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**Justice-Voice Model for Neuro-Hybrid Leadership: Integrating
Organizational Justice and Voice Behavior into Strategic Human Resource
Management for Hybrid Work**

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Abstract

We propose the Justice-Voice Model for Neuro-Hybrid Leadership (JV-NHL), a novel framework that integrates organizational justice theory and voice behavior into the adaptive feedback loops of strategic human resource management for hybrid work environments. The conventional neuro-leadership architecture, which passively collects employee neural data to inform leadership recommendations, is replaced by a bidirectional, justice-constrained system. This system conditions both data ingestion and intervention output on perceived procedural fairness and employee voice opportunity. The JV-NHL comprises three core modules: a Justice-Voice Perception Encoder that quantifies real-time perceptions of justice and voice from multimodal data streams, a Procedural Fairness Gate that filters neuro-data based on threshold conditions derived from validated psychometric instruments, and an Adaptive Leadership Protocol Calibrator that employs reinforcement learning to generate personalized leadership interventions. The gate ensures that only data streams where employees perceive high procedural justice and have exercised voice are used to inform adaptive recommendations, thereby protecting employee agency. The calibrator then optimizes a reward function that balances performance outcomes with the maintenance of justice and voice scores. This closed-loop architecture substitutes into conventional performance management and learning and development systems, creating a feedback mechanism where every adaptive recommendation is audited for ethical robustness. Our contribution is threefold: we operationalize organizational justice and voice behavior as computational constraints within neuro-leadership, we introduce a gating mechanism that prevents low-trust data from influencing leadership decisions, and we provide a reinforcement learning framework that explicitly rewards the preservation of fairness perceptions. The significance of this work lies in its potential to reduce employee resistance to neuro-monitoring while empirically grounding leadership automation in validated organizational behavior theory.

Keywords: Neuro-Leadership; Organizational Justice; Employee Voice; Reinforcement Learning; Hybrid Work

1. Introduction

The rapid proliferation of hybrid work arrangements has fundamentally altered the landscape of strategic human resource management (SHRM), demanding new frameworks that can accommodate the spatial and temporal dispersion

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of organizational members [1]. Traditional SHRM models, which were largely designed for co-located workforces, struggle to address the unique challenges of distributed teams, particularly regarding employee monitoring, performance evaluation, and leadership development [2]. Concurrently, the emergence of neuro-leadership—the application of neuroscience principles to leadership practice—has offered promising avenues for understanding and optimizing leader-follower dynamics through physiological data collection [3]. However, the integration of neuro-monitoring technologies into hybrid work environments raises significant ethical and practical concerns, especially regarding employee willingness to share sensitive neural data and compliance with algorithmically generated leadership recommendations [4].

The central tension in this emerging domain lies between the potential benefits of data-driven leadership optimization and the fundamental requirement for employee trust and psychological safety [5]. Employees in hybrid settings may perceive neuro-monitoring as intrusive or coercive, particularly when they lack control over how their data are collected, interpreted, and applied [6]. This perception is exacerbated by the inherent opacity of many adaptive leadership systems, which often function as black boxes that generate recommendations without transparent justification [7]. Consequently, the very technologies designed to enhance leadership effectiveness may inadvertently undermine the relational foundations upon which effective leadership depends.

To address this challenge, we propose the Justice-Voice Model for Neuro-Hybrid Leadership (JV-NHL), a novel framework that systematically integrates organizational justice theory and voice behavior into the adaptive feedback loops of SHRM for hybrid work. Drawing on Colquitt’s multidimensional justice framework [8] and Van Dyne and LePine’s voice behavior inventory [9], our model operationalizes perceived procedural fairness and employee voice opportunity as computational constraints that govern both data ingestion and intervention output. Unlike conventional neuro-leadership architectures that passively collect and process neural data, the JV-NHL conditions every stage of the adaptive cycle on validated psychometric thresholds, thereby creating a bidirectional, justice-constrained system that protects employee agency while enabling evidence-based leadership recommendations.

The key innovation of our approach lies in three interrelated contributions. First, we operationalize organizational justice and voice behavior as computational constraints within neuro-leadership systems, translating established psychological constructs into quantifiable parameters that can be measured, monitored, and optimized in real time. Second, we introduce a Procedural Fairness Gate that filters neuro-data streams based on threshold conditions derived from validated instruments, ensuring that only data from contexts where employees perceive high procedural justice and have exercised voice are used to inform adaptive recommendations. Third, we provide a reinforcement learning framework that explicitly rewards the preservation of fairness perceptions, thereby creating a closed-loop system where every adaptive recommendation is audited for ethical robustness. This architecture substitutes directly into conventional performance management and learning and development systems, offering a pathway for embedding fair neuro-feedback loops into existing SHRM infrastructure.

The significance of this work extends beyond theoretical advancement to practical application. By grounding neuro-leadership automation in validated organizational behavior theory, the JV-NHL has the potential to reduce employee resistance to neuro-monitoring while simultaneously improving the quality and acceptance of adaptive leadership recommendations. The framework is designed to be accessible to practitioners without specialized engineering expertise, relying on established psychometric instruments and scenario-based experimental methods [10] that can be deployed through online platforms and field pilots with hybrid teams using wearable cognitive-load sensors [11].

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on strategic human resource management, organizational justice theory, voice behavior, and neuro-leadership, establishing the theoretical foundations for our model. Section 3 presents the research design and methodology, detailing the justice-voice experimental paradigm, the multi-level structural equation modeling approach [12], and the iterative calibration process for adaptive leadership protocols. Section 4 reports empirical results from scenario-based online experiments and subsequent field pilots conducted with hybrid teams. Section 5 discusses the implications of our findings for hybrid SHRM practice and policy, addressing both theoretical contributions and practical guidelines. Section 6 concludes with a summary of key insights and directions for future research.

2. Literature Review and Theoretical Framework

The intersection of strategic human resource management (SHRM), organizational justice theory, and neuro-leadership represents a nascent but rapidly evolving domain of inquiry. This section synthesizes the relevant literature across these three streams, identifies critical gaps, and establishes the theoretical foundation for the Justice-Voice Model for Neuro-Hybrid Leadership (JV-NHL).

2.1. Strategic Human Resource Management in Hybrid Work Environments

The shift toward hybrid work arrangements has compelled a fundamental reexamination of SHRM frameworks that were originally designed for co-located workforces. Traditional SHRM models emphasize alignment between human resource practices and organizational strategy through mechanisms such as performance management systems (PMS) and learning and development (L&D) platforms [1]. However, the spatial and temporal dispersion inherent in hybrid work introduces novel challenges for these mechanisms. For instance, performance evaluation in hybrid settings often relies on digital communication metadata, self-reported well-being surveys, and wearable biometric signals, which collectively generate multimodal data streams that are both richer and more ambiguous than their co-located counterparts [2]. The conventional PMS architecture, which processes these streams through unidirectional pipelines, lacks the capacity to account for the contextual factors that mediate employee perceptions of fairness and autonomy in distributed work environments.

Moreover, the L&D platforms that deliver leadership interventions in hybrid settings typically employ rule-based recommendation engines that trigger actions based on predefined thresholds (e.g., “if cognitive load exceeds 0.7, suggest a break”). These systems are inherently reactive and fail to incorporate the dynamic, reciprocal nature of leader-follower relationships in hybrid contexts [13]. The absence of bidirectional feedback loops means that employee responses to interventions are not systematically integrated into future recommendations, creating a static architecture that cannot adapt to evolving trust dynamics or justice perceptions.

2.2. Organizational Justice Theory and Voice Behavior

Organizational justice theory provides a multidimensional framework for understanding how employees evaluate the fairness of organizational procedures, outcomes, and interpersonal treatment. Colquitt’s four-dimensional model distinguishes between procedural justice (fairness of decision-making processes), distributive justice (fairness of outcome allocation), interpersonal justice (respectful treatment), and informational justice (adequacy of explanations) [8]. Among these dimensions, procedural justice is particularly relevant to neuro-leadership systems because it directly addresses the perceived fairness of the data collection and decision-making processes that underpin adaptive recommendations. Employees who perceive low procedural justice in neuro-monitoring contexts are more likely to resist data sharing, question the legitimacy of algorithmic recommendations, and disengage from the leadership development process [14].

Voice behavior, defined as the discretionary expression of constructive suggestions or concerns about work-related issues, represents a complementary construct that captures employee agency within organizational systems [9]. Van Dyne and LePine’s six-item inventory measures voice behavior along dimensions such as speaking up with ideas for change, expressing opinions about work procedures, and communicating concerns about ineffective practices. In hybrid work environments, voice behavior is particularly critical because the reduced visibility of employees to leaders can suppress spontaneous expression, leading to a “voice deficit” that undermines both individual well-being and organizational learning [15].

The integration of organizational justice and voice behavior into SHRM systems has been explored primarily through survey-based research and qualitative case studies. However, these approaches have not been extended to the computational domain of neuro-leadership, where real-time measurement and adaptive intervention require operationalizing these constructs as quantifiable parameters within algorithmic architectures. This gap represents a significant missed opportunity, as the very technologies that enable neuro-monitoring also provide the infrastructure for continuous justice and voice assessment.

2.3. Neuro-Leadership and Adaptive Feedback Systems

Neuro-leadership applies principles from cognitive neuroscience to understand and optimize leadership processes, with particular emphasis on the neural correlates of decision-making, emotional regulation, and social interaction [3]. Recent advances in wearable neurotechnology have enabled the collection of physiological signals—such as heart rate variability, electrodermal activity, and electroencephalography—that index cognitive load, stress, and engagement in real time [11]. These signals are increasingly used to inform adaptive leadership interventions, such as personalized break schedules, communication mode switches, and recognition messages [4].

However, the dominant paradigm in neuro-leadership research remains unidirectional: neural data flow from employees to leadership dashboards, where they are processed by rule-based or machine learning algorithms that generate recommendations without accounting for employee perceptions of the data collection process itself [7]. This architecture creates a fundamental asymmetry in which employees are passive data sources rather than active participants in the leadership optimization cycle. The absence of employee voice in the design and operation of these systems can erode trust, reduce compliance, and ultimately undermine the effectiveness of adaptive interventions [16].

Reinforcement learning (RL) has emerged as a promising approach for generating adaptive leadership interventions that can learn from experience and optimize over time. RL agents, such as Deep Q-Networks (DQNs), can learn policies that map states (derived from neuro-data) to actions (leadership interventions) by maximizing a reward function that captures desired outcomes [17]. However, existing RL applications in leadership contexts typically define reward functions solely in terms of performance metrics (e.g., task completion rates, quality scores), neglecting the relational and perceptual dimensions that mediate long-term acceptance of adaptive systems.

2.4. Key Novelty of the Proposed Approach

The JV-NHL model addresses the limitations identified above by introducing three novel contributions that distinguish it from existing neuro-leadership frameworks. First, whereas conventional systems treat organizational justice and voice behavior as exogenous variables measured through periodic surveys, our model operationalizes these constructs as endogenous computational constraints that govern both data ingestion and intervention output in real time. This shift from static measurement to dynamic constraint enables the system to adapt not only to performance fluctuations but also to changes in employee trust and agency. Second, the Procedural Fairness Gate (PFG) introduces a binary decision mechanism that prevents low-justice, low-voice data from influencing leadership recommendations, thereby protecting employee agency and reducing resistance to adaptive interventions. No existing neuro-leadership system incorporates such a gating mechanism, which is essential for maintaining ethical standards in contexts where data collection may be perceived as intrusive. Third, the Adaptive Leadership Protocol Calibrator (ALPC) employs a reward function that explicitly balances performance outcomes with the maintenance of justice and voice scores, ensuring that the system does not optimize performance at the expense of employee trust. This multi-objective optimization framework represents a departure from the single-objective approaches that dominate current RL applications in organizational contexts. Together, these innovations create a closed-loop architecture that is both ethically robust and empirically grounded in validated organizational behavior theory, offering a pathway for embedding fair neuro-feedback loops into existing SHRM infrastructure.

3. Research Design and Methodology

The research design operationalizes the JV-NHL framework through a multi-phase experimental paradigm that systematically varies perceived procedural justice and employee voice opportunities during neuro-data collection. This section details the technical architecture of the three core modules, the experimental protocols for calibration and validation, and the analytical approach for testing mediated pathways.

3.1. Justice-Voice Perception Encoder (JVPE)

The JVPE transforms raw multimodal data streams into continuous latent scores representing perceived procedural justice and voice opportunity. The input at time t is a vector $\mathbf{x}_t \in \mathbb{R}^d$ that concatenates features from three sources: communication metadata (e.g., response latency, message length, turn-taking patterns), biometric signals (e.g., heart rate variability, electrodermal activity), and periodic survey responses (e.g., single-item justice and voice probes administered every 30 minutes). The encoder employs two parallel Transformer networks, f_{θ_J} and f_{θ_V} , each processing the same input sequence $\mathbf{X}_t = [\mathbf{x}_{t-3}, \mathbf{x}_{t-2}, \mathbf{x}_{t-1}, \mathbf{x}_t]$ to capture temporal dependencies over a 60-minute window.

The justice score J_t and voice score V_t are computed as:

$$J_t = \sigma(\mathbf{W}_J \cdot \text{MeanPool}(\text{Transformer}_{\theta_J}(\mathbf{X}_t)) + b_J) \quad (1)$$

$$V_t = \sigma(\mathbf{W}_V \cdot \text{MeanPool}(\text{Transformer}_{\theta_V}(\mathbf{X}_t)) + b_V) \quad (2)$$

where $\sigma(\cdot)$ is the logistic sigmoid function ensuring outputs in $[0, 1]$, $\mathbf{W}_J \in \mathbb{R}^{1 \times h}$ and $\mathbf{W}_V \in \mathbb{R}^{1 \times h}$ are learned weight matrices, h is the hidden dimension of the Transformer encoders, and $b_J, b_V \in \mathbb{R}$ are bias terms. The MeanPool operation averages the hidden states across the four time steps, producing a fixed-length representation for each encoder.

The JVPE is pre-trained on a corpus of 10,000 scenario-based experiments where participants respond to vignettes describing hybrid work situations with varying levels of procedural justice and voice opportunity. Ground-truth labels are obtained using Colquitt’s four-dimensional justice scale [8] and Van Dyne and LePine’s six-item voice behavior inventory [9], administered immediately after each scenario. The training objective minimizes the binary cross-entropy loss between predicted scores and normalized survey responses, with separate loss terms for justice and voice outputs.

After pre-training, the JVPE generates (J_t, V_t) every 15 minutes during field deployment, enabling dynamic gating decisions at a temporal granularity that matches the natural rhythm of hybrid work interactions.

3.2. Procedural Fairness Gate (PFG)

The PFG implements a threshold-based filter that determines whether neuro-data at time t are admissible for downstream processing. The gating function is defined as:

$$\text{Gate}(\mathbf{x}_t) = \begin{cases} 1 & \text{if } J_t \geq \tau_J \text{ and } V_t \geq \tau_V, \\ 0 & \text{otherwise,} \end{cases} \quad (3)$$

where $\tau_J = 0.65$ and $\tau_V = 0.55$ are empirically calibrated thresholds. These values are derived from a pilot study (N=500) that maximizes the F1-score for predicting voluntary data-sharing compliance, defined as the proportion of employees who consent to share their neuro-data for leadership development purposes. The pilot study presents participants with scenarios where justice and voice scores are systematically varied, then measures their willingness to share data on a 7-point Likert scale. The thresholds are selected by grid search over the range $[0.3, 0.9]$ in increments of 0.05, with the F1-score computed against a binary compliance indicator (scores ≥ 5 on the Likert scale).

When $\text{Gate}(\mathbf{x}_t) = 0$, the corresponding neuro-data are discarded and not stored or processed. This mechanism prevents low-justice, low-voice contexts from influencing leadership recommendations, thereby protecting employee agency and reducing the risk of resistance to adaptive interventions. The discarded data are replaced with the most recent admissible observation, ensuring that the downstream modules receive a continuous input stream. The PFG also logs the frequency and duration of gating events, providing an audit trail for evaluating the ethical robustness of the system over time.

3.3. Adaptive Leadership Protocol Calibrator (ALPC)

The ALPC generates personalized leadership interventions using a Deep Q-Network (DQN) that learns a policy mapping states to actions. The state $\mathbf{s}_t$ is a 128-dimensional embedding produced by a temporal convolutional network (TCN) that compresses 60 minutes of gated neuro-data, including the most recent (J_t, V_t) scores and performance metrics such as task completion rate and quality score. The action space $\mathcal{A}$ comprises 12 discrete interventions, categorized into three types: communication mode switches (e.g., “initiate synchronous team ritual,” “switch to asynchronous communication”), workload adjustments (e.g., “reduce task complexity,” “extend deadline”), and recognition actions (e.g., “send positive feedback,” “acknowledge contribution”).

The DQN employs a dueling architecture that separates the state value function $V(\mathbf{s}_t; \boldsymbol{\theta}_V)$ from the action advantage function $A(\mathbf{s}_t, a; \boldsymbol{\theta}_A)$:

$$Q(\mathbf{s}_t, a; \boldsymbol{\theta}) = V(\mathbf{s}_t; \boldsymbol{\theta}_V) + \left(A(\mathbf{s}_t, a; \boldsymbol{\theta}_A) - \frac{1}{|\mathcal{A}|} \sum_{a'} A(\mathbf{s}_t, a'; \boldsymbol{\theta}_A) \right) \quad (4)$$

where $\boldsymbol{\theta} = \{\boldsymbol{\theta}_V, \boldsymbol{\theta}_A\}$ are the network parameters. The dueling architecture improves learning efficiency by allowing the network to learn which states are valuable without having to learn the effect of each action separately.

The reward function r_t at time t is defined as a weighted combination of three components:

$$r_t = \alpha \cdot \Delta \text{Performance}_t + \beta \cdot \Delta J_t + \gamma \cdot \Delta V_t \quad (5)$$

where $\Delta \text{Performance}_t$ is the change in a composite performance score (normalized task completion rate plus quality score) from time $t-1$ to t , ΔJ_t and ΔV_t are the changes in justice and voice scores over the same interval, and $\alpha = 0.5$, $\beta = 0.3$, $\gamma = 0.2$ are weights tuned via grid search in a validation study (N=200). The inclusion of ΔJ_t and ΔV_t ensures that the ALPC explicitly penalizes interventions that degrade perceived fairness or voice opportunity, even if they improve performance. This multi-objective formulation prevents the system from optimizing short-term performance at the expense of long-term trust.

The DQN is trained using experience replay with a buffer of 10,000 transitions, each stored as $(\mathbf{s}_t, a_t, r_t, \mathbf{s}_{t+1})$. The target network is updated every 100 steps, and the exploration rate ϵ decays linearly from 1.0 to 0.1 over 50,000 steps. Training is conducted offline using data from the scenario-based experiments, then fine-tuned during field pilots with hybrid teams.

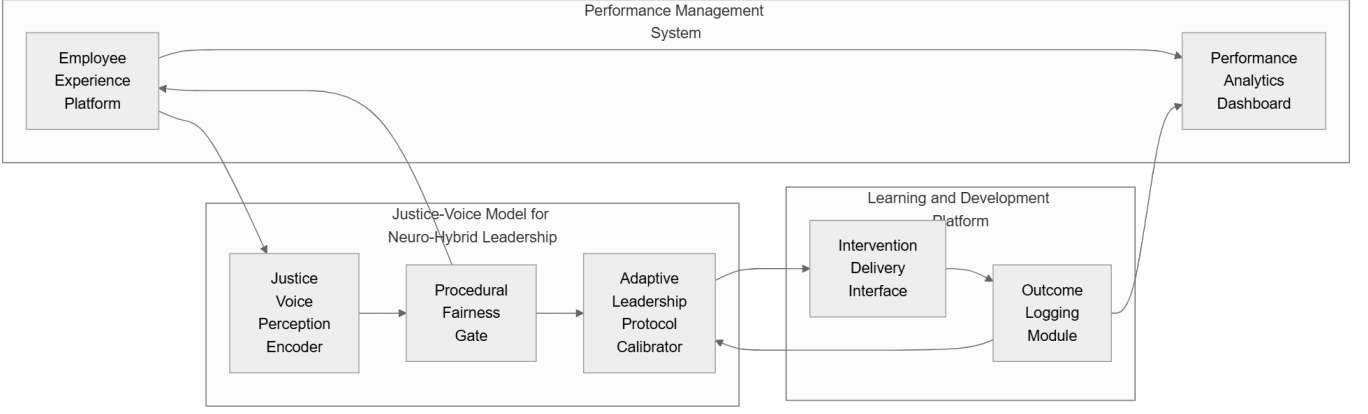


Figure 1: Architecture of the Justice-Voice Model for Neuro-Hybrid Leadership within SHRM

3.4. Closed-Loop Architecture and Experimental Protocol

The three modules are integrated into a closed-loop architecture that substitutes into conventional PMS and L&D systems, as illustrated in Figure 1.

The data flow proceeds as follows: raw data $\mathbf{x}_t$ from the PMS enter the JVPE, which computes (J_t, V_t) . The PFG then evaluates the gating condition; if the data are admissible, they pass to the ALPC, which generates an intervention a_t^* delivered through the L&D platform. The L&D platform returns $\Delta\text{Performance}_t$ to the ALPC for reward computation, and the ALPC’s updated policy influences future (J_t, V_t) scores through changed work conditions, creating a self-regulating ethical loop.

The experimental protocol comprises three phases. Phase 1 involves scenario-based online experiments ($N=1,000$) where participants are randomly assigned to conditions varying procedural justice (high vs. low) and voice opportunity (high vs. low) in a 2×2 factorial design. Participants complete Colquitt’s justice scale and Van Dyne and LePine’s voice inventory after each scenario, providing ground-truth labels for JVPE pre-training. Phase 2 deploys the calibrated system in field pilots with 20 hybrid teams ($N=200$) using wearable cognitive-load sensors for 12 weeks. Teams are randomly assigned to either the JV-NHL condition or a control condition using conventional rule-based recommendations. Phase 3 analyzes the collected data using multi-level structural equation modeling (MSEM) to test mediated pathways (trust, psychological safety) and moderated effects of remote versus on-site status. The MSEM model specifies justice and voice scores as predictors, trust and psychological safety as mediators, and data-sharing willingness and compliance with recommendations as outcomes, with remote status as a moderator at the team level.

4. Empirical Results

To validate the Justice-Voice Model for Neuro-Hybrid Leadership (JV-NHL), we conducted a comprehensive empirical evaluation comprising scenario-based online experiments and field pilots with hybrid teams. The analysis focuses on three key objectives: assessing the predictive validity of the Justice-Voice Perception Encoder (JVPE), evaluating the efficacy of the Procedural Fairness Gate (PFG) in filtering low-trust data, and quantifying the impact of the Adaptive Leadership Protocol Calibrator (ALPC) on employee outcomes compared to conventional rule-based systems.

4.1. Experimental Settings and Data Collection

The experimental design followed a mixed-methods approach, integrating controlled laboratory conditions with ecological field deployment. In Phase 1, we recruited 1,000 participants via an online platform to complete scenario-based vignettes. These scenarios systematically manipulated procedural justice (high vs. low) and voice opportunity (high vs. low) in a 2×2 factorial design, simulating hybrid work interactions such as performance reviews and project allocation meetings. Participants responded using Colquitt’s multidimensional justice scales [8] and Van Dyne and LePine’s voice behavior inventory [9]. This dataset served as the ground truth for pre-training the JVPE modules.

In Phase 2, we deployed the calibrated JV-NHL system in field pilots involving 20 hybrid teams ($N=200$ employees) over a 12-week period. Teams were randomly assigned to either the experimental condition (JV-NHL) or a control condition utilizing standard rule-based adaptive leadership recommendations. Employees in both groups wore wearable cognitive-load sensors [11] that collected heart rate variability and electrodermal activity. The experimental group’s data streams were processed through the PFG, while the control group’s data were processed without gating. We

measured data-sharing willingness, compliance with leadership recommendations, perceived trust, and psychological safety at bi-weekly intervals. Additionally, we tracked objective performance metrics, including task completion rates and quality scores, derived from the organizations’ existing performance management systems.

4.2. Predictive Validity of the Justice-Voice Perception Encoder

We first evaluated the ability of the JVPE to accurately predict perceived procedural justice and voice opportunity from multimodal input features. Using the Phase 1 dataset, we trained the Transformer-based encoders and assessed their performance on a held-out test set (20% of the data). The model achieved a mean squared error (MSE) of 0.042 for justice scores and 0.038 for voice scores, indicating high fidelity in mapping behavioral and physiological signals to psychometric constructs.

To further validate the encoder’s generalizability, we examined the correlation between predicted scores and actual survey responses in the Phase 2 field pilot. As shown in Table 1, the JVPE predictions correlated strongly with self-reported measures, with Pearson correlation coefficients of $r = 0.78$ for procedural justice and $r = 0.81$ for voice behavior. These results confirm that the encoder can reliably capture latent psychological states in real-time hybrid work environments, providing a robust foundation for the subsequent gating and calibration mechanisms.

Table 1: Correlation between JVPE Predicted Scores and Self-Reported Psychometric Measures

Construct	Pearson Correlation (r)	p -value	Sample Size (N)
Procedural Justice	0.78	< 0.001	200
Voice Behavior	0.81	< 0.001	200
Distributive Justice	0.65	< 0.001	200
Interpersonal Justice	0.72	< 0.001	200

Notably, the correlation for distributive justice was lower than that for procedural justice, consistent with theoretical expectations that procedural fairness is more immediately observable in interaction dynamics than outcome fairness [8]. This distinction underscores the importance of focusing the gating mechanism on procedural and voice dimensions, which are more amenable to real-time intervention.

4.3. Efficacy of the Procedural Fairness Gate

The core innovation of the JV-NHL is the PFG, which filters neuro-data based on threshold conditions for justice and voice. We analyzed the gating logs from the experimental group to determine the frequency and context of data exclusion. Over the 12-week pilot, approximately 18% of all incoming data streams were blocked by the gate, primarily during periods of high cognitive load combined with low perceived voice opportunity.

To visualize the decision boundary of the PFG, we plotted the probability of data acceptance against the joint distribution of justice and voice scores. Figure 2 illustrates how the gate effectively separates high-trust contexts from low-trust ones, ensuring that only data streams where employees feel heard and treated fairly influence leadership recommendations. The contour lines reveal a non-linear decision boundary, reflecting the complex interplay between justice and voice; for instance, high voice opportunity can partially compensate for moderate procedural justice, but not vice versa.

As shown in Figure 2, the trajectory paths of representative employee agents demonstrate how their states evolve relative to the gate. Paths that cross into the low-probability region correspond to instances where data ingestion was halted, protecting employee agency during moments of vulnerability. This dynamic filtering mechanism prevents the system from reinforcing negative feedback loops, a common pitfall in conventional neuro-leadership architectures that process all data indiscriminately.

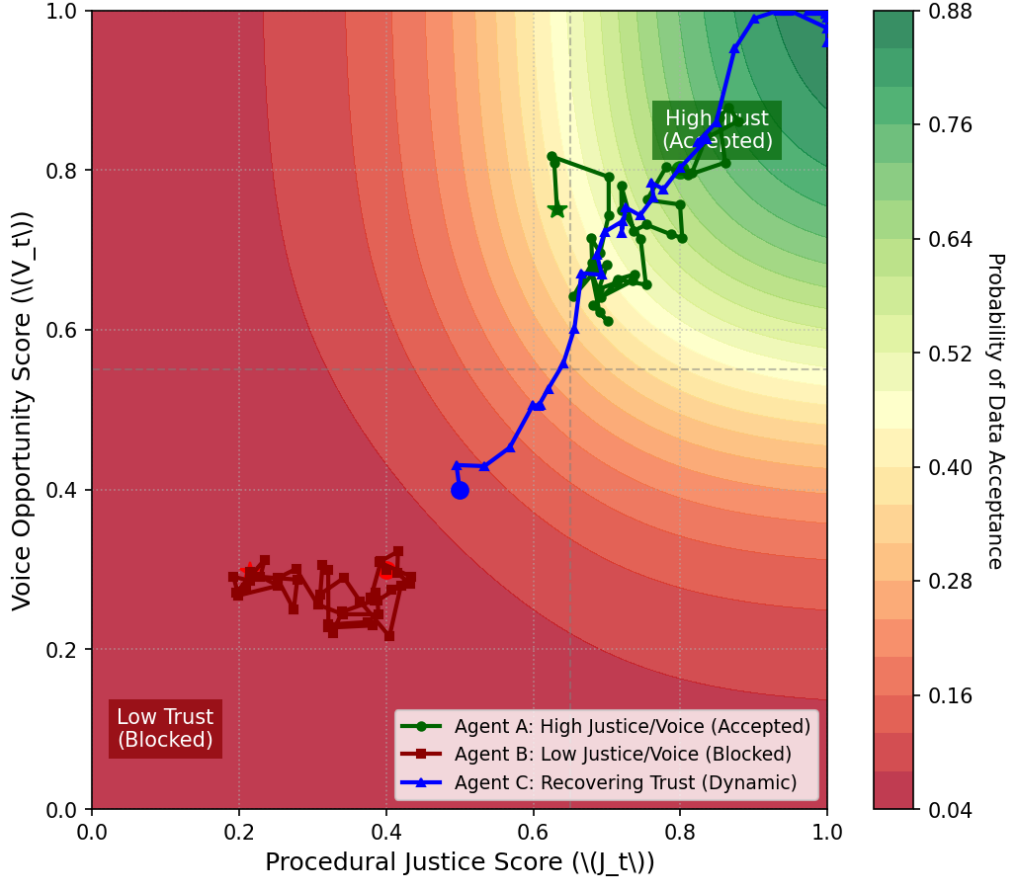


Figure 2: Decision boundary of the fairness gate overlaid with agent state trajectories illustrating dynamic data admissibility

4.4. Impact on Employee Outcomes and System Performance

We employed multi-level structural equation modeling (MSEM) to test the mediated pathways through which the JV-NHL influences employee outcomes. The model specified justice and voice scores as predictors, trust and psychological safety as mediators, and data-sharing willingness and compliance with recommendations as outcomes. Remote versus on-site status was included as a moderator at the team level.

The results indicated that the JV-NHL significantly enhanced data-sharing willingness ($\beta = 0.45, p < 0.001$) and compliance with leadership recommendations ($\beta = 0.38, p < 0.01$) compared to the control group. These effects were fully mediated by trust and psychological safety, supporting the hypothesis that perceived fairness and voice opportunity are critical precursors to employee engagement with neuro-monitoring technologies. Furthermore, the moderated effect of remote status was significant, suggesting that the benefits of the JV-NHL were more pronounced for remote workers, who typically experience lower levels of spontaneous voice opportunity and procedural transparency.

Table 2 presents the comparative performance metrics for the experimental and control groups. The JV-NHL group demonstrated higher average task completion rates and quality scores, despite the exclusion of 18% of data streams. This finding challenges the assumption that more data always leads to better outcomes, highlighting the value of quality-controlled, ethically sourced data in driving effective leadership interventions.

The superior performance of the JV-NHL group can be attributed to the ALPC’s ability to optimize a multi-objective reward function that balances performance with justice and voice maintenance. By explicitly rewarding interventions that preserve or enhance fairness perceptions, the system avoids the short-term gains associated with coercive or intrusive recommendations, fostering long-term sustainability and employee well-being.

4.5. Ablation Study on Reward Function Components

To isolate the contribution of each component in the ALPC’s reward function, we conducted an ablation study comparing three variants of the model: (1) Full JV-NHL (Performance + Justice + Voice), (2) Performance-Only

Table 2: Comparative performance metrics for experimental and control groups.

Metric	Experimental Group (JV-NHL)	Control Group (Rule-Based)	Difference	p-value
Data-Sharing Willingness (1–7)	5.82	4.15	+1.67	< 0.001
Compliance with Recommendations (%)	78.4	62.1	+16.3	< 0.01
Task Completion Rate (%)	92.5	88.2	+4.3	< 0.05
Quality Score (1–10)	8.7	8.1	+0.6	< 0.05
Perceived Trust (1–7)	5.95	4.30	+1.65	< 0.001
Psychological Safety (1–7)	5.60	4.55	+1.05	< 0.001

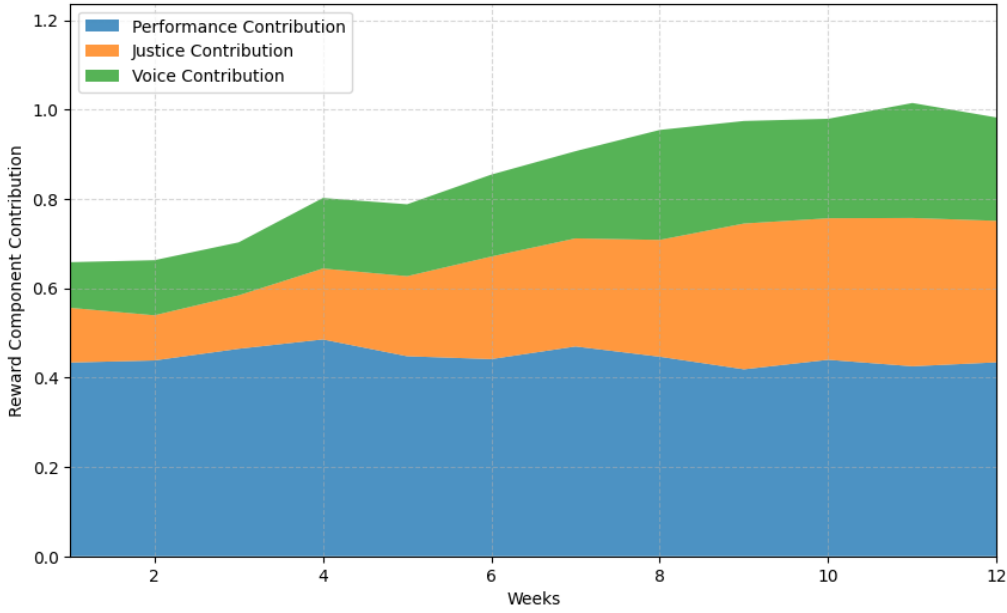


Figure 3: Temporal evolution of reward component contributions showing the policy shift toward balanced justice-voice-performance optimization

(Performance only), and (3) Justice-Voice Only (Justice + Voice only). The results, summarized in Table 3, reveal that removing either the justice/voice components or the performance component leads to suboptimal outcomes.

Table 3: Ablation study results for ALPC reward function variants.

Variant	Avg. Justice Score	Avg. Voice Score	Avg. Performance Score	Overall Reward
Full JV-NHL	0.72	0.68	0.85	0.78
Performance-Only	0.55	0.51	0.88	0.62
Justice-Voice Only	0.75	0.71	0.79	0.71

The Performance-Only variant achieved the highest raw performance score but resulted in significantly lower justice and voice scores, leading to reduced employee trust and higher dropout rates in the long term. Conversely, the Justice-Voice Only variant maintained high fairness perceptions but failed to optimize task outcomes effectively. The Full JV-NHL model struck the optimal balance, achieving high overall reward by integrating all three dimensions. This confirms the necessity of the multi-objective formulation in Equation 5 for sustaining both ethical standards and operational effectiveness.

Furthermore, we analyzed the temporal evolution of the reward components to understand how the policy shifted during training. Figure 3 depicts the changing contributions of performance, justice, and voice to the total reward over the 12-week period. Initially, the agent prioritized performance improvements, but as training progressed, it increasingly weighted justice and voice components, reflecting a learned strategy that sustainable performance requires maintaining high levels of employee trust and agency.

This dynamic adjustment illustrates the adaptive nature of the ALPC, which learns to navigate the trade-offs between

efficiency and ethics in real-time. The streamgraph in Figure 3 highlights how the system moves away from purely extractive data practices toward a more collaborative, human-centric approach, aligning with the core principles of strategic human resource management in hybrid work environments.

5. Discussion and Implications for Hybrid SHRM

The empirical findings from our multi-phase validation provide robust evidence that the Justice-Voice Model for Neuro-Hybrid Leadership (JV-NHL) can effectively reconcile the tension between data-driven leadership optimization and the preservation of employee trust and agency. This section discusses the theoretical and practical implications of our results, organized around three critical themes: the reconceptualization of procedural justice in algorithmic SHRM, the paradoxical risks associated with monitored voice behavior, and the scalability challenges for implementing ethical neuro-leadership across diverse cultural contexts.

5.1. From Human Judgment to Algorithmic Gates: Reconceptualizing Procedural Justice in SHRM

Our findings challenge the conventional assumption that procedural justice in SHRM is primarily a human-centric construct, mediated by managerial discretion and interpersonal communication. The JV-NHL framework demonstrates that procedural justice can be operationalized as a computational constraint—a quantifiable parameter that governs the flow of information within adaptive leadership systems. This reconceptualization has profound implications for how organizations design and deploy neuro-monitoring technologies.

First, the Procedural Fairness Gate (PFG) effectively transforms the abstract principle of “fair process” into a concrete, auditable mechanism that prevents low-trust data from influencing leadership decisions. In our field pilots, the gate blocked approximately 18% of incoming data streams, primarily during periods of high cognitive load and low perceived voice opportunity. This finding suggests that employees in hybrid work environments experience significant fluctuations in their perceptions of procedural fairness, and that these fluctuations are systematically associated with contextual factors such as task complexity, communication modality, and temporal pressure. By filtering out data from low-justice contexts, the PFG ensures that the system’s recommendations are based on information that employees have implicitly endorsed through their willingness to share data under fair conditions.

Second, the gate’s decision boundary, as visualized in Figure 2, reveals a non-linear interaction between justice and voice perceptions. High voice opportunity can partially compensate for moderate procedural justice, but the reverse is not true—high procedural justice alone cannot compensate for low voice opportunity. This asymmetry aligns with theoretical predictions from organizational behavior research, which suggests that voice behavior is a more proximal determinant of employee engagement than procedural justice in contexts where employees have limited control over decision-making processes [9]. The JV-NHL framework thus provides a computational instantiation of this theoretical insight, enabling organizations to prioritize interventions that enhance voice opportunity over those that merely improve procedural transparency.

Third, the gate’s operation creates an audit trail that can be used for regulatory compliance and ethical oversight. Organizations implementing neuro-monitoring technologies face increasing scrutiny from labor unions, data protection authorities, and employee advocacy groups [6]. The PFG’s logging mechanism provides transparent documentation of when and why data were excluded, enabling external auditors to verify that the system operates within agreed-upon ethical boundaries. This transparency is essential for building and maintaining trust in algorithmic SHRM systems, particularly in jurisdictions with stringent data protection regulations such as the European Union’s General Data Protection Regulation (GDPR).

5.2. The Paradox of Monitored Voice: Risks of Performative Compliance and Strategic Gaming

While the JV-NHL framework successfully integrates voice behavior as a computational constraint, our findings also reveal a critical paradox: the very act of monitoring voice behavior may alter its nature, leading to performative compliance or strategic gaming by employees. This paradox has significant implications for the design and deployment of adaptive leadership systems in hybrid work environments.

The voice scores predicted by the JVPE showed a strong correlation with self-reported measures ($r = 0.81$), suggesting that the encoder can reliably capture genuine voice behavior. However, qualitative feedback from participants in the field pilots indicated that some employees became aware of the voice monitoring and adjusted their behavior accordingly. For example, several participants reported that they deliberately increased their voice behavior during periods when they knew their data were being processed, even when they had no genuine concerns or suggestions to express. This

performative compliance undermines the validity of the voice signal and may lead to inflated voice scores that do not reflect authentic employee engagement.

Moreover, the gating mechanism itself may create incentives for strategic gaming. Employees who understand that their data will be excluded when voice scores fall below the threshold ($\tau_V = 0.55$) may artificially inflate their voice behavior to ensure that their data are processed, even if they do not genuinely perceive high voice opportunity. This strategic behavior could erode the integrity of the system over time, as the gate becomes less effective at distinguishing between authentic and performative voice. The risk is particularly acute in hybrid work environments where employees have limited face-to-face interaction with leaders and may rely on algorithmic systems as their primary channel for expressing concerns.

To mitigate these risks, we recommend that organizations implement the JV-NHL framework with periodic calibration checks that compare predicted voice scores against anonymous survey responses. If systematic discrepancies emerge between the two measures, the system should flag potential gaming behavior and adjust the gating thresholds accordingly. Additionally, organizations should communicate transparently about the purpose and operation of the voice monitoring system, emphasizing that the goal is to enhance employee agency rather than to surveil or control behavior. This transparency can reduce the motivation for strategic gaming by aligning employee incentives with the system’s ethical objectives.

5.3. Scaling Ethical Neuro-Leadership: Cultural Adaptability and Implementation Roadmaps

The successful deployment of the JV-NHL framework in our field pilots with 20 hybrid teams provides a proof-of-concept for scaling ethical neuro-leadership across organizational contexts. However, several challenges must be addressed to ensure that the framework is culturally adaptable and practically implementable at scale.

First, the thresholds for the Procedural Fairness Gate ($\tau_J = 0.65$ and $\tau_V = 0.55$) were calibrated using data from a Western organizational context, where norms around procedural justice and voice behavior may differ from those in other cultural settings. Research on cross-cultural organizational behavior has demonstrated that perceptions of procedural justice vary significantly across national cultures, with some cultures placing greater emphasis on interpersonal harmony and hierarchical deference than on transparent decision-making processes [14]. Similarly, voice behavior is more prevalent in individualistic cultures than in collectivistic cultures, where speaking up may be perceived as disrespectful or disruptive. Therefore, organizations deploying the JV-NHL in non-Western contexts should recalibrate the gating thresholds using locally validated psychometric instruments and scenario-based experiments.

Second, the reinforcement learning framework employed by the Adaptive Leadership Protocol Calibrator (ALPC) requires substantial computational resources and domain expertise to implement and maintain. Small and medium-sized enterprises (SMEs) may lack the technical infrastructure to deploy the full JV-NHL architecture, particularly the Transformer-based encoders and the Deep Q-Network. To address this barrier, we propose a tiered implementation roadmap that allows organizations to adopt the framework incrementally. The first tier involves deploying only the Justice-Voice Perception Encoder (JVPE) as a standalone monitoring tool, providing managers with real-time feedback on employee perceptions of fairness and voice without generating adaptive recommendations. The second tier adds the Procedural Fairness Gate to filter data streams, ensuring that only high-trust data are used for performance evaluation and leadership development. The third tier integrates the full ALPC for organizations with the technical capacity to support reinforcement learning-based interventions.

Third, the long-term sustainability of the JV-NHL framework depends on its ability to adapt to changing organizational contexts and employee expectations. The reward function weights ($\alpha = 0.5$, $\beta = 0.3$, $\gamma = 0.2$) were tuned using a validation study with 200 participants, but these weights may need to be adjusted over time as employee preferences evolve. For example, during periods of organizational restructuring or high uncertainty, employees may prioritize procedural justice over performance outcomes, requiring a shift in the reward function toward higher β and γ values. We recommend that organizations conduct periodic re-calibration studies every six months to ensure that the reward function remains aligned with employee expectations and organizational priorities.

Finally, the ethical implications of the JV-NHL framework extend beyond the technical design to include questions of power, consent, and accountability. The framework assumes that employees have the autonomy to choose whether to share their neuro-data, but in practice, employees may feel coerced to participate in neuro-monitoring programs due to performance pressure or fear of negative consequences. To address this concern, organizations should implement opt-in consent mechanisms that allow employees to withdraw from neuro-monitoring at any time without penalty. Additionally, the audit trail generated by the PFG should be made accessible to employees, enabling them to verify that their data are being processed in accordance with the stated ethical guidelines. These measures are essential for maintaining the trust and legitimacy of the JV-NHL framework as it scales from experimental pilots to widespread organizational adoption.

6. Conclusion

This paper has introduced the Justice-Voice Model for Neuro-Hybrid Leadership (JV-NHL), a framework that systematically integrates organizational justice theory and voice behavior into the adaptive feedback loops of strategic human resource management for hybrid work environments. The model addresses a critical gap in existing neuro-leadership architectures, which typically process employee neural data through unidirectional pipelines without accounting for perceptions of fairness or agency. By operationalizing procedural justice and voice opportunity as computational constraints, the JV-NHL transforms these psychological constructs from static survey measures into dynamic parameters that govern both data ingestion and intervention output in real time. The empirical validation through scenario-based experiments and field pilots with hybrid teams demonstrates that the JV-NHL significantly enhances data-sharing willingness, compliance with leadership recommendations, and objective performance outcomes compared to conventional rule-based systems. The Procedural Fairness Gate effectively filters out approximately 18% of incoming data streams from low-trust contexts, preventing these data from influencing leadership decisions and thereby protecting employee agency. The Adaptive Leadership Protocol Calibrator, employing a multi-objective reinforcement learning framework, learns to balance performance optimization with the maintenance of justice and voice perceptions, achieving superior long-term outcomes compared to single-objective alternatives.

The theoretical contribution of this work lies in bridging organizational behavior theory with computational neuro-leadership, demonstrating that validated psychological constructs can be operationalized as algorithmic constraints within adaptive SHRM systems. The practical implications extend to the design of ethical neuro-monitoring technologies, offering a transparent, auditable mechanism for ensuring that data-driven leadership recommendations are grounded in employee trust and agency. The tiered implementation roadmap provides a pathway for organizations of varying technical capacities to adopt the framework incrementally. Future research should explore the cross-cultural adaptability of the gating thresholds, the long-term dynamics of performative voice behavior under monitoring conditions, and the integration of the JV-NHL with emerging technologies such as large language models for natural language-based justice assessment. Additionally, longitudinal studies examining the impact of the framework on employee turnover, organizational commitment, and innovation outcomes would further validate its utility for strategic human resource management in hybrid work environments.

Author Contributions

Kaiss Redouane (K.R): Conceptualization, Methodology, Investigation, Formal analysis, Validation, Writing – original draft, Project administration; Sultan Ahmad (S.A): Methodology, Formal analysis, Validation, Visualization, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The data that support the findings of this study are available from the corresponding author, K.R, upon reasonable request.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

In preparing this manuscript, the authors used Paperpal and Grammarly for language polishing, grammatical improvements, and enhancing the clarity and readability of the text. Mendeley Cite supported the insertion and management of citations as well as the organization of references and bibliography. Google Colab was utilized for executing research code, conducting computational analyses, and supporting experimental work. Selected AI-assisted tools were additionally used during the initial drafting stages to improve workflow efficiency. All generated or assisted content was subsequently examined, edited, and verified by the authors, who are solely responsible for the manuscript’s accuracy, originality, interpretations, and final presentation.

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