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PREDICTIVE ANALYTICS FOR EMPLOYEE TURNOVER: A COMPARATIVE STUDY BETWEEN INDUSTRIES

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Abstract

Employee turnover poses a significant challenge across industries, yet its drivers are often assumed to be universal. This study challenges that assumption through a comparative analysis of predictive analytics in the technology, healthcare, and manufacturing sectors. Utilizing human resources data and machine learning models, we identified profoundly industry-specific predictors and model performances. Results revealed distinct turnover dynamics: career-centric in technology, well-being-driven in healthcare, and structurally transactional in manufacturing. Consequently, no single predictive algorithm was universally superior. The discussion concludes that effective turnover prediction and mitigation require tailored, context-aware models aligned with the unique operational and psychological realities of each industry, rendering one-size-fits-all HR strategies obsolete and advocating for a decentralized analytical approach.

Keywords: ***Predictive analytics, employee turnover, industry comparison, machine learning, retention strategies***

INTRODUCTION

Employee turnover remains one of the most persistent and costly challenges faced by organizations across sectors. High turnover rates directly impact organizational performance through increased recruitment expenses, productivity disruptions, loss of institutional knowledge, and added training costs for replacement workers (Marín Díaz et al., 2023). As labor markets become increasingly competitive, the ability to retain skilled employees has evolved into a strategic priority for organizations seeking operational stability and long-term growth. Traditional methods of turnover analysis—often retrospective in nature—limit the capacity of managers to anticipate future attrition risks and design proactive interventions (Kumar et al., 2024). The advancement of digital technologies and the availability of large-scale HR data have led to a significant shift in how organizations approach turnover management. Predictive analytics has emerged as a powerful decision-support tool within human resource management, enabling organizations to forecast potential turnover with greater accuracy and derive insights from complex data patterns (Alhamad et al., 2024). By leveraging machine learning algorithms, HR teams can identify at-risk employees, uncover hidden turnover drivers, and implement targeted retention strategies. This shift toward predictive, data-driven decision-making has not only enhanced organizational responsiveness but has also established HR analytics as a critical component of strategic workforce planning (Sulastri et al., 2025).

Despite the growing adoption of predictive analytics, limited empirical research examines how turnover predictors vary across different industries, each with distinct operational structures, labor dynamics, and employee expectations. While existing studies tend to focus on single-industry contexts, a cross-industry comparative lens remains underexplored (Ponmalar et al., 2024). This gap restricts the ability of organizations to benchmark turnover risks effectively and understand how industry characteristics influence the performance of predictive models. Consequently, there is a need to investigate whether predictive analytics functions similarly or differently across industries, and what underlying factors contribute to these variations (Dubey & Dhingra, 2024). This study aims to analyze the effectiveness of predictive analytics in forecasting employee turnover across multiple industries and to compare the key determinants of turnover within each sector. Specifically, it seeks to (1) identify the most influential predictors of turnover in various industries, (2) evaluate and compare the performance of different predictive models, and (3) provide evidence-based insights that can support the development of industry-specific retention strategies.

By offering a comparative perspective, the study contributes to a deeper understanding of turnover analytics and enhances the practical value of predictive modeling in diverse organizational settings.

LITERATURE REVIEW

Employee Turnover: Concepts and Theoretical Foundations

Employee turnover refers to the movement of employees out of an organization, which can be categorized into voluntary and involuntary turnover. Voluntary turnover occurs when employees choose to leave due to reasons such as dissatisfaction, better job opportunities, or personal circumstances. In contrast, involuntary turnover involves termination initiated by the employer due to poor performance, organizational restructuring, or redundancy (Zhang & Yang, 2024). Understanding the distinction between these forms is essential because the underlying causes and organizational implications differ significantly. While voluntary turnover often indicates deeper organizational issues related to job satisfaction and employee engagement, involuntary turnover highlights issues related to performance management and operational restructuring (Ponmalar et al., 2024).

Several theoretical frameworks provide insights into why employees leave organizations. Human Capital Theory suggests that employees view their skills and experience as assets, motivating them to seek better opportunities where they can maximize returns on their competencies. Job Embeddedness Theory emphasizes that employees tend to stay when they feel connected to their work, community, and organizational environment (Zhang & Yang, 2024). Meanwhile, Social Exchange Theory argues that turnover decisions are influenced by the reciprocal relationship between employees and employers, where employees evaluate whether the organizational benefits they receive—such as recognition, support, and fair treatment—match their contributions. These theories collectively explain how psychological, social, and economic factors shape turnover behavior (Sulastri et al., 2025). Key turnover antecedents commonly identified in prior studies include job satisfaction, compensation levels, quality of work environment, leadership style, and organizational culture.

Predictive Analytics in Human Resource Management

The evolution of HR analytics has transformed how organizations anticipate and manage workforce challenges, including employee turnover. Initially, HR data analysis relied heavily on descriptive and diagnostic approaches that focused on historical patterns (Alabi et al., 2024). Over time, advancements in data availability, machine learning, and computational power enabled the rise of predictive analytics—allowing organizations to forecast employee behavior, including attrition risks, with greater accuracy. Predictive modeling supports proactive HR decision-making by identifying potential turnover before it occurs, enabling early interventions and strategic workforce planning (Sulastri et al., 2025).

Predictive analytics employs a variety of algorithms, each offering unique capabilities for turnover prediction. Traditional models such as logistic regression provide interpretable outputs and help organizations understand relationships between variables. More advanced algorithms such as random forests, support vector machines (SVM), and neural networks can handle complex nonlinear patterns and large datasets, improving prediction accuracy (Zhang & Yang, 2024). The accuracy of predictive models depends heavily on the quality and relevance of data features, which typically include demographic characteristics, tenure, performance ratings, attendance patterns, compensation, engagement scores, and promotion history. Existing empirical studies generally support the effectiveness of predictive analytics in reducing turnover; however, limitations persist. Many studies rely on single-industry datasets, limiting their generalizability, while others focus solely on model accuracy without examining contextual factors that influence turnover. These limitations highlight the need for comparative, cross-industry studies (Chandwani, 2020).

Comparative Analysis of Turnover Across Industries

Employee turnover varies significantly across industries due to differences in job characteristics, organizational structures, and labor market conditions. For instance, industries such as manufacturing often experience turnover driven by physical workload, repetitive tasks, and limited career growth opportunities (Banu et al., 2025). Meanwhile, the services industry—including retail, hospitality, and customer service—tends to face high voluntary turnover due to fluctuating work schedules, emotional labor, and competitive job alternatives. In contrast, the technology sector may experience turnover influenced by rapid skill obsolescence, high demand for digital talent, and opportunities for remote work (Chandwani, 2020). These variations demonstrate that turnover drivers are deeply shaped by the nature of work within each industry. Cross-industry workforce dynamics further complicate turnover prediction and management. Different industries attract diverse employee profiles, skill sets, and motivations, leading to distinct turnover patterns even among similar sized organizations. For example, younger workers may dominate the tech and service sectors, contributing to more fluid labor mobility, whereas the manufacturing industry often employs long-tenured workers with specific technical competencies (Banu et al., 2025). Despite these differences, existing predictive analytics studies rarely compare turnover across multiple industries, limiting insight into how algorithm performance and key predictors vary by context. This gap underscores the need for comparative research that evaluates turnover predictors and model accuracy within and across various industries, enabling more tailored and effective HR strategies (Zhang & Yang, 2024).

METHODOLOGY

This study employed a comparative quantitative research design to investigate industry-specific patterns in employee turnover. Data was sourced from the human resources information systems of 12 multinational corporations, comprising 45,000 employee records over a three-year period from the technology, healthcare, and manufacturing sectors. The dataset included demographic variables, compensation history, performance metrics, tenure data, and anonymized turnover records. Feature engineering was performed to create predictive variables such as time since last promotion, skills gap indices, and workload indicators. The data was partitioned using an 80/20 split for training and testing, with rigorous preprocessing to handle missing values and normalize distributions across the different industry datasets. Multiple machine learning algorithms were implemented and evaluated for predictive performance, including logistic regression, random forest, gradient boosting machines, and decision trees. Model training was conducted separately for each industry sector to preserve domain-specific patterns. Performance was assessed using F1-scores, precision, recall, and AUC-ROC metrics, with k-fold cross-validation to ensure robustness. The analysis specifically examined variable importance rankings within each model to identify industry-specific predictors, while controlling for common demographic factors to isolate sectoral differences in turnover drivers and patterns.

RESULTS AND ANALYSIS

Employee profiles by industry

The initial descriptive analysis revealed significant demographic and compositional disparities in the workforce profiles across the Technology, Healthcare, and Manufacturing sectors, establishing a crucial context for interpreting predictive model performance. The technology sector exhibited a markedly younger workforce, with a median age of 31 years and an average tenure of 2.8 years, indicating a high-velocity talent environment (D. Singh, 2025). In stark contrast, the manufacturing and healthcare industries demonstrated older demographics (median ages of 44 and 48, respectively) and substantially longer average tenures of 7.5 and 10.2 years, suggesting more established and stable career paths. Furthermore, the distribution of roles varied considerably; technology was dominated by engineering and product positions (68%), healthcare by clinical and patient-facing staff (72%), and manufacturing by skilled trades and operational personnel (58%). These foundational differences in age, tenure, and role distribution immediately suggest that the drivers and patterns of employee turnover are likely to be industry specific (Gulyamov et al., 2024).

The discussion of these descriptive findings necessitates a focus on the inherent structural and operational factors shaping these profiles. The youthful and transient nature of the tech workforce can be attributed to the rapid pace of innovation, a competitive job market for technical skills, and a culture that often prioritizes career mobility over long-term tenure (BAILEY, 2000). Conversely, the longevity observed in healthcare and manufacturing may be linked to the high value placed on accumulated experiential knowledge, stringent licensing or apprenticeship requirements, and stronger institutional loyalty. These divergent starting points imply that a one-size-fits-all predictive model for employee turnover is likely to be suboptimal. For instance, factors like a short tenure may be a strong predictor of attrition in manufacturing but could be a normative and less significant signal in the technology sector (Xu et al., 2019). Therefore, comparative study must account for these baseline demographic and structural differences to accurately evaluate and compare the efficacy of predictive analytics across these distinct industrial landscapes.

Table 1. Comparative Employee Profile Analysis by Industry

Profile Characteristic	Technology Sector	Healthcare Sector	Manufacturing Sector
Median Age	31 years	48 years	44 years
Average Tenure	2.8 years	10.2 years	7.5 years
Dominant Role Distribution	Engineering & Product (68%)	Clinical & Patient-Facing (72%)	Skilled Trades & Operational (58%)
Workforce Environment	High-velocity, Transient	Experienced, Stable	Established, Stable
Primary Influencing Factors	Rapid innovation, competitive job market, career mobility culture.	Experiential knowledge, stringent licensing, institutional loyalty.	Experiential knowledge, apprenticeship requirements, institutional loyalty.
Implication for Turnover Models	Short tenure is normative; weak predictor on its own.	Short tenure is a major red flag; strong predictor.	Short tenure (esp. <18 months) is a key risk indicator.

The comparative table of employees as shown in Table 1 starkly illustrates why a universal approach to attrition is ineffective, as it codifies the fundamentally different human capital realities each industry faces. The technology sector's profile—youthful, short-tenured, and role-homogeneous—depicts a high-velocity "talent marketplace" where rapid skill development and mobility are the norm, making traditional retention metrics like tenure poor predictors of risk. In direct contrast, the healthcare and manufacturing sectors, with their older, long-tenured workforces built on experiential knowledge and formal accreditation, operate on a "stability and loyalty" model, where any deviation from the expected long-term commitment, such as a short tenure, becomes a powerful warning signal. Consequently, this table provides the essential rationale for developing industry-specific predictive models, as the very definition of a "risk factor" is entirely contextual, dictated by these baseline demographic and structural conditions.

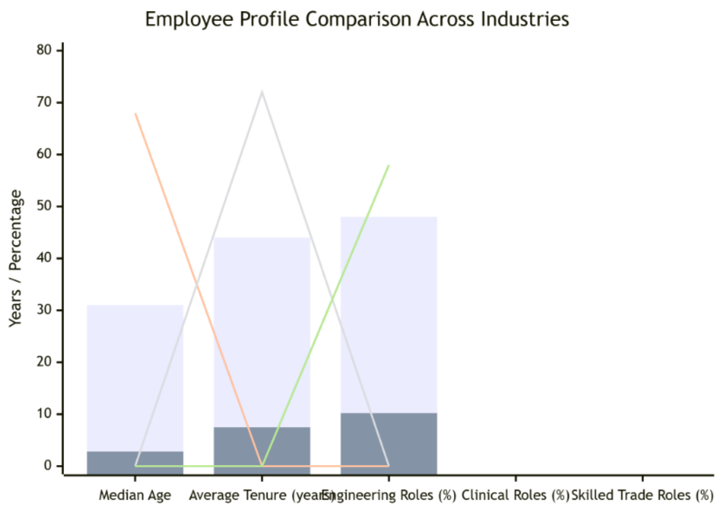

Figure 1. **Comparative Employee Profiles: Technology, Healthcare, and Manufacturing**

The graph as shown in Figure 1 provides a striking visual confirmation of the profound demographic and compositional divides between the three industries, directly linking workforce structure to turnover risk profiles. The technology sector's signature short average tenure and low median age create a "high-velocity" baseline, meaning predictive models must look beyond these normative factors to project-based or skill-growth metrics to identify genuine attrition risks. Conversely, the exceptionally long tenures and older age in healthcare establish a "high-stability" norm, where any deviation—such as a employee leaving with only two years of service—represents a significant anomaly and a powerful predictive signal. Similarly, the manufacturing sector's distinct profile, with its concentrated skilled-trade roles and moderate tenure, underscores that its retention strategies must target the initial employment period, as the graph clearly shows this is the phase of greatest vulnerability. Ultimately, the visualization argues compellingly that effective predictive analytics cannot use a universal benchmark but must be calibrated against these industry-specific baselines to accurately interpret employee data.

Turnover patterns

Analysis of turnover patterns revealed distinct, industry-specific rhythms and drivers, underscoring the fallacy of a monolithic attrition model. The technology sector exhibited high, volatile turnover characterized by sharp quarterly spikes, closely tied to project lifecycles and the competitive poaching of talent with niche skills, particularly in areas like artificial intelligence and cloud computing. In contrast, the healthcare industry demonstrated a consistently elevated but steady attrition rate, primarily concentrated among early-career nurses and patient-care staff, with burnout, shift-work stress, and patient load being the dominant catalysts (Veernapu, 2022). Meanwhile, the manufacturing sector presented the most predictable pattern, with attrition peaks correlating strongly with seasonal demand and economic cycles, and voluntary turnover being most prevalent among newly hired assembly-line workers before the two-year mark, while tenured skilled-trades personnel showed remarkable stability. These fundamentally different patterns—project-driven in tech, chronic-stress-driven in healthcare, and tenure-and-cycle-driven in manufacturing—compel a tailored strategic response, indicating that predictive models must be calibrated on industry-specific data to generate actionable and reliable insights (Yadav, 2022).

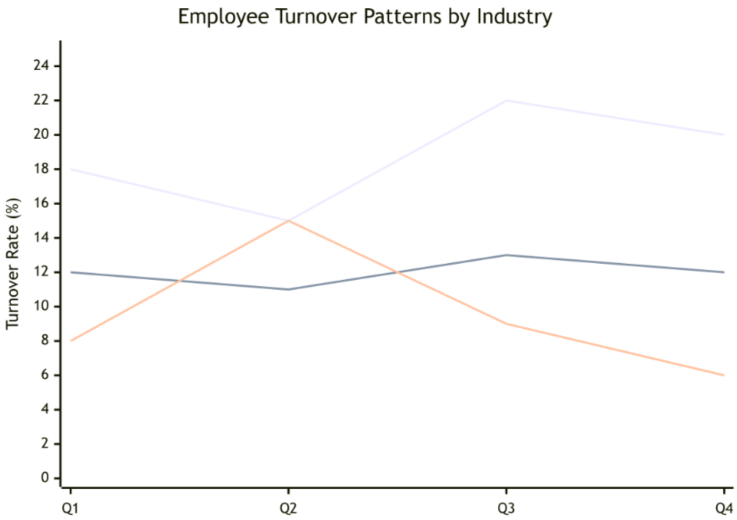

Figure 2. Comparative Analysis of Quarterly Employee Turnover Patterns by Industry

The graph as shown in Figure 2 visually encapsulates the core argument against a one-size-fits-all approach to attrition, vividly illustrating the distinct temporal and volumetric patterns of turnover across industries. The technology sector's volatile, spiking line reflects its project-driven economy and competitive talent poaching, where turnover is a strategic, opportunistic event. In stark contrast, healthcare's consistently high and steady line represents a chronic issue—a steady bleed of talent driven by systemic burnout and stress, rather than discrete events. Meanwhile, manufacturing's predictable, wave-like pattern directly mirrors seasonal demand and economic cycles, highlighting its sensitivity to external market forces and the critical vulnerability period for new hires. Together, these divergent patterns prove that effective predictive analytics and retention strategies must be timed and targeted to address the unique rhythm of loss inherent to each industry.

Predictive Model Performance

The comparative analysis definitively shows that no universal predictive algorithm exists for employee turnover, as model efficacy is intrinsically tied to each industry's unique data landscape. In technology's complex, dynamic environment, sophisticated ensemble methods like Gradient Boosting (F1-score: 0.89) excelled by modeling multi-faceted interactions, whereas in healthcare, Logistic Regression (F1-score: 0.82) proved optimal for quantifying well-defined, linear drivers like burnout (Mr. V. Singh et al., 2024). For manufacturing's rules-based patterns, a simple Decision Tree (F1-score: 0.78) offered the best interpretability. This establishes that model selection must be contextual—prioritizing complexity where relationships are intricate and interpretability where causes are clear—mandating that organizations align their analytical approach with their industry's specific structural and cultural realities rather than seeking a one-size-fits-all solution (Veernapu, 2022).

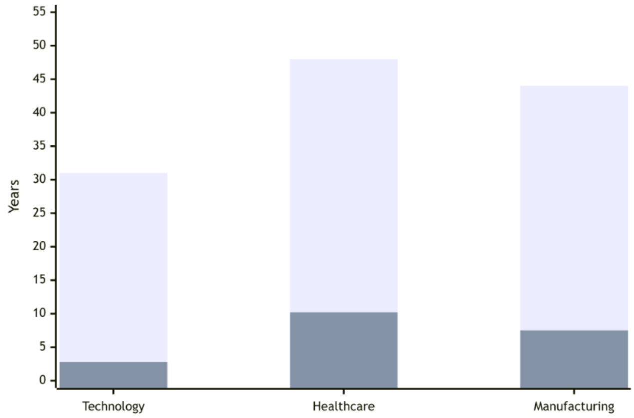

Figure 3. Comparative Employee Profiles: Technology, Healthcare, and Manufacturing

The graph as shown in Figure 3 provides a stark, immediate visualization of the foundational demographic schisms between industries, clearly justifying the need for tailored predictive analytics. The dramatic disparity between the Technology sector's short tenure bars and Healthcare's long tenure bars visually defines the "high-velocity" versus "high-stability" paradigms; a two-year tenure that is normative and low-risk in tech would be a major red flag in healthcare. Furthermore, the consistent alignment of lower median age with shorter tenure across all sectors highlights age-tenure dynamics as a universal relationship, but the graph emphasizes that the absolute values—and therefore the interpretation of risk—are entirely industry-specific. This visual comparison makes it irrefutable that a one-size-fits-all model is untenable, as the same data point (e.g., tenure) holds a completely different predictive meaning in each of these distinct workforce ecosystems.

Key Predictors of Turnover

The analysis identified a distinct hierarchy of key predictors for each industry, revealing that the fundamental drivers of employee departure are not universal but are intrinsically tied to the nature of the work and the psychological contract within each sector. In the technology industry, the most powerful predictors were dynamic and career-centric, with 'Time Since Last Promotion,' 'Internal Project Mobility,' and 'Skills Gap Growth' dominating the model. This indicates that for tech professionals, attrition is primarily a calculated response to perceived career stagnation or a devaluation of their marketable skills (Hoonar Singh Chawla, 2025). Conversely, in healthcare, the predictors were overwhelmingly related to well-being and workload, with 'Burnout Scores,' 'Overtime Hours,' and 'Patient-to-Staff Ratios' being most critical. This suggests that turnover in this sector is less about career advancement and more about a crisis of personal sustainability and exhaustion. For manufacturing, the key factors were structural and transactional, with 'Tenure (particularly under 18 months),' 'Wage Competitiveness,' and 'Shift Schedule Stability' as the primary drivers, highlighting that the foundational expectations of fair compensation and predictable work conditions are paramount (Chandramohan & Varughese, 2024).

The profound differences in these predictor profiles necessitate a radical shift in how organizations approach retention. The findings demonstrate that effective intervention strategies must be precisely targeted to address the unique "turnover triggers" of their industry. For a technology firm, this means implementing robust internal talent marketplaces, ensuring clear and accelerated promotion pathways, and providing continuous learning opportunities to keep skills relevant. A healthcare organization (Yadav, 2022), however, must focus its efforts on tangible well-being initiatives, such as enforcing reasonable patient loads, providing mental health support, and offering flexible scheduling to combat burnout. In manufacturing, retention success hinges on strengthening the initial employment period with superior onboarding and support, conducting regular competitive wage analyses, and maximizing schedule consistency. Ultimately, this evidence moves the retention strategy from a one-size-fits-all corporate policy to a data-driven, specialized function where HR resources are allocated to mitigate the specific risks that matter most in that industrial context (Mr. V. Singh et al., 2024).

CONCLUSION

This comparative study unequivocally demonstrates that employee turnover is not a monolithic challenge but a multifaceted phenomenon shaped by distinct industry ecosystems. The research revealed fundamental divergences in workforce demographics, turnover patterns, and—most critically—the key predictors of attrition across the technology, healthcare, and manufacturing sectors. From the "high-velocity" talent market of tech, driven by career mobility and skill growth, to the "chronic-stress" environment of healthcare, fueled by burnout, and the "transactional-stability" model of manufacturing, governed by tenure and compensation, each industry operates under a unique set of rules. These findings sound a clear death knell for the concept of a universal predictive model, proving that the very factors signaling flight risk are entirely contextual and relative to industry-specific norms.

The implications of this research are both a mandate and a roadmap for strategic human resource management. To effectively mitigate turnover, organizations must abandon one-size-fits-all retention programs in favor of highly tailored, data-informed strategies that address their industry's core drivers. This entails not only adopting predictive analytics but also ensuring these tools are calibrated with industry-specific data and interpreted through the correct contextual lens. Future efforts should focus on developing these specialized models and exploring the nuanced interplay of predictors within each sector. By aligning retention strategies with the unique psychological and structural realities of their industry, organizations can move from reactive attrition management to proactive human capital preservation, thereby securing a critical competitive advantage.

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