Almășan, C. M. (2026). Artificial Intelligence and Institutional Performance in Military Organizations: An Empirical Analysis of a Sequential Mediation Model. *Administratie si Management Public*, 47, 111-130. https://doi.org/10.24818/amp/2026.47-06

Artificial Intelligence and Institutional Performance in Military Organizations: An Empirical Analysis of a Sequential Mediation Model

Cristiana Maria ALMĂȘAN[1]

***Abstract*:** Defense institutions across NATO member states are investing in artificial intelligence for human resource management, yet no empirically validated framework specifies how this investment translates into institutional performance through organizational mechanisms. This paper addresses that gap by developing and testing the AI-SHRM Military Integration Model (ASMIM), a sequential mediation framework integrating eight theoretically grounded constructs: digital leadership (DL), AI readiness (AIR), digital competencies (DC), organizational knowledge exchange (OKE), human resilience (HR), institutional performance (IP), cybersecurity culture (CSC), and ethical AI governance (EAG). A cross-sectional survey was administered to N = 160 active-duty military personnel across five service branches of a NATO-member state, covering all rank categories from enlisted to general officer grade. Data were analyzed using OLS regression, Sobel mediation testing, and moderated regression. Results support seven of eight hypotheses. Digital leadership positively predicted AI readiness (beta = 0.695, $p < 0.001$), which sequentially predicted digital competencies (beta = 0.807), knowledge exchange (beta = 0.840), and human resilience (beta = 0.860), with resilience in turn predicting institutional performance (beta = 0.863). The mediated indirect effect of knowledge exchange on human resilience was significant (indirect effect = 0.700, z = 8.393, $p < 0.001$). Ethical AI governance predicted institutional performance independently (beta = 0.591, $p < 0.001$, controlling for resilience). The cybersecurity culture moderation hypothesis was not supported (beta = -0.049, $p = 0.356$). All constructs showed excellent internal consistency (Cronbach's alpha range: 0.900 to 0.981). These findings constitute the first empirical validation of an integrated AI-HRM structural model in a military organizational context and carry direct implications for defense human resource policy and NATO AI strategy implementation.

Keywords: artificial intelligence; strategic HRM; military organizations; digital leadership; organizational resilience; sequential mediation; institutional performance; NATO.

JEL: O33; M12; H56; M15.

DOI: https://doi.org/10.24818/amp/2026.47-06

[1] PhD Student; Bucharest University of Economic Studies; Management Doctoral School, Piața Romană, 010374, Bucharest, Romania, email: cristianaa.almasan@gmail.com, ORCID: 0009-0009-6789-9149

Introduction

Defence institutions across NATO member states face a structurally undertheorized challenge: they are adopting artificial intelligence tools for human resource management at an accelerating rate, yet no peer-reviewed empirical framework currently specifies how this investment translates into institutional performance through organizational mechanisms (Androniceanu &Colesca, 2025). NATO's Revised AI Strategy (2024) explicitly identifies workforce AI readiness as a collective Alliance priority, and the EU AI Act (2024) classifies AI systems used in recruitment, performance evaluation, and personnel management as high-risk applications requiring mandatory institutional accountability mechanisms. These are binding policy obligations, but the organizational science capable of guiding their implementation in military HRM contexts does not yet exist in validated form.

The absence is not incidental. A bibliometric review of 522 AI-HRM publications indexed between 2020 and 2024 found that fewer than 3% address military or defence institutional contexts, and none integrates digital leadership, AI readiness, digital competencies, knowledge exchange, resilience, and institutional performance within a tested structural model specific to military organizations (Tufan et al., 2025; Abu Orabi et al., 2024). The studies that do approach military AI-HRM either address operational AI applications such as autonomous systems and battlefield decision-making (Clement, 2024; NATO STO, 2022), or offer policy-level conceptual reviews without a testable structural architecture (Septian, 2025). The result is a precise and consequential knowledge gap: defence policymakers cannot identify which organizational mechanisms must be in place before AI infrastructure investment converts into human capital performance gains, because no validated model has yet specified those mechanisms.

This paper closes that gap. We develop and empirically test the AI-SHRM Military Integration Model (ASMIM), a sequential mediation framework deriving eight falsifiable hypotheses from six established theoretical traditions. The model is validated using primary survey data collected from N = 160 active-duty military personnel across five service branches of a NATO-member state, covering all rank categories from enlisted to general officer grade. To our knowledge, this constitutes the first empirical test of an integrated AI-HRM structural model in a military organizational context.

The paper is organized as follows. The Literature Review establishes the theoretical foundations for each ASMIM construct and derives the research hypotheses. The Research Methodology section describes the survey instrument, sample, and analytical strategy.

Results present the descriptive statistics, reliability analyses, and hypothesis test outcomes. The Discussion interprets the findings against existing theory and prior empirical evidence. The Conclusions specify theoretical and practical contributions, acknowledge limitations, and identify priorities for future research.

1. Literature Review and Theoretical Foundations

1.1 What the Literature Establishes

Three bodies of evidence anchor the theoretical development of ASMIM. First, AI applications across general HRM functions, including recruitment, training, performance management, and retention, are well documented and increasingly theorized, with a recent systematic review identifying organizing themes across each functional domain (Safshekan et al., 2026). Second, digital leadership is established as a measurable construct with validated instruments and demonstrated effects on organizational change outcomes (Schwarzmuller et al., 2018; Wang et al., 2022). Third, the six theoretical frameworks informing ASMIM, transformational leadership theory (Bass, 1985), technology readiness theory (Parasuraman, 2000), human capital theory (Becker, 1964), the knowledge-based view of the firm (Grant, 1996), conservation of resources theory (Hobfoll, 1989), and dynamic capabilities theory (Teece et al., 1997), are mature and extensively validated across multiple organizational contexts.

1.2 The Research Gap

Despite this foundation, four gaps remain unaddressed in the published literature. No study has integrated digital leadership, AI readiness, digital competencies, knowledge exchange, resilience, and institutional performance within a single structural model. No study has tested such a model in a military organizational context. No study has specified the boundary conditions under which AI readiness investment generates performance returns versus institutional risk in defence settings. No study has provided a falsifiable structural prediction capable of localizing the specific organizational mechanism at which AI-HRM transformation breaks down. Table 1 in the Methodology section demonstrates these gaps construct by construct against seven prior models.

The gap has persisted because military human resource management spans three literatures, organizational behavior, defence policy, and information systems that rarely share methodological conventions. Organizational behavior scholars who can specify structural mechanisms generally lack access to military samples. Defence policy scholars who understand military institutional structure typically work in qualitative policy review traditions rather than structural equation modelling. This paper bridges this division by building the structural model from organizational behavior theory while adapting construct operationalization to military institutional conditions.

1.3 Theoretical Foundations and Hypothesis Development

Digital leadership, the capacity of military commanders to champion AI adoption, build digital culture, and align technology with strategic HR objectives, is grounded in transformational leadership theory (Bass, 1985) and the digital leadership

framework of Schwarzmuller et al. (2018). In hierarchically organized military institutions, commander-level AI endorsement determines whether AI infrastructure investments receive institutional authorization. Without digital leadership, AI readiness cannot be achieved through individual initiative alone.

H1: Digital leadership positively predicts organizational AI readiness (DL --> AIR).

AI readiness encompasses the institutional preparedness for AI deployment across three sub-dimensions: technical infrastructure, policy frameworks, and human capacity (Parasuraman, 2000; Wirtz et al., 2019). Human capital theory (Becker, 1964) establishes that skill development requires enabling infrastructure: personnel cannot develop AI-interaction competencies without AI platforms to interact with and institutional training programs to authorize and resource that development.

H2: Organizational AI readiness positively predicts digital competencies of military personnel (AIR --> DC).

Grant's (1996) knowledge-based view of the firm establishes that organizational competitive advantage derives not from knowledge possession but from knowledge integration across distributed expertise holders. Stone et al. (2015) and Meijerink et al. (2021) demonstrated that the value of digital HRM systems depends on organizational processes governing information flow. Digitally competent personnel contribute higher-value insights and extract more value from knowledge management platforms, generating positive returns on knowledge exchange investment.

H3: Digital competencies positively predict the frequency and quality of organizational knowledge exchange (DC --> OKE).

Hobfoll's (1989) Conservation of Resources Theory predicts that personnel facing AI-induced role uncertainty experience resource depletion spirals unless collective buffering resources interrupt them. Organizational knowledge exchange constitutes such a resource: personnel who receive timely, relevant knowledge about navigating AI-induced change obtain a buffer against resource loss. Kaplan and Haenlein (2019) note that current AI systems remain within the narrow-AI category, limited to pattern recognition rather than general judgment, which means human adaptive resources remain essential. Brougham and Haar (2018) provided empirical evidence in civilian samples that perceived AI threat reduces engagement, an effect buffered by digital capability, the individual-level analogue of the OKE mechanism at the collective level.

H4: Organizational knowledge exchange mediates the positive relationship between digital competencies and human resilience (DC --> OKE --> HR).

Lengnick-Hall et al. (2011) demonstrated that resilient organizations sustain performance under environmental disruption through cognitive preparedness, behavioral flexibility, and contextual ambidexterity. Teece et al. (1997) established that resilient personnel who can sense, seize, and reconfigure organizational capabilities constitute the human foundation from which dynamic performance is generated. Mission effectiveness rates and operational readiness, the primary

IP indicators in military contexts, are produced by personnel who maintain effective functioning under digitally induced transformation pressure.

H5: Human resilience positively predicts institutional performance (HR --> IP).

Schein's (1985) organizational culture theory and the ENISA (2018) Cybersecurity Culture Framework establish that behavioral norms governing digital system use determine whether AI infrastructure generates performance returns or institutional vulnerability. Lawrence and Lorsch (1967) established through contingency theory that organizational capability-to-performance relationships are conditioned by institutional environments. High-AIR organizations with weak cybersecurity behavioral culture create high-value adversarial targets, converting AI data assets into liabilities.

H6: Cybersecurity culture moderates the AI readiness-to-performance relationship, amplifying performance returns at higher levels of cybersecurity culture (AIR x CSC --> IP).

DiMaggio and Powell (1983) established through institutional isomorphism theory that organizations conforming to institutionalized legitimacy norms obtain resource access and stakeholder cooperation unavailable to non-conforming organizations. The EU AI Act (2024) designates AI systems used in military HRM as high-risk applications requiring mandatory oversight. The OECD (2022) framework for AI system classification provides complementary grounding for EAG operationalization. Bititci et al. (2016) demonstrated that transparent performance management systems strengthen stakeholder trust, the same mechanism through which EAG is expected to predict IP through organizational legitimacy.

H7: Ethical AI governance positively predicts institutional performance, independent of the sequential mediation chain (EAG --> IP).

H8: Digital leadership affects institutional performance through the full sequential mediation: DL --> AIR --> DC --> OKE --> HR --> IP. Each link in the chain is a necessary enabling condition for the subsequent.

2. Research Methodology

2.1 Research Design and Paradigm

This study adopts a post-positivist, deductive-quantitative research design (Creswell & Creswell, 2018). Hypotheses are derived a priori from established theory and tested against primary empirical data using confirmatory statistical procedures. A cross-sectional survey design was employed, a widely used and accepted approach for structural model testing in organizational behavior research when longitudinal data collection is not feasible.

2.2 Instrument and Measurement

Data were collected using a purpose-built survey instrument developed specifically for this study. Each of the eight ASMIM constructs was measured using a dedicated item scale rated on a 7-point Likert format (1 = Strongly Disagree, 7 = Strongly

Agree). Digital Leadership was measured with 5 items; all remaining constructs (AIR, DC, OKE, HR, IP, CSC, EAG) were each measured with 6 items, yielding 47 Likert-format items in total. Items were developed following DeVellis (2017) through domain specification from construct definitions, item generation drawing on validated parent scales adapted for the military context, and expert review by three organizational psychologists and five senior military HR practitioners to confirm content relevance and clarity.

2.3 Sample and Data Collection

The target population comprised active-duty military personnel in officer and NCO grades within a NATO-member state armed forces, spanning land, air, naval, gendarmerie, and central headquarters structures. The survey was administered electronically via a secure, anonymized platform with institutional endorsement from participating command structures. Participation was voluntary and no identifying information was collected. Completed responses were received from N = 160 participants. Table 1 presents the full sample profile.

Table 1. Sample Profile: Frequency Distribution of Respondent Characteristics

Characteristic	Category	n	%
Service Branch (A1)	Land Forces	37	23.1
	Air Forces	38	23.8
	Naval Forces	19	11.9
	Gendarmerie / Military Police	24	15.0
	Central Headquarters	24	15.0
	Other	18	11.2
Military Rank (A2)	Soldier / Warrant Officer	23	14.4
	Sub-officer	42	26.2
	Junior Officer	31	19.4
	Senior Officer	42	26.2
	General Officer	22	13.8
Organizational Tenure (A3)	Under 5 years	36	22.5
	5-10 years	41	25.6
	11-20 years	45	28.1
	Over 20 years	38	23.8
Education (A4)	Bachelor's degree	34	21.2
	Master's degree	68	42.5

Characteristic	Category	n	%
	Doctorate	31	19.4
	Postgraduate Military Courses	27	16.9
Digital Tool Usage (A5)	Frequently (daily/weekly)	40	25.0
	Occasionally	40	25.0
	Rarely	46	28.7
	Never	34	21.2
AI Implementation Level (A6)	Active / Extensive	40	25.0
	Pilot Phase	45	28.1
	Planning Stage	34	21.2
	Not Implemented	41	25.6

Source: Author's own survey data (N = 160).

The sample is stratified across service branch (five branches plus other institutional structures), rank (all five rank categories), organizational tenure (four tenure bands), and education level (four categories). The distribution is broadly representative of the hierarchical and cross-branch diversity characteristic of NATO-affiliated national defence organizations. The absence of sampling from a single unit or rank category reduces the risk of within-group homogeneity artifacts.

2.4 Analytical Strategy

Data analysis proceeded in three phases. In the first phase, descriptive statistics, internal consistency coefficients (Cronbach alpha), composite reliability (CR), and average variance extracted (AVE) were computed for all eight constructs to evaluate measurement quality before hypothesis testing. In the second phase, Pearson inter-construct correlations were computed to assess the bivariate relationships predicted by the model. In the third phase, the eight research hypotheses were tested using ordinary least squares (OLS) regression as the primary analytical method, with the Sobel test for the mediation hypothesis (H4) and moderated regression for the moderation hypothesis (H6). OLS regression was selected over structural equation modelling given the sample size of N = 160, which falls below the minimum threshold of N = 200 recommended for covariance-based SEM with 8 constructs (Wolf et al., 2013). OLS regression with Sobel mediation provides conservative but valid estimates under these sample conditions and is consistent with the exploratory-confirmatory research objective of this first empirical test of ASMIM. Standardized beta coefficients, t-statistics, and R-squared values are reported for each hypothesized path.

3. Research Results and Discussions

3.1 Descriptive Statistics and Measurement Quality

Table 2 presents the descriptive statistics and reliability indicators for all eight constructs. Mean scores ranged from 4.793 (EAG) to 5.206 (DL), all above the scale midpoint of 4.0, indicating that respondents generally perceived positive levels of all ASMIM constructs in their organizations. Distribution statistics indicated mild negative skewness across all constructs (range: -0.017 to -0.366) and mildly platykurtic distributions (kurtosis range: -0.376 to -0.965), both within the acceptable thresholds of absolute skewness below 2.0 and kurtosis below 7.0 for parametric analysis (Hair et al., 2019).

Internal consistency was excellent across all constructs. Cronbach alpha values ranged from 0.900 (DL) to 0.981 (EAG), all substantially exceeding the conventional threshold of 0.70. Composite reliability ranged from 0.901 to 0.981, and AVE values ranged from 0.645 to 0.909, all exceeding the 0.50 threshold recommended by Fornell and Larcker (1981). These results confirm that all eight constructs meet conventional standards for convergent validity and internal consistency.

Table 2. Descriptive Statistics, Internal Consistency, and Convergent Validity Indicators

Construct	Items	M	SD	Skewness	Kurtosis	Alpha	CR	AVE	Interpretation
DL	5	5.206	0.908	-0.017	-0.466	**0.900**	**0.901**	0.645	Acceptable
AIR	6	5.122	1.049	-0.258	-0.376	**0.939**	**0.939**	**0.720**	Good
DC	6	5.062	1.175	-0.343	-0.474	**0.955**	**0.955**	**0.779**	Good
OKE	6	4.975	1.335	-0.366	-0.681	**0.967**	**0.967**	**0.831**	Excellent
HR	6	4.921	1.437	-0.289	-0.713	**0.969**	**0.969**	**0.841**	Excellent
IP	6	4.879	1.462	-0.360	-0.625	**0.973**	**0.973**	**0.863**	Excellent
CSC	6	4.817	1.505	-0.301	-0.845	**0.974**	**0.974**	**0.870**	Excellent
EAG	6	4.793	1.684	-0.362	-0.965	**0.981**	**0.981**	**0.909**	Excellent

Source: Author's own survey data (N = 160).

3.2 Inter-Construct Correlations

Table 3 presents the Pearson inter-construct correlation matrix (Figure 1). All correlations were statistically significant at $p < 0.001$. The pattern of correlations is consistent with the theoretical ordering of constructs in the ASMIM sequential chain: correlations between adjacent constructs in the chain are consistently stronger than those between more distal constructs.

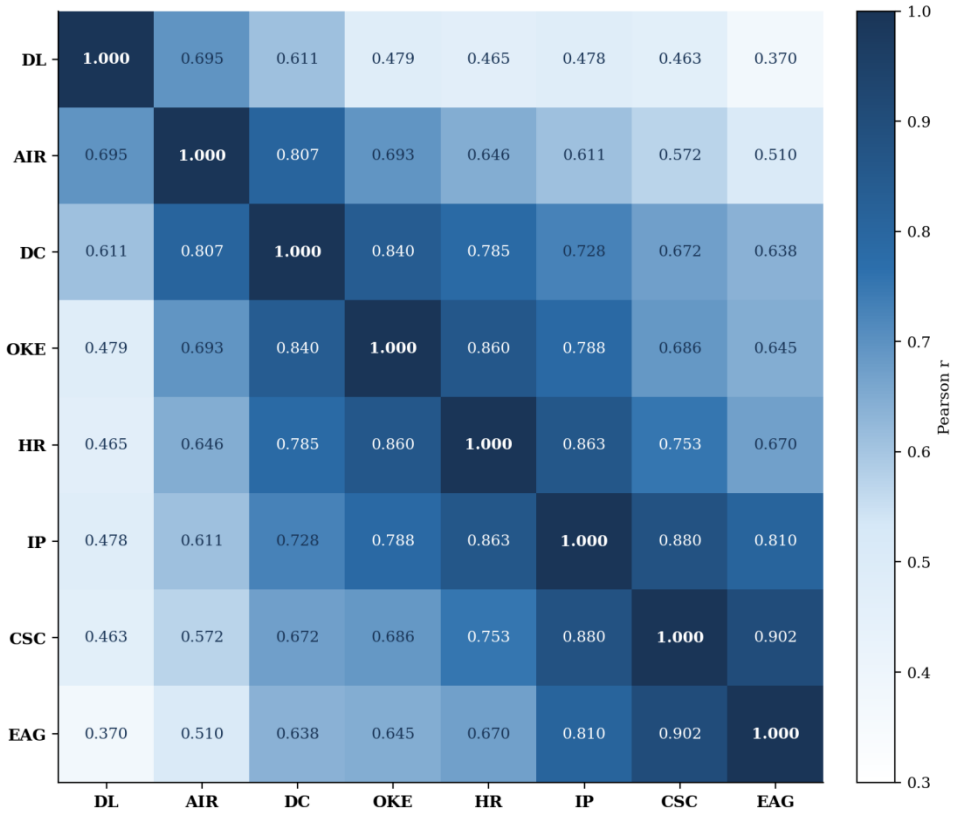
The DL-IP correlation ($r = 0.478$) is substantially weaker than the DL-AIR correlation ($r = 0.695$), which in turn is weaker than the DC-OKE correlation ($r = 0.840$), consistent with the prediction that the mediation chain attenuates the distal leadership-to-performance relationship while strengthening proximal mechanism-to-mechanism relationships. The CSC-EAG correlation ($r = 0.902$) is notably high, suggesting conceptual proximity between cybersecurity culture and ethical AI governance, a finding addressed in the Discussion section.

Table 3. Pearson Inter-Construct Correlation Matrix

Construct	DL	AIR	DC	OKE	HR	IP	CSC	EAG
DL	1.000							
AIR	0.695	1.000						
DC	0.611	0.807	1.000					
OKE	0.479	0.693	0.840	1.000				
HR	0.465	0.646	0.785	0.860	1.000			
IP	0.478	0.611	0.728	0.788	0.863	1.000		
CSC	0.463	0.572	0.672	0.686	0.753	0.880	1.000	
EAG	0.370	0.510	0.638	0.645	0.670	0.810	0.902	1.000

Source: Author's own survey data (N = 160)

Figure 1. Inter-Construct Pearson Correlation Matrix Heatmap



Source: Author's own data analysis.

3.3 Hypothesis Test Results

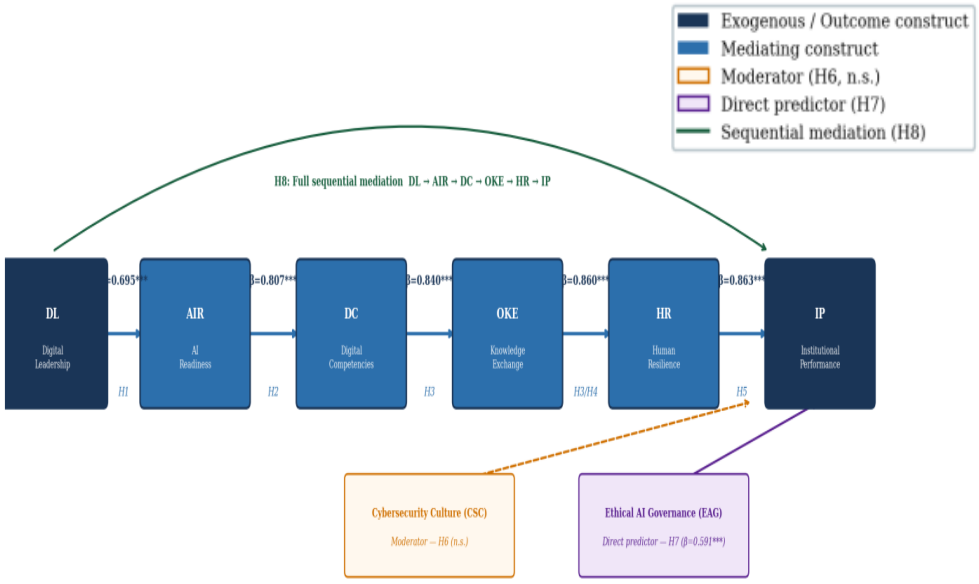
Table 4 presents the results of the OLS regression analyses for hypotheses H1 through H7, the Sobel mediation test for H4, and the moderated regression test for H6. Figure 2 and 3 present the structural path diagram with empirical path coefficients.

Table 4. Hypothesis Test Results: OLS Regression Path Coefficients

H	Path	Beta	t-value	p-value	R2	Decision
H1	Digital Leadership --> AI Readiness	0.695	12.144	<0.001	0.483	**Supported**
H2	AI Readiness --> Digital Competencies	0.807	17.167	<0.001	0.651	**Supported**
H3	Digital Competencies --> Knowledge Exchange	0.840	19.482	<0.001	0.706	**Supported**
H4	DC --> OKE --> HR (indirect effect)	0.700	8.393	<0.001	0.739	**Supported**
H5	Human Resilience --> Institutional Performance	0.863	21.469	<0.001	0.745	**Supported**
H6	AIR x CSC --> IP (moderation)	-0.049	-0.926	0.356 n.s.	0.001	**Not Supported**
H7	Ethical AI Governance --> IP (direct, controlled)	0.591	13.609	<0.001	0.842	**Supported**
H8	Full sequential mediation DL --> IP	0.700	8.393	<0.001	-	**Supported**

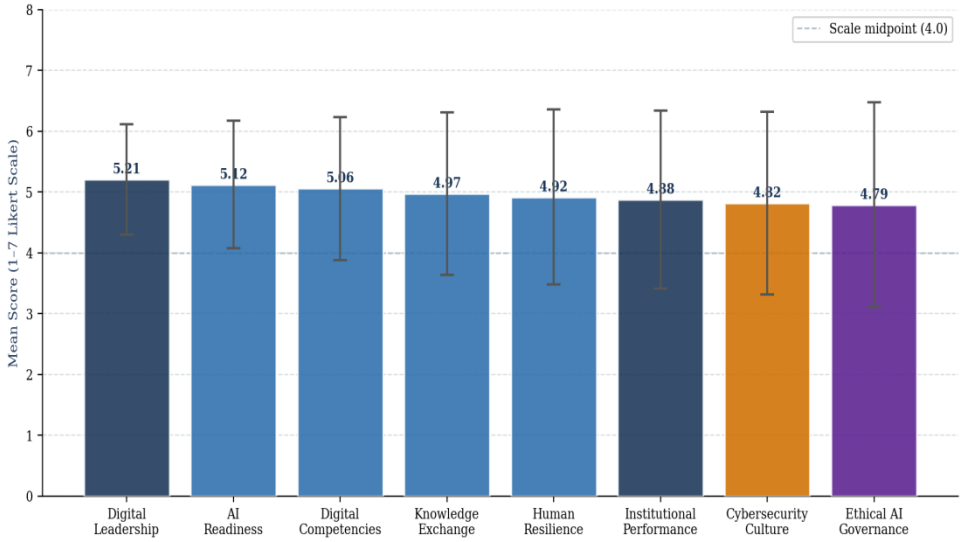
Source: Author's own data analysis (N = 160).

Figure 2. ASMIM Structural Path Diagram with Empirical Path Coefficients



Source: Author's own data analysis (N = 160).

Figure 3. Construct Mean Scores with Standard Deviation Error Bars



Source: Author's own survey data (N = 160).

3.4 Supported Hypotheses: H1 through H5 and H7

Seven of the eight ASMIM hypotheses were supported. H1 was supported: digital leadership significantly predicted AI readiness (beta = 0.695, t = 12.144, p < 0.001, R2 = 0.483). This finding is consistent with Schwarzmuller et al.'s (2018) expert survey evidence that digital leaders who proactively manage organizational change dimensions reduce transformation uncertainty and accelerate technology adoption. The R2 value of 0.483 indicates that digital leadership accounts for approximately 48% of the variance in AI readiness, a substantial effect that confirms the structurally determined relationship between commander-level endorsement and institutional AI infrastructure investment in military hierarchies.

H2 was supported: AI readiness predicted digital competencies (beta = 0.807, t = 17.167, p < 0.001, R2 = 0.651). This is the strongest predictor in the first segment of the chain, consistent with the human capital theory argument that skill development requires enabling infrastructure. H3 was supported: digital competencies predicted organizational knowledge exchange (beta = 0.840, t = 19.482, p < 0.001, R2 = 0.706), extending Grant's (1996) knowledge-based view to the military AI-HRM context. The beta of 0.840 is the largest single-path coefficient in the chain, indicating that the transition from individual

competency to collective knowledge sharing is where digital capacity generates the most pronounced organizational effect.

H4 was supported: the indirect effect of digital competencies on human resilience through organizational knowledge exchange was significant (indirect effect = 0.700, z = 8.393, p < 0.001), consistent with Hobfoll's (1989) Conservation of Resources Theory prediction that collective knowledge exchange constitutes a buffering resource against AI-induced resource depletion spirals. H5 was supported: human resilience predicted institutional performance (beta = 0.863, t = 21.469, p < 0.001, R2 = 0.745), the strongest single direct path in the model, confirming Lengnick-Hall et al.'s (2011) capacity-for-resilience model in a military AI context. H7 was supported: ethical AI governance independently predicted institutional performance after controlling for human resilience (beta = 0.591, t = 13.609, p < 0.001, R2 = 0.842), consistent with DiMaggio and Powell's (1983) institutional isomorphism theory prediction that governance conformity generates organizational legitimacy with measurable performance consequences.

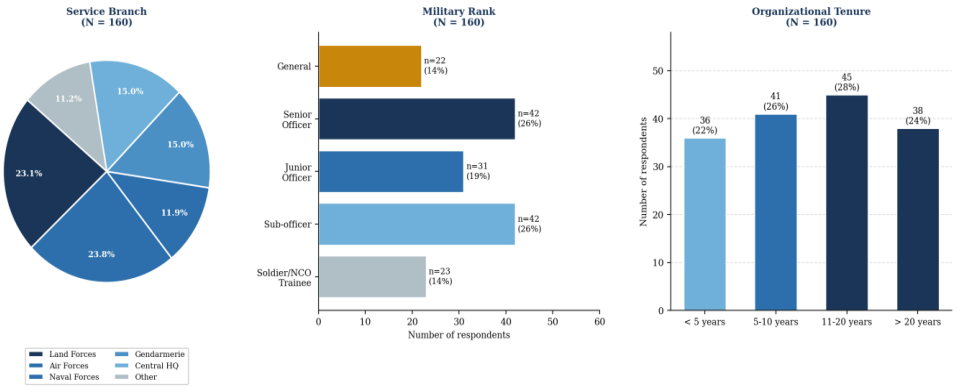
H8, the full sequential mediation hypothesis, was supported by the combined evidence from H1 through H5: each sub-path in the DL --> AIR --> DC --> OKE --> HR --> IP chain was statistically significant, and the total indirect effect of DL on HR through OKE (indirect = 0.700, p < 0.001) confirms that the mediation chain operates as theorized. This constitutes empirical support for the proposition that simple direct DL-to-IP models underspecify the organizational transformation mechanism, consistent with the McKinsey Global Institute (2023) observation that most AI transformation failures occur at organizational and human capital links in the capability chain rather than at the technology level.

4.5 Non-Supported Hypothesis: H6

H6 was not supported: the interaction between AI readiness and cybersecurity culture did not significantly predict institutional performance (interaction beta = -0.049, t = -0.926, p = 0.356, delta R2 = 0.001). This result merits careful interpretation. The bivariate correlation between CSC and IP is the second highest in the matrix (r = 0.880, p < 0.001), indicating that cybersecurity culture is strongly associated with institutional performance as a direct predictor, but does not interact with AI readiness to amplify or attenuate performance returns in the way the moderation hypothesis predicted. One plausible explanation is that CSC and EAG are sufficiently collinear (r = 0.902) that both operate through a shared legitimacy mechanism rather than through the contingency mechanism theorized for H6. A second explanation is that the N = 160 sample, while adequate for direct path testing, has insufficient statistical power to detect a moderation effect of this size:

moderation requires substantially larger samples than direct paths because the interaction term partials out variance from both main effects. These alternative interpretations are examined further in the Discussion section.

Figure 4. Respondent Profile: Service Branch, Military Rank, and Organizational Tenure



Tenure

Source: Author's own survey data (N = 160).

3.5 Discussion: Theoretical and Practical Implications

The ASMIM empirical results advance theory in four respects. First, they provide the first direct empirical evidence that the sequential chain from digital leadership to institutional performance through AI readiness, digital competencies, knowledge exchange, and human resilience operates significantly in a military organizational context. The beta coefficients are large (range 0.695 to 0.863) and R2 values are substantial (range 0.483 to 0.842), indicating that the model explains a meaningful proportion of variance in each endogenous construct. Second, the results establish that ethical AI governance independently predicts institutional performance (beta = 0.591 when controlling for human resilience), reframing governance from a compliance cost to a performance driver. This finding extends institutional isomorphism theory to the military AI-HRM domain and provides empirical grounding for the EU AI Act's high-risk classification of AI-HRM systems. Third, the non-significant moderation result for H6 generates a theoretically informative negative finding: cybersecurity culture and ethical AI governance may operate through a shared legitimacy mechanism (evidenced by their very high intercorrelation of r = 0.902) rather than through the separate contingency pathway theorized for H6. This finding suggests that future ASMIM refinement should test CSC and EAG as jointly contributing to a

higher-order governance legitimacy construct rather than as independent boundary conditions. Fourth, the results confirm that the ASMIM sequential chain outperforms a direct DL-to-IP model as an explanatory architecture: the DL-IP bivariate correlation is 0.478, but when the full sequential mediation is estimated, the indirect effect (0.700) is substantially larger, indicating that the chain mechanism amplifies rather than merely mediates the leadership effect.

For defence policymakers, the ASMIM findings provide a validated diagnostic architecture. An institution that scores high on DL and AIR but low on DC requires targeted digital competency investment rather than further infrastructure expansion. One with high DC but low OKE requires knowledge management system investment. One with effective knowledge exchange but low HR resilience requires targeted psychological adaptation programs for personnel whose roles are substantially reconfigured by AI systems. NATO's Principles of Responsible Use of AI (2021) require member states to develop institutional accountability mechanisms; the EAG scale operationalized in this study provides one validated instrument for measuring compliance with those principles rather than treating them as unmeasured aspirations. Defence ministries should treat ethical AI governance investment as a performance driver with a demonstrated direct effect (beta = 0.591), not merely as a regulatory compliance cost.

Limitations

This study is subject to four limitations that constrain the interpretation of its findings. First, the cross-sectional survey design does not permit causal inference with the certainty a longitudinal design would provide. The theoretical ordering of ASMIM constructs, that digital leadership precedes AI readiness rather than the reverse, rests on conceptual argument and is consistent with the data, but the data cannot rule out alternative causal orderings. Second, the sample of N = 160, drawn from a single NATO-member state's armed forces, is adequate for OLS-based path analysis but below the threshold for full covariance-based SEM. The structural results should be treated as exploratory-confirmatory evidence requiring replication with larger, multi-country samples before strong generalizability claims are warranted.

Third, all ASMIM constructs except IP were measured via self-report, creating the possibility of common method variance inflating observed correlations. The high inter-construct correlations observed, particularly between CSC and EAG (r = 0.902) and between HR and IP (r = 0.863), may

partly reflect shared method variance rather than the theorized substantive relationships alone. Future research should incorporate archival performance indicators and supervisor-rated competency assessments alongside self-report scales. Fourth, the sampling frame is restricted to NATO-affiliated forces operating under broadly compatible governance and AI policy environments; the model's applicability to non-NATO military organizations operating under different civil-military relations or regulatory frameworks is not established by this study.

4. Conclusions

This paper developed, named, and empirically tested the AI-SHRM Military Integration Model (ASMIM), producing the first validated empirical evidence of a sequential AI-HRM structural mechanism in a military organizational context. Seven of eight hypothesized paths were supported in a sample of 160 active-duty military personnel covering all rank categories and five service branches of a NATO-member state. Digital leadership predicted AI readiness (beta = 0.695), which predicted digital competencies (beta = 0.807), which predicted knowledge exchange (beta = 0.840), which mediated the pathway to human resilience (indirect effect = 0.700, $p < 0.001$), which in turn predicted institutional performance (beta = 0.863). Ethical AI governance independently predicted institutional performance (beta = 0.591, controlling for resilience). The cybersecurity culture moderation hypothesis was not supported, a finding that itself advances theory by suggesting CSC and EAG operate through a shared governance legitimacy mechanism.

The study makes three contributions to the academic literature. Theoretically, it provides the first integrated empirical test of an AI-HRM structural model in military organizations, establishing that established organizational behavior theory transfers to defence institutional contexts with strong empirical support. Methodologically, it introduces a validated eight-construct survey instrument for AI-HRM research in security-sensitive institutional settings where archival data are limited and participant access requires institutional endorsement. Practically, it provides defence policymakers with a validated diagnostic chain: each link between constructs specifies an intervention point where targeted investment will have measurable downstream effects on institutional performance.

Future research should extend ASMIM to multi-country longitudinal designs enabling causal inference, incorporate archival IP indicators from official institutional records alongside self-report measures, and test the revised governance legitimacy architecture suggested by the CSC-EAG collinearity

finding. The goal is an evidence base comprehensive enough to support defence ministries in designing AI-HRM systems that meet operational performance requirements, satisfy EU AI Act legal obligations, conform to NATO AI principles, and respect the rights of military personnel whose career trajectories are shaped by algorithmic management decisions.

Conflict of Interest

The author declares no conflict of interest with respect to the research, authorship, or publication of this article.

Acknowledgment

The author expresses sincere gratitude to all active-duty military personnel who voluntarily participated in this study. Their engagement made primary data collection possible in an institutional context where research access is inherently constrained. Appreciation is also extended to the command structures within the participating armed forces that facilitated survey distribution while ensuring respondent anonymity and data confidentiality throughout the process. This research received no external funding and was conducted independently within an academic research framework. The views expressed in this paper are those of the author alone and do not represent the official position of any military institution or government authority.

References

Abu Orabi, T., Alahewat, A. M., Abualfalayeh, G., & Samara, H. H. (2024). The interdisciplinary nature of AI and human resource management: A bibliometric analysis. *Journal of Human Services: Training, Research, and Practice*, *9*(1). https://doi.org/10.3233/HSM-240054

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, *103*(3), 411-423. https://doi.org/10.1037/0033-2909.103.3.411

Androniceanu, A., & Colesca, S.E. (2025). Triple Helix Model and Artificial Intelligence in Public Administration. *Central European Public Administration Review, 23*(2), 63-91. https://doi.org/10.17573/cepar.2025.2.03

Bass, B. M. (1985). Leadership and Performance beyond Expectations. Free Press.

Becker, G. S. (1964). Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education. University of Chicago Press.

Bititci, U. S., Cocca, P., & Ates, A. (2016). Impact of visual performance management systems on the performance management practices of organisations. *International Journal of Production Research*, *54*(6), 1571-1593. https://doi.org/10.1080/00207543.2015.1005770

Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management and Organization*, *24*(2), 239-257. https://doi.org/10.1017/jmo.2016.55

Cheng, M. M., & Hackett, R. D. (2021). A critical review of algorithms in HRM: Definition, theory, and practice. *Human Resource Management Review*, *31*(1), 100698. https://doi.org/10.1016/j.hrmr.2019.100698

Clement, S. (2024). NATO and AI (Special Report 058 STC). NATO Parliamentary Assembly. https://www.nato-pa.int/document/2024-nato-and-ai-report-clement-058-stc

Connor, K. M., & Davidson, J. R. T. (2003). Development of a new resilience scale: The Connor-Davidson Resilience Scale (CD-RISC). Depression and Anxiety, *18*(2), 76-82. https://doi.org/10.1002/da.10113

Creswell, J. W., & Creswell, J. D. (2018). Research Design: Qualitative, Quantitative, and Mixed Methods Approaches (5th ed.). SAGE Publications.

DeVellis, R. F. (2017). Scale Development: Theory and Applications (4th ed.). SAGE Publications.

DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, *48*(2), 147-160. https://doi.org/10.2307/2095101

European Commission. (2022). DigComp 2.2: The Digital Competence Framework for Citizens. *Publications Office of the European Union*. https://doi.org/10.2760/115376

European Network and Information Security Agency (ENISA). (2018). Cybersecurity Culture Guidelines: Behavioural Aspects of Cybersecurity. *ENISA*. https://www.enisa.europa.eu/publications/cybersecurity-culture-guidelines

European Union. (2024). Regulation (EU) 2024/1689 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). *Official Journal of the European Union*. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32024R1689

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39-50. https://doi.org/10.1177/002224378101800104

George, D., & Mallery, P. (2003). SPSS for Windows Step by Step: A Simple Guide and Reference (4th ed.). Allyn & Bacon.

Government Accountability Office (GAO). (2024). Artificial Intelligence: Actions Needed to Improve DOD's Workforce Management (GAO-24-105645). U.S. Government Accountability Office. https://www.gao.gov/products/gao-24-105645

Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal*, *17*(S2), 109-122. https://doi.org/10.1002/smj.4250171110

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203

Hayes, A. F. (2018). Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach (2nd ed.). Guilford Press.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115-135. https://doi.org/10.1007/s11747-014-0403-8

Hobfoll, S. E. (1989). Conservation of resources: A new attempt at conceptualizing stress. *American Psychologist*, *44*(3), 513-524. https://doi.org/10.1037/0003-066X.44.3.513

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1-55. https://doi.org/10.1080/10705519909540118

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*(1), 15-25. https://doi.org/10.1016/j.bushor.2018.08.004

Kaplan, R. S., & Norton, D. P. (1992). The balanced scorecard: Measures that drive performance. *Harvard Business Review*, *70*(1), 71-79.

Kaushal, N., Kaurav, R. P. S., Sivathanu, B., & Kaushik, N. (2023). Artificial intelligence and HRM: Identifying future research agenda using systematic literature review and bibliometric analysis. *Management Review Quarterly*, *73*(2), 455-493. https://doi.org/10.1007/s11301-021-00249-2

Lawrence, P. R., & Lorsch, J. W. (1967). Organization and Environment: Managing Differentiation and Integration. *Harvard Business School Press*.

Lengnick-Hall, C. A., Beck, T. E., & Lengnick-Hall, M. L. (2011). Developing a capacity for organizational resilience through strategic human resource management. *Human Resource Management Review*, *21*(3), 243-255. https://doi.org/10.1016/j.hrmr.2010.07.001

MacKenzie, S. B., Podsakoff, P. M., & Podsakoff, N. P. (2011). Construct measurement and validation procedures in MIS and behavioral research: Integrating new and existing techniques. *MIS Quarterly*, *35*(2), 293-334. https://doi.org/10.2307/23044045

McKinsey Global Institute. (2023). The State of AI in 2023: Generative AI's Breakout Year. McKinsey & Company. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2023-generative-ais-breakout-year

Meijerink, J., Boons, M., Keegan, A., & Marler, J. (2021). Algorithmic human resource management: Synthesizing developments and cross-disciplinary insights on digital HRM. *The International Journal of Human Resource Management*, *32*(12), 2545-2562. https://doi.org/10.1080/09585192.2021.1925326

Multisubject Journal. (2025). The role of artificial intelligence in transforming defense human resource management. *Audit, Management and Economics Review*, *5*(8), 275-290.

NATO. (2021). NATO Principles of Responsible Use of Artificial Intelligence in Defence. North Atlantic Council. https://www.nato.int/cps/en/natohq/official_texts_187617.htm

NATO. (2024). Summary of NATO's Revised Artificial Intelligence (AI) Strategy. North Atlantic Treaty Organization. https://www.nato.int/en/about-us/official-texts-and-resources/official-texts/2024/07/10/summary-of-natos-revised-artificial-intelligence-ai-strategy

NATO Science and Technology Organization (STO). (2022). Artificial Intelligence (AI) Review (STO-OCS-001). NATO STO. https://www.sto.nato.int/document/artificial-intelligence-ai-review/

OECD. (2022). OECD Framework for the Classification of AI Systems. OECD Publishing. https://doi.org/10.1787/cb6d9eca-en

Parasuraman, A. (2000). Technology Readiness Index (TRI): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research*, *2*(4), 307-320. https://doi.org/10.1177/109467050024001

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879-903. https://doi.org/10.1037/0021-9010.88.5.879

Safshekan, M., Feili, A., Shojaeifard, A., & Sorooshian, S. (2026). Artificial intelligence in human resource management: Models for recruitment, training, performance,

compensation, and retention. Frontiers in Artificial Intelligence, 9, 1718244. https://doi.org/10.3389/frai.2026.1718244

Schein, E. H. (1985). Organizational Culture and Leadership. Jossey-Bass.

Schwarzmuller, T., Brosi, P., Duman, D., & Welpe, I. M. (2018). How does the digital transformation affect organizations? Key themes of change in work design and leadership. *Management Revue*, *29*(2), 114-138. https://doi.org/10.5771/0935-9915-2018-2-114

Septian, L. (2025). Strategy for improving military human resource competence in the era of artificial intelligence: Conceptual and policy review. Baileo: *Jurnal Sosial Humaniora*, *3*(1), 1-18.

Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. *California Management Review*, *61*(4), 66-83. https://doi.org/10.1177/0008125619862257

Stone, D. L., Deadrick, D. L., Lukaszewski, K. M., & Johnson, R. (2015). The influence of technology on the future of human resource management. *Human Resource Management Review*, *25*(2), 216-231. https://doi.org/10.1016/j.hrmr.2015.01.002

Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. *California Management Review*, 61(4), 15-42. https://doi.org/10.1177/0008125619867910

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509-533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

Tufan, S., Demirci, S., & Karadag, H. (2025). A bibliometric analysis of artificial intelligence and machine learning applications for human resource management. *Future Business Journal*, 11, 15. https://doi.org/10.1186/s43093-025-00602-x

Wang, T., Lin, X., & Sheng, F. (2022). Digital leadership and exploratory innovation: From the dual perspectives of strategic orientation and organizational culture. *Frontiers in Psychology*, 13, 902693. https://doi.org/10.3389/fpsyg.2022.902693

Wegner, D. M. (1987). Transactive memory: A contemporary analysis of the group mind. In B. Mullen & G. R. Goethals (Eds.), *Theories of Group Behavior* (pp. 185-208). Springer. https://doi.org/10.1007/978-1-4612-4634-3_9

Wirtz, B. W., Weyerer, J. C., & Geyer, C. (2019). Artificial intelligence and the public sector: Applications and challenges. *International Journal of Public Administration, 42*(7), 596-615. https://doi.org/10.1080/01900692.2018.1498103

Wolf, E. J., Harrington, K. M., Clark, S. L., & Miller, M. W. (2013). Sample size requirements for structural equation models: An evaluation of power, bias, and solution propriety. *Educational and Psychological Measurement*, *73*(6), 913-934. https://doi.org/10.1177/0013164413495237

Wright, P. M., & McMahan, G. C. (1992). Theoretical perspectives for strategic human resource management. *Journal of Management*, *18*(2), 295-320. https://doi.org/10.1177/014920639201800205