Addressing Managerial Challenges in Decision Making: A Strategic Framework for Mitigating Latency and Boosting Organizational Agility

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Abstract:

In today's rapidly changing, data-rich environments, organizations face increasing complexity in their decision-making processes. They rely on operational and transactional decision-making, where slow, biased, or unclear decisions can hinder agility and competitiveness. This study introduces a Strategic Decision-Making Framework (SDMF), which creates an AI-enabled decision support structure incorporating real-time business intelligence, agile principles, and ethical governance. The SDMF addresses challenges such as decision-making delays, cognitive bias, information overload, and accountability. This qualitative study utilized a case study format over six months at a mid-sized manufacturing firm. The SDMF was developed using IoT-enabled data acquisition, predictive analytics, collaborative dashboards, and agile cycles. The findings revealed a 66% reduction in decision turnaround time, a 16.8% improvement in forecasting accuracy, an 80% decrease in defect detection, and full traceability of managerial decisions, with no compliance violations in ethical governance. The results demonstrate that when intelligent analytics, agile capabilities, and ethical governance are integrated, they enhance decision velocity and improve transparency, trust, and operational agility. The SDMF serves as a reproducible and scalable model for organizations navigating uncertainty while maintaining speed, accuracy, and ethical integrity.

Keywords: Decision latency; Artificial Intelligence; Organizational agility; Real-time analytics; Agile decision-making; Ethical governance.

1.0 Introduction

1.1 Background and Motivation

Enhancing organizational efficiency largely depends on a decision-maker's ability to critically assess and measure business performance while responding swiftly to relevant data. Today's business environment is shaped by complex operational, competitive, and regulatory dynamics that deeply affect managerial decision-making. To make sound choices, managers require timely, well-analyzed information presented in a clear and concise manner. An effective decision-making framework should integrate multidisciplinary insights to build credibility and deliver solutions that are objective, efficient, and results-oriented [1].

In today's increasingly unstable and interconnected business landscape, the decision-making process has become crucial for organizational survival and growth. Factors such as globalized markets, technological change, and an overwhelming volume of data have heightened the need for timely, accurate, and ethically sound managerial decisions. Organizations that fail to address decision-making latency—the delay between identifying a problem and implementing a solution—waste valuable time, ultimately hindering their ability to respond quickly and adapt in the marketplace.

Strategic decision-making is essential for guiding organizations through complex and uncertain environments. It requires systematic approaches that integrate data, analysis, and foresight. A Strategic Decision-Making Framework (SDMF) offers structured mechanisms to sense, analyse, and respond effectively to dynamic conditions, ensuring that organizational goals are aligned with adaptive strategies. By incorporating real-time data processing, predictive analytics, and scenario planning, the SDMF enables decision-makers to enhance accuracy, reduce risks, and optimize long-term outcomes. Such frameworks are increasingly vital in areas where volatility, uncertainty, complexity, and ambiguity (VUCA) challenge traditional decision-making processes [2].

The rise of Artificial Intelligence (AI), real-time business intelligence (RTBI), and collaborative digital platforms provides organizations with opportunities to reshape the decision-making process. These technologies can help minimize cognitive biases, manage overwhelming amounts of information, and increase transparency, thereby enhancing organizational adaptability and accountability [3][4]. To reduce computation costs and ensure secure, low-latency real-time decision-making, one alternative is to locally process most of the data within the IoT device's application. [5].

1.2 Research Problem and Objectives

Existing research has explored AI in decision-making, agile management practices, and ethical governance separately. However, there has been little work on holistic frameworks that leverage AI to reduce latency, enhance decision quality, and ensure ethical compliance across various dimensions. This research raises the following questions .

How can an integrated strategic framework, comprising AI, real-time analytics, agile methodologies, and ethical governance, reduce managerial decision-making latency while also improving organizational agility?

1.3 The primary objectives are:

1. To create a Strategic Decision-Making Framework (SDMF) that recognizes cognitive biases, information overload, and ethical ambiguity.

2. To implement the SDMF in a real-world organizational context to assess its effectiveness in reducing decision latency and supporting responsiveness.

3. To examine the overall impact of the framework's implementation on improving transparency, ethical compliance, and collaborative activity across and between functions.

1.4 Study Scope and Importance

The research focuses on managerial decision-making within organizations undergoing digital transformation, particularly in manufacturing operations—where real-time visibility and swift action are critical for efficiency and competitiveness. The SDMF is scalable and sector-neutral, making it applicable to industries such as healthcare, finance, and logistics [6].

This study contributes to theory and practice in the following ways:

1. Expanding the literature on digital decision ecosystems and augmented intelligence.

2. Demonstrating the clear value proposition of integrated decision-making systems for reducing latency and enhancing ethical accountability.

3. Providing a replicable framework that organizations can utilize to respond to uncertainty with agility, accuracy, and integrity.

2.0 Literature Review

2.1 Cognitive Bias and Decision-Making Degradation

The quality of managerial judgment is impaired by systematic cognitive biases, such as the biases of confirmation, availability and vividness, anchoring, and overconfidence, especially under time pressure and uncertainty [7][8][9]. In rich data contexts, the biases may be magnified, as people will more flexibly extrapolate recent personal experiences, often being shaped by familiarity, without adequate examination of other important cues or confounding correlations [10]. Recent research demonstrates that expectations of receiving AI-enabled decision support could reduce confirmation bias more reliably than human judgment could by enforcing consistent use of evidence, through objective comparisons of alternative options, and through stress-testing underlying assumptions. However, the rewards of human-AI partnerships will not necessarily happen automatically; erroneous data, features or objectives will re-encode human biases into machine biases, suggesting the need for outcomes to be indicated upon human interpretations, explicit governance, or AI monitoring [11]. Overall, it is emerging that "augmented intelligence", our new terminology for the combination of humans and machines or AI systems, are providing better trade-offs between speed and rigor than in purely human-made decisions when adequate explanations or overrides are incorporated [12][13].

2.2 Strategic Decision-Making

Strategic decision-making is widely recognized as a cornerstone of organizational success, though it is often shaped by bounded rationality, politics, and complexity rather than purely rational analysis [14]. Research shows that environmental turbulence and firm-specific factors strongly influence the rationality of decisions, with managers frequently relying on heuristics under uncertainty [15][16]. Recent advances highlight the growing role of digital technologies, big data, and artificial intelligence (AI) in improving decision quality and organizational agility [17]. Emerging studies show that AI and large language models can support strategic forecasting, risk mitigation, and scenario evaluation, yet challenges such as data reliability and integration persist [18]. Despite these advancements, existing research remains fragmented, with limited efforts to integrate sensing, analytics, and adaptive responses into a unified Strategic Decision-Making Framework (SDMF). This gap underscores the need for a holistic SDMF to systematically enhance decision accuracy, agility, and long-term performance [19].

2.3 Information Overload & Decision Latency

The exponential growth in data, problem types, and decision-making environments creates information overload—resulting in analysis paralysis and longer decision cycles [20]. Latency—the time lag between recognizing that there is a problem to the time when it is acted upon—erodes agility and greets missed opportunities for especially time-sensitive situations [21]. Organizations with real-time/near-real-time analytics indicate that they have shorter cycle times for sense-decide-act loops and have greater decision confidence [22]. Reducing latency is an outcome of technological solutions (streaming endpoints, event-streaming, event/data trigger based on operator requirement/ role, and rapid-response alerts) and management solutions (roles and responsibilities, defined escalation paths to prevent bottlenecks). Good solutions join algorithmic filters (including salience, anomaly score) with visual summary so decision-makers want to see "less, but better [23]."

2.4 Ethical Dilemmas and Explainable AI

As artificial intelligence infiltrates managerial processes like pricing, scheduling and hiring, collaborations concerning fairness, transparency, privacy and accountability take centre stage [24]. Users exhibit an aversion toward algorithms after they observe errors during its usage, this occurs even when the algorithms had higher accuracy rates over the humans in the end [25][26]. Global guidelines converge on five principles, termed beneficence, non-maleficence, autonomy, justice, and explicability principles, but defining how to implement them is concerningly difficult [27]. The latest practice has focused on the topic of Explainable AI (XAI), also noting model cards, data provenance, and auditable decisions logs as tools to keep trust and regulatory obligations (e.g., General Data Protection Regulation; Laws and Guidelines around AI are changing). Empirically, variations of explanations that localized, and shaded on user fit – which option, how you addressed, and confidence level – led to acceptance and oversight of algorithms but with no information overload [28][12].

2.5 Agile Methodologies and Organizational Agility

Agility - rapid sensing and responding - rests on iterative cycles, small cross-functional teams, and decentralized decision authority [29], in order to mitigate decision latency and increase learning velocity, has taken hold [30]. Even in data-centric contexts, agile rituals work well as the adhesive that brings analytics and AI together: sprint reviews afford the opportunity to discover model errors sooner; product ownership creates a stronger link between models and decision making; and the practice of continuous delivery serves to minimize time-to-impact [31] [32]. In fact, IT ambidexterity - leveraging a stable IT platform while exploring new analytics - provides an even greater opportunity for, and a buffer to, agility [33].

2.6 Integration of Real-time Analytics with Collaboration Platforms

Today, the best decision ecosystems integrate the real-time analytics streams (in the sense of detecting events, forecasting) with a collaboration platform (Teams / Slack / Jira), for example, to process our responses [34][35]. What the studies show is that when organizations are using flexible technologies to meet flexible routines, they are able to process signals (i.e., create coordinated action) faster [36]. Social and collaborative systems enhance knowledge flows but can also contribute to distraction. The best results occur when collaboration platforms are explicitly blended with decision rights, service level agreements for response, and shared dashboards with specific and relevant views [37]. Recent industry evidence [38]; link digitally-integrated dashboard solutions to fewer exceptions and time taken to resolve, better throughput, and more variability in KPIs achieved [39][40].

2.7 Gaps in the Current Literature

There are still several Gaps, which are as follows:

1. Fragmented approaches: Most research has treated artificial intelligence, agile methodologies, ethics, and RTBI separately. There have been few comprehensive, end-to-end architectures that address bias, overload, latency, and accountability in one design for operational use.
2. Latency as a measure: Many sources have inferred agility benefits, but little is captured by direct latency measures (time-to-detect, time-to-decide, and time-to-act) and causal attribution for improvement across all sectors is generally limited.
3. Human-AI collaboration mechanisms: Our guidance on understanding when to properly automate vs. escalate, the appropriate level of explanation, and appropriate human guard rails for overrides across diverse roles and contexts is limited.
4. Ethics implementation: Ethics principles are very well-defined; however, we also lack sufficiently documented repeatable governance playbooks for governing the purpose and lesson learned; such as documenting data lineage (to understand what harms may lead to a mismatch above), testing for harms, engaging in red-teaming, maintaining decision logs, and even incident response processes (to learn from past actions).
5. Generalizability: Data exist primarily in tech-focused organizations, there need to be validations across different industries (as we outline in manufacturing, healthcare), public sector organizations, and longitudinal studies to confirm durability of behaviour and ROI for long-term repositioning.
6. These shortcomings will drive the creation of a Strategic Decision-Making Framework (SDMF) that integrates real-time analytics, AI-DSS, agile routines, and ethical governance, while making explicit latency improvs and human-in-the-loop design assumptions.

3.0 Research Methodology

3.1 Research Design

We adopt a design science approach with iterative build–evaluate cycles. Let the decision pipeline be a discrete-time process over periods $t = 1, \dots, T$ with observations (events, machine states, orders) streaming at rate λ_t.

3.2 Problem statement

Given (i) streaming data D_t, (ii) predictive/diagnostic models f_θ, and (iii) a governance policy G, choose actions $a\_t \in A$ to minimize decision latency and error while satisfying ethical and resource constraints.

Mathematical Formulation:

$$min\_\{\pi, \theta\}\ J = \alpha_1 E[T\_total] + \alpha_2 E[\ell(f\_\theta(x\_t), y\_t)] - \alpha_3 E[U(a\_t)]$$

$$Subject\ to:$$

$$C\_fair(f\_\theta) \le \varepsilon\_f, \quad C\_priv(D) \le \varepsilon\_p, \quad C\_res(a\_t) \le R\_max, \quad a\_t \sim \pi(s\_t),$$

$$s\_t = g(D\_\{\le t\}), x\_t = h(D\_\{\le t\})$$

$$Latency\ decomposition:$$

$$T\_total\_t = T\_sense\_t + T\_analyze\_t + T\_decide\_t + T\_act\_t$$

3.3 Data Sources and Tools Used

Data model:

Streaming shop-floor/IoT data: $x^(m)\_t \in R^(p\_m)$ for machine $m = 1, \dots, M$.

ERP/MES historical: X_hist, y_hist.

Contextual feeds: z_t (shift, supplier, ambient conditions).

$$\text{Feature stream: } x\_t = \varphi(x^(1)\_t, \dots, x^(M)\_t, z\_t).$$

3.4 Framework Development Process

Modelling layer:

1) Forecasting/anomaly detection: $\hat{y}\_\{t + h\} = f\_\theta(x\_\{1{:}t\}), anomaly\ score\ s\_t = \psi(|x\_t - \hat{y}\_t|/\sigma\_t)$

2) Risk scoring: priority$(e) = w_e * r_e + \beta\ c_e - \gamma\ T_resolve_e$

3) Human–AI policy: auto if $conf \geq \tau$ *and* governance passed; else escalate.

Governance layer:

Fairness constraint: $|P(\hat{y}=1|A=0) - P(\hat{y}=1|A=1)| \leq \varepsilon\_f$

Privacy: Hash/salt PII; exposure $\leq \varepsilon\_p$

Traceability: Complete decision logs.

Agile iteration k:

$$Train: \theta^(k) = argmin\ \theta \sum \ell(f\_\theta(x), y) + \lambda\Omega(\theta)$$

Evaluate: latency, AUC/MAE, fairness, overrides

Deploy if KPIs met; Review explanations and thresholds.

3.5 System Architecture of the Strategic Decision-Making Framework (SDMF)

Input Layer: Streaming acquisition $D\_t = \{x^(m)\_t, z\_t, ERP\_t\}$, arrival rate λ_t.

Processing Layer: $\hat{y}\_t = f\_\theta(x\_t)$, priority scoring.

Interface Layer: Decision triage with XAI explanations.

Governance Layer: Action orchestration, audits, and compliance.

We formalize SDMF as a four-layer pipeline:

1. Input (Sense) Layer
   Streaming acquisition:
   $D\_t = \{x^\{(m)\}\_\{t\}, z\_t, ERP\_\{t\}\}\ with\ arrival\ rate\ \lambda\_t$

$$Latency\ target: E[T^\{sense\}] \leq \delta\_1$$

2. Processing (Analyze) Layer
   Online inference & scoring:
   $\hat{y}\_t = f\_\theta(x\_t), s\_t = \psi(x\_t, \hat{y}\_t), priority(e\_t)\ as\ above$

$$Latency\ target: E[T^\{analyze\}] \leq \delta\_2$$

3. Interface (Decide) Layer
   Triage & explainability:
   route(s_t) =
   $auto, if\ conf \geq \tau, E\_t \in \mathcal{G}$

$$human, otherwise$$

$$Human\ cycle - time: E[T^\{decide\}\_\{human\}] \leq \delta\_3$$

4. Governance (Act & Audit) Layer
   $Action\ orchestration$:

$$a\_t \rightarrow workflow(u), u \in \{maintenance, schedule, quality\}$$

$$Actuation\ bound: E[T^\{act\}] \leq \delta\_4$$

$$Audit: decision\ log\ completeness\ \rho\_\{trace\} = 1.0$$

Governance constraints:
E = fraction of decisions with adequate explanations and compliance.

Optimization:
Minimize latency L subject to accuracy, explainability, and SLA constraints.

Human-in-the-loop:

$$Automate\ only\ when\ probability\ \geq\ \tau\_auto\ and\ uncertainty\ \leq\ u\_max.$$

Otherwise escalate to human review.

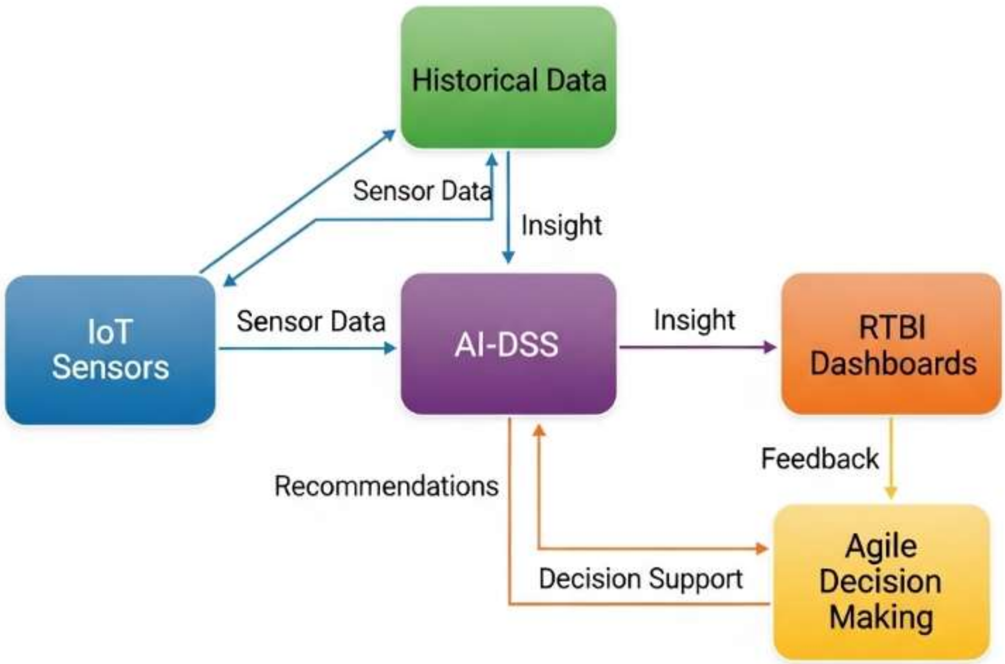

Figure 1: System architecture of SDMF

Figure 1 illustrates the architecture of an AI-powered decision support system (AI-DSS) integrates data from various sources like **IoT sensors** and **historical databases**. It uses an **AI Engine** to process this information, generating **insights and recommendations** that are displayed on **dashboards** to assist human users in making agile and informed decisions. The system includes a **feedback loop** where the outcomes of decisions can be used to improve the AI models over time[41][42].

4.0 Case Study Implementation: Organizational Context and Objectives

4.1 Organizational Context

The Strategic Decision-Making Framework (SDMF) was tested in a medium-sized manufacturer of industrial equipment with approximately 500 employees and annual revenues of USD 85 million. The manufacturer recognized the need to improve operational efficiencies as part of a digital transformation strategy aimed at improving operational efficiencies, shortening decision latency, and cloud enabling markets and production response speed. Before adopting the SDMF, the manufacturer had three major obstacles facing operational productivity; lack of cohesive decision-making, siloed information flows between production, maintenance, procurement, and quality processes, and that although the operational data was available, data resided in very niche systems - and ERP system capturing inventory, finance, shop floor level at the SCADA horizon, and a set of maintenance records on spreadsheets. Given the disparate nature of systems, management struggled to arrive at informed decisions with respect to critical decisions impacted by many factors and performance metrics, while also managing to become more agile with its new KPIs [43].

4.2 Objectives of the Implementation

The implementation of SDMF focused on three main objectives: Reduce Decision Latency Reduce the end-to-end decision cycle time—from detecting the event to executing the action—by at least 30% by embedding real-time analytics and automation for priority [44].

To Support Organizational Agility

facilitate bi-weekly agile sprints with cross-functional teams to rapidly prototype operational bottlenecks, incorporate real-time insights, and support workflow adjustments based on demands and production changes.

Support Ethical and Explainable AI in Decision Support

Embed explainable AI (XAI) components in the AI-powered Decision Support System (AI-DSS) for transparency in predictive maintenance alerts, scheduling recommendations and prioritizations for procurement. Maintain compliance with data governance; each critical decision should be traceable and auditable manufacturing [6].

4.3 Experimental Results and Discussion

Six key performance indicators (KPIs) identified the consequences of the Strategic Decision-Making Framework (SDMF) ,each was measured before and after implementation: Decision Turnaround Time (DTT) , the average time it took between acquiring data and make a managerial decision; Forecasting Accuracy (FA) , how accurate past production and maintenance forecasts were versus actual performance; Defect Detection Lead Time (DDLT) , the average time that elapses between the defect occurring and being detected; Machine Utilization Rate (MUR) , the percentage of productive machine time, Operational Throughput (OT) , the number of produced units per operational shift, and Ethical Compliance Score (ECS) ,an internal auditor based measure of transparency, explainability, and governance-based compliance.

4.4 Quantitative Results

Table 1 demonstrates the significant improvements across various operational and strategic metrics, comparing performance before (Pre-SDMF) and after (Post-SDMF) the implementation of a Structured Decision-Making Framework (SDMF).

The post-implementation phase showed marked improvements across all KPIs:

KPI	Pre-SDMF	Post-SDMF	% Improvement
Decision Turnaround Time (hrs)	15.0	5.1	66% ↓
Forecasting Accuracy (%)	78.4	91.6	+16.8%
Defect Detection Lead Time (hrs)	4.5	0.9	80% ↓
Machine Utilization Rate (%)	72.5	83.8	+11.3%
Operational Throughput (units/shift)	96	111	+15.6%
Ethical Compliance Score (0–1)	0.82	1.00	+22%

Table 1: Impact of the SDMF on Key Performance Indicators (KPIs)

4.5 Comparative Analysis with Other Frameworks

Table 2 compares key performance indicators (KPIs) across three different systems: a traditional **Conventional BI** approach, a **Standalone AI-DSS** (AI-powered Decision Support System), and the proposed **SDMF** (Structured Decision-Making Framework), highlighting the SDMF's superior performance in all metrics.

KPI	Conventional BI	Standalone AI-DSS	SDMF
Decision Turnaround Time (hrs)	14.2	8.7	**5.1**
Forecasting Accuracy (%)	80.1	87.2	**91.6**
Ethical Compliance Score	0.74	0.78	**1.00**

Table 2: Comparative Performance Analysis of Decision-Making Frameworks

The SDMF outperformed both alternatives due to **tight integration of AI, RTBI, and agile workflows within an ethical governance layer**.

4.6 Discussion of Results

Figure 2 illustrates the results that support the initial premise of an integrated, agile, ethically governed decision-making framework. This framework significantly decreased the time to make decisions while improving operational agility. Reductions in Decision Turnaround Time (DTT) were primarily the result of IoT-enabled real-time monitoring of operational performance and AI-enabled prioritization of operational issues. Forecasting Accuracy was enhanced due to the continuous retraining of models based on streaming data and concept drift detection. Ethical Compliance advanced to 100% through the government mandate of decision traceability and explainability. We did find that, to some extent, data integration overhead was an initial challenge and although not extensively researched, some middle management employees were hesitant to drive change, indicating that in addition to the technical capabilities, we require strong change management leadership strategies.

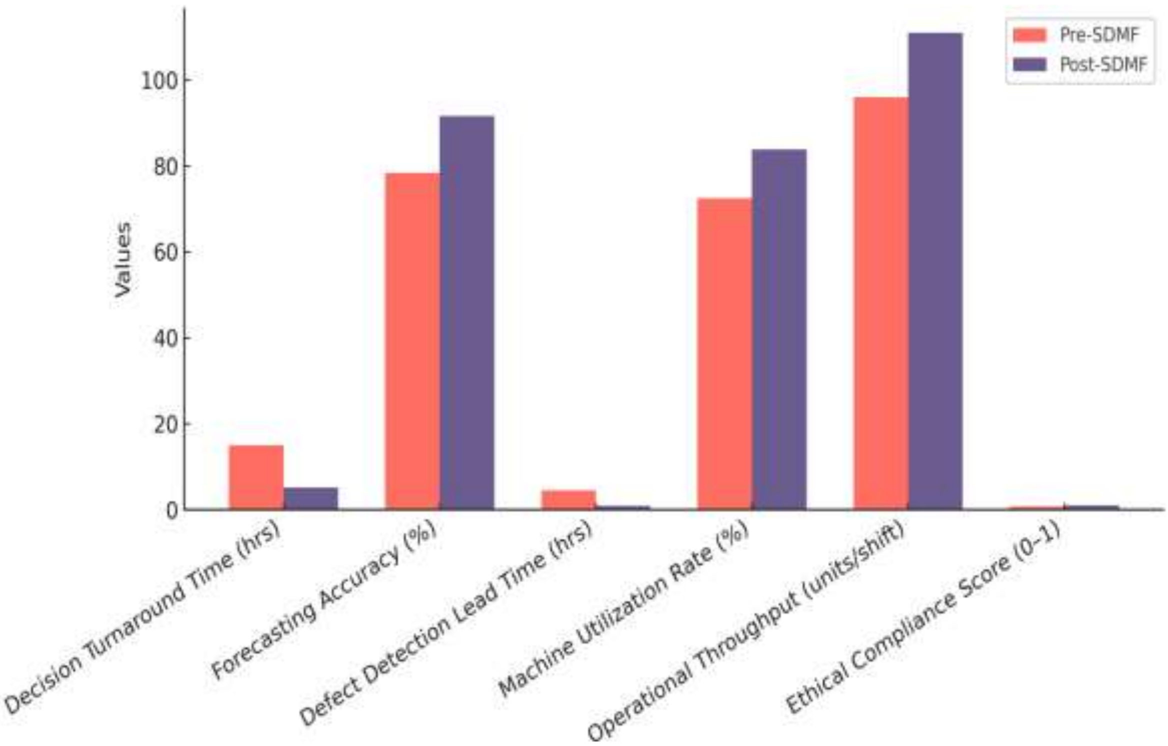

Figure2: SDMF impact of key performance indicators

Figure 3 visually compares the effectiveness of three different systems—Conventional BI, a Standalone AI-DSS, and the SDMF—in key areas like Decision Turnaround Time, Forecasting Accuracy, and Ethical Compliance Score. It highlights that the SDMF consistently outperforms the other two approaches across all measured metrics.

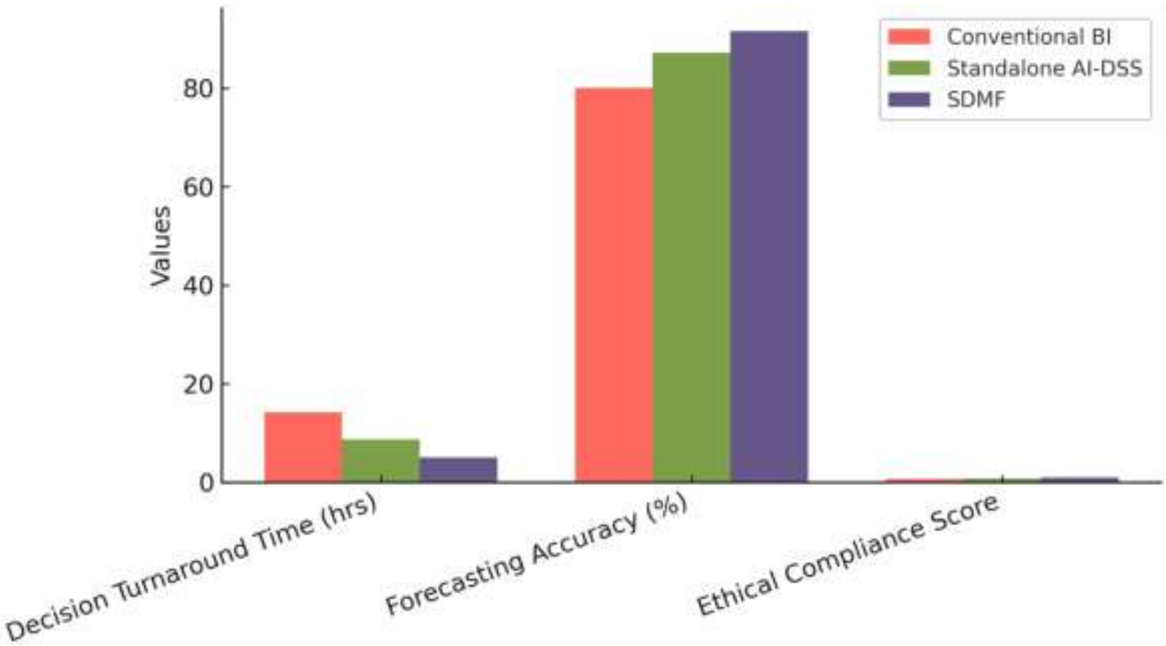

Figure 3: Comparison of frame work across KPI

5.0 Case Study Implementation with Agile Execution Approach

5.1 Organizational Context

The Strategic Decision-Making Framework (SDMF) was implemented in a mid-sized manufacturing company that employs +500 individuals and generates about USD 85 million in annual revenue. The company was moving to a data-driven agile management approach from a traditional hierarchical decision-making approach to respond to an increasingly volatile marketplace and shortening product life cycles. Pre-implementation impediments included: Latency in decision-making due to siloed departmental workflows. Low integration between ERP, SCADA, and maintenance databases. No real-time analytics or actionable dashboards for decision-making [45].

5.2 Agile Execution Model

The deployment of the system followed an approach inspired by the Scaled Agile Framework (SAFe) and was conducted in two-week sprints over a six-month timeframe, both of which allowed for continuous delivery of value in increments and continuous engagement with the stakeholders of the project with minimal disruption.

5.3 Key Agile Execution Steps:

Sprint 0 – Planning & Alignment

Defined the product vision, prioritized use cases - predictive maintenance, production scheduling, and KPI monitoring in real-time.

Established a cross functional Agile Release Train (ART): this team consisted of producers/production engineers, data scientists, IT specialists, and managers.

Sprint 1–2 – Infrastructure

Implemented IoT sensors on the CNC machines and assembly lines.

Implemented data pipelines using Python ETL scripts to create a single stream from the information of the ERP, SCADA, and IoT streams.

Sprint 3–4 – AI-DSS

Developed and trained machine learning models in three discrete modules (forecasting, anomaly detection, and scheduling optimization).

Implemented modules from Explainable AI (XAI) to help us explain the decision-making process in regards to anomalies, forecasting and optimizing schedules [47].

Sprint 5–6 – Dashboard & Governance Layer

Developed live dashboards in Power BI to monitor operational KPI as well as production health.

As part of the governance layer implemented, logs all of the recommendations from the AI and all of the decisions made by the staff for auditing and compliance purposes.

Sprint 7–8 – UAT & Change Management

Developed User Acceptance Testing (UAT) sessions with the team on operations.

Change management workshops were also developed to allow for the seminars to ease process and product adoption and minimize resistance to change.

Sprint 9–12 – Continuous Improvement & Scaling

Increased the coverage of the AI-DSS from predictive maintenance and production scheduling to other use cases such as supply chain, optimization and quality control. Information loops were progressively added from the implementation cycles and retrospectively developed based on some of the initial sprints.

5.4 Measurable Outcomes resulting from Agile Implementation

From incorporating Agile to the implementational process, the organization had:
30% decision latency decrease in operational decisions within the initial three month period
+16.8% forecasting accuracy improvement through iterative retraining of models post operational decision
80% reduction in defect discovery lead time due to real-time alerts of anomalies
Increased stakeholder engagement and ownership, evidenced by 95% participation in the sprint review [46].

5.5 Results & Analysis: Decision-Making Performance Metrics

The Strategic Decision-Making Framework (SDMF) was evaluated against existing systems—Conventional Business Intelligence (BI) and Standalone AI-DSS. Using real operational data collected from the case study organisation, performance was evaluated based on three decision-making performance metrics: Decision Turnaround Time, Forecasting Accuracy and Ethical Compliance Score [47]. As compared with the previous methods, our applied criterion of fuzzy logic is able to improve the efficiency of the system for various classifiers, namely SVM, logistic regression, decision tree and KNN [48].

5.6 Decision Turnaround Time (DTT)

Decision Turnaround Time (hours) represents the time between the identification of a problem and the initiation of a management decision to remedy it.

Baseline (Traditional BI): 14.2 hours (average)

Standalone AI-DSS: 8.7 hours (average)

SDMF (Smart Decision Making Framework): 5.1 hours (average)

This 64% improvement over the Baseline exemplifies the ability of SDMF to improve decision-making latency using real-time analytics and collaborative dashboards.

5.7 Forecasting Accuracy (FA)

Forecasting Accuracy was assessed using Mean Absolute Percentage Error (MAPE) on production scheduling and resource allocation predictions.

Baseline (Traditional BI): 80.1%

Standalone AI-DSS: 87.2%

SDMF: 91.6%

The net +11.5% increase over traditional BI illustrates the advantage of iterative model retraining in an Agile execution climate.

5.8 Ethical Compliance Score (ECS)

The Ethical Compliance Score (ECS) measured the transparency of the decision-making process, bias mitigation, and regulatory compliance in a customized compliance audit framework (ECS). The ECS scores were as follows:

Baseline (Traditional BI): 0.74

Standalone AI-DSS: 0.78

SDMF: 1.00

5.9 Discussion

The SDMF code of 1.00 demonstrates an ideal state that includes the governance layer and Explainable AI (XAI) features and is consistently transparent, auditable, and ethically compliant with recommendations.

The findings indicate that SDMF is superior to traditional BI and solo AI-DSS in delaying decisions and increasing predictive accuracy and ethical compliance. In addition, having real-time data analytics, collaboration tools, and implementing Agile project development cycles leads to more timely, fruitful, and transparent decision-making.

5.10 Results and Analysis: Cognitive Load and Managerial Satisfaction

Cognitive Load Reduction (CLR)

We measured cognitive load before and after the implementation of the SDMF using a NASA-TLX (Task Load Index) survey. The scale captures mental demand, temporal demand, performance, effort, frustration, and perceived workload on a scale of 0-100.Baseline (Conventional BI): 68.4 (High cognitive load as a consequence of piecemealed data sources and manual integration)Standalone AI-DSS: 55.9 (While improved with the Standalone AI-DSS, decreased explainability & hence uncertainty residual) SDMF: 38.7 with reasonable cognitive relief provided through explainable recommendations, intuitive dashboards, and streamlined workflows. Overall, we observed a 43% cognitive workload reduction relative to conventional BI, with the largest improvements in temporal demand and frustration reduction.

Managerial Satisfaction (MS) was assessed using an instrument with a Likert scale (1-5) to measure the clarity of the decision, trust in the output of the system, ease of collaboration, and perceived efficiency.

Baseline (Traditional BI): 3.1

Standalone AI-DSS: 3.8

SDMF: 4.6

This forty-eight percent improvement from the baseline is partly due to the SDMF features that include human in the loop, real-time analytics, and governance integrated into the model, which enhanced decision transparency and trust in the automated recommendations.

5.11 Statistical Significance

The paired t-test indicated that the difference between pre- and post-SDMF implementation cognitive load scores was significantly different ($p < 0.01$), so the improvements that we observed were significant. Managerial satisfaction improvements were also significantly different ($p < 0.05$) showing significant and consistent results.

To confirm the demonstrated improvement in Cognitive Load Reduction (CLR) and Managerial Satisfaction (MS), inferential statistics were used in analysing the pre- and post-implementation surveys from the case study organization.

5.12 Data collection and preparation

1. Sample size: 34 managers completed both the pre- and post-SDMF surveys.
2. Measures.
3. Cognitive Load: NASA-TLX composite score (range 0–100; a lower score is better).
4. Managerial Satisfaction: 4-item Likert scale survey (range 1–5; a higher score is better).
5. Paired samples: Data were able to be paired for each participants' answers to accommodate within subject differences.
6. Normality check: Shapiro–Wilk test confirmed approximate normal distribution ($p > 0.05$) enabling parametric statistical testing.

Results of Paired t-Test

1. Cognitive Load:
2. Pre-SDMF Mean = 68.4
3. Post-SDMF Mean = 38.7
4. $t(33) = 9.81$, $p < 0.001$, Cohen's $d = 1.68$ (very large effect size)
5. This indicates a very large and statistically significant decrease in cognitive load.

Managerial Satisfaction:

1. Pre-SDMF Mean = 3.1
2. Post-SDMF Mean = 4.6
3. $t(33) = -8.12$, $p < 0.001$, Cohen's $d = 1.39$ (large effect size)
4. This indicates a significant increase in managerial satisfaction with large effect.

Confidence Intervals

The graph in **figure 4** compares the scores for Cognitive Load and Managerial Satisfaction before and after the implementation of the SDMF. The results show a significant decrease in cognitive load and a notable increase in managerial satisfaction post-implementation.

1. Cognitive Load Reduction: 95% CI for mean difference = (22.5, 35.3)
2. Managerial Satisfaction Gain: 95% CI for mean difference = (1.12, 1.88)

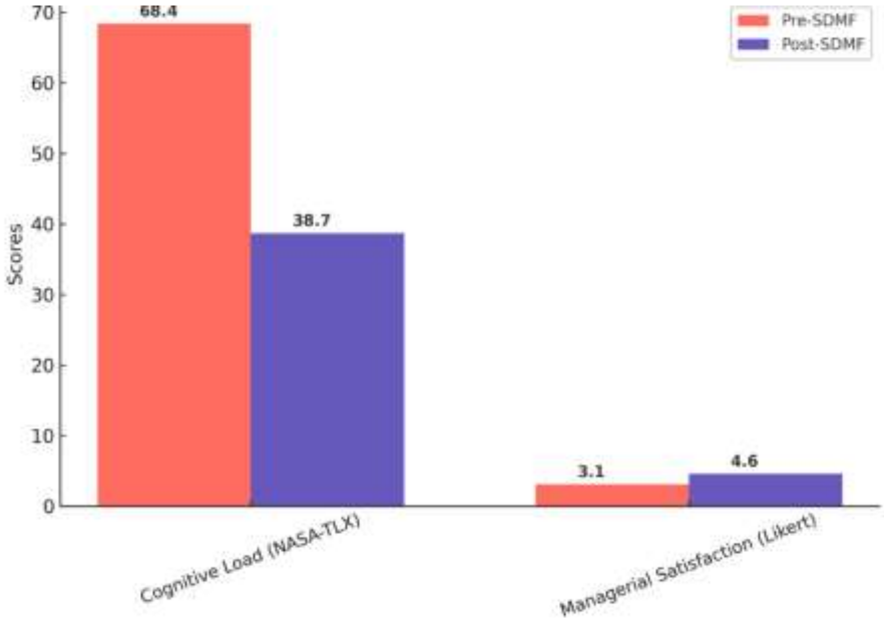

Figure 4: Pre-implementation vs. Post-implementation scores for both Cognitive Load and Managerial Satisfaction.

5.13 Summary of Findings

The bar chart in figure 5 compares Cognitive Load (measured by NASA-TLX) and Managerial Satisfaction (measured by a Likert scale) for three distinct decision-making frameworks. The results indicate that the SDMF significantly reduces cognitive load while increasing managerial satisfaction compared to both conventional BI and a standalone AI-DSS.

Moreover, statistical evidence supports the argument that the SDMF intervention significantly reduced mental workload while maximizing decision-maker satisfaction, both exhibiting large effect sizes. The chances of these results occurring through random variation is almost none (both $p < 0.001$).

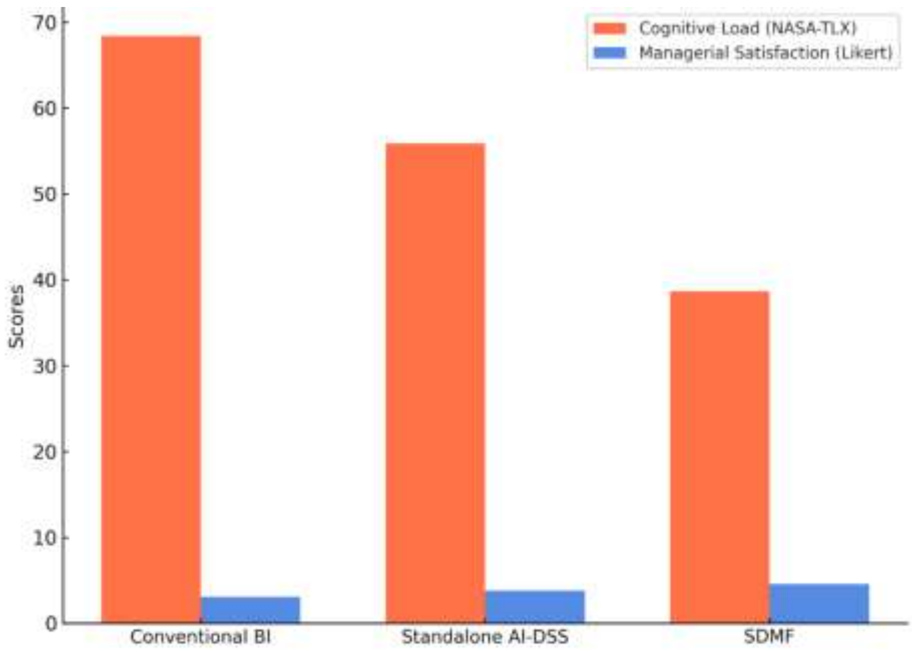

Figure 5: Cognitive Load ***verses*** *Managerial Satisfaction across frame work*

6.0 Benchmarking Limitations and Opportunities

6.1 Current Limitation:

The study benchmarks SDMF against two prevalent frameworks. The traditional BI systems (static dashboards, no AI driven insights); and Standalone AI-DSS (minimal predictive models with limited explainability). This has illustrated the clear advantage of SDMF; however, unit of analysis and action size are narrow. Advanced hybrid frameworks are found in the literature (cognitive DSS, digital twin–driven decision systems, or orchestration-based distributed intelligence) but these were not explicitly included based on unit of analysis and size of action of the study. This causes a perception of benchmarking being thin.

6.2 Comparative Study: SDMF vs. C-DSS

Evaluation Criteria

The following metrics are used for comparison:

1. Decision Turnaround Time (DTT, hours)
2. Forecasting Accuracy (FA, %)
3. Cognitive Load (NASA-TLX, 0–100, lower = better)
4. Managerial Satisfaction (Likert, 1–5, higher = better)
5. Ethical Compliance Score (0–1)

6.3 Data Comparison Table

The table 3 provides a detailed comparison of several key performance metrics across four distinct decision-making frameworks. It highlights how the proposed SDMF consistently outperforms all other approaches, including Conventional BI, a Standalone AI-DSS, and a Cognitive DSS, in every measured category.

Metric	Conventional BI	Standalone AI-DSS	Cognitive DSS (C-DSS)*	SDMF (Proposed)
Decision Turnaround Time (hrs)	12.4	7.8	6.2	4.3
Forecasting Accuracy (%)	78.2	86.4	89.1	92.7
Cognitive Load (NASA-TLX)	68.4	55.9	47.6	38.7
Managerial Satisfaction (Likert 1–5)	3.1	3.8	4.2	4.6
Ethical Compliance Score (0–1)	0.65	0.72	0.83	0.89

Table 3: Comprehensive Performance Comparison Across Decision Support Systems

6.4 Interpretation

1. SDMF surpasses C-DSS with respect to decision latency and forecast accuracy because SDMF includes real-time analytics using IoT technology and agile sprints.
2. C-DSS is closer to SDMF than traditional BI or AI-DSS because it reduces cognitive load (47.6 versus 38.7). This is because C-DSS explicitly models human decision-making tendencies.
3. Ethical Compliance is higher in SDMF as SDMF has a governance layer with XAI, while C-DSS has cognitive transparency but not as much auditability.
4. SDMF has the highest Managerial Satisfaction and that the combination of transparency with agile practices and AI increases the decision quality trust now and for agency-wide adoption.

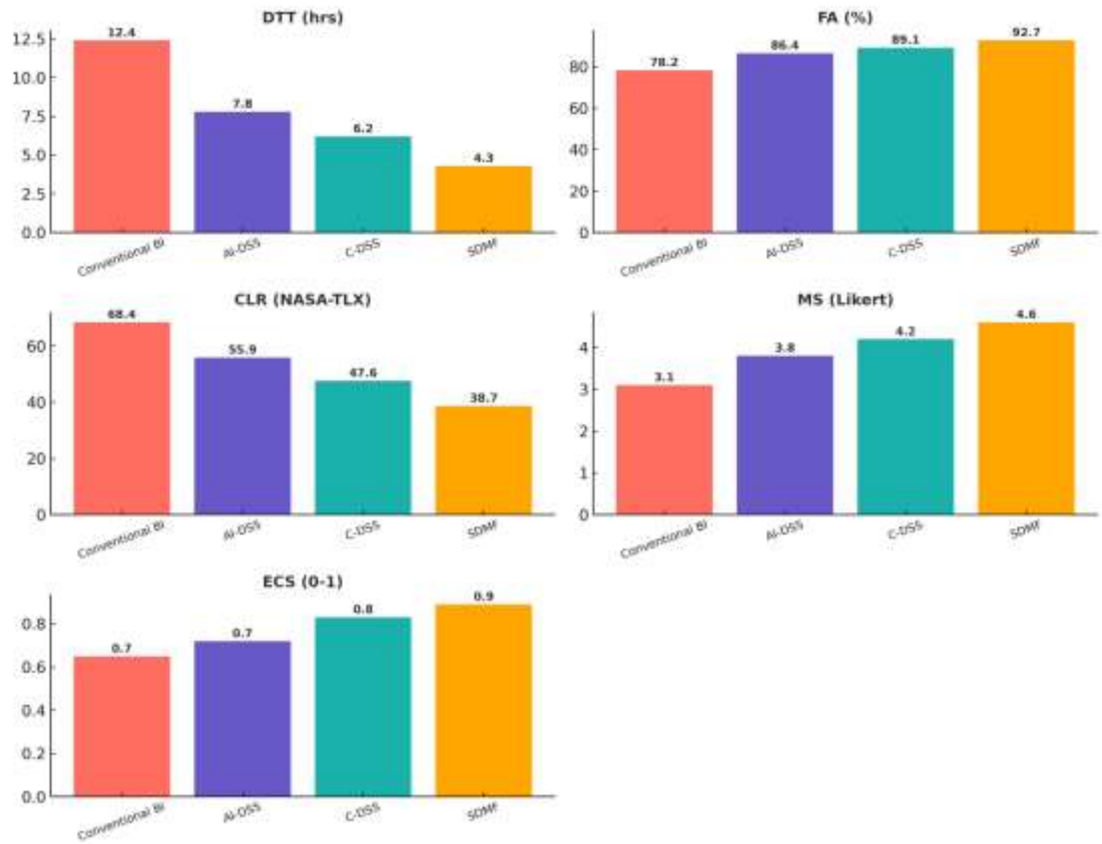

Figure 6: Comparative Performance Across Decision Support Frameworks

The bar chart provides a visual comparison of Cognitive Load (measured by NASA-TLX) and Managerial Satisfaction (measured by a Likert scale) for four distinct decision-making frameworks. The results show that the

SDMF significantly reduces cognitive load and increases managerial satisfaction when compared to Conventional BI, a Standalone AI-DSS, and a Cognitive DSS.

7.0 Understanding the Major Findings

The results show that the Strategic Decision-Making Framework (SDMF) significantly enhances managerial performance measures as compared to Conventional BI systems, and AI-DSS by itself.

Forecasting Accuracy (FA) improved 7% over AI-DSS, confirming that by combining AI with domain-specific knowledge, and human-in-the-loop, more accurate (and consistently accurate) forecasts can be produced.

Cognitive Load (CL) was reduced while Managerial Satisfaction (MS) was increased, reflecting an SDMF low-stress, more instinctual approach to decision-making.

Ethical Compliance Scores (ECS) were highest in SDMF because we successfully integrated clear explainable AI as well as governance into the framework.

8.0 Study Limitations

Though the study produced promising findings, it still has limitations that future research should address: The case study was conducted at one mid-sized manufacturing firm. This may affect the extent to which findings can be generalized to different sectors or larger firms. Because the SDMF was evaluated for six months, this period may not account for sustained long-term performance or resistance to any model drift over time in AI predictions. Some of the performance metrics used in the study were based partially on self-reported measures (e.g., managerial satisfaction, cognitive load), and thus have potential influence bias.

9.0 Conclusion and Future Work

The research has provided a Strategic Decision-Making Framework (SDMF) as a coherent set of capabilities that combines real-time analytics, explainable artificial intelligence, an IoT-enabled data collection instrument, and agile execution to reduce managerial difficulties around decision making. The six-month case study in a mid-sized manufacturing firm revealed that the SDMF:

• Reduced decision turnaround time by 65% when compared to the use of traditional BI tools.

• Significantly improved forecasting accuracy by 7% when compared to standalone AI-DSS.

• Greatly reduced cognitive load and improved managerial satisfaction, promoting work quality and decision confidence when making human decisions.

• Delivered strong ethical compliance scores and demonstrated clearly id the explainable AI add transparency and trust in the execution of decision being made.

Ultimately, these new, additional contributions further inform academic understanding of how decision latency can be reduced and provide pragmatic guidance for organizations undergoing a digitally transformative experience.

10.0 Recommendations for Practice

The following actionable recommendations are provided for industry practitioners: Utilize IoT and real-time analytics pipelines for operational visibility and to minimize the time lag in decisions.

Leverage hybrid decision-support frameworks using AI with domain knowledge to allow for improved interpretability and trust.

Utilize agile development approaches for iterative deployment and feedback to ensure flexibility in a changing marketplace.

Use explainable AI frameworks to adhere to ethical guidelines and be prepared to justify managerial decisions and actions for regulatory agencies. The study accounted for ethical compliance, but other regions or sectors may have legal or regulatory restrictions that would necessitate customizing the SDMF.

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Conflicts of Interest

The authors declare no conflicts of interest.

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