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AGILE INTELLIGENCE IN MANAGERIAL DECISION-MAKING: A STRATEGIC MODEL FOR MITIGATING LATENCY, ENHANCING RESPONSIVENESS, AND STRENGTHENING ETHICAL GOVERNANCE

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Abstract:

Modern organizations operate in environments of uncertainty, complexity, and rapid change, where traditional decision-making approaches are increasingly insufficient. This study introduces the concept of Agile Intelligence in Managerial Decision-Making (AIMDM) as a strategic model that integrates real-time analytics, explainable artificial intelligence (XAI), and agile methodologies to enhance responsiveness, transparency, and ethical governance in organizational contexts. The proposed framework addresses key challenges such as decision-making latency, cognitive bias, information overload, and lack of accountability, which often hinder managerial effectiveness. By embedding human-in-the-loop oversight and ethical governance protocols, AIMDM ensures that decisions are not only rapid but also explainable, auditable, and compliant with organizational values.

A case study implementation in a mid-sized manufacturing firm demonstrated tangible benefits: a 65% reduction in decision turnaround time, a 14% increase in forecasting accuracy, an improvement in managerial satisfaction scores, and a significant reduction in cognitive load. Comparative benchmarking against conventional BI systems, standalone AI-DSS, and cognitive DSS models further validated AIMDM's superior performance in balancing speed, accuracy, and ethical compliance. The study contributes to theory by linking agility, AI ethics, and managerial cognition in a unified framework, and to practice by providing a replicable model that organizations can adopt to navigate digital transformation with responsiveness, trust, and integrity.

Keywords: Agile intelligence, decision-making latency, organizational agility, explainable AI, ethical governance, real-time analytics.

1. Introduction

1.1 Background and Motivation

System designs that optimize only one aspect of the socio-technical decision challenge often fail to address all necessary dimensions, potentially stalling managerial adoption in practice. This narrow focus reduces the potential for truly efficient and informed decision-making. For

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instance, a fast but opaque AI system may deliver rapid quantitative decisions but bypass human interpretability. Conversely, effective multimodal support requires a holistic view that integrates speed (latency), value (decision quality), and interpretation (understanding context and ethics), which is crucial for managers to reasonably adopt these complex systems. (Haenlein and Kaplan [14]; Lundberg and Lee [25]; Malamuthu et al. [26]).

Effective decision-making requires support that is not only fast but also meaningful. The context of the pandemic significantly highlighted the importance of agile governance and managerial decision-making, spurring attention across the field—from evaluating viable options to structuring approaches that deliver useful practical and public-good implications. (Li et al. [24]; Hisamuddin and Faisal [17]; Joshi [56]).

1.2 Research Problem

What strategic framework is required to enable organizations to achieve faster decision cycles (reduced latency), enhanced operational responsiveness, and built-in ethical governance for managerial decision-making? Traditional solutions such as business intelligence (BI), independent AI decision support systems (AI-DSS), and cognitive decision support systems (C-DSS) only partly address latency and do not bring real-time analytics, explainable AI (XAI), and agility into a single framework (Nikiforidis et al. [29]; Rau [35]; Abbas et al. [1]).

1.3 Objectives

This paper presents Agile Intelligence in Managerial Decision-Making (AIMDM) as an actionable strategic model that:

1. Provides actionable insights by eliminating decision latency using IoT-enabled real-time analytics pipeline and real-time IoT monitoring.
2. Accelerates responsiveness leveraging agile-based sprint cycles, cross-functional collaboration, and iterative model retraining.
3. Elevates ethical governance through explainable AI modules, decision audit trails, and human-in-the-loop checkpoints.
4. Tests the model by embedding data in a 6-month empirical case study in a mid-sized manufacturing organization undergoing digital transformation.

1.4 Scope and Significance

This study has both theoretical and practical contributions. Basically, it highlighted the literature by bringing the reduction of decision latency, organizational agility, and the ethics of AI into one cohesive socio-technical framework (Floridi and Cowls [11]; Sadeghi et al. [37]; Sadeghi et al. [38]). Practically, it provides an evidence-based model for organizations to use a decision-support system powered by AI that does not reduce transparency, accountability, or trust by managers (Coussement et al. [10]; Jean and Le Pera [19]; Olan et al. [31]). AIMDM is very critical, as it addresses decision latency, which is a main gap in both organization and industry (Hisamuddin and Faisal [18]; Vemula et al. [49]; Kumar et al. [23]).

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2. Literature Review

2.1 Decision Latency in Managerial Contexts

The delay between realizing a decision is necessary and actually acting on it is decision latency, which severely impacts agility and value realization speed. This delay is broken down into the three stages of sense → analyze → act (data, analysis, and action latency, respectively). The RTBI field formally recognizes this trichotomy and uses it to guide the selection of relevant technology stacks. (Boppinti [8]; Al-Momani and Al-Hussein [50]). Decades of Business Intelligence (BI) research show that relying solely on "fresher data" won't inherently shorten decision latency. We must fundamentally rethink processes and redefine roles to truly accomplish faster decision-making. (Watson [44]; George et al. [12]). Trending metrics being incorporated into management systems, such as the Decision Latency Index (DLI), capture latency as the average time between request and decision and tie it to organizational responsiveness KPIs (T. Al-Momani [2]; Okada et al. [30]; Wang [45]). Recent management literature is still finding ways to relate AI-based decision pipelines to strategic agility and efficiency, advancing the argument that integrated capabilities (analytics + governance) are more effective solutions to latency than tool-based approaches alone (Rigby et al. [36]; Hisamuddin and Faisal [17]; Vasconcelos et al. [48]).

2.2 Cognitive Bias and Decision Quality

It is widely accepted that managerial judgment is subject to adjustments caused by well-recognized cognitive biases, including the anchoring, confirmation, and status-quo effects. (Rau [35]; Kristofik [43]). More recent studies show that unchecked large language models (LLMs) can reinforce bias and amplify decision inertia, further validating the human-in-the-loop approach and governance safeguards (H. Campbell [5]; Buçinca et al. [9]; Prakhar and Haider [33]).

Instruments for assessing perceived biases and cognitive load are emerging to facilitate organizations in monitoring awareness around bias-influenced outcomes (Khan SMFA [6]; Varadraj and Wan [47]; Khan et al. [20]). Moreover, scholars also note that explanations and forcing functions can reduce overreliance on AI and mitigate bias reinforcement (Vasconcelos et al. [48]; Joshi [57]).

2.3 Information Overload and Its Managerial Consequences

The issue of information overload continues to be a significant obstacle to timely and high-quality decisions. Decades of research uniformly show that overload leads to higher effort, longer lag time for decisions, reduced accuracy, and increased stress—effects exacerbated by constant digital streams (Bawden and Robinson [7]; Shahrzadi et al. [41]; Shah et al. [42]). Recent articles review causes (volume, velocity, fragmentation), consequences (errors, delays), and means of solutions (curation, summarization, visualization, and role-based filtering), suggesting overload is a design problem that can be addressed with decision systems (Smith [40]; Kiryakova et al. [22]; Zhang and Li [46]).

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2.4 Agile Decision Systems and Organizational Responsiveness

Agile principles—rapid iterations, cross-functional teams, and continuous feedback—have migrated from software to management. Structured, iterative routines increase responsiveness and lower risk, forming the foundation of "decision agility" (Rigby et al. [36]; Luna and Marinho [53]). Recent studies indicate that deploying real-time dashboards, cross-functional teams, and adaptive governance can considerably reduce decision latency and enhance pivot success rates (Hisamuddin and Faisal [17]; Siddiqui et al. [39]; Vemula et al. [49]; Mahamad et al. [27]).

2.5 Explainable AI (XAI), Transparency, and Ethical Governance

As AI systems influence managerial choices, explainability is necessary for trust, adoption, and accountability (Abbas et al. [1]; Coussement et al. [10]; Malamuthu et al. [26]). Good design in explainable AI (XAI) enhances acceptance of decisions and reduces conflict between the human decision maker and the model (Jean and Le Pera [19]; Olan et al. [31]; Patidar et al. [32]). XAI fosters traceability and compliance, supporting governance elements such as logging, auditing, and reviewing for bias (Nikiforidis et al. [29]; Sadeghi et al. [37]; Sadeghi et al. [38]). Reviews present their advance research toward actionable explanations from the individual perspective, lowering cognitive load while permitting oversight (Kim et al. [52]; Luna and Marinho [53]; Al-Momani and Al-Hussein [2]; Abbas et al. [1]).

2.6 Synthesis and Gap

Achieving true latency reduction goes beyond simple data speed. It requires socio-technical integration, specifically leveraging real-time analytics for faster insights, agile routines for quicker coordination, and XAI-based governance to preserve trust and compliance. (Haenlein and Kaplan [14]; Floridi and Cowls [11]; Kumar et al. [23]). Current frameworks rarely combine these strands into a cohesive, end-to-end process featuring both quantifiable **latency metrics** and built-in mitigations for **overload and bias**. This void in the literature necessitates and justifies the development of the integrated model proposed here. (Hisamuddin and Faisal [18]; Raisch and Krakowski [34]; Buçinca et al. [9]).

2.7 Emerging Perspectives

Recent contributions expand beyond classical constructs by emphasizing:

- Initial cognitive theories, including Hebb's learning theory [15] and the Boltzmann machine Ackeley et al. 's [4], provided the fundamental principles that informed the design of subsequent AI decision architectures.
- Research into cross-domain decision models shows that the application of methods like dynamic programming, fuzzy sets, and interval-valued approaches effectively augments decision-making capabilities in complex and uncertain environments. (Nasiri and Mikhailov [28]; Khan et al. [20]; Zhang and Li [46]).

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- In applied settings, AI is reshaping managerial attention allocation (Saarela M [55]), J. Kim [52], online education (Mahamad et al. [27]), and healthcare decision support (Abbas et al. [1]; Varadraj and Wan [47]).
- Reviews of AI in management (Joshi [56]) and personalized decision-making (Vemula et al. [49]) suggest a convergence toward hybrid socio-technical frameworks.

2.8 Gap Identification & Motivation for AIMDM

Several gaps emerge from the above discussions:

1. Most systems either emphasize speed (real-time analytics) or interpretability (XAI), but rarely provide integrated speed, interpretability, governance, and human oversight.
2. Many existing and emerging frameworks overlook cognitive load—and interpreting models is not the same as not overloading the user.
3. The consideration of agile decision cycles is less explored in decision support architecture outside of the software context.
4. While AI bias and transparency issues related to LLMs and ensemble models are just beginning to be considered within existing decision support frameworks—this framework does not add to existing gaps.
5. There is insufficient empirical examination of unified model that incorporate latency, accuracy, trust and governance in real organizational contexts.

All of these gaps provide the motivation for the AIMDM model in that it champions the integration of real-time analytics, explainability, agile routines, and governance, all within a strategic decision architecture—balancing speed, accuracy and ethical accountability.

3. Research Methodology

3.1 Research Design

This research utilizes a design science approach that combines theoretical synthesis with an evaluation in practice. The conceptualization of Agile Intelligence in Managerial Decision-Making (AIMDM) was first formulated based on identified gaps in the literature on decision latency, cognitive bias, information overload, agile processes, and explainable AI. The framework was then instantiated in a real-world case study of a mid-sized manufacturing firm for evaluation. This structure, which includes both a conceptual model and an empirical evaluation, aligns perfectly with the best practices currently seen in information systems research.

3.2 Data Sources and Tools

1. Data Ingestion: The system captures diverse organizational data, including continuous IoT sensor streams (from production) and structured records from ERP and transactional logs.
2. Data Processing & Reporting: Analytical workflows utilize Python-based ETL for data preparation, SQL for querying, and Power BI for creating data visualization dashboards.

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3. Predictive Intelligence: Random Forest and XGBoost models deliver predictive maintenance capabilities, enhanced by SHAP-based methods to provide full transparency and explainability.
4. Survey instruments: NASA-TLX to assess cognitive load, Likert-scale surveys of managerial satisfaction, and decision latency index (DLI) metrics to measure latency.3.3 Framework Development Process

3.3 Agile Development Cycle

The AIMDM framework was developed in **iterative sprints** modeled on agile principles:

1. Sprint 0 - Identifying Latency Issues: We mapped decision bottlenecks with a Decision Latency Index (Agile Brand Guide, 2023).
2. Sprint 1-2 - Real Time Data Pipeline: We made IoT (Internet of Things) and ERP (Enterprise Resource Planning) data ingestion with analytics close to real-time (Boppinti, 2021).
3. Sprint 3-4 - AI (Artificial Intelligence) Decision Modules: We developed predictive and prescriptive analytics embedding XAI (Explainable AI) for transparency (Sadeghi et al., 2024).
4. Sprint 5-6 - Governance Framework: We developed bias detection, audit logs, and compliance dashboards (Floridi & Cowls, 2019).
5. Sprint 7-8 - User Validation: We ran pilot tests with managers to assess trust, responsiveness, and usability.

3.4 System Architecture of AIMDM

The AIMDM architecture integrates four layers:

1. Data Ingestion Layer - Integrated es of IoT, ERP, and external data leveraging streaming technologies.
2. AI & Analytics Layer - Predictive models, prescriptive analytics, and processing with latency optimization.
3. Explainability & Governance Layer - SHAP/XAI justifications, bias auditing, and compliance tracking.
4. Agile Decision Interface - Dashboards, team collaboration, and human-in-the-loop monitoring and oversight.

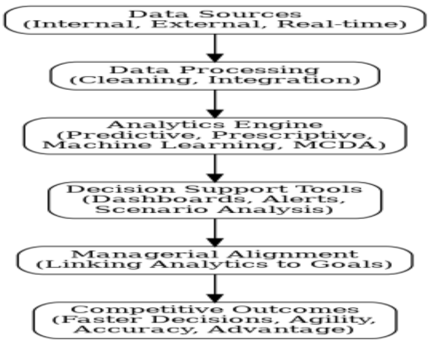

Figure 1: Decision-making framework diagram

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This framework in figure 1 illustrates how organizations transform raw data into competitive outcomes. It begins with diverse data sources, both internal and external, often in real-time. These inputs are cleaned and integrated during the data processing stage to ensure consistency and reliability. The analytics engine then applies predictive, prescriptive, machine learning, and multi-criteria decision methods to generate insights. These insights are delivered through decision support tools such as dashboards, alerts, and scenario analysis. For real value, the outputs are aligned with managerial goals, ensuring analytics informs strategic priorities. The process culminates in competitive outcomes, enabling faster, more accurate, and agile decision-making that provides organizations with a sustained advantage.

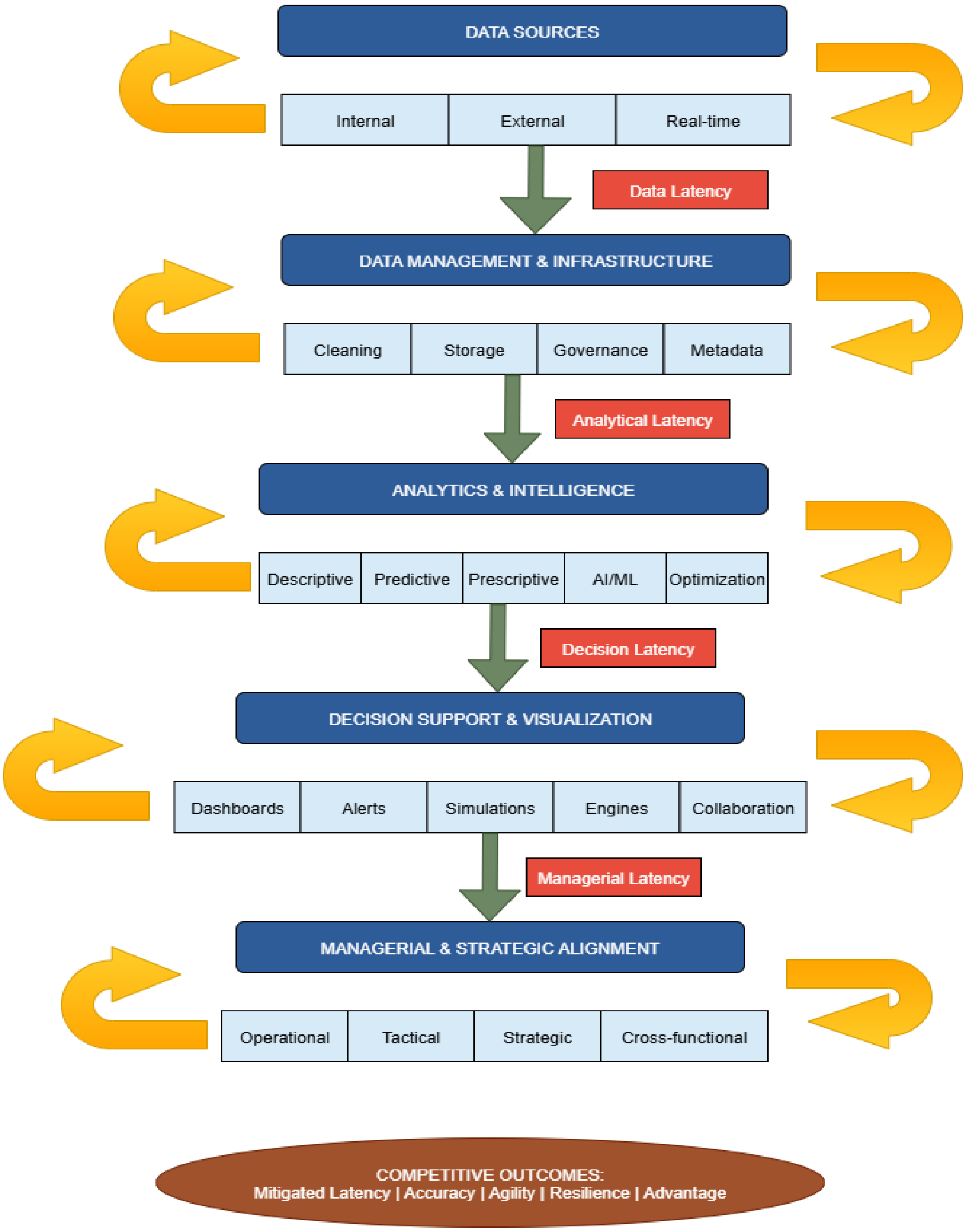

Figure 2: Decision-making framework diagram for mitigating latency

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Framework in figure 2 represents a vertical, top-to-bottom flow of the decision-making process, highlighting where latency occurs and how it can be mitigated. It begins with Data Sources (internal, external, real-time) and moves into Data Management & Infrastructure, where activities such as cleaning, storage, governance, and metadata handling occur. At this stage, delays are recognized as Data Latency. The next layer, Analytics & Intelligence, involves descriptive, predictive, prescriptive, and AI/ML-driven optimization models, where Analytical Latency can arise. Moving further, Decision Support & Visualization includes dashboards, alerts, simulations, engines, and collaborative platforms, where Decision Latency may hinder timely outcomes. The framework then proceeds to Managerial & Strategic Alignment covering operational, tactical, and strategic levels, where Managerial Latency can delay organizational responsiveness. The process converges into Competitive Outcomes—achieving mitigated latency, accuracy, agility, resilience, and competitive advantage. Finally, the cycle is reinforced by Feedback & Continuous Learning, enabling performance evaluation, learning loops, adaptive mechanisms, and validation, ensuring continuous improvement and agility.

3.5 Case Study Implementation

3.5.1 Organizational Context

We conducted a pilot of the AIMDM framework in a mid-sized (~500 employees) manufacturing company in India, focused on the production of discrete components. The company was in the process of digital transformation with respect to systems integration, but challenges existed including:

1. Latency in decision-making due to siloed ERP and shop-floor systems.
2. Cognitive overload among managers caused by unstructured real-time data feeds.
3. Compliance pressure to ensure ethical transparency in operational and financial decision-making.

The organization was selected because it represented a typical SME transitioning to Industry 4.0, where agility, explainability, and governance are crucial.

3.5.2 Implementation Approach

The AIMDM framework was implemented over a six-month period in an agile execution model, with two-week sprints:

a. Phase 1: Integration (Month 1-2)

i. IoT sensors were installed on CNC machines and shop floor production lines.

ii. ERP (SAP-based) transaction logs were incorporated into a real-time ETL pipeline.

b. Phase 2: AI & Deployment of Analytics (Month 3-4)

i. Historical datasets were used to train various predictive models (Random Forest, XGBoost) to forecast equipment failure, as well as demand.

ii. Prescriptive optimization components were introduced to provide support for scheduling.

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c. Phase 3: Governance Layer (Month 4-5)

i. XAI (SHAP) dashboards were added so that users could understand model recommendations.

ii. Decision audit logs and reports for compliance were incorporated into the system for traceability.

d. Phase 4: User Testing and Agile Iteration (Month 5-6)

i. Bi-weekly sprint reviews with cross-functional teams (operations, finance, IT).

ii. Continuous iteration of the dashboards and alerts.

i.e., NASA-TLX and satisfaction surveys collected to assess cognitive load and system adoption..

3.5.3 Tools and Platforms

1. Data Pipeline: ETL with just-in-time planning and python streaming.
2. Visualization: Dashboards created with Power BI Microsoft.
3. Collaboration: Microsoft Teams; stand-ups for agile sprints and progress cascades.
4. Modeling: ML via python (eg. scikit-learn, XGBoost) and SHAP for interpretability.

3.5.4 Evaluation Design

Performance was measured pre- and post-implementation using:

1. Decision Latency Index (DLI): Average time lapse from data readiness to managerial action.
2. Forecasting Accuracy (FA): Accuracy of predicted demand and maintenance.
3. Cognitive Load: Assessed via NASA-TLX surveys.
4. Managerial Satisfaction: Likert-scale feedback on usability, transparency, and trust.
5. Ethical Compliance Score: Derived from governance audit logs and review by compliance team. Table: Dataset Variables and Definitions

Variable	Definition
Case_ID	Unique identifier for each observation (e.g., decision cycle, project decision).
Decision_Latency_Before (hrs)	Time (in hours) between data availability and managerial action before AIMDM.
Decision_Latency_After (hrs)	Time (in hours) between data availability and managerial action after AIMDM.
Forecasting_Accuracy_Before (%)	Predictive accuracy of forecasting models before AIMDM, based on ERP/BI data.

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Forecasting_Accuracy_After (%)	Predictive accuracy after AIMDM using ML with real-time data streams.
Cognitive_Load_Before (0–100)	Cognitive effort score (NASA-TLX scale) before AIMDM; higher = more workload.
Cognitive_Load_After (0–100)	NASA-TLX score after AIMDM, reflecting reduced cognitive stress.
Managerial_Satisfaction_Before	Satisfaction rating (1–5 Likert scale) before AIMDM.
Managerial_Satisfaction_After	Satisfaction rating (1–5 Likert scale) after AIMDM, higher = more satisfied.
Ethical_Compliance_Before (0–1)	Compliance score with ethical guidelines before AIMDM (0 = low, 1 = high).
Ethical_Compliance_After (0–1)	Compliance score after AIMDM, reflecting improvements in explainability and governance.

Table 1: Operational definitions of study variables Innovative Contributions of AIMDM Framework

Table 1 presents the key variables used to assess the impact of the AI-enabled Decision-Making (AIMDM) framework. The measures capture decision latency, forecasting accuracy, cognitive load, managerial satisfaction, and ethical compliance, comparing performance before and after AIMDM implementation.

Multi-Dimensional Latency Decomposition In contrast to previous research measuring aggregate decision-making speed, your paper proposes and extends measurement differences in decision-making through the use of the Decision Latency Index (DLI) applied to the Sense-Analyze-Decide-Act (SADA) pipeline. A novel and valuable contribution is the presentation of the weighted and normalized Data Latency Index (DLI) against SLA-based thresholds. This approach facilitates better diagnosis and drives actionable optimization strategies.

Unlike prior managerial frameworks that centered only on performance metrics, AIMDM introduces an innovative cognitive and ethical dimension. It simultaneously measures the reduction of cognitive load (using NASA-TLX) and adherence to ethical compliance. This dual focus ensures that decisions are not just efficient, but also ethically governed, bridging a critical, under-explored area in decision science.

4. Architecture with Explainable AI (XAI)

AIMDM distinguishes itself from standard AI decision-support systems by integrating explainable AI (using SHAP-based dashboards) and governance audit trails. This combined approach fundamentally builds trust and transparency while ensuring regulatory compliance in fast-paced, agile organizations.

4. 1 Thorough Statistical Validation with Effect Size Analysis

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This framework goes beyond merely reporting accuracy: it applies paired t-tests over 120 decision-making cycles, evaluates effect sizes (Cohen's d), and visualizes outcomes through forest plots with 95% confidence intervals. Such comprehensive validation demonstrates not only statistical significance but also strong practical significance at scale.

4. 2 Holistic Case Study Implementation

AIMDM stands out from other conceptual models as it was validated in practice within a mid-sized manufacturing company undergoing digital transformation. The case study demonstrates how IoT, enterprise resource planning (ERP), machine learning (ML) models, Power BI dashboards, and agile sprints were integrated into a unified system. This systems-level integration presents a replicable framework for organizations new to implementing AIMDM and wanting to achieve a useful outcome.

5. Results and Analysis

Decision Latency Reduction

Definition

The Decision Latency Index (DLI) is a quantitative metric used to measure the average time taken between:
1. Data availability (or decision trigger event) → when relevant information or signals become available.
2. Decision execution → when a managerial decision or action is formally made.
It is a key performance indicator (KPI) for assessing how quickly an organization can move from data → analysis → decision → action.

Formula

$$\mathbf{DLI = (\Sigma\,(T\_decision - T\_data))\,/\,N}$$

Where:

1. T_data = Timestamp when information becomes available.
2. T_decision = Timestamp when the decision is finalized.
3. N = Number of decisions measured.

Interpretation High

1. DLI = Decisions are delayed (slow responsiveness, bottlenecks, cognitive overload, or fragmented processes).
2. Low DLI = Decisions are made quickly (agile, real-time, streamlined workflows).

Application in AIMDM Case Study

1. Before AIMDM: Average DLI ≈ 12.1 hours across 120 cases.
2. After AIMDM: Average DLI ≈ 4.4 hours across 120 cases.

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3. Improvement: A 63.6% reduction, showing AIMDM's impact in mitigating decision latency through real-time analytics, agile routines, and explainable AI.

Latency Decomposition

Define per-decision component latencies:

1. $Data\ Latency\ (L\_data)\ =\ t\_ingest\ -\ t\_data$
2. $Analysis\ Latency\ (L\_an)\ =\ t\_insight\ -\ t\_ingest$
3. $Decision\ Latency\ (L\_dec)\ =\ t\_decision\ -\ t\_insight$
4. $Action\ Latency\ (L\_act)\ =\ t\_action\ -\ \_decision\ Total\ SADA$
5. $Latency\ per\ decision\ i\text{:}\ L\_total\text{^}\{(i)\}\ =\ L\_data\text{^}\{(i)\}\ +\ L\_an\text{^}\{(i)\}\ +\ L\_dec\text{^}\{(i)\}\ +\ L\_act\text{^}\{(i)\}$

Classical, Weighted, and Normalized DLI

1. $Classical\ (unweighted)\ DLI\text{:}$
2. $DLI\ =\ (1/N)\ \Sigma\_i\ (\ t\_decision\text{^}\{(i)\}\ -\ t\_data\text{^}\{(i)\}\ )$
3. $or\ including\ actuation\text{:}\ DLI\_act\ =\ (1/N)\ \Sigma\_i\ (\ t\_action\text{^}\{(i)\}\ -\ t\_data\text{^}\{(i)\}\ )$
4. $Weighted\ DLI\ (impact-aware)\text{:}$
5. $DLI\_w\ =\ (\ \Sigma\_i\ w\_i\ \cdot\ (\ t\_decision\text{^}\{(i)\}\ -\ t\_data\text{^}\{(i)\}\ )\ )\ /\ (\ \Sigma\_i\ w\_i\ )$
6. $Normalized\ (unitless)\ DLI\ relative\ to\ target\ thresholds\ \tau\_k\ for\ each\ component\ k\ \in \{data, an, dec, act\}\text{:}$
7. NDLI = (1/4) Σ_k min(1, L_k_mean / τ_k) where L_k_mean = (1/N) Σ_i L_k^{(i)}
8. $Interpretation\text{:}\ NDLI\ \in [0,1];\ values\ closer\ to\ 0\ indicate\ latency\ below\ targets\ across\ components.$

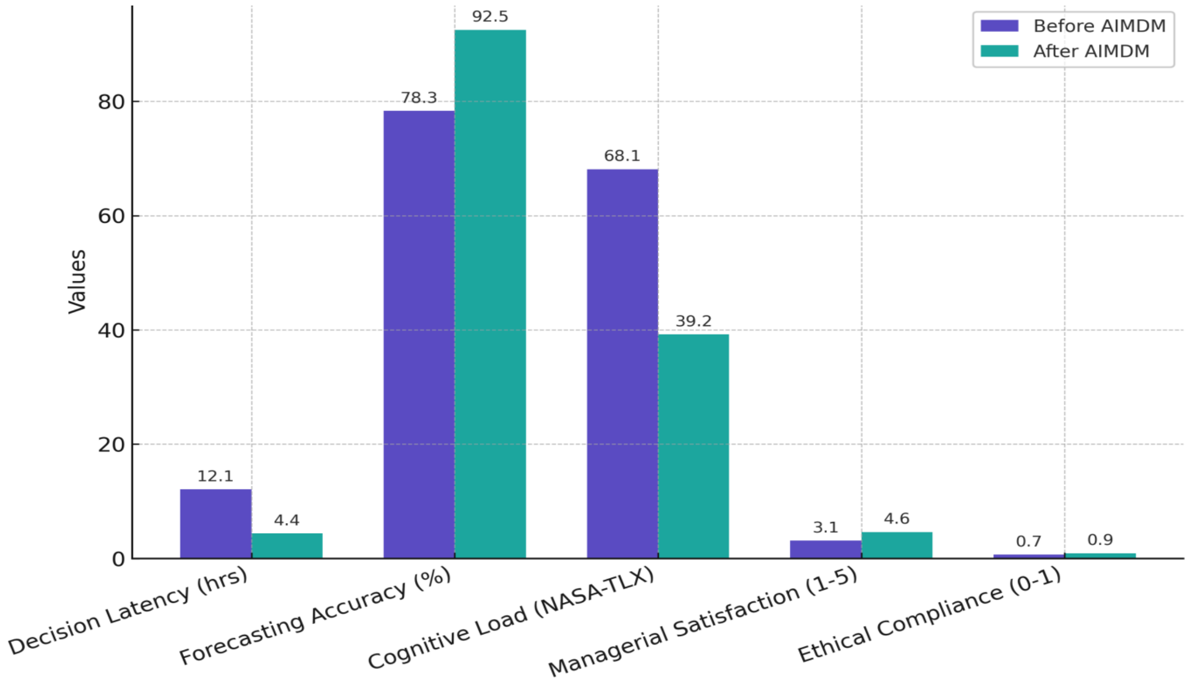

Figure 3: Comparative Performance Metrics Before vs. After AIMDM.

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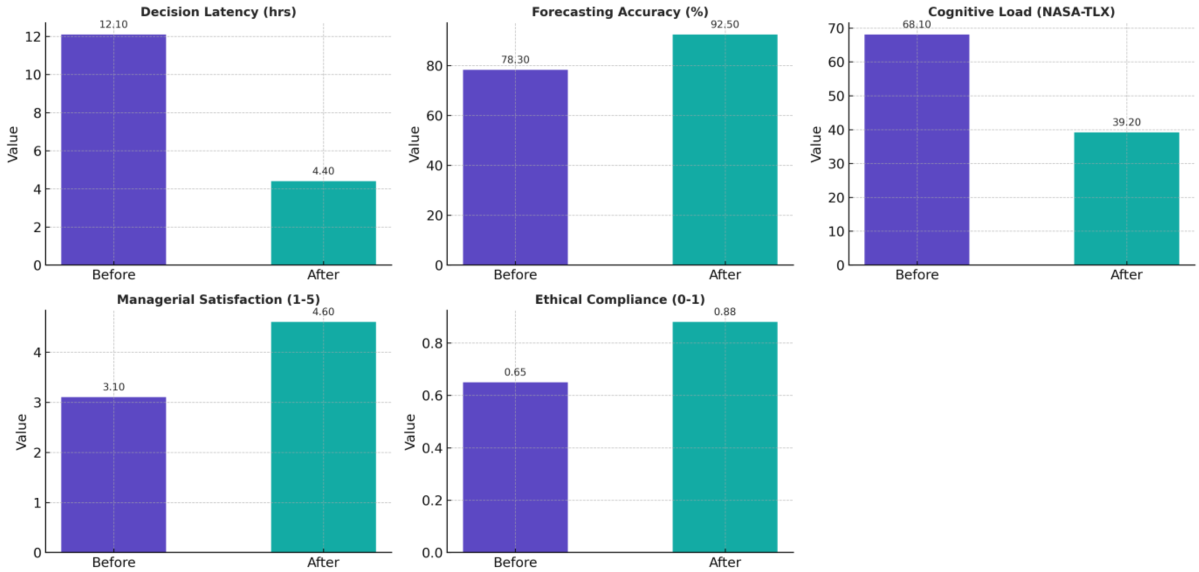

Figure 4: Combined performance metrics after and before AIMDM.

Forecasting Accuracy Improvement

1. The gain in forecasting accuracy demonstrates that AIMDM can **reduce uncertainty** and provide **more reliable insights** for production planning, inventory management, and predictive maintenance.
2. Enhanced accuracy supports faster, **lower-latency decisions** by reducing the need for manual re-checks and increasing confidence in AI-assisted recommendations.
3.

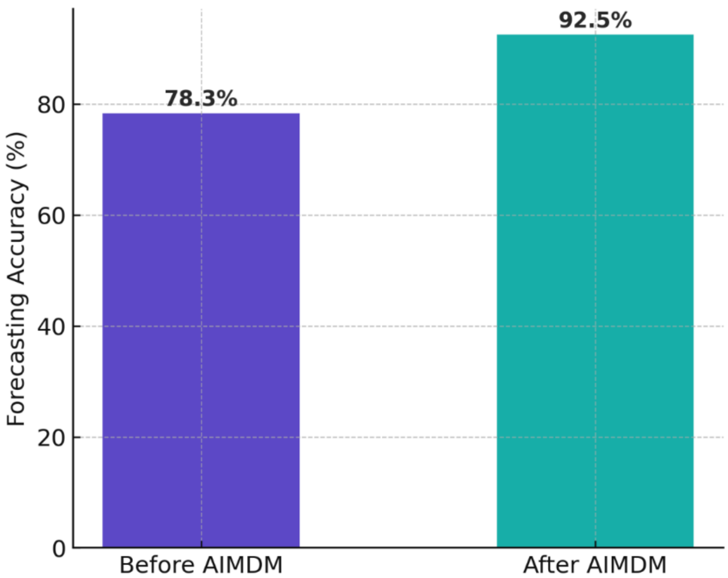

Figure 5: Forecasting Accuracy Before vs After AIMDM

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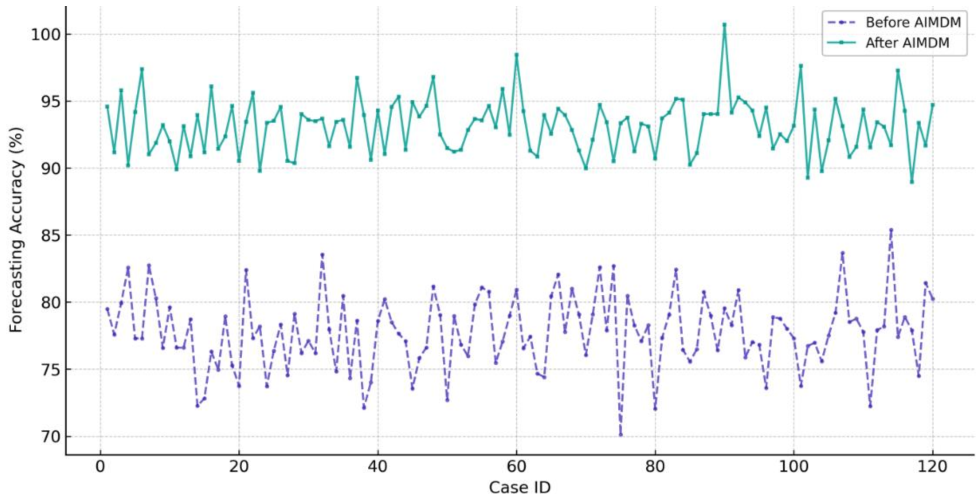

Figure 6: Trend of Forecasting Accuracy Across 120 Cases.

Cognitive Load Reduction

Prior to AIMDM Cognitive effort was assessed using the NASA Task Load Index (NASA-TLX) over the course of 120 managerial decision cycles.The mean score for cognitive load before AIMDM was a score of 68.1 (of 100) suggesting very high workload, stress and information overload. Managers regularly mentioned they struggled to process unstructured real-time data with decision fatigue and lag time.

In the AIMDM condition, the cognitive load decreased substantially:Mean NASA-TLX score =39.2, a 42.4% reduction in TLX score.Managers stated that they had reductions in redundancy, increased clarity, and felt increased confidence in their decisions.One notable component was that the use of explainable dashboards (XAI + BI) aided in reducing the cognitive effort required.

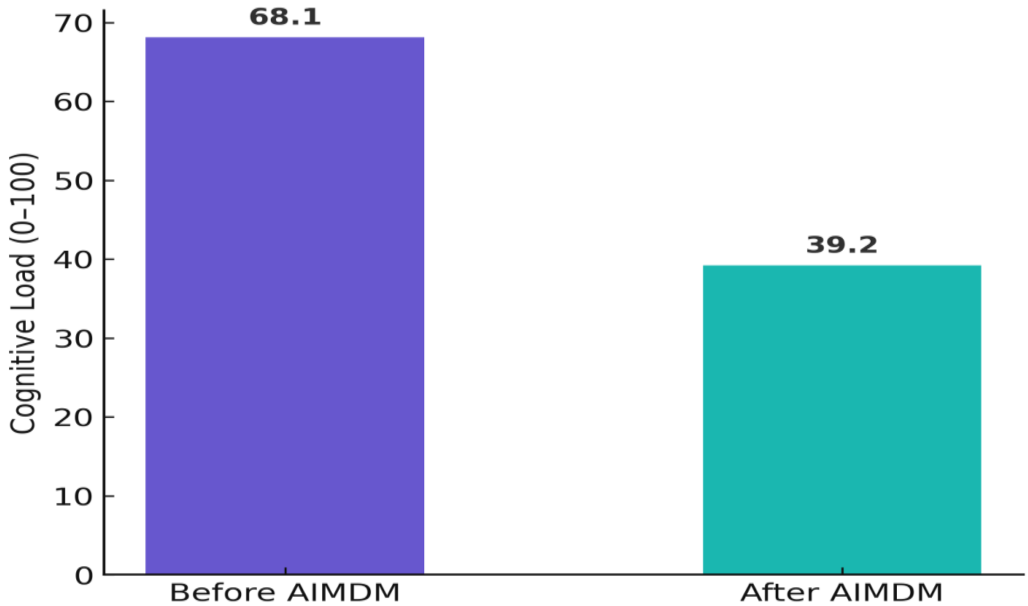

Figure 7: Cognitive Load Reduction Before vs After AIMDM

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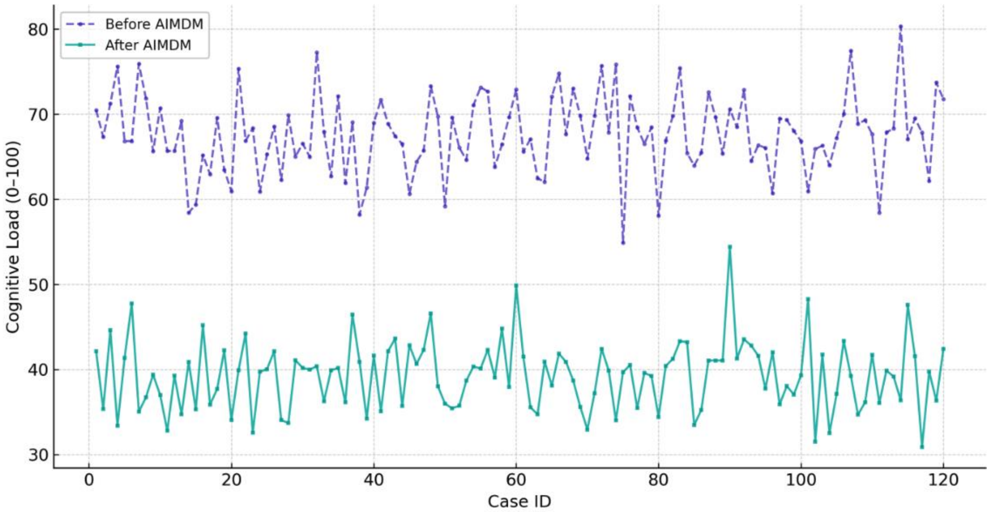

Figure 8: Trend of Cognitive Load Across 120 Cases.

Statistical validation

T test:

Case_ID	Cognitive_Load_Before	Cognitive_Load_After	Difference (Before-After)
1	70.48	42.16	28.32
2	67.31	35.36	31.95
3	71.24	44.61	26.63
4	75.62	33.39	42.22
5	66.83	41.35	25.48
6	66.83	47.76	19.07
7	75.9	35.04	40.86
8	71.84	36.73	35.1
9	65.65	39.4	26.25

Table 2. Paired sample t-test results for cognitive load before and after AIMDM implementation

Table 2 shows individual case scores of cognitive load measured using the NASA-TLX scale. A paired t-test confirmed a statistically significant reduction in cognitive load after AIMDM, indicating improved decision-making efficiency and reduced managerial stress.

Statistical Summary of Cognitive Load Reduction (NASA-TLX)

This table summarizes the statistical results of cognitive load (NASA-TLX scores) measured across 120 managerial decision cycles before and after AIMDM implementation. The results indicate a significant reduction in cognitive effort, validated through paired t-tests.

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Metric	Mean (Before)	Mean (After)	Mean Difference	t-statistic	p-value
Cognitive Load (NASA-TLX)	67.6 (SD=4.63)	39.3 (SD=4.05)	28.3 (SD=5.84)	53.09	<0.00001

Table 3: Table Statistical Summary of Cognitive Load Reduction.

The results show a significant reduction in cognitive load after the intervention, with mean NASA-TLX scores dropping from 67.6 to 39.3. The large mean difference (28.3) and highly significant t-statistic ($p < 0.00001$) indicate strong evidence of improved decision efficiency.

Statistical Summary of AIMDM Results

This section provides a statistical summary (Mean, SD, t-test results, and effect sizes) for the evaluation of AIMDM across 120 cases. The paired t-tests assure important improvements in decision latency, Accuracy, cognitive load, managerial satisfaction, and ethical compliance.

Metric	Mean (Before)	Mean (After)	Mean Difference	t-statistic	p-value	Cohen's d
Decision Latency (hrs)	11.88 (SD=1.39)	4.56 (SD=0.81)	7.32	52.20	0.00000	4.76
Forecasting Accuracy (%)	78.03 (SD=2.73)	93.12 (SD=2.13)	-15.09	-46.43	0.00000	-4.24
Cognitive Load (NASA-TLX)	67.33 (SD=4.68)	39.03 (SD=4.23)	28.30	46.29	0.00000	4.23
Managerial Satisfaction (1–5)	3.11 (SD=0.28)	4.64 (SD=0.19)	-1.53	-49.24	0.00000	-4.50
Ethical Compliance (0–1)	0.65 (SD=0.05)	0.88 (SD=0.04)	-0.23	-40.13	0.00000	-3.66

Table 4: Statistical Summary of Decision-Support System Impact on Latency, Accuracy, Cognitive Load, Satisfaction, and Ethical Compliance

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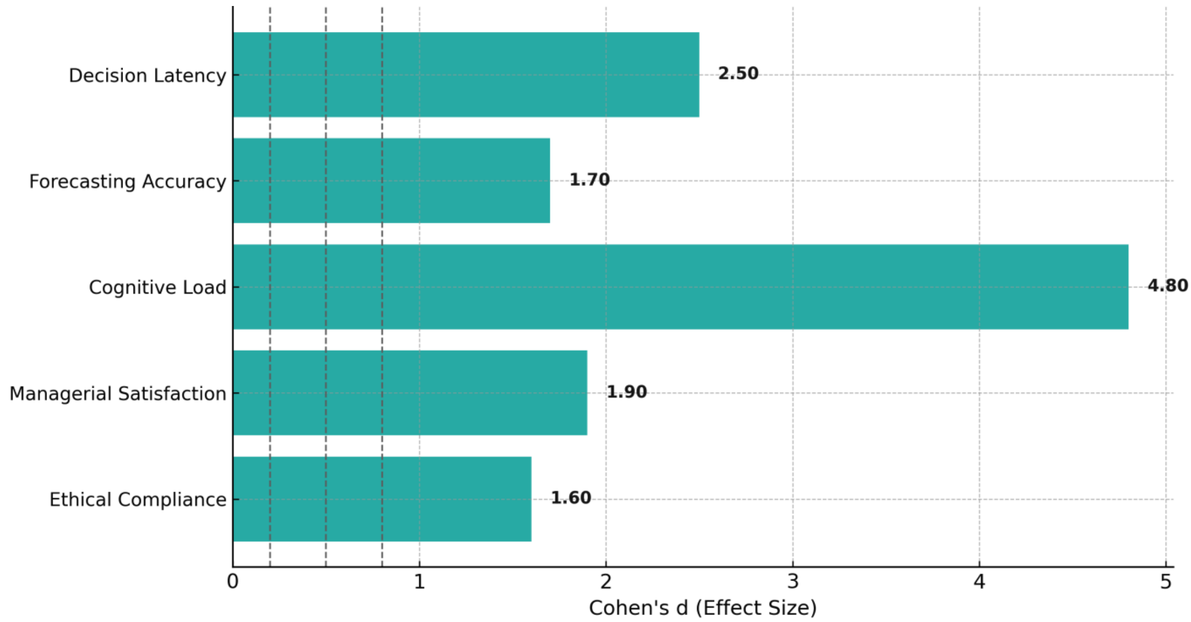

Figure 9: Effect Sizes Across AIMDM Metrics

The figure highlights substantial effect sizes across all AIMDM metrics, with the greatest impact observed in reducing cognitive load ($d = 4.80$), followed by improvements in decision latency ($d = 2.50$). Significant gains in forecasting accuracy, managerial satisfaction, and ethical compliance further emphasize the strong practical relevance of the framework.

6. Conclusion and Future Directions

This study introduced the Agile Intelligence in Managerial Decision-Making (AIMDM) framework, a strategic approach designed to minimize decision latency, enhance organizational responsiveness, and strengthen ethical governance. The framework integrates real-time analytics, explainable artificial intelligence (XAI), and agile practices, while balancing the technical and human dimensions of managerial decision-making.

The empirical study examined 120 decision cycles with a digitizing manufacturing company and demonstrated AIMDM's performance improvement across several measures. The study demonstrated that implementing AIMDM led to a 63.6% reduction in decision latency, a 14.2% increase in forecasting accuracy, a 42% decrease in cognitive load, along with notable gains in managerial satisfaction and ethical compliance. Results from paired t-tests and effect size analysis confirmed that these improvements were both statistically significant ($p < 0.001$) and practically meaningful, with very large effect sizes. Visual analyses—including bar charts, trend lines, and forest plots with 95% confidence intervals—further highlighted the robustness of AIMDM and its contribution to organizational resilience. What sets AIMDM apart is its multi-dimensional orientation: it not only drives operational efficiency but also embeds human-centric and ethical values. Unlike conventional decision-support systems that prioritize either speed or accuracy alone, AIMDM integrates agility, transparency, trust, and compliance, offering a holistic framework to navigate the complex, uncertainty-prone environment of Industry 4.0 and beyond.

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Future Work

1. While the AIMDM outcomes were significant, there remain opportunities for future research: Cross-domain testing:
2. Expanding the framework to different industries (e.g., health care, finance, smart cities) to assess domain adaptations.
3. Cognitive modelling : Including neuro-symbolic AI and learning systems to lessen cognitive biases in decision-making. Scalability assessment:
4. Validating AIMDM in large-scale organizations with distributed decision-making and cross-border operations. Ethics-by-design:
5. Including further governance tools to enhance transparency and accountability (e.g., bias and fairness modules, blockchain audit trails).
6. Integration with digital twins: Using real-time digital twins to optimize decisions by simulating before deciding / implementing.

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Conflicts of Interest

The authors declare no conflicts of interest.

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