guerra del Ejército del Perú. Se evalúan siete hipótesis relacionadas con los efectos directos y mediadores del liderazgo sobre la adopción de la analítica de grandes datos. Los hallazgos confirman que el liderazgo servicial promueve significativamente la adopción de la analítica de grandes datos al fomentar una cultura organizacional empoderada y orientada a los datos. El liderazgo del conocimiento también cumple un rol mediador clave, facilitando la implementación exitosa de dicha analítica mediante mecanismos de intercambio de conocimiento. No obstante, el capital intelectual no influye directamente en la adopción de la analítica de grandes datos, lo que indica que su impacto depende de otros factores estratégicos como el compromiso del liderazgo, la transformación digital y los marcos de inteligencia operativa. Los resultados ofrecen orientaciones concretas para instituciones militares interesadas en fortalecer sus capacidades analíticas. El estudio destaca la importancia de los programas de formación en liderazgo para fomentar la toma de decisiones basada en datos, el intercambio de conocimientos y el desarrollo de estrategias de inteligencia colaborativa. Asimismo, se resalta la necesidad de institucionalizar el liderazgo del conocimiento como parte integral de la modernización militar para optimizar operaciones de inteligencia, planificación de misiones y gestión estratégica de la logística. Este estudio contribuye al campo de la investigación sobre liderazgo y analítica en contextos de defensa, al proporcionar evidencia empírica sobre cómo los modelos de liderazgo influyen en la adopción de la analítica de grandes datos en instituciones militares. La integración del liderazgo servicial y del liderazgo del conocimiento en la estrategia militar representa un enfoque novedoso para mejorar la eficiencia operativa mediante sistemas de inteligencia basados en datos. Esta investigación es especialmente valiosa para líderes militares, responsables de políticas de defensa y planificadores estratégicos que buscan modernizar los procesos de toma de decisiones dentro del Ejército del Perú y otras organizaciones castrenses.

Palabras clave: Capital intelectual, analítica de grandes datos, Escuela Superior de Guerra del Ejército del Perú

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The Role of Servant Leadership and Knowledge Leadership in Big Data Analysis: Perspectives of Military Officers at the Peruvian Army War College.

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Abstract

This study explores the impact of Servant Leadership (SL) and Knowledge Leadership (KL) on the adoption of Big Data Analytics (BDA) within military institutions. Specifically, it analyzes how leadership influences data-driven decision-making and whether Intellectual Capital (IC) mediates this relationship. The study employs a quantitative research design, using Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze data from 187 officers enrolled in the Command and General Staff Course at the Peruvian Army War College (Escuela Superior de Guerra del Ejército del Perú). The model tests seven hypotheses regarding leadership's direct and mediating effects on BDA adoption. The results confirm that Servant Leadership (SL) significantly enhances BDA adoption by fostering an empowered, data-driven organizational culture. Knowledge Leadership (KL) also serves as a key mediator, facilitating the successful implementation of BDA through knowledge-sharing mechanisms. However, Intellectual Capital (IC) does not directly influence BDA adoption, suggesting that its role depends on additional strategic enablers, such as leadership commitment, digital transformation, and operational intelligence frameworks. These findings provide practical insights for military institutions seeking to enhance their analytics capabilities. The study highlights the importance of leadership development programs in promoting data-driven decision-making, knowledge-sharing, and collaborative intelligence strategies. In addition, it emphasizes the need to institutionalize knowledge leadership within the military to optimize intelligence operations, mission planning, and strategic logistics management. This study contributes to the growing body of research on leadership and military analytics by providing empirical evidence on how leadership models impact BDA adoption in defense institutions. Integrating Servant Leadership and Knowledge Leadership into military strategy introduces a novel framework for enhancing operational efficiency through data-driven intelligence systems. This study is particularly valuable for military leaders, defense policymakers, and strategic planners looking to modernize decision-making processes within the Peruvian Army and other military organizations.

Keywords: Intellectual capital, big data analytics, Army War College

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1. Introducción

In defense, particularly in the Army, strategic decision-making must be guided by data. According to Chen and Zhang, in 2023, adopting Big Data Analytics (BDA) has become essential for improving operations and organizational performance. However, effectively implementing BDA in military institutions depends on several organizational and leadership factors (Rettore et al., 2024). In this context, leadership fosters an organizational culture that values data-driven decision-making (Kokkinou et al., 2024).

This study explores how Servant Leadership (SL) and Knowledge Leadership (KL) influence the adoption of Big Data Analytics (BDA) in military institutions. It determines how these leadership styles support the integration of analytical tools and whether Intellectual Capital (IC) acts as a mediator in this relationship. The relevance of this research lies in the need to understand how leadership capabilities can strengthen the digitalization and modernization of military operations in a strategic defense context (Liwång et al., 2023). In various organizations, BDA enhances planning, supply chain management, and data-driven decision-making (Roßmann et al., 2017). Recent research from indexed databases such as Web of Science and Scopus underscores that the successful implementation of BDA in dynamic institutions depends not only on technological advancements but also on leadership's ability to cultivate an analytical culture (Bag et al., 2021; Schmidt et al., 2023). In particular, Servant Leadership fosters team autonomy and encourages the adoption of new technologies (Hamyeme et al., 2024), while Knowledge Leadership facilitates the efficient transfer and application of information in strategic decision-making processes (Mahdi, 2021).

Despite the growing interest in studying BDA across various settings, significant gaps in the global literature, particularly in the military domain, require further exploration. First, the combined impact of Servant Leadership and Knowledge Leadership on adopting BDA in the military sector has not been analyzed, limiting the understanding of how these leadership styles can enhance data-driven decision-making. Second, the role of Intellectual Capital as a potential mediator in the relationship between these leadership styles and BDA adoption remains unexplored, highlighting the need for studies that delve deeper into its influence within this strategic context. This study contributes to the literature by addressing these gaps through an empirical analysis that evaluates the impact of different leadership styles on BDA adoption in the military field. Unlike previous studies, this research examines the direct relationship between leadership and BDA. It explores the mediating role of Intellectual Capital, providing a more comprehensive model of how analytical capabilities develop within defense institutions.

This research is grounded in two key theories: the Resource-Based View (RBV) and the Dynamic Capabilities Theory (DCT). RBV emphasizes the importance of resources, skills, competencies, and capabilities in generating sustainable competitive advantage. Over time, this theory has evolved by incorporating approaches such as the knowledge-based view and dynamic capabilities, which have expanded its conceptual framework (Barney, 1991).

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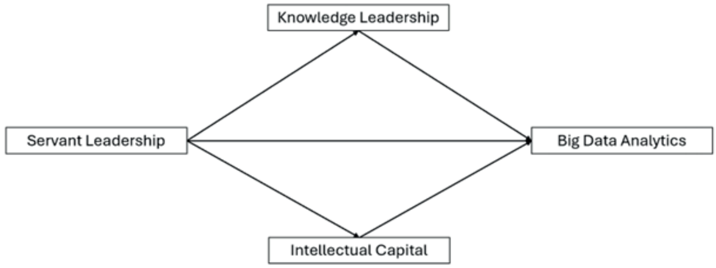
Meanwhile, dynamic capabilities represent the organizational and strategic processes that enable companies to adapt and evolve in dynamic environments. These capabilities involve creating, reconfiguring, and renewing resources, highlighting interaction and continuous learning within the organization as key factors for achieving sustainable competitive advantage (Teece et al., 1997).

Figure 1 presents the proposed research model.

Figure 1:
Proposed Model



2. Literature Review and Hypothesis Development

2.1 Servant Leadership

Servant leadership is a leadership philosophy rooted in values, emphasizing the well-being of others and advocating for social justice, as Eva et al. (2019) highlighted. This leadership style is defined by its focus on empowering and nurturing individuals, demonstrating humility, authenticity, interpersonal acceptance, and stewardship while also providing clear guidance, according to Van Dierendonck (2011). Servant leaders strongly emphasize fostering their followers' growth and development, creating an environment where individuals can flourish, as noted by Lee et al. (2019). Their role encompasses strategic and operational responsibilities, which are reinforced by specific servant leadership traits and competencies, as discussed by Coetzer et al. (2017). In comparison to other leadership approaches, servant leadership plays a crucial role in strengthening trust within groups, which enhances organizational commitment and employee engagement, ultimately boosting overall work performance, as observed by Ling et al. (2017).

2.2 The Relationship Between Servant Leadership and Big Data Analytics

Big Data Analytics examines large and varied data sets to uncover hidden patterns, unknown correlations, market trends, customer preferences, and other

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helpful information (Hariri et al., 2019). Big data is characterized by its large volume, high velocity of data generation, and variety of data types, including structured and unstructured data (Lee, 2017). Servant leadership positively influences Big Data Analytics by empowering employees to embrace data-driven decision-making (Kumar & Chauhan, 2024). Servant leadership positively influences Big Data Analytics by fostering a team-oriented environment; servant leaders encourage open discussions about data insights. Servant leaders remove bureaucratic barriers, allowing data scientists and analysts to experiment with new BDA techniques (Oratis, 2022).

H1: Servant leadership has a positive influence on Big Data Analytics.

2.3 Mediating Effect of Knowledge Leadership

Knowledge leadership involves creating a climate that supports learning and innovation. Leaders act as role models and facilitate learning processes, crucial for enhancing organizational capabilities and innovation performance (Viitala, 2004). Key characteristics of knowledge leadership include intellectual, open, multi-dimensional, innovative, transformative, and strategic characteristics, which play different roles in the knowledge management process (Qiong, 2010). Servant leadership promotes a knowledge-sharing culture by building trust and encouraging open communication among employees (Zaher, 2015). Servant leadership positively influences knowledge leadership through public service motivation and corporate social responsibility (Tuan, 2016). Servant leadership positively correlates with knowledge management, which has a significant positive relationship with cost-saving innovation (Bazyar et al., 2024). Moreover, servant leadership positively influences employee creativity and work role performance, with knowledge sharing partially mediating this relationship (Zada et al., 2023). Based on this literature review, the following hypothesis is developed:

H2: Servant leadership positively influences knowledge leadership.

Leadership centered on knowledge is crucial in strengthening innovation capabilities by fostering a culture that prioritizes data analytics maturity, as Kadarsah et al. (2023) emphasized. Leadership focusing on knowledge management can facilitate integrating and effectively using data analytics, resulting in improved decision-making and a more decisive competitive edge, as Ferraris et al. (2019) noted. Knowledge Leadership is essential for building key BDA competencies, including data analytical skills and problem-solving abilities, which are critical for enhancing security, privacy, and innovation, ultimately leading to improved organizational performance, as Koohang et al. (2023) highlighted. Based on this literature review, the following hypothesis is proposed:

H3: Knowledge leadership positively influences big data analytics.

H4: Knowledge leadership mediates the relationship between servant leadership and big data analytics

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2.3 Mediating Effect of Intellectual Capital

Intellectual capital refers to an organization's intangible assets and resources that contribute to its value and competitive advantage, encompassing the workforce's knowledge, skills, competencies, and other intangible organizational factors (Singhania et al., 2025). Intellectual capital components include human capital, structural capital, relational capital, and innovation capital (Kweh et al., 2024). Human capital includes employees' knowledge, skills, experience, and competencies, often considered the most crucial component as it directly influences innovation and organizational performance (Pigola et al., 2021). Structural capital refers to the supportive infrastructure, processes, databases, organizational culture, and intellectual property that enable human capital to function effectively, including business models and organizational routines (Castro & Sáez, 2008). Relational capital encompasses the relationships and networks a company maintains with external stakeholders, such as customers, suppliers, and partners, playing a vital role in maintaining competitive advantage and fostering innovation (Ali et al., 2021). Servant leadership positively influences intellectual capital by fostering an environment that enhances employees' innovative capabilities and organizational performance (Alasmari et al., 2025). Servant leadership, particularly in academic settings, enhances the intrapreneurial ability of working professionals by boosting their self-efficacy, which augments the organization's intellectual capital through continuous innovation and effective change management (Khatri et al., 2023). Based on this literature review, the following hypothesis is developed:

H5: Servant leadership positively influences Intellectual capital

Intellectual capital (IC) significantly enhances big data analytics (BDA) by providing the necessary intangible resources and capabilities that drive effective data utilization and innovation (Alkhatib & Valeri, 2024). Intellectual capital, comprising human, structural, and relational capital, positively correlates with developing big data analytical capabilities. These capabilities, in turn, improve internal integration and operational performance within organizations (Chen & Chen, 2021). The human capital within a business equips employees to evaluate and interpret big data insights proficiently, resulting in enhanced decision-making (Ferraris et al., 2019). Based on this literature review, the following hypothesis is developed:
H6: Intellectual capital positively influences big data analytics

3. Methodology

The research followed a post-positivist epistemological paradigm grounded in a critical realism ontology, which assumes that reality exists independently of human perception but can only be understood imperfectly and probabilistically through empirical observation (Guba & Lincoln, 1994). The study adopts an objectivist axiology, acknowledging that while values may influence research, their impact is mitigated through systematic methodological rigor, triangulation, and falsifiability (Creswell & Creswell, 2018). The research employed a quantitative approach, utilizing Partial Least Squares Structural Equation

Modeling (PLS-SEM) as the primary method for data analysis, ensuring robust statistical inference in the evaluation of complex relationships. A back-translation process was conducted to enhance the validity of the measurement instruments, following established guidelines to ensure linguistic and conceptual equivalence. Additionally, all participants were informed about the research objectives and consented before participating, aligning with ethical research practices (Blaikie, 2007). Furthermore, the praxeological approach is explanatory and applied, seeking not only to identify underlying causal mechanisms but also to generate actionable insights that inform decision-making and improve practices in the field of study.

Big Data Analytics (BDA) was assessed using a four-item scale developed by Lin et al. (2022). Intellectual Capital (IC) was measured based on three key components: Human Capital, Relational Capital, and Structural Capital, following the scale developed by Hsu and Fang (2009). Specifically, Human Capital was evaluated with four items, Structural Capital with seven items, and Relational Capital with four items. Knowledge Leadership was measured using a five-item scale developed by Donate and Pablo (2015). This study employed well-established and validated scales to ensure the reliability and validity of the constructs in the research model

4. Results

The measurement model assessment demonstrates acceptable reliability and validity across the examined constructs, including Big Data Analytics (BDA), Human Capital (HC), Knowledge Leadership (KL), Relational Capital (RC), Structural Capital (SC), and Servant Leadership (SL). The outer loadings indicate that most items meet the recommended threshold (≥ 0.708) (Hair et al., 2022), with powerful indicators in BDA3 (0.840), HC3 (0.971), KL2 (0.861), and SC7 (0.915). However, some items exhibit weaker loadings, such as SL4 (0.589), SL5 (0.545), and RC2 (0.598), which may require further review, as indicators with values below 0.70 can reduce construct reliability and validity (Henseler, Ringle, & Sarstedt, 2015).
Regarding internal consistency, both Cronbach's alpha and composite reliability (rho_c) are above the acceptable threshold (≥ 0.7) (Henseler et al., 2015), confirming construct reliability. However, Relational Capital (RC) and Servant Leadership (SL) show relatively lower Cronbach's alpha values (0.702 and 0.760, respectively), suggesting that these constructs might benefit from refinement to improve their reliability. The Average Variance Extracted (AVE) values confirm convergent validity, as all constructs surpass the 0.50 threshold (Fornell & Larcker, 1981), except for Servant Leadership (0.500), which is borderline acceptable. According to Fornell and Larcker (1981), an AVE above 0.50 indicates that the construct explains more than half of the variance in its indicators, strengthening convergent validity. These findings suggest that while the measurement model is generally robust. Table 1 provides an overview of the model's reliability and validity assessments.

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Table 1:
Reliability and validity

Construct	Item	Outer loadings	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
Big Data Analytics	BDA2	0.735	0.700	0.824	0.610
	BDA3	0.840			
	BDA4	0.763			
Human Capital	HC1	0.644	0.794	0.837	0.639
	HC2	0.748			
	HC3	0.971			
Knowledge Leadership	KL1	0.754	0.828	0.876	0.587
	KL2	0.861			
	KL3	0.822			
	KL4	0.702			
	KL5	0.674			
Relational Capital	RC1	0.659	0.702	0.799	0.504
	RC2	0.598			
	RC3	0.669			
	RC4	0.882			
Structural Capital	SC5	0.837	0.820	0.879	0.708
	SC6	0.767			
	SC7	0.915			
Servant leadership	SL1	0.743	0.760	0.828	0.500
	SL2	0.817			
	SL3	0.786			
	SL4	0.589			
	SL5	0.545			

The Fornell and Larcker criterion (1981) is a widely used method for assessing discriminant validity in Partial Least Squares Structural Equation Modeling (PLS-SEM) by comparing the square root of the Average Variance Extracted (AVE) with construct correlations. Table 1 presents the discriminant validity analysis for six constructs: Big Data Analytics (BDA), Human Capital (HC), Knowledge Leadership (KL), Relational Capital (RC), Structural Capital (SC), and Servant Leadership (SL). The diagonal values represent the square root of the AVE for each construct, while the off-diagonal values denote the correlations between constructs. According to the Fornell and Larcker criterion, discriminant validity is established if the square root of the AVE for each construct (diagonal values) is greater than its highest correlation with any other construct. In this analysis, BDA (0.781) exhibits stronger self-association compared to its correlations with HC (0.005), KL (0.601), RC (-0.098), SC (-0.144), and SL (0.564). Similarly, HC (0.799), KL (0.766), RC (0.710), SC (0.842), and SL (0.705) all have square root AVE values exceeding their respective inter-construct correlations, confirming the discriminant validity of the model. This ensures that each construct is empirically distinct and measures a unique concept within the research framework. Therefore, the model meets the necessary validity conditions for further hypothesis testing. Table 2 shows the Fornell-Larcker criterion.

Table 2:
Fornell-Larcker criterion

	BDA	HC	KL	RC	SC	SL
BDA	0.781					
HC	0.005	0.799				
KL	0.601	0.097	0.766			
RC	-0.098	0.311	-0.124	0.71		
SC	-0.144	0.321	-0.171	0.619	0.842	
SL	0.564	0.05	0.474	-0.058	0.015	0.705

The Heterotrait-Monotrait (HTMT) Ratio of Correlations is a statistical method used to assess discriminant validity in Partial Least Squares Structural Equation Modeling (PLS-SEM), as recommended by Henseler et al. (2015). Table 3 presents the HTMT values for six constructs: Big Data Analytics (BDA), Human Capital (HC), Knowledge Leadership (KL), Relational Capital (RC), Structural Capital (SC), and Servant Leadership (SL). The HTMT criterion suggests that discriminant validity is achieved when the HTMT values are below 0.90 (or a more conservative threshold of 0.85) for conceptually distinct constructs. In this table, all HTMT values fall below the 0.90 threshold, indicating sufficient discriminant validity among the constructs. The highest HTMT value is 0.868 (SC and RC), which remains within the acceptable range. Lower HTMT values, such as 0.052 (BDA and HC) and 0.08 (HC and SL), further confirm that the constructs are not highly correlated, reinforcing their distinctiveness. Since none of the construct pairs exceed the established HTMT thresholds, the measurement model demonstrates strong discriminant validity, ensuring that each construct captures a unique theoretical concept. Table 3 shows the HTMT criterion.

Table 3:
HTMT criterion

	BDA	HC	KL	RC	SC	SL
BDA						
HC	0.052					
KL	0.743	0.135				
RC	0.123	0.431	0.182			
SC	0.157	0.455	0.214	0.868		
SL	0.671	0.08	0.548	0.136	0.093	

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Next, the structural model is assessed to substantiate the proposed relationships. The structural model reflects the paths hypothesized in the research framework. Higher-order construct validation (IC) was conducted, where IC is formed from human capital (HC), relational capital (RC), and structural capital (SC). The Variance Inflation Factor (VIF) was used to check for multicollinearity. According to Hair et al. (2021), VIF values below 5 indicate no multicollinearity. Since all VIF values were less than 5 (Table 4), collinearity did not threaten this investigation. Finally, outer weights' statistical significance and relevance were analyzed (Sarstedt et al., 2019). The results indicate that outer weights mattered, and each IC indicator had strong outer loadings, further validating IC (Sarstedt et al., 2019). Table 5 presents the results for the higher-order constructs. Table 4 presents the higher-order construct for intellectual capital.

Table 4:
Higher-order construct for intellectual capital

	VIF	Outer Weights	T statistics	P-values	Outer loadings	P-values
HC->IC	1.219	0.069	0.189	0.425	0.468	0.050
RC->IC	1.515	0.464	1.610	0.050	0.846	0.001
SC->IC	1.674	0.624	2.100	0.018	0.922	0.000

The results of this study provide a comprehensive understanding of the relationships among Servant Leadership (SL), Knowledge Leadership (KL), Big Data Analytics (BDA), and Intellectual Capital (IC) by testing seven hypotheses. The findings strongly support H1 (SL BDA), indicating that SL has a significant and positive impact on BDA (β = 0.335, T = 5.042, p = 0.000), suggesting that organizations with strong servant leadership are more likely to foster data-driven decision-making and analytics adoption. Similarly, H2 (SL KL) is supported (β = 0.445, T = 5.388, p = 0.000), reinforcing that SL is crucial in enhancing knowledge leadership. Additionally, H3 (KL BDA) shows a strong and positive effect (β = 0.442, T = 6.494, p = 0.000), confirming that knowledge-driven leadership significantly contributes to implementing and utilizing BDA. However, the results do not support H5 (SL IC), as the relationship was non-significant (β = -0.020, T = 0.178, p = 0.430), suggesting that SL does not directly influence IC within this model. Furthermore, H6 (IC BDA) is also non-significant (β = -0.075, T = 1.272, p = 0.102), indicating that IC does not play a direct role in the adoption or effectiveness of BDA. These findings suggest that while SL and KL are essential drivers of BDA adoption, IC does not exhibit a significant direct influence on BDA, which may imply that its impact is indirect or mediated by other organizational factors. This highlights the need for further research to explore potential moderating or mediating variables that could clarify the role of IC in data-driven organizations. From a managerial perspective, companies seeking to enhance their BDA capabilities should focus on strengthening Servant Leadership and Knowledge Leadership, as they have been empirically validated as key enablers of analytics adoption. Meanwhile, the non-significant role of IC suggests that its contribution to BDA may be more context-dependent, requiring a more nuanced understanding of its interplay with other strategic variables. Table 5 presents the hypotheses results.

Table 5:
Hypotheses results

	Original sample (O)	Standard deviation (STDEV)	T statistics	P values
H1:SL -> BDA	0.335	0.066	5.042	0.000
H2: SL -> KL	0.445	0.083	5.388	0.000
H3:KL -> BDA	0.442	0.068	6.494	0.000
H5:SL -> IC	-0.020	0.112	0.178	0.430
H6:IC -> BDA	-0.075	0.059	1.272	0.102

The mediation analysis reveals that Knowledge Leadership (KL) acts as a partial mediator in the relationship between Servant Leadership (SL) and Big Data Analytics (BDA), as indicated by the significant indirect effect (β = 0.197, T = 4.549, p = 0.000). This suggests that SL enhances KL, which facilitates the adoption and utilization of BDA, though SL still directly influences BDA. Therefore, organizations aiming to strengthen their BDA capabilities should focus on developing knowledge leadership practices alongside servant leadership. In contrast, Intellectual Capital (IC) does not mediate the relationship between SL and BDA, as evidenced by the non-significant indirect effect (β = 0.001, T = 0.148, p = 0.441), reinforcing the findings from the previous table where neither SL IC nor IC BDA showed statistical significance. This indicates that IC does not serve as a conduct between SL and BDA, suggesting that its role in data-driven decision-making may be indirect or dependent on additional moderating variables. Table 6 presents the mediation analysis results.

Table 5:
Hypotheses results

	Original sample (O)	**Standard deviation (STDEV)**	T statistics	**P values**
H4: SL -> KL -> BDA	0.197	0.043	4.549	0.000
H7: SL -> IC -> BDA	0.001	0.010	0.148	0.441

5. Discussion

The findings strongly support H1, indicating that Servant Leadership (SL) has a significant and positive impact on Big Data Analytics (BDA) (β = 0.335, T = 5.042, p = 0.000). These results align with existing literature, highlighting that servant leaders empower employees, foster a collaborative environment, and remove bureaucratic barriers, all enhancing data-driven decision-making and analytics adoption (Kumar & Chauhan, 2024; Oratis, 2022). By focusing on employee development, ethical leadership, and open communication, servant leaders create

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an organizational culture that encourages experimentation with new BDA techniques (Eva et al., 2019; Van Dierendonck, 2011). This reinforces the notion that leadership plays a fundamental role in driving data analytics capabilities in organizations.

The results confirm the mediating role of Knowledge Leadership (KL) in the relationship between SL and BDA, supporting H2 (SL KL) and H3 (KL BDA). The mediation effect is statistically significant (β = 0.197, T = 4.549, p = 0.000), demonstrating that KL enhances BDA adoption by fostering a knowledge-sharing culture, data literacy, and analytics capabilities (Kadarsah et al., 2023; Viitala, 2004). This finding reinforces previous research showing that servant leadership promotes knowledge-sharing behaviors and creates a collaborative learning environment that facilitates analytics-driven innovation (Tuan, 2016; Zaher, 2015). The strategic role of knowledge leadership in BDA adoption suggests that organizations should invest in KM systems, analytics training, and cross-functional collaboration initiatives to maximize their data-driven decision-making capabilities.

Contrary to expectations, H5 (SL IC) was not supported (β = -0.020, T = 0.178, p = 0.430), and H6 (IC BDA) was also non-significant (β = -0.075, T = 1.272, p = 0.102). These findings suggest that Intellectual Capital (IC) does not play a direct role in adopting BDA within this model. Previous studies emphasized that IC, particularly human and structural capital, is a key driver of innovation and technological capabilities (Ferraris et al., 2019; Chen & Chen, 2021). However, the lack of significance in this study implies that IC's impact on BDA might be contingent on other moderating variables, such as organizational culture, technological readiness, or leadership influence.

The mediation analysis for H7 (SL IC BDA) found no significant indirect effect (β = 0.001, T = 0.148, p = 0.441), confirming that Intellectual Capital does not mediate the relationship between SL and BDA. This suggests that IC is not a primary conduit through which SL enhances BDA capabilities. A potential explanation for this result is that while IC provides essential intangible assets, its role in data analytics adoption is likely indirect, requiring strong leadership and strategic alignment. For instance, while human capital equips employees with analytical skills, it may not automatically translate into improved BDA adoption without adequate leadership and a supportive knowledge-sharing environment.

6. Theoretical Implications

This study contributes to the theory of leadership and organizational analytics by demonstrating the strategic role of Servant Leadership (SL) and Knowledge Leadership (KL) in enhancing Big Data Analytics (BDA) adoption. The findings reinforce that leadership is crucial to data-driven decision-making in military and defense organizations.This study aligns with contemporary theories emphasizing ethical leadership, team empowerment, and data-driven strategies in complex environments.The Peruvian Army, as a knowledge-driven organization, can leverage SL and KL to integrate intelligence, logistics, and operational data into strategic decision-making.

The confirmed mediation effect of Knowledge Leadership (KL) in the SL BDA relationship highlights the importance of knowledge-sharing mechanisms within military institutions.This supports the argument that knowledge-driven leadership models should be institutionalized to improve intelligence gathering, mission planning, and operational efficiency.The study challenges traditional views on Intellectual Capital (IC) as a direct enabler of BDA, suggesting that its impact may depend on additional factors such as strategic alliances, digital infrastructure, and leadership frameworks. This calls for future research on how military institutions can maximize their intellectual assets to improve defense analytics and strategic capabilities.

7. Practical Implications

The findings provide actionable insights on how leadership can enhance military intelligence, strategic planning, and operational efficiency through BDA adoption for military institutions such as the Peruvian Army and Escuela Superior de Guerra.Military leaders should embrace Servant Leadership principles to create an adaptive, intelligence-driven command structure that promotes teamwork and strategic thinking.Training programs should emphasize data literacy, analytics-based leadership, and operational intelligence applications.Given the confirmed role of Knowledge Leadership (KL) in BDA adoption, the Peruvian Army should integrate knowledge-sharing frameworks to facilitate: Real-time intelligence exchange across units.Data-driven mission planning and logistics optimization. Integration of military and geopolitical analytics in high-stakes decision-making. Military academies and war colleges should adopt a knowledge-oriented leadership model, ensuring officers are trained to manage, interpret, and apply complex data in military scenarios. The non-significant impact of Intellectual Capital (IC) on BDA suggests that military organizations should not rely solely on human and structural capital for digital transformation. Instead, they should strengthen leadership frameworks and technological infrastructure to create a comprehensive defense analytics ecosystem. The findings indicate the need for enhanced collaboration between military institutions, academia, and the private sector to develop advanced analytics capabilities.

8. Conclusion

This study provides critical insights into how leadership influences the integration of Big Data Analytics (BDA) in military and defense institutions. The findings confirm that Servant Leadership (SL) directly enhances BDA adoption, as leaders who empower teams, reduce bureaucracy, and promote ethical decision-making are more effective in integrating data-driven intelligence frameworks. Knowledge Leadership (KL) also plays a key mediating role, demonstrating that leadership models emphasizing knowledge-sharing and collaborative intelligence significantly enhance military analytics capabilities. In contrast, Intellectual Capital (IC) does not directly influence BDA adoption, suggesting that its impact depends on additional strategic enablers such as leadership commitment, digital transformation, and geopolitical intelligence structures. These results highlight the crucial role of leadership in shaping military analytics capabilities and underscore the need for leadership-driven strategies to maximize the effectiveness of BDA in defense operations.

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