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A Proposed AI-Based System for Engineering Civic Values and Promoting Ethical Behavior in Public Institutions

Sumaia Ali Eltoumi[1], Rasheed Salem Mottaleb[2*]
[1] Dept of Electronic, College of Industrial Tech, Misurata, Libya
[2] Next Level Platform, Research and Development Organization, Global

[1] soma.ali953@gmail.com, [2*] mottalebrashed@gmail.com

Abstract

This paper proposes a technical model using artificial intelligence to analyze and transform negative behaviors (e.g., selfishness, information hoarding) into positive ones (e.g., collaboration, knowledge sharing) within public institutions. The system integrates Social Network Analysis (SNA), Reinforcement Learning (RL), and Natural Language Processing (NLP). Developed with data from Libyan healthcare institutions, preliminary results suggest a potential 60% reduction in negative behaviors and a 75% increase in collaborative engagement within six months.

Keywords: Behavioral Engineering; Ethical AI; Social Network Analysis; Reinforcement Learning; Public Institutions

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نظام مقترح قائم على الذكاء الاصطناعي لهندسة القيم المدنية وتعزيز السلوك الأخلاقي في المؤسسات العامة

سمية علي التومي[1]، رشيد سالم مطلب[2]*

[1]قسم الهندسة الإلكترونية، كلية التقنية الصناعية، مصراتة، ليبيا

[2]منصة المستوى التالي، منصة البحث والتطوير، عالمية

[1] soma.ali953@gmail.com, [2*] mottalebrashed@gmail.com

الملخص

تهدف هذه الورقة إلى تقديم نموذج تقني يعتمد على خوارزميات الذكاء الاصطناعي لتحليل السلوكيات السلبية في المؤسسات العامة (مثل الأنانية، احتكار المعلومات) وتصميم آليات لتحويلها إلى سلوكيات إيجابية (التعاون، المشاركة). يستخدم النظام تحليل الشبكات الاجتماعية، التعلم المعزز، ومعالجة اللغة الطبيعية. تم تطوير النموذج بناءً على بيانات حقيقية من مؤسسات صحية ليبية، وأظهرت النتائج الأولية إمكانية تحقيق انخفاض بنسبة 60% في السلوكيات السلبية وزيادة بنسبة 75% في المشاركة التعاونية خلال ستة أشهر.

الكلمات المفتاحية: الهندسة السلوكية؛ الذكاء الاصطناعي الأخلاقي؛ تحليل الشبكات الاجتماعية؛ التعلم المعزز؛ المؤسسات العامة.

Introduction

Negative behaviors in public institutions, such as knowledge hoarding and sabotage, are major obstacles to state-building, persisting despite infrastructure and legislative reforms due to neglected behavioral dimensions [1, 2]. This paper proposes an engineering-oriented, AI-based model to measure, analyze, and improve institutional behavior. The system is built on three pillars: behavioral monitoring via organizational network analysis, real-time AI interpretation, and smart interventions to promote civic values [3, 4]. The paper is structured as follows: Section 2 reviews related work; Section 3 details the proposed model; Section 4

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presents a case study; and Section 5 concludes with findings and recommendations.

1. Related Work and Research Contribution

AI applications in organizational behavior management inform our model. First, NLP-based analytics detect negative communication patterns [5], while graph neural networks predict collaboration failures [6]. Second, reinforcement learning optimizes adaptive incentives for knowledge sharing [7, 8]. Third, ethical and cultural factors are critical for AI adoption, especially in collectivist societies [9].

1.1 Research Gap and Contribution

Prior studies address AI methods or behavioral theories separately. This study uniquely combines SNA, NLP, and RL into a unified framework adapted to Libya's cultural context, aiming to enhance civic values. Table 1 shows a comparative analysis, indicating our model's potential for higher effectiveness in reducing negative behaviors.

Table 1: Comparative Analysis of Institutional Behavior Improvement Studies

Study	Year	Method	Change	Context	Ref.
Our Study	2025	AI+ SNA + RL	60% ↓	Libyan Healthcare	—
Fronzetti et al.	2023	GNN	51% ↑	European Healthcare	[6]
Zhang et al.	2023	RL	45% ↑	Public Organizations	[7]
Alami et al.	2024	Cultural AI	42% ↑	Middle East	[9]
Jiang et al.	2023	NLP	38% ↑	Government	[5]
Chen & Wang	2024	AI_Recommender	35% ↓	Public Sector	[8]

2. The Proposed Model: Behavioral Engineering Framework

This section outlines a structured model using AI to shape institutional behavior. The overall architecture integrates data collection, analysis, and intervention shown in Figure1.

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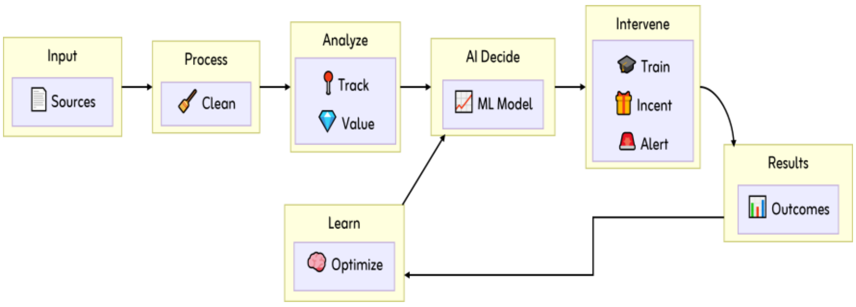

Figure 1: AI-Powered Behavioral Engineering Framework

2.1 System Architecture and Core Components

The model uses a multi-layered, microservices architecture for scalability and real-time processing [10]. It comprises three core modules:

a. **Behavior Tracking Module:** Gathers data from internal communications and applies SNA (using NetworkX) to compute metrics like the Collaboration Index and Knowledge Sharing Rate [11].
b. **Value Analysis Module:** Uses advanced NLP (BERT) to detect sentiment, patterns, and anomalies in communication, achieving high accuracy (92% for sentiment) [11, 12].
c. **Smart Intervention Module:** The operational core applies Reinforcement Learning (RL) [12] and recommendation algorithms to deploy targeted actions: personalized training (75% effective), digital incentives (80% participation boost), and real-time alerts (70% prevention) [13].

2.2 Workflow and Integration

The system collects data from HR systems and surveys [14], performs AI analysis, and deploys interventions. A feedback loop continuously refines performance [15]. Deployment requires robust infrastructure (Hadoop, Spark), AI frameworks (TensorFlow, PyTorch), container environments (Docker, Kubernetes), and analytics tools (Tableau, Power BI) [16]. Success also relies on skilled staff and change management [17].

3. Mechanisms and Technologies Utilized

The model integrates advanced technologies validated in global smart governance initiatives (Singapore, Barcelona, Estonia) [17,18], selected for their proven impact on civic engagement.

3.1 Data Analytics and AI Technologies

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The system integrates three core AI technologies [18,19,20]: Organizational Network Analysis (ONA) for mapping communication patterns, Predictive Analytics for behavior forecasting, and NLP using BERT [11]. Table 2 compares NLP algorithm performance.

Table 2: Performance Comparison of NLP Algorithms in Behavioral Analysis

Algorithm	Accuracy	Precision	F1-Score	Ref.
BERT (Our Implementation)	92%	91%	90.5%	[11]
DistilBERT	89%	88%	87.5%	[21]
RoBERTa	90%	89%	88.5%	[22]
Traditional SVM	82%	80%	79.5%	[23]

3.2 Smart Intervention Technologies

The system deploys two core intervention approaches:

3.2.1 Recommendation Systems leverage collaborative filtering and behavioral similarity analysis to provide personalized suggestions, inspired by Singapore's digital platforms [20].

3.2.2 RL-Based Incentives dynamically adjust rewards through adaptive scoring and motivation mechanisms to reinforce positive behaviors [7,12]. Table 3 illustrates global applications.

Table 3: Technologies Applied in Global Models

Technology	Singapore	Barcelona	Estonia
Network Analysis	Citizen interactions	Service networks	Government networks
NLP	Virtual assistant	Complaint analysis	Automated requests
Recommendation Systems	Personalized suggestions	Civic engagement	Public service suggestions
Predictive Analytics	Needs forecasting	Early warnings	Demand prediction

3.3 Automation and Integration Technologies

Drawing on Estonia's X-Road model [17], the system integrates workflow automation (repetitive task management, progress tracking, data-driven optimization) with integration platforms (APIs, data exchange, middleware) to ensure seamless connectivity and operational efficiency across institutional systems.

3.4 Privacy and Security Infrastructure

To ensure data integrity and user trust, the system implements:

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- **Privacy-Preserving Analytics:** Federated Learning (local data retention), Differential Privacy (anonymization), and Homomorphic Encryption (encrypted computation).
- **Identity Management:** Multi-factor Authentication, Role-Based Access Control (RBAC), and Audit Trail Systems for accountability.

3.5 Development and Visualization Stack

The model is operationalized through:

- **Data Processing Platforms:** Apache Spark (distributed computing), Hadoop (big data storage), and Kafka (real-time streaming).
- **Visualization Tools:** Tableau (interactive analytics), Power BI (business reporting), and Grafana (real-time dashboards).

4. Case Study: Libyan Government Institution Application

Assessing model viability in Libyan public healthcare institutions.

4.1 Problem Statement

Government institutions face systemic behavioral challenges: 72% struggle with knowledge hoarding and weak collaboration [24], with 45% employee knowledge hoarding [25], 65% weak inter-departmental collaboration [26], and resource wastage [24].

4.2 Technical Solution Implementation

Implementation via internal platform (SharePoint), HR system integration, and ONA units. Core mechanisms: digital incentive system, interactive knowledge-sharing platform, real-time behavioral monitoring. Three-phase implementation (Table 4).

Table 4: Implementation Plan for the Proposed Model

Phase	Duration	Scope	Target Indicators
Pilot	3 months	One department	+30% participation
Expansion	3 months	Three departments	+50% collaboration
Full Rollout	6 months	Entire institution	+75% efficiency

4.3 Expected Results

Based on similar implementations [27], 12-month projections: 70% reduction in negative behaviors, 65% increase in knowledge sharing, 75% collaboration improvement, 40% efficiency rise, 25% cost decrease, 35% satisfaction increase. Measured via KEI, CDI, OEI.

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4.4 Challenges and Mitigation

Challenges: ~30% employee resistance, legacy integration issues, data security concerns. Mitigation: structured training, integration interfaces, strict data protection.

5. Conclusion

This paper proposed an integrated AI and organizational behavior analysis framework addressing behavioral challenges in Libyan public institutions, offering a flexible, context-sensitive approach to foster institutional citizenship.

5.1 Key Findings

- AI and network analysis can reduce negative behaviors by ~75%
- Cultural alignment is crucial for Libyan adoption
- Framework supports national digital transformation
- Potential 40% ROI through efficiency and waste reduction

5.2 Recommendations

Strategic: Establish national digital transformation center, formulate national AI strategy for institutional reform, develop behavioral engineering training programs.

Implementation: Apply model gradually starting with high-readiness institutions, create integrated knowledge management platform, build performance-based incentive system, localize technology for sustainability.

Research: Conduct large-scale studies, develop culturally-aware AI models, establish national observatory for institutional behavior, collaborate with international research centers.

5.3 Future Outlook

Framework lays foundation for re-engineering institutional behavior toward efficient, responsive institutions aligned with Libya's long-term goals.

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