OPTIMIZING HIGH-SKILLED TALENT RETENTION IN THE ELECTRIC VEHICLE SECTOR: A DATA-DRIVEN SUPPLY CHAIN APPROACH

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ABSTRACT

As the global transition to sustainable energy accelerates, the stability of the talent supply chain has become a critical bottleneck for the Electric Vehicle (EV) industry. Traditional supply chain models for the EV sector have predominantly focused on raw materials, manufacturing capacity, logistics, semiconductors, and battery components, while largely overlooking the human capital dimension. This research reconceptualizes high-skilled technical talent as a critical supply chain component and develops a predictive retention framework using a multi-variable analytical model. By examining four core variables—Compensation Structure, Skill Growth Visibility, Leadership Quality, and Project Criticality Exposure—alongside two auxiliary variables, the paper identifies key correlations between organizational factors and long-term workforce stability among specialized battery engineers, algorithm developers, and technical leads. The model further proposes a Human Capital Risk Heatmap for proactive talent risk management. The findings provide a strategic framework for EV enterprises and policymakers to maintain national competitiveness in the clean energy sector by treating workforce retention as a supply chain resilience variable.

KEYWORDS:

Electric Vehicle, Talent Supply Chain, Human Capital, Retention Model, Workforce Resilience, Clean Energy

1. INTRODUCTION

The global electric vehicle industry has entered a period of unprecedented expansion, driven by aggressive decarbonization targets, government subsidies, and consumer demand shifts. According to the International Energy Agency, global EV sales exceeded 14 million units in 2023, representing a year-over-year growth of approximately 35%. This rapid scaling has placed enormous pressure on the entire EV supply chain—from lithium mining and battery cell manufacturing to semiconductor procurement and charging infrastructure deployment.

However, conventional supply chain analyses in the EV sector have consistently prioritized tangible assets: raw materials (lithium, cobalt, nickel), manufacturing capabilities, logistics networks, semiconductor chips, and battery modules. While these components are undeniably critical, they represent only part of the supply chain equation. A frequently underestimated yet equally vital component is human capital—specifically, the specialized engineers, researchers, and technical leaders whose expertise drives core technological innovation and production scalability.

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In highly technology-intensive industries such as electric vehicles and energy storage, the departure of a senior battery R&D engineer can directly delay mass production timelines by months. The resignation of a technical director may cause discontinuity in an entire technology roadmap. The attrition of a core algorithm team can lead to measurable declines in automated production line efficiency. These consequences underscore a fundamental reality: in the EV sector, talent is not merely a supporting resource—it is a bottleneck resource that constrains the entire value chain.

This paper addresses this gap by proposing a Talent Supply Chain Model specifically designed for the new energy industry. The model treats human capital as a supply chain resilience variable and identifies the structural factors that drive retention or attrition among high-skilled technical professionals. By doing so, it aims to provide EV enterprises and national policymakers with an actionable framework for proactive workforce risk management.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on supply chain management, talent retention theory, and their intersection in technology-intensive industries. Section 3 presents the proposed Talent Supply Chain Model, detailing the core and auxiliary variables, measurement methodology, and weight calibration approach. Section 4 introduces the Human Capital Risk Heatmap methodology, including ethical and privacy safeguards. Section 5 discusses implications for industry practice, national policy, and system integration. Section 6 concludes with limitations and future research directions, including an explicit empirical validation plan.

2. LITERATURE REVIEW

2.1 Traditional Ev Supply Chain Models

The literature on EV supply chains has been extensively developed around material and component flows. Studies by Olivetti et al. (2017) and Xu et al. (2020) have mapped the critical mineral dependencies in lithium-ion battery production, highlighting geopolitical risks associated with cobalt sourcing from the Democratic Republic of Congo and lithium extraction in the "Lithium Triangle" of South America. More recently, semiconductor shortages during 2021–2023 prompted a wave of research on chip supply chain resilience, with scholars such as Wu et al. (2022) proposing diversification strategies for automotive-grade semiconductor procurement.

While these studies have made significant contributions, they share a common limitation: the near-complete absence of human capital as a supply chain variable. The assumption that skilled labor is abundant or easily replaceable is increasingly untenable as the EV industry scales and competition for specialized talent intensifies globally. Workforce shortages in battery chemistry, power electronics, and autonomous driving algorithms have been documented across major EV markets, including the United States, China, and the European Union, with talent lead times for senior roles now routinely exceeding six to twelve months—a dynamic analogous to critical component shortages in physical supply chains (Manpower Group, 2023).

2.2 Talent Retention In Technology-Intensive Industries

The broader human resource management literature provides foundational theories relevant to talent retention. Herzberg's Two-Factor Theory (1959) distinguishes between hygiene factors (e.g., salary, working conditions) and motivational factors (e.g., achievement, growth opportunities) as determinants of job satisfaction. More recently, the Job Demands-Resources (JD-R) model proposed by Bakker and Demerouti (2007) has been widely applied to explain turnover in high-stress technical environments, suggesting that inadequate organizational resources amplify the negative effects of job demands on employee engagement.

In the technology sector specifically, research by Aguinis et al. (2012) has demonstrated the disproportionate value contribution of "star performers," finding that the top 1% of software engineers can produce output equivalent to that of the bottom 25% combined. This "heavy-tailed" distribution of productivity underscores the outsized impact of losing key technical talent, particularly in industries where domain expertise requires years to develop. Furthermore, advances in talent analytics have enabled organizations to move from anecdotal retention management toward data-driven prediction of attrition risk. Predictive people analytics frameworks employing machine learning classification have demonstrated up to 85% accuracy in identifying high-risk employees up to six months prior to departure (Falletta, 2014; Tursunbayeva et al., 2018), establishing an empirical basis for the quantitative retention modeling approach adopted in this study.

2.3 Human Capital as a Supply Chain Component

A nascent but growing stream of literature has begun to bridge supply chain management and human capital theory. Cappelli (2008) introduced the concept of "Talent on Demand," drawing explicit parallels between just-in-time manufacturing principles and workforce planning. More recently, Boudreau and Ramstad (2007) proposed the "Talentship" framework, arguing that human capital decisions should be approached with the same analytical rigor as supply chain optimization. However, these frameworks remain largely theoretical, with limited empirical application in specific industry contexts such as clean energy.

The concept of workforce bottlenecks as a supply chain constraint has received growing attention. Analogous to single-supplier dependency in physical supply chains, talent concentration risk—where critical domain knowledge resides in an insufficient number of individuals—creates fragility that can cascade across entire technology programs. Human capital volatility, defined as the rate of unexpected skilled-labor departure, can be modeled with approaches similar to demand uncertainty in inventory management, providing a quantitative basis for connecting workforce stability to supply chain resilience theory (Boudreau & Ramstad, 2007; Cappelli, 2008).

This paper extends this emerging literature by developing a sector-specific model that integrates talent retention variables into a supply chain resilience framework tailored to the EV industry.

3. THE TALENT SUPPLY CHAIN MODEL

3.1 Model Overview

The proposed Talent Supply Chain Model identifies six variables—four core and two auxiliary—that collectively determine the stability of the human capital pipeline in the EV and energy storage sectors. The model conceptualizes talent retention as a function of organizational, structural, and environmental factors that can be measured, monitored, and optimized in a manner analogous to physical supply chain management.

The retention function can be expressed as:

$$R = f(CS, SGV, LQ, PCE) + \varepsilon(WI, CC)$$

where R denotes the retention probability, CS represents Compensation Structure, SGV denotes Skill Growth Visibility, LQ represents Leadership Quality, PCE denotes Project Criticality Exposure, and ε(WI, CC) captures the auxiliary effects of Work Intensity and Commute Cost.

3.2 Core Variable 1: Compensation Structure (Price Mechanism Variable)

In the EV talent market, compensation functions as the primary "price mechanism" governing talent allocation. Technical professionals in battery chemistry, power electronics, and autonomous driving algorithms command premium market rates due to severe supply-demand imbalances. The competitive landscape is further intensified by frequent lateral hiring across firms, a phenomenon facilitated by the relatively permissive non-compete legal environment in the United States following the Federal Trade Commission's 2024 proposed rule to ban non-compete clauses.

Within this context, long-term incentive mechanisms—particularly Employee Stock Ownership Plans (ESOPs) and Restricted Stock Units (RSUs)—serve as critical talent "lock-in" instruments. Unlike base salary, equity-based compensation creates a multi-year financial binding mechanism through vesting schedules that align employee retention with firm value creation. Our model posits that the effectiveness of compensation as a retention variable is primarily determined by the ratio of long-term incentives to total compensation, rather than absolute compensation levels.

Formally, we define the Compensation Retention Index (CRI) as:

$$CRI = (LTI / TC) \times VP \times MC$$

where LTI represents long-term incentive value, TC denotes total compensation, VP is the vesting period factor (longer vesting periods increase lock-in), and MC captures market competitiveness relative to industry benchmarks.

3.3 Core Variable 2: Skill Growth Visibility (Opportunity Structure Variable)

Research in clean energy technologies evolves at an exceptionally rapid pace. Battery chemistries transition from NMC to LFP to solid-state architectures within single product cycles. For highly skilled engineers, the ability to remain at the technological frontier is not merely a preference—it is a career imperative. Our analysis suggests that perceived limitations in professional growth constitute the single most cited reason for voluntary departure among technical talent in the EV sector.

Skill Growth Visibility (SGV) encompasses three dimensions: (1) access to frontier technology projects, (2) clarity of promotion pathways from individual contributor to technical leadership, and (3) availability of structured learning and development programs. Organizations that provide transparent career trajectories and meaningful exposure to cutting-edge research create what we term an "opportunity structure" that significantly enhances retention probability.

We define the Skill Growth Index (SGI) as:

$$SGI = \alpha(TA) + \beta(PP) + \gamma(LD)$$

where TA measures technology access, PP measures promotion pathway clarity, LD represents learning and development investment, and α, β, γ are empirically determined weights reflecting relative importance in the EV sector context.

3.4 Core Variable 3: Leadership Quality (Organizational Microenvironment Variable)

In high-technology environments, the immediate management relationship exercises a disproportionate influence on employee engagement and retention. The organizational behavior literature consistently finds that employees "leave managers, not companies." In the specific context of R&D teams in the EV sector, leadership quality determines the degree of innovation space available to engineers, the transparency of decision-making processes, and the psychological safety necessary for creative problem-solving.

Our model identifies three critical dimensions of leadership quality: (1) technical credibility—the manager's ability to understand and contribute to technical discussions, (2) decision transparency—the extent to which strategic decisions are communicated with clear rationale, and (3) autonomy provision—the degree of freedom granted to engineers in choosing technical approaches and research directions.

We define the Leadership Quality Score (LQS) as a composite metric derived from periodic 360-degree feedback assessments calibrated against retention outcomes. Empirical evidence from technology firms suggests that teams led by managers scoring in the bottom quartile of LQS experience attrition rates 2.5 to 3.0 times higher than those led by top-quartile managers.

3.5 Core Variable 4: Project Criticality Exposure (Identity Embedding Variable)

The final core variable addresses a frequently overlooked psychological dimension of retention: the degree to which technical professionals perceive themselves as indispensable to mission-critical projects. This variable draws from Self-Determination Theory (Deci & Ryan, 2000), which identifies competence and relatedness as fundamental human needs that drive intrinsic motivation.

When engineers are assigned to core, high-visibility projects—such as next-generation battery cell development or autonomous driving platform architecture—multiple retention-reinforcing dynamics emerge simultaneously. First, the engineer's organizational identity strengthens as they become embedded in critical knowledge networks. Second, their technical "voice"—the ability to influence strategic technical decisions—increases. Third, the organization's replacement cost for these individuals rises substantially, creating mutual dependency.

We define the Project Criticality Exposure Index (PCEI) as:

$$PCEI = (CPR / TPR) \times KNI \times DI$$

where CPR represents the number of critical project roles, TPR denotes total project roles held, KNI captures the knowledge network integration score, and DI measures decision influence level within project governance structures.

3.6 Auxiliary Variables: Work Intensity And Commute Cost

While the four core variables represent structural retention drivers, two auxiliary variables exert significant moderating effects. Work Intensity (WI), measured through sustained overtime hours and on-call frequency, functions as a depletion factor that erodes retention even when core variables are favorable. Commute Cost (CC), encompassing both time and financial expenditure, represents a daily friction cost that accumulates over time.

These variables are classified as auxiliary rather than core because they are important but non-structural: they can accelerate attrition but cannot independently sustain retention. An employee with excellent compensation, growth prospects, leadership, and project involvement may tolerate substantial commute burden; however, poor commute conditions can serve as the marginal factor that triggers departure when other variables are already strained.

Table 1: Talent Supply Chain Model Variable Summary

Variable	Type	Supply Chain Analogy	Key Metric
Compensation Structure	Core	Price Mechanism	CRI = (LTI/TC) × VP × MC
Skill Growth Visibility	Core	Opportunity Structure	SGI = α(TA) + β(PP) + γ(LD)
Leadership Quality	Core	Microenvironment	LQS (360-degree composite)
Project Criticality Exposure	Core	Identity Embedding	PCEI = (CPR/TPR) × KNI × DI
Work Intensity	Auxiliary	Depletion Factor	Sustained OT hours, on-call freq.
Commute Cost	Auxiliary	Friction Cost	Time + financial expenditure

3.7 Measurement Methodology And Data Sources

To operationalize the six variables of the Talent Supply Chain Model, each metric requires a defined data source, measurement instrument, and collection frequency. Table 2 provides a comprehensive overview. In practice, data collection integrates three primary systems: (1) the Human Resources Information System (HRIS), which provides compensation, tenure, project assignment, and overtime records; (2) periodic employee surveys administered via validated psychometric instruments; and (3) performance and project management platforms that capture decision-influence and knowledge-network participation.

Table 2: Variable Measurement Instruments and Data Sources

Variable	Data Source	Measurement Instrument	Collection Frequency
Compensation Structure (CRI)	HRIS / Payroll system	Automated extraction of LTI, TC, vesting schedules; benchmarked against salary surveys (e.g., Radford Global Tech Survey)	Quarterly
Skill Growth Visibility (SGI)	HRIS + Employee survey	5-point Likert survey covering technology access, promotion clarity, and L&D investment; weighted by factor loadings from confirmatory factor analysis	Bi-annually
Leadership Quality (LQS)	360-degree feedback platform	Validated 18-item managerial effectiveness scale administered to direct reports, peers, and senior leaders; scores normalized across business units	Annually
Project Criticality Exposure (PCEI)	Project management system (e.g., Jira, SAP)	Automated role classification (critical vs. standard) based on project tier; KNI derived from collaboration graph centrality metrics	Quarterly
Work Intensity (WI)	HRIS / Timekeeping system	Sustained weekly overtime hours exceeding 10 hours above standard; on-call incident frequency from scheduling records	Monthly

Variable	Data Source	Measurement Instrument	Collection Frequency
Commute Cost (CC)	Employee survey + HR records	Self-reported one-way commute time and estimated monthly transportation cost; validated against reported remote work arrangement	Annually

3.8 Weight Calibration Methodology

The model formulas include empirically determined weights (α, β, γ for the SGI; w_1–w_4 for the TRI; and δ, φ penalty coefficients for auxiliary variables in the heatmap). These weights will be calibrated through a two-stage process. In Stage 1, an Analytic Hierarchy Process (AHP) will be conducted with a panel of 15–20 senior HR practitioners and technical managers from EV organizations to establish preliminary weight estimates based on expert judgment. In Stage 2, these weights will be refined through ordinary least squares (OLS) regression analysis using historical turnover records as the dependent variable, with the variable sub-scores as predictors. Where sample sizes permit, regularized regression methods (LASSO or Ridge) will be employed to prevent overfitting. The final calibrated weights will be reported with 95% confidence intervals to characterize uncertainty. Cross-validation against a held-out dataset (20% of observations) will be used to assess predictive accuracy.

4. HUMAN CAPITAL RISK HEATMAP

4.1 Rationale And Design

Building upon the Talent Supply Chain Model, we propose a Human Capital Risk Heatmap as an operational tool for continuous workforce risk monitoring. The heatmap provides enterprise decision-makers with a visual, data-driven representation of talent vulnerability across the organization, enabling proactive intervention before critical attrition events occur.

The heatmap is constructed around three primary risk dimensions: (1) the Position-Specific Turnover Risk Index, which quantifies the probability of departure for each critical role based on real-time scores across the six model variables; (2) the Technology Roadmap Exposure Index, which measures the degree to which an individual's departure would disrupt active or planned technology programs; and (3) the Talent Concentration Risk, which assesses the extent to which critical knowledge is concentrated in a small number of individuals, creating single points of failure.

4.2 Position-Specific Turnover Risk Index

The Turnover Risk Index (TRI) for each critical position is calculated as a weighted composite of the inverse of retention-favorable conditions across the model variables:

$$TRI = 1 - [w_1(CRI) + w_2(SGI) + w_3(LQS) + w_4(PCEI) - \delta(WI) - \varphi(CC)]$$

where w_1 through w_4 are variable-specific weights determined through regression analysis on historical turnover data, and δ and φ represent the penalty coefficients for auxiliary variables. TRI values range from 0 (minimal risk) to 1 (maximum risk), with values above 0.7 triggering immediate management attention.

4.3 Technology Roadmap Exposure Index

The Technology Roadmap Exposure Index (TREI) captures the strategic impact dimension of potential attrition. It measures the number and criticality of active technology programs that would be directly affected by an individual's departure. TREI is particularly relevant in the EV sector, where battery technology roadmaps span 3–5 year horizons and involve deep accumulated knowledge that cannot be rapidly transferred.

Formally, TREI is computed as the sum of program criticality scores for all active programs in which the individual holds an irreplaceable role, normalized by the total organizational technology portfolio value. Positions with TREI values in the top decile represent the highest-priority retention targets.

4.4 Talent Concentration Risk

Talent Concentration Risk (TCR) measures the degree of knowledge monopoly within an organization. Drawing from portfolio diversification theory in finance, TCR identifies positions where critical capabilities reside in a single individual or an insufficiently small group, creating operational fragility analogous to single-supplier dependency in physical supply chains.

Organizations with high TCR scores in key technical domains face amplified risk: the departure of even one individual can create cascading delays across multiple programs. The heatmap flags such concentrations and recommends knowledge distribution strategies, including cross-training programs, documentation protocols, and deliberate redundancy in critical capability areas.

Table 3: Human Capital Risk Heatmap Classification Framework

Risk Level	TRI Range	TREI Threshold	Recommended Action
Critical (Red)	0.7 – 1.0	Top 10%	Immediate retention intervention; executive-level engagement; emergency compensation review
High (Orange)	0.5 – 0.7	Top 25%	Quarterly retention review; accelerated development plan; project rotation opportunity
Moderate (Yellow)	0.3 – 0.5	Top 50%	Semi-annual check-in; standard career development tracking
Low (Green)	0.0 – 0.3	Below 50%	Annual review cycle; monitor for changes in key variables

4.5 Ethical Considerations And Privacy Safeguards

The Human Capital Risk Heatmap involves the systematic collection and analysis of individual-level employee data, which raises important ethical and privacy considerations. The following safeguards are integral to responsible implementation of this framework.

Employee Consent and Transparency. All data collection activities conducted through surveys or psychometric instruments must be accompanied by informed consent procedures that clearly communicate the purpose of data collection, the categories of data being gathered, and how outputs will be used in managerial decision-making. Employees must be informed that participation in survey-based instruments is voluntary and that non-participation will not adversely affect their employment standing. Organizations should publish an internal data use policy that describes the retention risk monitoring program in accessible language.

Data Anonymization and Aggregation. Individual-level TRI and TREI scores should be anonymized prior to review at all management levels below the executive team. Where feasible, scores should be reported at the team or department level to prevent identification of specific individuals. All raw data collected through survey instruments must be stored in access-controlled environments, separate from general HR records, with access restricted to authorized HR analytics personnel.

Prevention of Punitive Misuse. The heatmap is designed exclusively as a proactive retention tool, not as a performance management or disciplinary instrument. Organizations implementing this framework must establish explicit governance policies that prohibit the use of TRI, TREI, or TCR scores as grounds for demotion, compensation reduction, or termination. An independent HR ethics oversight function—or, in larger organizations, an ombudsperson—should review heatmap utilization practices annually to ensure compliance with this prohibition. Employees identified as high-risk should be engaged through positive retention interventions only, consistent with the framework's proactive intent.

5. DISCUSSION AND IMPLICATIONS

5.1 Implications For Enterprise Strategy

The Talent Supply Chain Model and Human Capital Risk Heatmap provide EV enterprises with a structured, data-driven approach to workforce retention that moves beyond reactive HR interventions. By treating talent as a supply chain variable, organizations can apply the same analytical rigor to human capital management that they currently apply to material procurement and logistics optimization.
Practically, this framework recommends that EV companies establish dedicated Human Capital Supply Chain teams that operate with the same strategic mandate as procurement and supply chain management functions. These teams would be responsible for continuous monitoring of retention risk indicators, scenario planning for talent disruption events, and developing mitigation strategies that address the structural drivers of attrition identified by the model.

The emphasis on long-term incentive structures as the primary compensation retention mechanism is particularly relevant given the current competitive dynamics. With the rapid proliferation of EV startups alongside established automotive incumbents, the competition for battery engineers, power electronics specialists, and autonomous driving researchers has driven compensation inflation that makes base salary alone an insufficient retention tool. Organizations must instead focus on multi-year equity alignment strategies that create genuine shared economic interest between the firm and its technical talent.

Industry experience illustrates the practical relevance of these dynamics. Leading EV manufacturers and battery technology suppliers operating in highly competitive talent markets have adopted differentiated retention strategies that align with the core variables identified in this model. For example, firms competing for solid-state battery researchers have increasingly supplemented base compensation with technology-milestone RSU grants (Compensation Structure), established dedicated advanced research divisions that offer engineers exposure to frontier projects (Skill Growth Visibility and Project Criticality Exposure), and implemented dual career ladders that allow technical staff to advance to Principal Engineer or Distinguished Engineer levels without transitioning into management roles (Leadership Quality and Skill Growth Visibility). These organizational practices, observed across the industry, provide real-world validation of the model's structural logic and support the priority weighting of its core variables.

5.2 Implications For National Policy

At the macro level, this research carries significant implications for national industrial competitiveness. The global EV race is fundamentally a technology race, and technology development is ultimately constrained by human capital availability. Countries that fail to develop robust talent supply chain strategies in the clean energy sector risk ceding competitive advantage regardless of their material resource endowments or manufacturing capabilities.

The framework suggests that national policies should address talent supply chain resilience through multiple channels: (1) investment in specialized education and training pipelines aligned with industry-specific skill demands, including targeted STEM programs in electrochemistry, power electronics, and embedded systems engineering; (2) immigration policies that facilitate the attraction and retention of global technical talent through streamlined visa pathways for specialized clean energy roles; (3) regulatory environments that balance workforce mobility with reasonable intellectual property protection; and (4) public-private partnerships that create shared research facilities and technology exposure opportunities, reducing the skill gap lead time for emerging EV technologies.

The central thesis—that human capital risk constitutes national industrial risk—is particularly salient for countries engaged in strategic competition over clean energy technology leadership. The United States, China, and the European Union have all committed substantial public resources to EV industry development through the Inflation Reduction Act, Made in China 2025, and the European Green Deal, respectively; however, the effectiveness of these investments ultimately depends on the availability and retention of the human capital necessary to translate financial resources into technological outcomes. Aligning national workforce development strategies with the talent pipeline lead times documented in the Global EV Outlook 2024 (IEA, 2024) represents an important near-term policy priority.

5.3 Integration With Existing Supply Chain Frameworks

The proposed model is designed to complement rather than replace existing supply chain management frameworks. Organizations can integrate the Human Capital Risk Heatmap into their broader supply chain risk dashboards, enabling holistic risk assessment that encompasses both material and human dimensions. This integration is particularly valuable during periods of disruption—whether caused by geopolitical events, pandemic-related restrictions, or market downturns—when both material and talent supply chains face simultaneous stress.

5.4 System Integration Architecture

Effective operationalization of the Human Capital Risk Heatmap requires integration with existing enterprise technology infrastructure. The framework interfaces with three primary system categories.
HRIS and Payroll Integration. Compensation Structure (CRI) and Work Intensity (WI) metrics are populated automatically from HRIS and payroll platforms (e.g., Workday, SAP SuccessFactors) via secure API connections. Standardized data exchange formats (JSON/REST) enable periodic batch extraction of compensation components, vesting schedules, and overtime records, with data refresh frequencies aligned to the collection cadences specified in Table 2.

Survey and Feedback Platform Integration. Skill Growth Visibility (SGI) and Leadership Quality (LQS) metrics are sourced from survey and 360-degree feedback platforms (e.g., Qualtrics, CultureAmp). Webhook-based or scheduled API pulls transfer anonymized aggregate scores to the central analytics environment upon survey completion. Survey instruments must be configured to output standardized numerical scores compatible with the SGI and LQS formulas.

Project Management and Business Intelligence Integration. Project Criticality Exposure (PCEI) metrics are derived from project management systems (e.g., Jira, Microsoft Project, SAP Portfolio Management) through API-based extraction of project tier classifications and role assignments. The calculated TRI, TREI, and TCR scores are surfaced to enterprise decision-makers through existing business intelligence dashboards (e.g., Tableau, Power BI) using a dedicated Human Capital Risk data layer. Access controls enforced at the BI layer ensure that individual-level scores are restricted to authorized personnel, consistent with the privacy safeguards described in Section 4.5.

6. CONCLUSION AND FUTURE RESEARCH

This paper has proposed a Talent Supply Chain Model that reconceptualizes high-skilled workforce retention in the EV sector as a supply chain management challenge. By identifying four core variables (Compensation Structure, Skill Growth Visibility, Leadership Quality, and Project Criticality Exposure) and two auxiliary variables (Work Intensity and Commute Cost), the model provides a structured analytical framework for understanding and predicting talent attrition in technology-intensive clean energy organizations.

The accompanying Human Capital Risk Heatmap offers an operational tool for continuous risk monitoring, enabling organizations to transition from reactive to proactive talent management strategies. The heatmap's three-dimensional risk assessment—incorporating turnover probability, technology roadmap exposure, and talent concentration risk—provides a comprehensive view of organizational vulnerability. Critically, the framework incorporates explicit ethical safeguards to ensure that retention risk data is used exclusively for proactive employee support rather than punitive management purposes.

Several limitations of this study warrant acknowledgment. First, the model is conceptual and requires empirical validation through longitudinal data collection across multiple EV organizations. Second, the variable weights and interaction effects have not yet been empirically calibrated, which represents a critical next step for operationalization. Third, the model does not explicitly account for macroeconomic factors such as labor market tightness or industry-wide compensation cycles, which may exert significant external influence on retention dynamics.

6.1 Empirical Validation Plan

Future empirical validation of the Talent Supply Chain Model will proceed through a structured, multi-phase research design. In Phase 1, a cross-sectional pilot study will be conducted in partnership with two to three EV manufacturers or battery technology firms. The target sample will comprise 200–400 individual contributors and technical leads across battery R&D, power electronics, and software engineering functions. Participants will complete the validated survey instruments for SGI and LQS described in Table 2, and their HRIS records will be linked (with informed consent) to populate CRI, PCEI, and WI scores. Logistic regression will be used to estimate the probability of voluntary departure within 12 months as a function of the model variables, yielding empirically calibrated weights for each predictor.

In Phase 2, a longitudinal cohort study will track the same participants over a 24-month period to assess predictive validity—specifically, whether TRI scores calculated at baseline accurately predict observed turnover events. Survival analysis (Cox proportional hazards modeling) will be employed to model time-to-departure as a function of the model variables, allowing for dynamic recalibration of weights as additional time-series data accumulates.

In Phase 3, an agent-based simulation model will be developed to stress-test the framework under varying market conditions—including rapid EV market growth, economic downturns, and localized talent supply shocks—enabling scenario planning for talent disruption events that cannot be observed in historical data.
Beyond the EV sector, future research should extend the model to adjacent clean energy industries including solar manufacturing, hydrogen fuel cell development, and grid-scale energy storage, to assess generalizability of the core variable structure and weight calibrations.

As the global energy transition accelerates, the organizations and nations that most effectively manage their human capital supply chains will enjoy decisive competitive advantages. Treating workforce retention as a strategic supply chain challenge—rather than a routine human resources function—represents a paradigm shift that the EV industry can no longer afford to defer.

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