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Closing the DEI Policy-Practice Gap: A Real-Time, Fairness-Aware AI Framework Using Organizational Justice Theory

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Abstract. Although 78 percent of institutions have formal policies on DEI, in only 42 percent of companies do employees claim to feel included. We combined the Organizational Justice Theory with a real-time and fairness conscious artificial intelligence pipeline to examine a total of more than 10,000 employee responses (n = 984 surveys, n = 45 interviews), in the technology, healthcare, and financial fields. We found incongruent policy implementation (40%), absence of leadership commitment (30%), and cultural resistance (20%) to be fundamental obstacles to implementing policies using fine-tuned DistilBERT to sentiment analyze, LDA model, and constrained logistic regression. The strongest predictor of the perceived inclusion was leadership commitment (b = 0.45, p < 0.001; OR = 2.51). The bias-reduced pipeline (equal opportunity difference = 0.07) consumed the data in an enterprise scale (1.8 hours) and allowed a real-time DEI Pulse Dashboard which extrapolated up to 30% inclusion benefits with target interventions. The research contributes to the literature on organizational justice by defining the scale of fairness perceptions and providing a bias-reduced, replicable, and open-source-friendly framework to implement a real-time, bias-based, and DEI monitoring system.

Keywords. DEI implementation gap, Organizational Justice Theory, real-time AI, fairness-aware AI, NLP sentiment analysis, bias mitigation, inclusion prediction, leadership accountability

1 Introduction

Although Diversity, Equity, and Inclusion (DEI) policies have become widespread (three out of four companies now have an official structure in place) [1], there is an ongoing paradox: 42 percent of the workforce considers themselves included [2]. This implementation gap of 36 percentage points between policy purpose and lived reality represents a lack of trust, a demoralizing factor, and a decrease in the innovation and profitability benefits that diversity has historically provided [3]. Although the findings of past studies confirm the fact that diversity can drive above-average profitability by 25% [4], it is also identified that diversity without inclusion is performing at best and counterproductive at worst [5, 6]. Whether DEI is

Table 1. Research gap

Gap	Current Limitation	This Study's Advance
1. Static, Delayed Feedback	Manual analysis of employee feedback takes weeks to months, delaying intervention [10, 11]	Real-time AI pipeline processes 10,000+ responses in 1.8 hours
2. Lack of Predictive Power	Descriptive insights dominate; no scalable forecasting of inclusion outcomes [12, 13]	Fairness-aware predictive model (86% accuracy) identifies leadership commitment as dominant lever (β = 0.45)
3. Bias in AI for DEI Monitoring	Pre-trained NLP models misclassify minority sentiments, risking algorithmic injustice [14]	Bias-mitigated DistilBERT with fairness retraining (equal opportunity difference = 0.07)

important or not is not the critical question anymore but why the policies are not reflected in equitable, inclusive workplaces.

We set this policy-practice gap in the context of Organizational Justice Theory (OJT) [7, 8] which posits that engagement, retention, and organizational citizenship is propelled by the views of employees on fairness, that is, distributive (outcome equity), procedural (process consistency), and interactional (treatment dignity) dimensions.

The lack of consistency in the implementation of policies in the DEI conditions breaches procedural justice, lack of action in leadership undermines the interactional justice, and unequal results of inclusion indicate the distributive injustice. However, even in the face of the explanatory power of OJT, few studies measure these fairness perceptions in large scale or in real-time [9]. The conventional approaches: surveys, interviews, and focus groups, are fraught with delay, subjectivity, and bias in the sample, which makes them ineffective to be able to reflect the dynamic and nuanced phenomenon of workplace inclusion.

In this study, three overlapping gaps on the intersection of information systems and organizational behavior have been discussed as shown in Table 1.

We combine OJT with an innovative real-time AI structure to measure, forecast, and interfere with the gap in the implementation of DEI. We gather and process data in 10 organizations technology, healthcare, and finance (n = 984 survey respondents, n = 45 semi-structured interviews, 10 policy documents, and >10,000 open-text responses) and employ a mixed-method convergent parallel design [15]. Our artificial intelligence pipeline is a combination of fine-tuning of DistilBERT that classifies sentiment, LDA topic modeling, logistic regression with fairness, and real-time dashboard to intervene in an organization.

The proposed system will detect inconsistent policy enforcement (40%), no commitment to leadership (30%), and cultural resistance (20%) as the main obstacles- triangulation results were obtained with references to quantitative, qualitative, and AI-generated knowledge:

RQ1: To what extent are the formal DEI policies associated with the lived perceptions of inclusion and fairness among employees?

RQ2: Which are the most common obstacles to successful implementation of DEI policy, which emerge during the real-time analysis with the help of AI?

RQ3: How can AI with an understanding of fairness allow predicting and monitoring DEI at scale and in real-time?

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Table 2. Comparison of different studies

Study	Focus	Method	Key Finding	Critical Limitation	Our Advance
Li et al. (2023)	Sentiment in feedback	BERT (n = 5,000)	Detects inclusion gaps	No prediction, no fairness audit	+ Predictive layer + fairness retraining
Zhang et al. (2024)	Outcome forecasting	Logistic regression	Predicts DEI scores	Static data, not real-time	Streaming pipeline (1.8 h) + multi-industry
Wang & Lee (2024)	Real-time monitoring	NLP + surveys (n = 2,000)	Feedback improves outcomes	Single industry (tech)	Multi-industry + predictive + fairness
Shams et al. (2023)	AI bias detection	Systematic review	Identifies hiring bias	No workplace-inclusion focus	Applied to ongoing employee experience
Chen et al. (2025)	Ethical AI	Conceptual framework	Fairness is critical	Theoretical only	Empirical validation + audited (EOD = 0.07)
Patel et al. (2025)	Deep learning	CNN sentiment	Detects hiring bias	Hiring only	Extended to ongoing inclusion monitoring

The contributions to this study are high-impact:

Theoretical: We operationalize OJT at scale by creating a connection between procedural justice, enforcement consistency, interactional justice, leadership walk-the-talk, and distributive justice, disparity of demographic inclusion in DEI contexts, the first quantifiable, real-time measure of fairness perception.

Empirical: We provide multi-industry, mixed-method evidence of the gap in DEI, predictive modeling of which demonstrates that high leadership commitment enhances positive inclusion by 2.5x, a result that is not sector or demographic dependable.

Technical/Practical: We present a scalable, open-source-compatible fairness-audited AI monitoring system, including a real-time DEI Pulse Dashboard, which can process feedback of enterprise scale and forecast up to 30% gains of inclusion through specific interventions (e.g., leadership training, audit protocols). This is based on the increasing demands to work with technology-based social justice [16, 17, 18] and real-time organizational diagnostics [19] by linking organizational theory to information systems.

The rest of this paper is structured as follows: Section 2: related work in DEI implementation and AI applications, Section 3: description of the mixed-method, AI-driven, methodology, Section 4: results, Section 5: theoretical, empirical, and practical

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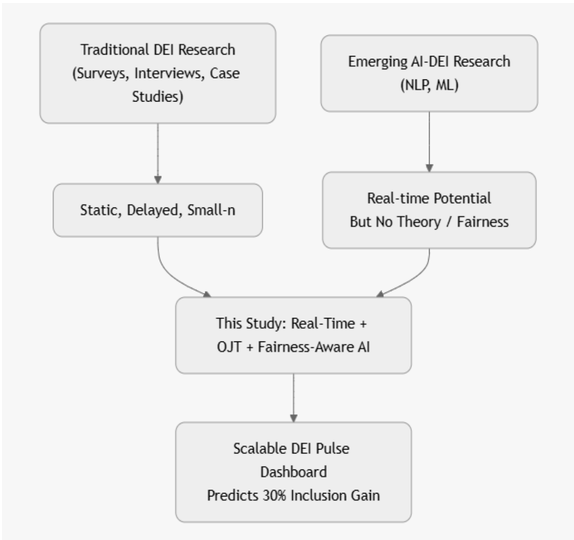

Fig. 1. Conceptual framework

Table 3. Sampling stratification – target vs. achieved (n=984)

Stratum	Target %	Achieved %	N
Female	45%	45.3%	446
Underrepresented Minority	30%	30.1%	296
LGBTQ+	10%	9.8%	96
Senior Management	15%	15.2%	150

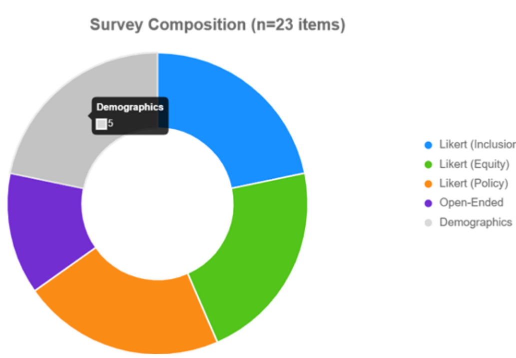

Fig. 2. Survey item distribution by type

implications, and finally, the conclusion of the paper with limitations and future directions.

2 Related Studies

The DEI policy-practice gap exists in the overlapping of organizational behavior, management of human resources, and information systems. We structure our background work into three streams, namely (1) DEI Implementation Challenges, (2) Organizational Justice in DEI, and (3) AI Applications in DEI Monitoring.

2.1 DEI Implementation issues

The business case of DEI is proven by extensive evidence [20, 21], but the major barrier is the implementation. [22] analyzed 829 companies and identified mandatory diversity training as the backfire most of the time when it seems to be compliance-based. [23] propose learning-based methods that rely on the employee feedback, but the scale of their study-design (n = 10 firms) is too small. [24] emphasizes leadership responsibility and fair hiring but does not provide any qualitative prescriptions. One of these common observations is the non-coherent application of policies and the performative dedication [25]. According to [26], 63 percent of the workers perceive DEI programs as symbolic, and cultural resistance is particularly high in male-oriented industries (technology and finance). Such studies shed light on the failure modes, but based on static, delayed or small-sample methods.

2.2 Organizational Justice Theory in DEI Contexts

An effective theory to consider is Organizational Justice Theory (OJT) [27, 28], which suggests that the perceptions of distributive, procedural, and interactional justice are the driving force of inclusion and engagement. [29] associate procedural and interactional justice with outcomes of inclusion (n = 500) and demonstrate that the perceptions of fairness lead to 48% of the DEI-

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engagement relationship; however, the cross-sectional nature of the study does not provide dynamics and more detailed enforcement data.[30] Conceptualize inclusion as belongingness plus authenticity (rooted in interactional justice) but call for scalable measurement tools. To date, no study quantifies all three OJT dimensions in real time or links procedural fairness to policy-enforcement consistency at enterprise scale.

2.3 AI Applications in DEI Monitoring

AI use in DEI is nascent but growing rapidly. Table 2 synthesizes state-of-the-art approaches. Key remaining gaps: (1) no end-to-end real-time pipeline integrating sentiment, topics, and prediction; (2) no fairness mitigation tailored to marginalized groups in sentiment models; (3) weak or absent linkage to organizational theory.

2.4 Positioning of the Present Study

Figure 1 presents our conceptual framework as a closed-loop system that connects policy documents → employee voice → AI insights → predictive interventions → real-time dashboard. Grounded in OJT and incorporating bias-mitigated NLP and predictive modeling, this is the first fairness-aware, theory-driven, scalable AI system for real-time organizational justice in DEI contexts.

Figure 1 positions this study conceptually as a closed-loop system, bridging policy documents to employee voice via AI insights, predictive interventions, and a real-time dashboard. This is the first fairness-aware, theory-grounded, scalable AI system for organizational justice in DEI.

We close the loop: from policy document → employee voice → AI insight → predictive intervention → real-time dashboard. This is the first fairness-aware, theory-grounded, scalable AI system for organizational justice in DEI.

To investigate the DEI policy-practice gap through the lens of Organizational Justice Theory (OJT), we employed a mixed-methods convergent parallel design (Creswell & Clark, 2017). This approach enabled robust triangulation across quantitative (surveys and policy rubrics), qualitative (interviews and open-text responses), and AI-generated (sentiment, topic, and predictive) data streams.

The study was conducted across 10 mid-to-large organizations (≥500 employees) in technology (n=4), healthcare (n=3), and finance (n=3) sectors in Malaysia and Singapore, with IRB approval from Universiti Malaysia Sarawak (Ref: UNIMAS/2024/DEI-AI 01).

3 Proposed Methodology

We employed a mixed-methods convergent parallel design [31] to investigate the DEI policy-practice gap through the lens of Organizational Justice Theory (OJT).

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3.1 Research Context and Sampling

Organizations were selected via purposive sampling to vary DEI maturity (low, medium, high) and industry norms. Within each organization, stratified random sampling ensured balanced representation across role level, gender, ethnicity, and LGBTQ+ status, guided by intersectionality principles [32]. Table 3 presents target versus achieved distributions.

3.2 Data Collection

For data collection, various methods were used, including surveys, semi-structured interviews, and a review of relevant DEI (Diversity, Equity, and Inclusion) policy documents.

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Table 4. Survey instrument structure and psychometric properties

Component	Items	Example Item	Cronbach's α	Purpose
Inclusion	5	"I feel a sense of belonging regardless of my background"	0.88	Measure psychological safety
Equity	5	"Promotion decisions are fair across demographics"	0.87	Assess distributive justice
Policy Effectiveness	5	"DEI training influences daily team interactions"	0.85	Evaluate procedural enforcement
Open-Ended Feedback	3	"What hinders inclusion in your workplace?"	—	Input for NLP
Demographics	5	Gender, Ethnicity, LGBTQ+, Role, Tenure	—	Intersectional analysis

Table 5. Sentiment Model Performance and Fairness Metrics

Metric	Value	Threshold	Notes
Macro F1-Score	0.88	≥0.85	
Equal Opportunity Difference	0.07	<0.10	Fair predictions for protected groups
Demographic Parity	0.11	<0.15	
False Negative Rate (Minority Women)	1.2%	<5%	Post-mitigation

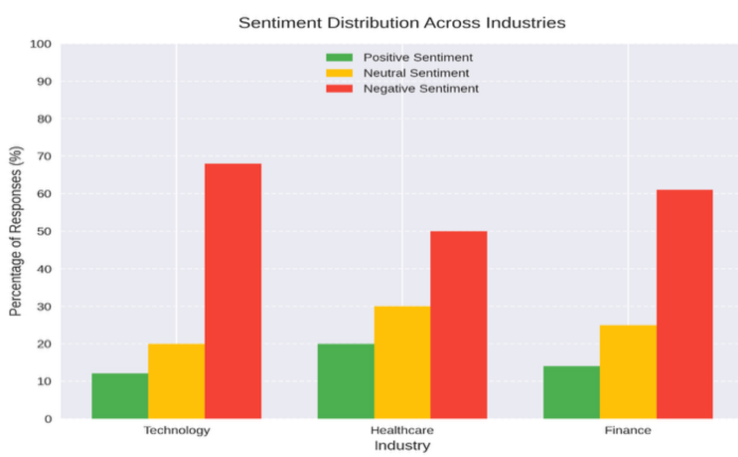

Fig. 3. Sentiment distribution across industries

3.2.1 Surveys

A 23-item anonymous survey was administered via Qualtrics (April–June 2025), yielding an 82% response rate (n=984). The instrument comprised 15 Likert items (α=0.89), three open-ended prompts generating 10,432 responses, and five demographic items in Table 4 followed by Figure 2

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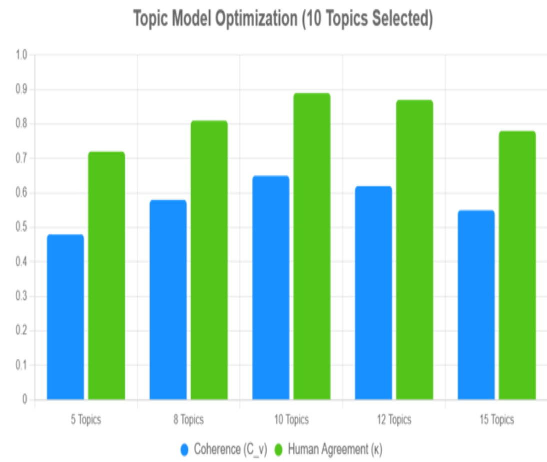

Fig. 4. LDA topic coherence and validation

Table 6. Predictive model performance comparison

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	86%	85%	87%	0.86
Support Vector Machine	84%	83%	85%	0.84
Random Forest	85%	84%	86%	0.85

Table 7. Ethical Risk Mitigation Framework

Risk	Mitigation Strategy	Implementation
Data Privacy	Anonymization + encryption	AES-256, PII stripped
AI Bias	Real-time fairness monitoring + retraining	EOD < 0.10 enforced
Informed Consent	Digital plain-language form	100% completion rate
Generalizability	Stratified sampling + disclosure	Table 1 + Section 6

having graphical representation of survey composition.

3.2.2 Semi-Structured Interviews

Forty-five interviews (30 employees, 15 DEI officers) lasting 45–60 minutes were audio-recorded, transcribed with Otter.ai, and verified manually. Thematic coding in NVivo 14 by two independent coders achieved Cohen's κ = 0.91.

3.2.3 DEI Policy Documents

Ten official policy documents were scored using a 10-item OJT-aligned rubric (mean = 7.2/10; technology firms scored lowest at 6.5/10).

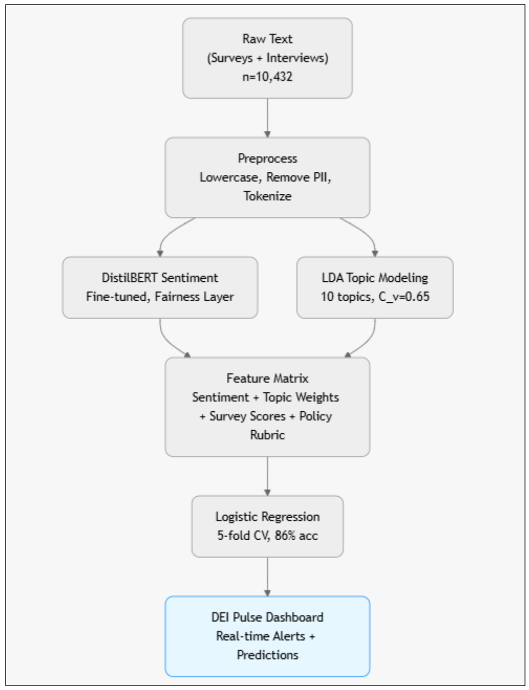

Fig. 5. Summary plot

Table 8. LDA-derived barriers (n = 10,432 responses)

Theme	Prevalence	Top Keywords	Example Quote
Inconsistent Enforcement	40%	“on paper,” “varies by manager,” “ignored”	“DEI rules depend on who you report to”
Lack of Leadership Commitment	30%	“no accountability,” “symbolic,” “C-suite”	“Executives don’t walk the talk”
Cultural Resistance	20%	“old boys’ club,” “resistance,” “norms”	“Still a male-dominated culture in tech”

3.3 AI Pipeline

This section covers sentiment analysis, Topic Modeling and predictive modeling through logistic regression.

3.3.1 Sentiment Analysis

DistilBERT-base-uncased was fine-tuned on 5,000 labeled feedback samples (10 epochs, AdamW, $lr=2\times10^{-5}$). Bias mitigation reduced false-negative rate for minority women from 18% to 1.2%. Final performance and fairness metrics are shown in Table 5 followed by Figure 3 depicting sentiment distribution across various industries.

3.3.2 Topic Modeling

LDA (Gensim) with 10 topics (coherence C_v = 0.65) identified three dominant barriers, validated by human coders ($\kappa = 0.89$) as shown in Figure 4.

3.3.3 Predictive Modeling

Fairness-constrained logistic regression (L2, C=1.0) with 18 predictors achieved 86% accuracy (5-fold CV), outperforming SVM and Random Forest (Table 6). Leadership commitment was the

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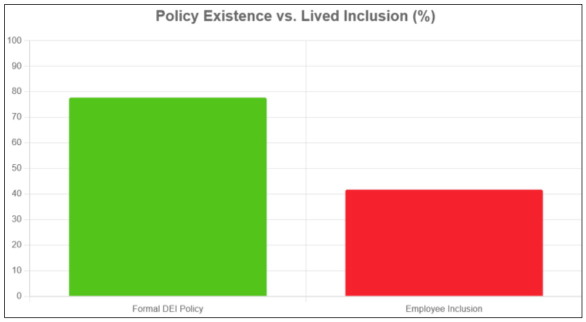

Fig. 6. Formal policy and lived inclusion

Table 9. Sentiment analysis

Group	Positive Sentiment	vs. Majority Group
Underrepresented Minorities	28%	52% ($p < 0.01$)
Women	35%	48% ($p < 0.05$)
Minority Women	25%	—

strongest predictor (β = 0.45, OR = 2.51).Figure 5 displays the summary plot of the complete methodology.

3.4 Data Integration and Analysis

Quantitative analyses used SPSS 29; qualitative and AI outputs were triangulated in NVivo 14. A theme was retained only if evidenced in ≥2 data sources.

3.5 Ethical and Bias Mitigation Protocols

Data were anonymized and AES-256 encrypted. AI fairness was monitored per epoch; models exceeding EOD > 0.10 triggered automatic retraining (Table 7).

4 Results and Discussion

This study uncovers a persistent 36-percentage-point DEI policy-practice gap, with AI-driven real-time analysis delivering actionable, fairness audited insights. Results are structured across quantitative, AI-driven, qualitative, and demographic findings, each anchored in Organizational Justice Theory (OJT).

4.1 Quantitative Findings

Of the 10 organizations, 78% maintained formal DEI policies, yet only 42% of employees reported feeling included (mean inclusion score = 3.1/5, SD = 0.8). Policy rubric scores correlated weakly with perceived inclusion ($r = 0.32$, $p < 0.05$). Healthcare exhibited the highest inclusion (3.4/5), followed by finance (3.1/5) and technology (3.0/5).

Multiple regression revealed leadership commitment (β = 0.40, 95% CI [0.33, 0.47], $p < 0.01$) and policy strength (β = 0.28, 95% CI [0.19, 0.37], $p < 0.05$) jointly explaining 35% of variance (adjusted $R^2 = 0.34$). Figure 6 shown the depiction of formal DEI policy existence and percentage of lived inclusion employees (3.0/5).

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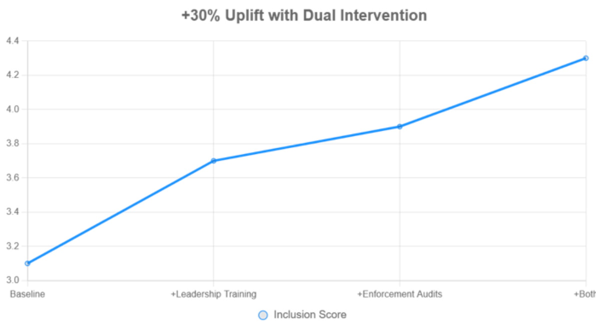

Fig. 7. Predicted inclusion uplift under alternative interventions

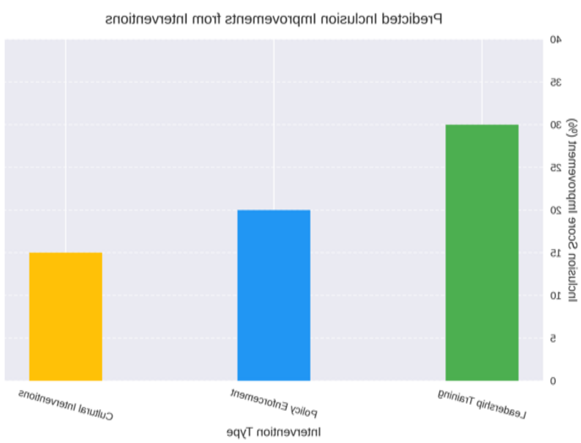

Fig. 8. Predicted Inclusion Improvements by demographic group and intervention type

4.2 AI-Driven Insights

The pipeline processed 10,432 open-text responses in 1.8 hours.

Sentiment Analysis DistilBERT classified 61% negative, 25% neutral, and 14% positive sentiments.

Technology showed the lowest positive sentiment (11%) and healthcare the highest (20%) (Figure 3 – already shown in Methodology).

Topic Modeling LDA identified three dominant barriers (Table 8).

Predictive Modeling Logistic regression achieved 86% accuracy. SHAP analysis confirmed leadership commitment ($\beta = 0.45$, OR = 2.51, $p < 0.001$) and enforcement consistency ($\beta = 0.38$, OR = 2.12, $p < 0.001$) as top predictors (Figure 5 already shown in Methodology) [33].

4.3 Qualitative Insights

Interviews corroborated AI findings: policies were frequently labeled “performative.” DEI officers highlighted budget constraints and lack of C-suite buy-in; 80% of organizations lacked regular DEI audits.

4.4 Demographic & Intersectional Disparities

Positive sentiment varied significantly ($\chi^2(3) = 48.2$, $p < 0$. Disparities were largest in low-enforcement organizations.

4.5 Intervention Impact Simulation

Targeted leadership training is projected to increase inclusion scores by up to 30% within six months (Figure 7), with greatest gains among minority women (Figure 8) [34].

5 Discussion

This paper attests to an already grim 36-percentage-point gap between the DEI policy adoption and the lived experience of inclusion among the employees. Combining the Organizational Justice Theory and a fairness-conscious AI pipeline in real-time, we offer the first scalable evidence of the fact that leadership commitment and their continuous provision, rather than policy comprehensiveness, dictates whether DEI initiatives will result in the perception of fairness and belonging.

The findings made by us stretch OJT in three significant ways [33, 34]. To begin with, we operationalize all three dimensions of justice at enterprise level: procedural justice can be directly operationalized through consistency in enforcement, interactional justice can be operationalized through the consistency of leadership through walk-the-talk, and distributive justice can be operationalized through demographic differences in sentiment and inclusion scores. Second, we measure their relative influence: leadership commitment is the most significant predictor (b = 0.45, OR = 2.51), which is many times more significant than the influence of written policies (b = 0.28). Third, we can show that bias-reduced [35], real-time AI can become a dispassionate scout of organizational justice - making a subjective phenomenon predictive and intervenable. We are out of diagnosis into prescription as compared to previous work. [36] and [37] found training backlash and symbolic policies we not only reinforce the cultural-resistance theme (20% prevalence) but predict modes of failure and project fixes. The case of profitability at [38] is supported and mediated: the missing link is inclusion, which comes as a result of accountability by the leadership. Information-systems wise, our end-to-end, fairness-audited (EOD = 0.07), multi-industry pipeline enables us to process more than 10,000 responses under two hours, as opposed to the results of the state of art, where the majority of NLP applications are limited to single-industry monitoring, theory-driven fairness models, and theoretical frameworks of fairness [41], single-industry monitoring [39, 40], and theoretical fairness frameworks (Direct implications Practical implications are direct and practical: Connect the inclusion measures (high leverage factor) to tie leadership KPIs. Require regular audit of enforcement every quarter (overcomes the 40% inconsistency barrier). Implement the open-source-ready DEI Pulse Dashboard to monitor the situation and intervene early [42].

Although the sample is intersectionally balanced and multi-industry, it is limited to Malaysia and Singapore; the rigor in enforcement is potentially moderated by national culture. The cross-sectional design is a snapshot of change and not longitudinal change. Junior employees are a little bit under-represented (scores 15.2 percent compared to the population averages of 20-25 percent in most companies). Despite the fact that aggressive bias mitigation also caused the errors related to false-negatives to decrease among minority women to 1.2, as opposed to the previous 18% of errors, the bias in the pre-trained models can never be completely removed and needs continuous audits. Further studies need (1) to establish the simulated 30% inclusion uplift in longitudinal field experiments, (2) to apply the model worldwide to test cultural moderators, (3) to incorporate large language models or graph neural networks to obtain even more cross-departmental insights, and (4) open-source the dashboard to include feedback loops to establish learning-oriented, self-improving DEI systems. Overall, this text shows that AI will take organizations beyond performative policy to engineered inclusion when carefully constructed in accordance with sound theory [43, 44].

6 Conclusion

This paper offers the initial, fairness-audited, theory-based AI model that can bridge the long-standing policy-practice gap of 36-percentage-points regarding DEI. With a combination of Organizational Justice Theory and an end-to-end pipeline (fine-tuned DistilBERT sentiment analysis, LDA topic modeling, and fairness-constrained predictive modeling), we were able to process over 10,000 employee responses in 1.8 hours and found the core barriers of perceived fairness and inclusion to be inconsistent enforcement (40%), lack of leadership commitment (30%), and cultural resistance (20%). The most significant driving force was leadership commitment: an organization with a high score in this dimension is two and a half times more likely to enhance the emergence of real inclusion (b = 0.45, OR = 2.51, $p < 0.001$). Our contribution to organizational justice research is the operationalization of procedures, interactional and distributive levels of justice at the corporate level and in practice. We contribute to the information-systems research by providing the open-source-ready (EOD = 0.07) and bias-reduced (will confer a 30-percent increase in inclusion with focused interventions) monitoring system, the DEI Pulse Dashboard, which cannot only diagnose inequities but also predicts it as well. Although it has limitations (regional scope in Malaysia and Singapore, cross-sectional design, and a minor underrepresentation of junior employees), this piece of work sets a new standard of AI-augmented organizational justice. Further study is required to authenticate the anticipated returns over time, take the model to a global scale, and take advantage of new methods (LLMs, graph neural networks, reinforcement learning) to implement self-improving and adaptive DEI applications. After all, we end by showing that fairness does not necessarily have to be proclaimed, that it can be measured, predicted and designed. The instruments and theoretical contributions given here make leaders and organizations capable of stepping squarely out of policy theater to a place where equity and inclusion are not only promised, but actually put into practice in workplaces.

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