Sector-Based Socio-Psychological Decision-Making Patterns and Their Integration with AI-Enabled Decision Support Systems

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Abstract: Managerial decision-making is a socially embedded psychological process shaped by role expectations, institutional norms, and perceived responsibility under conditions of uncertainty and time pressure. This investigation explores sector-specific decision-making patterns and their practical integration with information technologies for leadership support in Uzbekistan. Leaders across different sectors participated (N=306; higher education: n=102; imam-khatibs: n=110; military: n=94). Decision-making tendencies were assessed using indicators aligned with the Melbourne Decision-Making framework (vigilance, avoidance, procrastination, and hypervigilance) together with subjective locus of control measures, allowing a socio-psychological interpretation of delayed or risk-averse choices. Intergroup differences were tested with Kruskal-Wallis procedures and supported by rank-based comparisons. Significant sector differences were identified for avoidance tendency, procrastination, and hypervigilance ($p \leq 0.002$), whereas vigilance did not vary meaningfully across groups, indicating that constructive decision orientation is relatively stable while maladaptive coping patterns are context sensitive. Building on these results, the paper proposes an applied integration pathway combining digital decision logs, structured decision protocols, and AI-assisted option summaries to improve transparency, feedback, and accountability in managerial workflows. Such tools can support human-AI collaboration by flagging delay risk, prompting timely review, and enabling reflective choices without replacing human judgment. The findings suggest that technology-assisted interventions should be tailored to psychological profiles and sector constraints to strengthen decision quality and timeliness.

1 INTRODUCTION

In contemporary organizations, leaders are expected to make timely, responsible, and ethically grounded decisions while facing incomplete information, competing stakeholder demands, and increasing accountability. Classical and contemporary theories suggest that managerial decisions are bounded by cognitive limitations and organizational constraints [1], yet they are also influenced by situational pressure, social dynamics, and the leader's perceived control over outcomes [2]. Therefore, decision-making competence can be understood as a multidimensional construct integrating cognitive appraisal, emotional regulation, and social-psychological adaptation.

Applied IT relevance: modern organizations increasingly institutionalize managerial decision-making through digital workflows (D-HRM, task-tracking platforms, e-governance logs). Therefore, psychological decision-style profiles can be embedded into decision-support software to detect delays, provide structured prompts, and enable auditable human-in-the-loop governance. This paper contributes an Applied IT decision-support framework grounded in sector-sensitive socio-psychological evidence.

Empirical studies in decision sciences demonstrate that rapid choices in uncertain environments can still be effective when leaders rely on structured sense-making and adaptive routines [3]. However, group and institutional contexts may trigger maladaptive patterns such as premature consensus-seeking, defensive avoidance, or heightened anxiety-driven scanning, which can distort judgment [4]. From a socio-psychological perspective, these patterns are particularly relevant in professional systems where decisions carry high symbolic or operational consequences (e.g., education, religious leadership, military command).

In Uzbekistan, ongoing modernization efforts in public administration and education increase the demand for evidence-based development of leadership competence, which is also consistent with the strategic priorities of the New Uzbekistan Development Strategy for 2022-2026 [5]. Within this context, the present study focuses on decision-making characteristics among leaders from three sectors, emphasizing cross-sector differences and their psychological interpretation.

1.1 Theoretical Background

Decision-making research has long emphasized that people evaluate options not in purely rational terms but through subjective value functions and perceived risk, leading to systematic deviations from normative models [6]. In organizational settings, these deviations may appear as hesitation, avoidance, escalation of commitment, or overreactive vigilance. The Melbourne Decision-Making framework operationalizes individual differences in decision patterns by distinguishing adaptive vigilance from maladaptive strategies such as avoidance, procrastination, and hypervigilance [7].

From an applied innovations perspective, socio-psychological decision models can be embedded with AI-enabled information technologies to operationalize early warning signals (e.g., decision delay, avoidance tendencies) and to support structured reflection through digital prompts and evidence summaries. Contemporary machine learning approaches enable pattern recognition and predictive analytics that can be adapted into decision-support tools for leaders, while maintaining human accountability and ethical oversight [8], [9].

Another influential determinant is locus of control, conceptualized as generalized expectations about whether outcomes depend primarily on one's own actions (internal control) or external forces (external control) [2]. Leaders with stronger internal control beliefs often show greater initiative and accountability, whereas external control beliefs may be associated with passivity or reliance on circumstances. Recent research further indicates that perceived control plays a role in self-regulation and psychological resilience under stress, which can indirectly shape decision processes [10].

In educational systems, digital and personalized learning initiatives demand managers who can align decisions with evidence and system optimization. For instance, Askarova et al. reported the relevance of well-designed personalized and optimized model systems for specific education settings, emphasizing decision quality at the implementation stage [11]. Although this study has a different focus, it supports the broader view that managerial decisions influence system-level effectiveness and innovation adoption.

1.2 Aim and Research Design

The goal of this research was to identify socio-psychological features of decision-making within managerial activity and to compare decision-related indicators across sector groups (higher education leaders, imam-khatibs, and military leaders) in Tashkent, Uzbekistan. The study relies on psychodiagnostic assessment and nonparametric statistical comparison of group distributions.

2 METHODS

Participants. The empirical sample consisted of 306 leaders from three professional groups: higher education leaders (n=102), imam-khatibs (n=110), and military leaders (n=94). All participants were surveyed in Tashkent, Uzbekistan.

Measures. The research employed psychodiagnostic instruments referenced in the dissertation abstract, including assessments of decision-making styles in management, decision-making determination, leadership personal qualities, and subjective locus of control. Decision-making patterns were operationalized via four indicators commonly linked to the Melbourne Decision-Making approach: vigilance, avoidance tendency, procrastination, and hypervigilance [7].

Data analysis. Group differences were evaluated using the Kruskal-Wallis H-test, which is suitable when the assumptions of normal distribution are uncertain and when comparing more than two independent groups [12]. Where relevant, additional statistical procedures (factor analysis, Student's t-test, Pearson correlation) were reported in the dissertation abstract as part of the broader analysis strategy.

Table 1: Decision-making pattern indicators across leader groups (Kruskal-Wallis test).

Scale	Higher education (n=102)	Imam-khatibs (n=110)	Military (n=94)	H	p
Vigilance	133.38	139.86	126.13	1.64	0.43
Avoidance tendency	116.15	160.53	113.31	23.59	0.001***
Procrastination	114.81	162.20	112.25	26.65	0.001***
Hypervigilance	117.47	152.62	121.70	11.99	0.002**

Table 2: Subjective locus of control indicators across leader groups (Kruskal-Wallis test).

Scale	Higher education (n=102)	Imam-khatibs (n=110)	Military (n=94)	H	p
Internal locus of control	125.64	129.99	142.80	2.26	0.32
External locus of control	137.28	137.57	126.24	1.30	0.52

Table 3: Decision-making style indicators in management across leader groups (Kruskal-Wallis test).

Scales	Higher education leaders (n=102)	Imam-khatibs (n=110)	Military leaders (n=94)	H	p
Striving for dominance	164.27	145.25	99.46	30.91	0.001***
Self-control in problematic situations	119.15	149.10	124.71	7.91	0.005*
Decision-making style	147.15	152.86	101.84	24.86	0.001***

3 RESULTS

The primary results are summarized in three empirical tables. The Kruskal-Wallis test compares the mean ranks across leader groups. Higher mean rank values indicate stronger expression of the corresponding indicator within the group's distribution.

3.1 Statistical Comparison of Leadership Decision-Making Indicators

Table 1 summarizes cross-sector group differences and highlights statistically significant indicators; the key takeaway is that maladaptive strategies avoidance/procrastination/hypervigilance) vary by sector, supporting tailored interventions.

Vigilance reflects structured information processing and careful option evaluation. Avoidance tendency and procrastination indicate a preference to delay or evade responsibility for choosing, while hypervigilance captures anxiety-driven urgency and fragmented scanning for solutions. The observed p-values show statistically meaningful between-group differences in avoidance, procrastination, and hypervigilance ($p \leq 0.002$), but not in vigilance ($p=0.43$).

As shown in Figure 1, the distribution of mean ranks across the compared decision-style scales differs between groups; the main implication is that sector context shapes decision tendencies and should be considered in leadership development and IT-enabled support.

Table 2 summarizes cross-sector group differences and highlights statistically significant indicators; the key takeaway is that maladaptive strategies (avoidance/procrastination/hypervigilance) vary by sector, supporting tailored interventions.

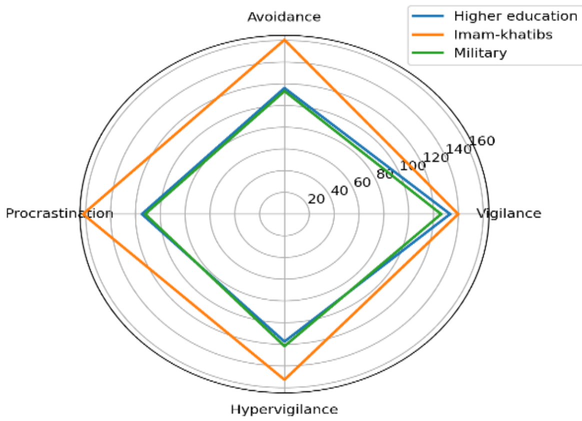

Figure 1: Sectoral comparison of mean ranks across MDMQ scales (Kruskal-Wallis).

Internal locus of control indicates the tendency to attribute outcomes to one's own actions and competence, whereas external locus of control reflects stronger attribution to circumstances, fate, or others [2]. In this comparison, neither internal nor external control differed significantly across groups

($p>0.05$). This pattern implies that sector differences in decision patterns may be more strongly linked to situational demands and role pressure than to generalized control beliefs alone.

Table 3 summarizes cross-sector group differences and highlights statistically significant indicators; the key takeaway is that maladaptive strategies (avoidance/procrastination/hypervigilance) vary by sector, supporting tailored interventions.

Dominance striving can be interpreted as leadership assertiveness and the motivation to influence outcomes, while self-control in problematic situations captures behavioral regulation and composure under strain. The overall decision-making style indicator summarizes sector-specific patterns of managerial choice. All three indicators show statistically reliable group differentiation ($p=0.001$), confirming that leadership behavior and decision orientation vary meaningfully across professional environments.

3.2 Qualitative Interpretation of Findings

Beyond statistical significance, the empirical picture can be interpreted through the lived professional realities of the sampled leader groups. Imam-khatibs displayed higher mean ranks in avoidance tendency and procrastination, which may reflect the sensitivity of religious leadership to social expectations, reputational risk, and the necessity to preserve community harmony. In such contexts, postponing a decision or choosing conservative options may be a protective strategy aimed at reducing interpersonal conflict.

Military leaders, in contrast, showed relatively lower mean ranks on dominance striving compared with educational and religious leaders, while maintaining moderate levels of self-control under difficulty. This profile can be understood through the formalized hierarchy of military systems, where decision authority is often distributed and regulated, potentially limiting the expression of individual dominance as a trait.

Higher education leaders exhibited strong dominance striving and notable differences in decision-making style. This may be associated with the strategic and competitive nature of university management, where leaders must negotiate institutional performance indicators, staff coordination, and innovation pressures (including digital and personalized models) that require proactive organizational agency [11].

Hypervigilance differences suggest that certain roles may induce heightened stress-related decision behaviors. When leaders experience responsibility overload or ambiguous accountability, decision-making can shift toward urgent, fragmented searching for a ‘safe’ solution, reducing coherence of reasoning. Such patterns resonate with risk-sensitive decision theories emphasizing the psychological weight of losses and uncertainty [6].

4 DISCUSSION

The findings demonstrate that managerial decision behavior is deeply contextual. While vigilance remained comparable across sectors, avoidance and procrastination varied substantially, indicating that sector-specific normative pressures shape how leaders respond to uncertainty. These results align with the view that organizational decision-making is bounded and conditioned by environmental complexity [1], and that effective strategic choices can still be achieved when leaders rely on structured processes [3].

Importantly, the absence of significant locus-of-control differences suggests that intergroup contrasts may not be reducible to generalized personality orientations. Instead, professional culture and institutional rules may activate or suppress particular decision strategies. This supports socio-psychological models emphasizing the interaction of individual dispositions with group norms and role-based demands. Additionally, the literature on groupthink warns that strong conformity pressure can narrow the perceived solution space and indirectly promote avoidance or deferral of responsibility [4].

From an applied perspective, the results highlight a key target for leadership development: strengthening decision self-efficacy and structured deliberation routines. When maladaptive strategies (e.g., delay, avoidance) become habitual, organizations may experience slower responsiveness and reduced innovation capacity. Conversely, improving decision clarity and accountability can increase organizational resilience and performance, especially in educational modernization programs [11].

4.1 Applied IT Decision-Support Framework (D-HRM/MSS Integration)

To meet the Applied IT focus, we specify a decision-support framework that integrates sector-sensitive decision-style indicators into Digital Human

Resource Management (D-HRM) workflows and a Management Support System (MSS). The system captures decision events, engineers features from psychometric inputs and digital decision logs, estimates delay risk via baseline rules or ML, and delivers human-in-the-loop nudges through dashboards and workflow prompts. Figure 2 summarizes the architecture.

As shown in Figure 2, the distribution of mean ranks across the compared decision-style scales differs between groups; the main implication is that sector context shapes decision tendencies and should be considered in leadership development and IT-enabled support.

4.2 Data Specification, Feature Engineering, and Label Definition

This subsection defines the analytical dataset and its variables. Each decision is modeled as a time-stamped event (type/domain, milestones, urgency, stakeholders, complexity) linked to leader-level psychometric profiles via an identifier. Features include (i) static indicators (sector, decision-style scores, locus of control) and (ii) process-derived measures from digital logs (elapsed time, deadline changes, escalation flags, workload proxies). The main label is a “decision delay event,” coded as 1 when elapsed time exceeds an operational threshold (e.g., SLA-based or ≥ 7 days in the PoC) and 0 otherwise, ensuring alignment with actionable managerial outcomes.

4.3 Workflow Logic and Baseline/ML Models

This subsection describes the end-to-end pipeline: log ingestion from D-HRM/MSS, feature computation for each decision event, risk scoring, and intervention triggering when risk exceeds a configurable threshold. Risk estimation is implemented with a transparent baseline ruleset and a parsimonious ML benchmark (e.g., logistic regression) to balance explainability and deployability. Human-in-the-loop control is preserved: dashboards and workflow nudges support reflection and timeliness, while final decisions and overrides remain with leaders and are recorded for monitoring and iterative refinement.

4.4 Proof-of-Concept Simulation and Reproducibility Package

This subsection presents an illustrative PoC using synthetic decision events to demonstrate technical feasibility, not full operational validity. The simulation generates bounded variables (delay, workload, complexity, psychometric proxies), constructs labels, trains baseline/ML models, and reports standard metrics (AUC, F1, precision, recall) under a fixed split. A reproducibility package specifies the random seed, data-generation rules, preprocessing, model settings, and evaluation protocol so the pipeline can be rerun and later adapted to real organizational logs under appropriate privacy and governance.

The technical framing is supported by standard AI foundations [8].

The operational workflow of the proposed AI-enabled decision-support pipeline is summarized in Algorithm 1. The algorithm formalizes the human-in-the-loop decision nudging process, including feature engineering, risk estimation, adaptive nudge generation, human validation, and audit trail creation. This workflow serves as the computational basis of the proof-of-concept implementation evaluated in the following experiments.

```
Input:
    Decision log D
    User profile P (MDMQ scores)
    Decision thresholds τ
    Prediction model M

Output:
    Audited decision trail
    Updated decision outcomes

for each new decision event e ∈ D do
    x ← FeatureEngineering(e, D, P)
    if model M is available then
        r ← M.predict_proba(x)
    else
        r ← RuleBasedRisk(x, τ)
    end if
    if r ≥ r0 then
        nudge ← SelectNudge(x)
        Deliver nudge to the decision maker
        Log(nudge, response)
    end if
    Human reviewer confirms the final decision
end for

Return audited decision trail and updated outcomes.
```

Algorithm 1. AI-enabled human-in-the-loop decision nudging.

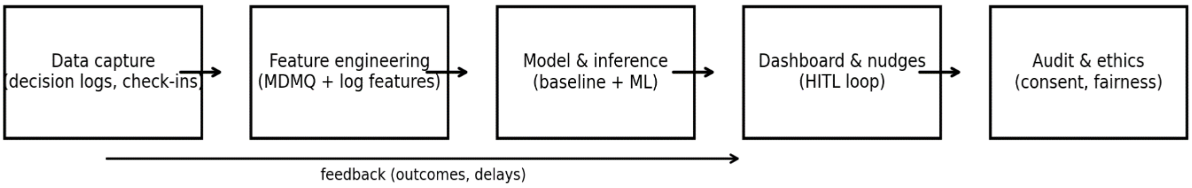

Figure 2: System architecture for AI-enabled decision support integrated with D-HRM.

Given that the empirical core is a socio-psychological survey, we do not present a deployed system evaluation. To illustrate implementability for ICAIIT, we ran an illustrative simulation using a synthetic dataset (n=2,500 decision events) reflecting plausible ranges of delays, workload, and decision-style features. A logistic regression classifier predicting the "decision-delay event" achieved: AUC=0.840, F1=0.767, Precision=0.797, Recall=0.738 on a held-out test split. These metrics are reported only as a proof-of-concept implementation demonstration and cannot substitute for empirical validation in operational settings.

Reproducibility details: the synthetic dataset (n=2,500 decision events) was generated with fixed random seed (seed=42). Continuous features were sampled from bounded distributions reflecting plausible ranges in managerial contexts: decision delay (0-30 days), workload index (0-100), decision complexity (1-10), and psychometric-style proxies for vigilance, avoidance, procrastination, and hypervigilance (1-5). The binary label "decision-delay event" was defined as delay ≥7 days. The feature list included: delay history, workload index, complexity, sector code (one-hot), and the four decision-style indicators. Data were split into train/test = 80/20 (stratified) using the same seed. Baseline rule: predict delay-event if (workload>70 AND procrastination>3) OR avoidance>3. ML model: LogisticRegression (scikit-learn) with L2 regularization (C=1.0), solver='liblinear', max_iter=1000. Evaluation used AUC, F1, Precision, and Recall on the held-out test set. Implementation note: Python 3.11; numpy, pandas, scikit-learn; a minimal pseudo-code block is provided in Appendix A to reproduce the pipeline.

Baseline logic can be implemented as a transparent rule engine (e.g., trigger a nudge when overdue_ratio > τ or when avg_delay_days increases across two periods). For the ML layer, logistic regression or gradient boosting can estimate decision-delay risk and support nudge selection. Pseudocode is provided below.

Label. A "decision-delay event" is defined as 1 when request-to-decision time exceeds a domain-specific threshold (e.g., SLA-based) or repeated deadline extensions occur. Features include delay statistics, overdue ratios, workload indicators, and stable psychometric profile scores.

Data capture. Each decision event is logged with: a) decision type and domain; b) timestamped milestones (request, analysis, decision, execution); c) optional short check-in (confidence, perceived risk); d) outcome marker (implemented/rolled back); and e) context tags (stakeholder count, urgency). Privacy and consent are enforced via role-based access, minimization, and transparent opt-in.

5 CONCLUSIONS

This study provides sector-sensitive empirical evidence that managerial decision-making patterns differ across higher education, religious leadership, and military leadership contexts in Tashkent, Uzbekistan. The nonparametric analysis demonstrated statistically significant differences in avoidance tendency, procrastination, hypervigilance, and several leadership-related characteristics, whereas vigilance remained comparatively stable across sectors. These findings suggest that managerial decision behavior is shaped by the interaction of institutional demands, professional responsibilities, and psychological coping mechanisms rather than by a single universal leadership profile.

From a practical perspective, the results support the development of targeted interventions aimed at reducing delay-oriented decision patterns, strengthening reflective decision-making, and improving leadership resilience under uncertainty. The findings also indicate that AI-enabled decision-support technologies, digital accountability tools, and structured decision protocols can complement managerial expertise by enhancing transparency, consistency, and organizational learning while preserving human responsibility for final decisions.

6 RECOMMENDATIONS

The findings of this study suggest several practical directions for improving managerial decision-making across different professional sectors. First, sector-specific decision-making training programs should be developed to reduce avoidance and procrastination tendencies. Such programs should address the psychological mechanisms underlying delayed decisions, including fear of negative evaluation, uncertainty intolerance, and accountability concerns. Scenario-based training, simulation exercises, and structured decision frameworks can help leaders develop the ability to make timely and balanced decisions under complex conditions while maintaining ethical and professional standards.

Second, organizations should introduce reflective decision protocols into routine managerial practice. Tools such as decision checklists, pre-mortem analysis, and structured option-mapping techniques can reduce impulsive reactions associated with hypervigilance and support more systematic evaluation of alternatives. By formalizing the decision process, organizations can improve consistency, transparency, and the quality of managerial choices.

Third, strengthening organizational feedback and accountability mechanisms is essential for promoting proactive decision behavior. Although the present study did not identify significant differences in locus of control between leader groups, institutional conditions can influence how responsibility is perceived and exercised. Clear allocation of responsibilities, transparent evaluation criteria, and constructive feedback systems can encourage leaders to take ownership of decisions and reduce tendencies toward postponement or avoidance.

Fourth, organizations should consider implementing psychological support mechanisms for leaders operating in high-responsibility environments. Elevated hypervigilance may reflect increased decision-related stress and uncertainty. Leadership coaching, professional consultation, and stress-regulation training can support emotional stability, reduce anxiety-driven urgency, and improve decision quality in demanding professional contexts.

Fifth, educational management systems should incorporate data-informed governance approaches and personalized optimization perspectives. Evidence-based management supported by analytical models can improve strategic planning, policy implementation, and monitoring of organizational outcomes. The integration of optimized implementation approaches provides additional opportunities for improving managerial rationality and supporting effective educational reforms [11].

Finally, the integration of AI-enabled decision-support and digital accountability tools should be considered as a complementary direction for leadership development. Decision logs, automated reminders, AI-assisted option summarization, and analytical dashboards can improve decision transparency, clarify responsibility distribution, and reduce delay-oriented behavior. Such technologies should support rather than replace human judgment, ensuring that final decisions remain under the responsibility of organizational leaders.

7 LIMITATIONS AND FUTURE WORK

This study is based on the empirical indicators and statistical summaries reported in the underlying dissertation research. Consequently, the present article does not include detailed psychometric reliability coefficients, factor-loading matrices, or extended correlation analyses, although these formed part of the broader dissertation methodology. In addition, the sample represents leadership groups from a single geographical region and should therefore not be interpreted as fully representative of all organizational contexts.

Future research should extend the empirical investigation to multiple regions and organizational sectors, evaluate longitudinal changes in managerial decision competence, and examine predictive relationships between decision-making styles and organizational performance. Further studies should also investigate the mediating effects of organizational climate, perceived role conflict, and group-pressure dynamics on leadership decisions. Finally, the proposed AI-enabled decision-support framework should be validated using real organizational decision logs and longitudinal field studies to assess its practical effectiveness in improving decision quality and organizational governance [4], [8], [11].

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APPENDIX

The following pseudo-code summarizes the main steps required to reproduce the illustrative proof-of-concept experiment described in Section 4.4. The procedure includes synthetic data generation, preprocessing, baseline evaluation, model training, and performance assessment.

Pseudo-code:

1) Set random seed = 42 and generate a synthetic dataset of n = 2,500 decision events with the following features: workload, decision complexity, sector category, vigilance, avoidance, procrastination, and hypervigilance indicators.
2) Define the binary target variable:
3) y = 1 if decision delay ≥ 7 days; otherwise y = 0.
4) Split the dataset into training and testing subsets using an 80/20 stratified split with random_state = 42.
5) Apply the baseline rule-based classifier and calculate AUC, F1-score, precision, and recall.
6) Train a Logistic Regression model with L2 regularization:
7) C = 1.0, solver = 'liblinear', max_iter = 1000.
8) Evaluate the trained model on the held-out test dataset using AUC, F1-score, precision, and recall.