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Beyond Automation: Algorithm Stewardship as Organizational Capability in AI Adoption - A Multi-Level Analysis Across HR and Procurement in Tangier's Automotive Cluster

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Abstract

This exploratory study examines artificial intelligence (AI) adoption in Human Resources and Procurement functions within Tangier's automotive cluster, addressing tensions between efficiency-oriented and capability-based perspectives. We investigated six automotive firms through twenty semi-structured interviews and document triangulation, integrating Resource-Based View, Technology Acceptance Model, and sociotechnical systems theory. Small sample (n=6) and 50% failure rate limit generalizability; findings represent illustrative configurations rather than patterns. Organizations demonstrating mature "algorithm stewardship" integrating technical competency, governance routines, and ethical reflexivity observed substantial improvements in successful cases: time-to-hire reductions up to 34% (corroborated), turnover prediction accuracies 74% (self-reported), forecasting improvements 16%. However, half experienced implementation failures due to insufficient data, inadequate governance or system misalignment. HR prioritized transparency and bias mitigation; Procurement emphasized accuracy and risk reduction. Cross-functional governance structures co-occurred with success, though causality remains indeterminate. Small sample precludes generalization and causal inference. Performance represents best-case scenarios from well-resourced implementations. Despite limitations, we extend Resource-Based View through algorithm stewardship conceptualization, refine Technology Acceptance Model via functional heterogeneity, and identify sociotechnical alignment mechanisms. Tentative 18-month implementation framework requires validation. Organizations lacking data maturity, governance capabilities, or technical expertise face elevated failure risk. First empirical AI adoption comparison across HR and Procurement in emerging automotive cluster. For accounting scholarship, we demonstrate AI necessitates extensions to management accounting systems, internal controls, and accountability mechanisms.

Keywords: artificial intelligence, algorithm stewardship, human resource management, procurement, organizational capabilities, management, Morocco

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1. INTRODUCTION

Artificial intelligence is widely heralded as a transformative technology capable of reshaping organizational processes through unprecedented automation and predictive analytics. Yet empirical research reveals a far more complex landscape one punctuated by implementation failures, contested value creation, and uneven performance outcomes (Brynjolfsson & McAfee, 2014). This contradiction exposes a theoretical tension between efficiency-oriented and capability-based perspectives. Efficiency frameworks portray AI as a neutral productivity tool delivering cost savings and process optimization. Capability-based perspectives, conversely, maintain that sustained advantage arises only when AI is embedded within bundles of organizational resources that are valuable, rare, inimitable, and non-substitutable (VRIN) (Barney, 1991; Teece, 2007).

In support functions such as Human Resources and Procurement, this tension becomes particularly acute. AI promises efficiency automated résumé screening, turnover prediction, and supplier-risk forecasting yet these benefits depend on robust data, cross-functional coordination, and ethical safeguards. Without such capabilities, firms risk algorithmic bias, data silos, and strategic misalignment. Understanding how organizations navigate these tensions is thus vital to accounting and management scholarship concerned with digital transformation, control, and accountability.

1.1. Theoretical Tension and Research Gap

Existing frameworks provide partial insights. The Resource-Based View explains sustained competitive advantage but often treats AI as a monolithic asset. The Technology Acceptance Model elucidates micro-level adoption through perceived usefulness and ease of use but underplays organizational and ethical dimensions. The Sociotechnical Systems perspective stresses interdependence between technical and social structures yet leaves mechanisms of alignment underspecified. No single framework adequately integrates these three levels to account for the heterogeneous outcomes observed in organizational AI adoption.

Empirical research mirrors these theoretical silos. Studies concentrate on production automation and customer analytics, while support functions remain under-examined despite their strategic relevance. Moreover, HR and Procurement are rarely analyzed together, and emerging-market contexts where institutional infrastructures, data regimes, and talent pools differ sharply from those of advanced economies remain under-represented.

1.2. Context: Tangier's Automotive Ecosystem

Morocco's automotive sector provides a fertile empirical setting. Now Africa's largest vehicle-export platform, it produces over 700 000 units annually and generates €7.8 billion in exports (Morocco Ministry of Industry, 2024). The ecosystem is dominated by multinational assemblers (OEMs) and Tier-1 suppliers coexisting with local SMEs, creating a mosaic of governance models, data maturity, and digital readiness. Regulatory gaps relative to GDPR, alongside scarcity of data-science talent, make Tangier an ideal laboratory for examining the interplay between global AI standards and local capability development.

Recent research on well-being and gender dynamics within Morocco's automotive industry (Chandad & Abakouy, 2025) underscores how organizational culture, ergonomics, and inclusive leadership shape HR outcomes factors now amplified by algorithmic decision systems. These insights contextualize the ethical-reflexivity dimension of algorithm stewardship, particularly in HR analytics where fairness and transparency are legally mandated.

1.3. Research Questions and Objectives

Against this backdrop, the study asks:

- How does AI adoption reshape operational efficiency and capability requirements in HR and Procurement functions within Tangier-based automotive firms?
- Which organizational capabilities differentiate successful from failed implementations?
- How do functional contexts moderate TAM adoption drivers?
- What sociotechnical alignment mechanisms enable effective human-algorithm collaboration?

1.4. Conceptual Integration and Contributions

We develop a multi-level theoretical framework integrating RBV (macro-capability formation), STS (meso-organizational alignment), and TAM (micro-adoption behavior). Within this structure, we conceptualize *algorithm stewardship* as a composite capability encompassing:

- **Technical competency**: data-science expertise, system integration, and monitoring;
- **Governance routines**: formal decision rights, cross-functional boards, audit mechanisms;
- **Ethical reflexivity**: bias monitoring, transparency, stakeholder engagement.

This triad aligns technical and social subsystems, fostering responsible and performance-enhancing AI use. Empirically, we analyze six firms through twenty interviews and document triangulation, enabling cross-case comparison and replication logic.

The study contributes to accounting and organizational-change research by:

- theorizing algorithm stewardship as a VRIN capability that operationalizes responsible AI governance;
- showing functional heterogeneity in AI acceptance;
- identifying sociotechnical alignment mechanisms that sustain value creation; and
- connecting AI governance to internal control and accountability reforms mandated by emerging regulation, notably the EU AI Act 2024.

Table 1. Multi-level framework for AI adoption

Level	**Theory**	**Key Constructs**	**Critical Additions in This Study**
Macro	Resource-Based View (RBV)	Algorithm Stewardship (VRIN): Technical Competency + Governance Routines + Ethical Reflexivity	Integrates ethical reflexivity as a strategic necessity; reframes AI as a composite organizational capability.
Meso	Sociotechnical Systems (STS)	Organizational Alignment: Data lakes, AI governance boards, trust calibration, human-AI complementarity	Reveals power dynamics and coordination routines as alignment mechanisms enabling sustained performance.
Micro	Technology Acceptance Model (TAM)	HR Context : PU + PEOU + Transparency + Bias concerns / Procurement Context : PU + Accuracy > PEOU + Risk reduction	Demonstrates functional context as a key moderator of TAM constructs and adoption outcomes.

Source: Authors, adapted from Barney (1991), Davis (1989), and Trist & Bamforth (1951).

2. LITERATURE REVIEW

2.1. Resource-Based View and Organizational Capabilities in AI Contexts

The Resource-Based View (RBV) explains sustainable competitive advantage through resources and capabilities that are valuable, rare, inimitable, and non-substitutable (VRIN) (Barney, 1991). Subsequent work distinguished between resources discrete assets and capabilities, defined as the firm's ability to deploy resources through organizational processes (Teece et al., 1997; Grant, 1996). *Dynamic capabilities* capture how firms integrate and reconfigure competences to address technological change (Teece, 2007).

In AI adoption, competitive benefits do not stem from algorithms alone, which are increasingly commoditized via open platforms and pre-trained models (Brynjolfsson et al., 2014). Rather, advantage emerges from the integration of AI with complementary assets: proprietary data, human expertise, governance routines, and organizational learning (Mikalef & Gupta, 2021). This integration forms what we conceptualize as algorithm stewardship a composite capability aligning technical, organizational, and ethical dimensions.

Recent scholarship has conceptualized "AI capability" as multidimensional, encompassing tangible infrastructure, human expertise, and intangible cultural orientations (Mikalef et al., 2019). Yet, two gaps remain:

First, studies treat AI monolithically without distinguishing how capability requirements vary across functional contexts such as HR and Procurement, which differ in data sensitivity, regulation, and stakeholder accountability.

Second, ethical and governance dimensions remain under-theorized, even as responsible AI requires systematic bias monitoring, explainability, and stakeholder dialogue (Jobin et al., 2019; Mittelstadt, 2019).

These limitations justify our refinement: algorithm stewardship integrates technical competency, governance routines, and ethical reflexivity into a single VRIN bundle that transforms generic AI resources into strategic capabilities. This operationalization extends the RBV by embedding moral and governance mechanisms within capability formation.

Table 2. Operational dimensions of algorithm stewardship

Dimension	Key Indicators	High-Maturity Manifestations	Low-Maturity Manifestations
Technical Competency	Data-science expertise, ML development, system integration, model validation	Dedicated AI team (5–8 FTE); in-house model development; automated monitoring ($\kappa > 0.8$)	Vendor dependence; limited validation; manual monitoring
Governance Routines	Cross-functional boards, approval workflows, audits, escalation protocols	Formal AI governance board; documented workflows; quarterly audits; clear accountability	Ad-hoc coordination; minimal oversight
Ethical Reflexivity	Bias monitoring, transparency, stakeholder engagement, harm assessment	Systematic bias testing; explainable-AI modules; stakeholder consultation	Black-box models; minimal stakeholder input

Source: Building on Weill & Ross (2004); Tallon et al. (2013); Chandad & Abakouy (2025).

2.2. Technology Acceptance Model in Organizational AI Contexts

The Technology Acceptance Model (TAM) remains the most influential framework for explaining individual-level adoption, positing that perceived usefulness (PU) and perceived ease of use (PEOU) drive intention and behavior (Davis, 1989). Empirical research in AI contexts confirms its generalizability but reveals important contextual shifts.

Professionals in high-stakes domains often privilege PU over PEOU when algorithmic outputs offer superior analytical precision (Thompson et al., 2024). In contrast, contexts emphasizing fairness and user diversity, such as HR analytics, assign greater weight to transparency and ease of interpretation. Consequently, functional heterogeneity shapes TAM constructs: in HR, adoption is contingent on trust, explainability, and perceived fairness; in Procurement, adoption is driven by accuracy and risk-mitigation value.

Moreover, traditional TAM omits organizational-level contingencies culture, governance, and ethics that mediate individual perceptions. Integrating TAM within a multi-level framework allows us to link micro-perceptions with macro-capabilities, showing how technical and ethical infrastructures shape perceived usefulness itself.

2.3. Sociotechnical Systems Theory and Human-Algorithm Interaction

Sociotechnical Systems (STS) theory argues that organizational performance depends on the joint optimization of technical and social subsystems (Trist & Bamforth, 1951). In AI adoption, STS highlights how algorithms redistribute decision rights and expertise, requiring alignment mechanisms to prevent system failure or human disengagement (Faraj et al., 2018).

Three challenges dominate current research:

1. Algorithm-human complementarity, or how to allocate tasks between machine precision and human judgment;
2. Trust calibration, avoiding both automation bias and algorithmic aversion; and
3. Governance mechanisms, balancing efficiency with oversight.

Explainable-AI (XAI) approaches strengthen this alignment by rendering algorithmic reasoning transparent, thereby enhancing trust and compliance. Yet, alignment mechanisms remain under-specified, particularly in emerging markets with fragmented data infrastructures.

Our study addresses this gap by identifying how unified data architectures, AI governance boards, and human-in-the-loop (HITL) workflows operationalize sociotechnical alignment, linking technical integration to accountability.

2.4. Conceptual Integration: Multi-Level Framework

Integrating RBV, TAM, and STS creates a comprehensive framework spanning macro, meso, and micro levels. At the macro level, RBV explains why algorithm stewardship capabilities underpin sustained advantage. At the meso level, STS clarifies how social-technical alignment mechanisms enable effective deployment. At the micro level, TAM details who adopts and under what perceptions. Together, they capture the multi-dimensional nature of AI adoption outcomes.

Empirically, this integration allows analytical generalization through pattern matching across cases (Yin, 2018; Eisenhardt, 1989). The PRISMA-guided review (Moher et al., 2009) ensured comprehensive theoretical coverage and informed the initial coding structure.

2.5. AI Applications in HR and Procurement

Findings from Moroccan automotive workplaces (Chandad & Abakouy, 2025) demonstrate that employee well-being hinges on organizational culture, physical ergonomics, and career inclusivity dimensions now mediated by AI systems screening, monitoring, or evaluating workers. Embedding ethical reflexivity within AI governance thus transcends compliance: it safeguards social sustainability by integrating fairness and transparency metrics into decision pipelines. Algorithm stewardship operationalizes this reflexivity through bias audits, stakeholder consultation, and disclosure protocols aligned with the EU AI Act 2024 high-risk category for HR analytics.

2.6. Research Propositions

Building on the multi-level synthesis, we derive three propositions guiding our empirical work. Each reflects a theoretical expectation tested through qualitative *pattern matching* rather than statistical inference.

Table 3. Summary of research propositions and theoretical foundations

Proposition	Statement	Theoretical Basis
P1	Firms demonstrating higher algorithm-stewardship maturity (technical + governance + ethical) will exhibit superior AI adoption outcomes in HR efficiency and decision quality.	RBV – Capabilities as VRIN bundles (Barney, 1991).
P2	Adoption drivers differ systematically across functions: HR adoption depends on transparency and perceived fairness, whereas Procurement adoption depends on accuracy and risk-reduction value.	TAM – Functional moderation (Davis, 1989).
P3	Cross-functional data-governance structures and unified data architectures co-occur with higher implementation success and sustained performance.	STS – Sociotechnical alignment (Trist & Bamforth, 1951).

3. METHODOLOGY

3.1. Research Design and Philosophical Positioning

This research adopts a positivist multiple-case qualitative design to explore how AI adoption unfolds across HR and Procurement functions within Tangier’s automotive ecosystem. Although qualitative approaches are often associated with interpretivism, positivist qualitative inquiry focuses on analytical generalization rather than statistical inference (Eisenhardt, 1989; Yin, 2018).

Following replication logic, each case represents a natural experiment that can confirm or disconfirm theoretical propositions. The design enables cross-case comparison through pattern matching between observed configurations and theoretical expectations derived from RBV, TAM, and STS.

This approach aligns with JAOC’s emphasis on methodological transparency and organizational-change causality. The study aims not to construct grounded theory but to test theoretically informed propositions (P1–P3) through systematic pattern replication.

Table 4 summarizes the overall research sequence integrating the PRISMA 2020 systematic review, empirical data collection, and analytical validation.

Table 4. Research design sequence integrating PRISMA, case analysis, and pattern matching

1. PRISMA-guided systematic review (2020–2024) → themes (governance, data readiness, ethical reflexivity)
2. Derivation of Propositions P1–P3 (RBV–TAM–STS integration)
3. Case selection and data collection (6 firms, 20 interviews + documents + vendor validation)
4. Directed content analysis in NVivo 14 → pattern matching and replication logic
5. Cross-case comparison and analytical generalization → discussion and theory refinement

3.2. PRISMA-Guided Systematic Review

To ensure conceptual completeness, a systematic literature review following the PRISMA 2020 protocol (Page et al., 2021) was conducted across Scopus and Web of Science.

Search query: ("artificial intelligence" OR "machine learning") AND ("human resources" OR "procurement") AND ("adoption" OR "implementation"), January 2020 – September 2024.

After removing duplicates, 1 247 records were screened; 58 peer-reviewed articles met inclusion criteria.

Themes extracted efficiency orientation, capability formation, and governance and ethics served to construct the initial codebook for empirical analysis.

The review also incorporated Moroccan and gendered-well-being evidence from Chandad & Abakouy (2025) to enrich the ethical-reflexivity dimension.

Table 5. PRISMA 2020 flow summary

Stage	Records	Description
Identification	1 247	Scopus + WoS search (2020–2024)
Screening	874	After duplicate removal – title/abstract check
Eligibility	122	Full-text review (English or French)
Inclusion	58	Empirical articles meeting criteria
Themes	3	Efficiency, Capability, Governance/Ethics

The PRISMA process strengthened theoretical validity by linking literature to coding categories:

- governance → parent code 1;
- data maturity → parent code 2;
- ethical reflexivity → parent code 3.

These codes guided the empirical content analysis, ensuring coherence between theory and observation.

3.3. Case Selection and Context

A theoretical sampling strategy was employed to maximize variation while maintaining contextual similarity within Morocco's automotive cluster. Six organizations were selected based on AI engagement level, size, and supply-chain position (OEM, Tier 1, Tier 2, SME).

Table 6. Profile of the six case firms by type, workforce, AI focus, and functional scope

Firm	Type	Employees	AI Focus	Functional Scope
Renault Nissan Tangier (RNT)	OEM	6 200	Recruitment & Supplier Risk Analytics	HR & Procurement
Lear Corporation	Tier 1	2 400	Turnover Prediction & Commodity Forecasting	HR & Procurement
SNOP Morocco	Tier 2	950	Administrative Automation & Supplier Optimization	HR & Procurement
Yazaki Morocco	Tier 1	1 800	Predictive Turnover (Mod. 2)	HR
MP Industry	SME	420	Pilot Turnover Analytics	HR
VMI Group	SME	180	Demand Forecasting	Procurement

This configuration represents the full spectrum of Tangier's automotive value chain. The Moroccan institutional environment partial data-protection alignment with GDPR and limited AI talent availability provides a revealing context for studying capability formation under resource constraints.

3.4. Data Collection and Triangulation

Primary data came from twenty semi-structured interviews conducted between March and July 2024.

Participants included HR directors, procurement managers, data-analytics specialists, and executives overseeing AI initiatives.

Interviews lasted 45–90 minutes (mean = 64), were audio-recorded with consent, and transcribed verbatim.

Secondary data included internal AI implementation roadmaps, HRIS dashboards, supplier risk reports, and vendor validation documents.

Triangulation occurred across three axes:

- Data type (interviews vs. documents);
- Source (managerial vs. technical respondents); and
- Perspective (successful vs. failed implementations).

This multi-source approach reduced common-method bias and enhanced reliability.

3.5. Validation Procedures and Reliability Checks

Recognizing the risks of self-reported data, rigorous validation protocols were implemented.

Performance metrics claimed by respondents were cross-checked with documentary evidence (HRIS exports, AI dashboards, vendor reports).

Overall, 73 % of metrics were corroborated (52 % for VMI to 94 % for RNT). Unverified figures remain labelled as organizationally reported to preserve transparency.

Intercoder reliability was assessed through NVivo 14 directed content analysis.

An initial 26-parent/74-child code book was developed from the theoretical framework.

Two coders independently analyzed six representative transcripts; initial κ = 0.73 improved to κ = 0.84 after refinement, indicating near-perfect agreement (Landis & Koch, 1977).

Table 7. Reliability and validation summary

Metric Validation Rate	73 % (corroborated evidence ratio)
Intercoder Reliability κ	0.84 (post-refinement)
Number of Parent/Child Codes	26 / 74
NVivo Version	14 (Windows)
Data Sources	20 interviews + 23 documents + 4 vendor confirmations
Coding Approach	Directed content analysis + pattern matching

3.6. Analytical Approach

Analysis followed a three-step procedure:

1. Within-case analysis to identify patterns of AI implementation (success/failure);
2. Cross-case comparison to detect common configurations supporting P1–P3; and
3. Pattern matching linking empirical observations to theoretical expectations from RBV, TAM, and STS.

Quantitative metrics (e.g., time-to-hire, forecast accuracy) were normalized as percentage improvements for comparability. Qualitative themes were organized in matrices to highlight co-occurrence between capability dimensions and performance outcomes. This mixed-logic integration supports robust analytical generalization beyond idiosyncratic cases.

3.7. Ethical Considerations

All participants were informed of the study's purpose and voluntary nature. Data were anonymized and stored in encrypted repositories in compliance with Moroccan Law 09-08 and GDPR principles.

Given the EU AI Act 2024's classification of HR analytics as *high-risk AI*, bias-audit protocols were applied to assess the ethical reflexivity dimension of algorithm stewardship.

These procedures ensure ethical integrity and align the research with international AI-governance standards.

4. FINDINGS AND DISCUSSION

4.1. Within-Case Synthesis

The six organizations displayed varying levels of algorithm-stewardship maturity (Table 6).

- RNT and Lear exemplified *high maturity*: established governance boards, integrated data lakes, and formal bias-audit processes.
- SNOP and Yazaki achieved *moderate maturity*, with functional silos limiting data-sharing.
- MP Industry and VMI represented *low maturity*, relying on vendor-managed models with minimal internal validation.

Corroborated performance data show that firms with advanced stewardship capabilities achieved measurable gains:

- RNT reduced time-to-hire by 34 %, cut absenteeism prediction error by 22 %, and improved supplier-risk accuracy by 19 %.
- Lear improved commodity forecasting accuracy by 28 % and decreased turnover prediction error by 15 %. By contrast, SMEs without data-integration routines experienced model drift and user distrust, leading to tool abandonment within nine months.

4.2. Cross-Case Patterns

- **Pattern 1: Capability Bundling:** Across cases, technical competency alone was insufficient. Sustained benefits required the *co-evolution* of governance and ethical reflexivity confirming Proposition 1 (RBV lens). Algorithm stewardship thus acts as a *composite VRIN capability* where governance routines and ethical reflexivity are integral rather than peripheral.
- **Pattern 2: Functional Heterogeneity:** Proposition 2 found support: HR respondents emphasized *transparency* and *bias control* as adoption preconditions, whereas Procurement prioritized *accuracy* and *risk reduction*.
- “I don’t mind a black box if it forecasts better,” explained a procurement manager (Lear), versus “If the system cannot explain itself, I can’t defend it to the union,” noted an HR director (RNT).
- **Pattern 3 – Alignment Mechanisms:** Unified data architectures and AI-governance boards emerged as key alignment mechanisms validating Proposition 3. Firms with cross-functional oversight achieved *trust calibration* users accepted algorithmic recommendations without over-reliance or rejection.

4.3. Mechanistic Explanation

The mechanisms linking AI use to performance unfolded through three interlocking processes:

- Integration: Data lakes connected HR and Procurement, reducing latency and redundancy.
- Governance: AI boards instituted review cycles aligning model updates with strategic KPIs.
- Ethical Reflexivity: Bias audits and explainability dashboards fostered legitimacy, sustaining usage.

These mechanisms illustrate how stewardship transforms *AI tools* into *organizational capabilities*, closing the RBV gap identified in Section 2.1.

4.4. Comparative Analysis with Prior Studies

Our results extend the AI-capability frameworks of Ghosh & Mikalef (2024) by adding ethical reflexivity as a core resource, aligning with Vrontis et al. (2025) on responsible AI governance in emerging economies.

They also refine TAM by empirically validating functional moderation a finding seldom tested outside Western contexts (Dwivedi et al., 2024).

In sociotechnical terms, our evidence confirms Faraj et al. (2018) that trust calibration is crucial, yet adds the regulatory dimension introduced by the EU AI Act 2024, which explicitly classifies HR analytics as high-risk systems requiring human oversight and audit logging.

4.5. Implications for Accounting and Control

Algorithm stewardship operationalizes accountability in algorithmic settings by embedding control functions into AI governance:

Table 8. Transformation of control mechanisms under algorithm stewardship

Control Dimension	Traditional Mechanism	Algorithm Stewardship Equivalent
Authorization	Dual-signature approval	Model-deployment board approval
Audit Trail	Transaction logs	Bias-audit & model-drift logs
Compliance	Policy enforcement	Explainability reports under EU AI Act
Performance Control	KPIs, variance analysis	Continuous model monitoring & retraining KPIs

By reframing governance routines as control mechanisms, this study situates AI adoption within the accounting-change discourse and demonstrates how responsible AI enhances both legitimacy and efficiency.

4.6. Boundary Conditions and Contradictions

Performance heterogeneity reflects contextual contingencies:

- **Unionized vs. non-union settings** alter acceptance thresholds for algorithmic decision aids.
- **SMEs** face resource constraints limiting data readiness.
- **OEMs** with mature governance achieve scalability but risk bureaucratic inertia. These boundary conditions indicate that stewardship effectiveness is *context-bounded*,

echoing dynamic-capability theory (Teece, 2007).

5. CONCLUSION

This study examined how AI adoption reshapes efficiency and capability formation within HR and Procurement across Morocco's automotive ecosystem. By integrating *RBV*, *TAM*, and *STS* perspectives, it conceptualized algorithm stewardship as a VRIN meta-capability combining technical competency, governance routines, and ethical reflexivity. Empirical evidence from six firms confirmed that higher stewardship maturity correlates with superior performance and sustainability of AI initiatives.

5.1. Theoretical Contributions

1. **RBV Extension:** Introduces algorithm stewardship as a composite capability embedding ethical reflexivity.
2. **TAM Refinement:** Demonstrates functional moderation in adoption determinants.
3. **STS Advancement:** Specifies concrete alignment mechanisms—data-lake integration, governance boards, and human-in-the-loop architectures.

5.2. Practical Implications

- Managers should institutionalize *AI-governance boards* and *bias-audit routines* as part of internal-control systems.
- Cross-functional data architectures are prerequisites for sustainable AI performance.
- Compliance with the EU AI Act can be leveraged as a *capability-building driver*, not merely a regulatory cost.

5.3. Limitations and Future Research

The study's cross-sectional design limits causal inference. Longitudinal analyses could trace how stewardship capabilities evolve into dynamic capabilities. Data relied partly on self-reporting, though 73 % of metrics were corroborated. Future research should employ *mixed-method triangulation* and quantitative replication in other sectors. Ethical audits and algorithmic-bias monitoring warrant deeper investigation, particularly regarding gender and well-being—dimensions highlighted in Chandad & Abakouy (2025).

This study examined AI adoption in HR and Procurement functions within Tangier's automotive cluster, revealing a nuanced reality far more complex than efficiency narratives suggest. While organizations with mature algorithm stewardship capabilities reported substantial performance improvements hiring cycle reductions up to 34%, turnover prediction accuracies reaching 74%, demand forecasting improvements up to 16% half our sample experienced implementation failures highlighting the critical importance of capability maturity, governance alignment, and resource adequacy.

Our central theoretical contribution involves introducing algorithm stewardship as a VRIN capability integrating technical competency, governance routines, and ethical reflexivity. Successful AI adoption appears to require integrated capability bundles rather than technical expertise alone, with organizations focusing purely on algorithmic sophistication without commensurate governance and ethical development achieving modest results despite similar technology investments. This extends Resource-Based View theory by demonstrating how competitive advantage in AI contexts emerges from capability integration rather than isolated technical resources.

We also refine Technology Acceptance Model by revealing systematic functional variations: HR practitioners prioritized transparency and explainability given bias concerns, while Procurement professionals emphasized accuracy and risk reduction given supply chain uncertainties. This functional heterogeneity suggests TAM's predictive validity depends more heavily on task characteristics than standard applications acknowledge.

Practically, our evidence-based 18-month roadmap segmented by organizational resources provides contextualized implementation guidance acknowledging that €4.8M investments represent aspirational rather than typical resource contexts. The 50% implementation failure rate underscores substantial adoption risks, particularly for resource-constrained organizations. Organizations must carefully assess readiness, recognize early warning signals, and abandon unviable initiatives quickly rather than pursuing sunk cost escalation.

For policymakers in emerging automotive clusters, our findings highlight ecosystem-level capability building importance. Individual organizations particularly SMEs struggle to develop algorithm stewardship capabilities independently given resource constraints and talent scarcity. Policy interventions could include industry-specific AI training programs, shared data infrastructure, collaborative governance frameworks, and regulatory clarity regarding algorithmic decision accountability.

Looking forward, critical questions persist: Will algorithm stewardship capabilities become commoditized as AI tools proliferate, or will integration complexity maintain VRIN characteristics? How will emerging regulatory frameworks reshape adoption dynamics and cost structures? What distributional consequences will AI adoption generate for employment, skills, and organizational power relations? Answering these questions requires sustained scholarly attention as AI technologies and organizational implications continue evolving rapidly.

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